

Predictive Pre-cooling of Thermo-Active Building Systems with Low-Lift Chillers. Part I: Control Algorithm

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ABSTRACT

This paper describes a predictive control algorithm that optimizes the control of a low-lift chiller, a chiller run at low pressure ratios, serving a thermo-active building system such as a radiant concrete-core slab. Prior research on control and optimization methods for pre-cooling buildings are reviewed. A predictive control algorithm is presented that incorporates a model of chiller performance at low pressure ratios, data-driven models of zone and thermal mass temperature response, and forecasts of outdoor temperatures and internal loads. The energy consumption of the cooling system, including chiller compressor, condenser fan, and chilled water pump energy consumption is minimized over a 24-hour look-ahead moving horizon. A generalized pattern-search optimization over compressor and condenser fan speed is performed to identify optimal chiller control schedules at every hour. The predicted temperature response of the thermo-active building system is especially important as it is directly related to chilled water return temperature and refrigerant evaporating temperature, and consequently to the efficiency of the chiller at each time step.

INTRODUCTION

Low-lift cooling combines variable capacity chillers operated at low pressure ratios with predictive pre-cooling of thermal energy storage (TES), such as thermo-active building systems (TABS). Low-lift cooling systems offer the potential for significant cooling energy savings in many climates and many building types, on average as much as 60 to 70 percent cooling energy savings relative to conventional variable air volume (VAV) systems in standard buildings (Armstrong et al 2009a, Armstrong et al 2009b, Katipamula et al 2010). This paper will describe the development of an important control element for low-lift cooling with TABS, a model-based predictive control algorithm that optimizes control of a low-lift chiller identifies to pre-cool TABS thermal storage.

BACKGROUND

Significant improvement in the coefficient of performance (COP) of variable capacity chillers can be achieved by operating them at low pressure ratios (Gayeski et al 2010). Typically, low pressure ratio operation is difficult to achieve because chillers operate during the day, when outdoor air temperatures are high, and with chilled water temperatures around 6.7°C (~44°F), such that condensing temperature is necessarily high and evaporating temperatures are low.

In a low-lift cooling system, predictive pre-cooling of thermal storage is utilized to spread the cooling load over a day and shift loads to the night and early morning hours, reducing condensing temperature by reducing the outdoor air temperature present during chiller operation and allowing more part-load operation. Combining this approach with a radiant cooling system, such as a concrete-core radiant TABS, allows for operation at higher chilled water temperatures and thus higher evaporating temperatures. Combining these two strategies allows a low-lift chiller to operate at part-load under low-lift conditions for more of the day, while still meeting cooling loads by pre-cooling TABS, which in turn passively cools thermal zones during occupied periods.

Past research has shown that low-lift cooling systems have large energy savings potential across a range of climates and building types. The estimated energy savings of low-lift cooling over typical variable air volume (VAV) systems common in the United States with conventional two-speed chillers are large.

For typical buildings, cooling energy savings range from 37 to 84 percent depending on the climate and building type [Katipamula et al 2010]. In high performance buildings, savings range from -9 to 70 percent of cooling energy consumption. The low end demonstrates that low-lift radiant cooling may not be attractive for high performance buildings in mild climates where free cooling through economizers is available. Although low-lift cooling is a relatively new concept from a systems integration viewpoint, the component cooling strategies, constituent systems and pre-cooling control strategies have a long history of research, development and implementation.

One key to achieving low-lift cooling is a predictive control algorithm which determines the optimal control of the low-lift chiller at each hour over a day to pre-cool thermal storage, such as TABS. The following section will review the significant past research on the use of pre-cooling and predictive control of cooling equipment to shift loads, reduce peak demand, reduce operating costs and energy consumption, and increase chiller efficiency. Recent research on control strategies for TABS will also be reviewed.

LITERATURE REVIEW

Past research on predictive control of cooling systems to pre-cool TES has covered a broad range of topics. These topics include pre-cooling of active TES such as ice-storage or stratified chilled water tanks, passive storage such as building thermal mass, and thermo-active TES such as TABS. Traditional, passive TES applications use conventional cooling equipment such as VAV systems to sub-cool zones and thereby pre-cool building thermal mass. TABS thermal storage utilizes pipe embedded in the building structure to actively charge building thermal mass, which then absorbs heat from occupied zones over the day subject to the temperature response of both the zone and TABS systems. This section will first review predictive pre-cooling control with conventional cooling equipment, such as pre-cooling with VAV systems, followed by a review of controls applied to TABS systems.

Passive pre-cooling of building thermal energy storage

In simplified pre-cooling strategies for passive TES a schedule of zone temperature setpoints for conventional VAV or other air handling systems are determined that reduce peak power demand or minimize energy or costs. Rabl and Norford (1991) used a first-order thermal resistance-capacitance (RC) model of zone temperature response to determine the duration of pre-cooling and a temperature setpoint schedule to reduce peak demand. Snyder and Newell (1990) use a first order thermal RC model to find optimal control strategies for cooling cost minimization to achieve load shifting and demand limiting. The optimization determines pre-cooling start time, the duration of time the zone is allowed to float until it reaches maximum allowed temperature, and the thermal mass temperature at the start of the occupied period.

Keeney and Braun (1997) applied a constant zone temperature setpoint schedule to pre-cool a large commercial building with conventional air handling units and demonstrated potential for \$25,000 savings per month in the peak cooling season. Braun and Lee (2006, 2008a, 2008b, 2008c) have extensively researched the use of optimal zone temperature setpoint trajectories to pre-cool small commercial buildings with conventional air handling systems to limit peak demand. Power consumption of the cooling system is assumed to be a linear function of the outdoor temperature. These approaches are relatively simple to implement in existing building automation systems, but make gross assumptions about cooling system power consumption as a function of operating conditions.

Henze et al (1997, 2004, 2005) developed an optimal chiller control algorithm to minimize cooling costs using passive TES, such as building thermal mass, and active TES, such as ice-storage, under a dynamic utility rate structure. However, they assume constant chiller coefficient of performance (COP) for chilled water and ice-making operation, independent of outdoor temperature and supply air or zone air temperature. The problem is thus split into two separate optimizations: one in which zone air temperature set points are optimized to minimize cooling load (where power consumption is assumed to be directly proportional to cooling load); and another in which an optimal charging and discharging schedule for active TES is determined to meet a total daily cooling calculated from the passive storage optimization.

By separating the passive and active TES optimization problems and treating chiller efficiency as a constant, the passive TES optimization remains a linear problem in which zone temperatures are adjusted to minimize cooling load under an assumed active TES charging and discharging schedule. This allows for the application of a quasi-Newton optimization method to the passive TES problem, coupled with a dynamic programming optimization for the active TES problem.

Additional research by Henze and others investigated the impact of forecasting uncertainty on the predictive optimal control of active and passive TES (Henze et al 1999), the impact of adaptive thermal comfort criteria and peak weather conditions (Henze et al 2007a), and optimal control in the presence of energy and demand charges (Henze et al 2008). Henze et al (2007b) investigated the sensitivity of optimal TES control to utility rate structure, occupancy schedules, internal gains, the amount of building thermal mass, temperature set-points, and climate conditions. Henze et al (2010) attempted to create near-optimal control trajectories using simplified relationships between optimal setpoints and measured variables for specific climates and utility rate structures, such as outdoor air temperature. They found that a simplified control relationship was not always achievable.

Liu and Henze (2004, 2006a, 2006b) applied simulated reinforcement learning to optimize pre-cooling of active and passive TES using a hybrid approach incorporating model-based control with reinforcement learning. This hybrid approach to pre-cooling control achieved 8.3 percent cost savings in an experiment at the Iowa Energy Resource Station relative to no pre-cooling control, but achieved only modest savings relative to other pre-cooling strategies.

The focus of all of this prior research is on the use of conventional cooling systems, such as VAV systems, to perform passive pre-cooling of zones and to coordinate passive pre-cooling with active TES systems. The research above does not significantly take into account the temperature and load dependent performance of chillers, which greatly influence the energy performance of pre-cooling strategies.

Incorporating chiller performance models into pre-cooling control optimization

A more rigorous approach, but one that requires significantly more information, model complexity, and computational resources and is more difficult to implement optimizes control schedules using models of zone temperature response *and* load-dependent cooling plant power consumption. Braun (1990) takes an approach similar to that developed in this research. An optimization is presented that uses a comprehensive room transfer function (CRTF) model (Seem 1987, Armstrong et al 2006a) of zone temperature response; a cooling plant power model as a function of chilled water loop load, outdoor wet-bulb temperature, and supply air temperature difference; and an air handler power consumption model. The zone temperature setpoints are optimized over a 24-hour look ahead to minimize energy cost, which depends on the zone temperature trajectories and resulting power consumption of the air handlers and chiller plant equipment. Forecasts of solar loads, internal loads and outdoor climate conditions are included in the model of zone temperature response. A direct search method to optimize zone temperature set points that minimize electric costs over a 24 hour period (Braun 1990).

Kintner-Meyer and Emery (1995) present a pre-cooling optimization in which the temperature and load dependent performance of chillers is taken into account for pre-cooling both passive TES and active TES in the form of ice or chilled water storage. An optimization over 24 hours is performed in which air flow rate, chiller part load fractions for two separate chillers, and charging and discharging rates for active TES are determined. They model cooling plant power consumption with a chiller efficiency that is a function of part load fraction, outdoor wet-bulb temperature and chilled water temperature.

Armstrong et al (2009a, 2009b) present an approach in which physics-based models of variable capacity chillers and CRTF-based temperature response models of zones are used to optimize the control of a low-lift chiller serving idealized TES. This work focuses primarily on optimizing the performance of the low-lift chiller, which when allowed to operate at low part-load, and thus low-lift conditions, is significantly more efficient (Armstrong et al 2009a, Gayeski 2010). Applying predictive pre-cooling to TES served by variable capacity low-lift chillers shows the potential for significantly more energy and cost

savings relative to prior approaches to pre-cooling with conventional cooling equipment (Armstrong et al 2009b).

Pre-cooling thermo-active building systems with predictively controlled low-lift chillers

This paper seeks to integrate the low-lift pre-cooling control strategies developed in Armstrong et al (2009a, 2009b), Katipamula et al (2007, 2010) with TABS, in which concrete-core radiant slabs are used as TES. TABS are particularly appropriate for pre-cooling because they can be actively charged by circulating moderate temperature chilled water through the concrete-core, but have high thermal storage efficiency and no additional transport energy costs like passive storage. TABS provide an inherent delay between active charging of the TES and passive discharge to the zones which must be incorporated into the predictive pre-cooling control schedule.

Caution must be exercised in the design and control of TABS, as in any radiant cooling system, because of condensation issues and cooling capacity limitations. TABS are most effective in buildings with high performance envelopes and moderate loads (Brunello et al 2003, Lehmann et al 2007). They also require careful humidity control, such as through a dedicated outdoor air system (DOAS), or chilled water and/or concrete surface temperature control to prevent condensation.

Research on control strategies for TABS has a relatively short history. Chen (2001, 2002) developed a predictive control algorithm to minimize cost or energy consumption of a radiant concrete-core floor heating system. Chen utilizes a detailed temperature response model of the zone and concrete-core slab, but, similar to other work in which chiller efficiency is constant, the efficiency of the heating plant is not weather dependent or dependent on past heating rates. Applying a similar approach to pre-cooling TABS with low-lift chillers would not sufficiently account for the load and temperature dependent performance of a low-lift chiller.

Olesen et al (2002) presented a study of control concepts that may be applied to concrete-core TABS providing both heating and cooling. These concepts included: “time of operation” control in which the concrete-core was only pre-cooled outside of occupied hours and a ventilation system was used during occupied hours; “intermittent operation of circulation pump” control in which the circulation pump for the concrete-core cooling system was shut off and turned back on at periodic intervals to save pumping energy; and “control of water temperature” control in which a variety of water temperature control strategies were investigated. Olesen determined that the best comfort and energy performance was achieved by a water temperature control strategy in which supply or average water temperature was controlled based on outdoor temperature.

Further advances in control for TABS incorporated room temperature feedback and pulse-width modulated (PWM) intermittent operation of the water circulation pump, combined with supply water temperature control (Gwerder et al 2007, Gwerder et al 2009). Room temperature feedback allows for better comfort control and easier tuning of the control algorithm. Gwerder et al (2009) use a first order thermal RC model of TABS to determine an optimal PWM schedule for operation of the circulation pump. Intermittent PWM control allows for dynamic evaluation of whether and how long the circulation pump should operate with a given supply water temperature to maintain comfort but reduce pumping energy.

None of the TABS control methods described above take into the account the temperature and load dependent efficiency of a chiller providing chilled water to a concrete-core cooling system. Furthermore, existing TABS control strategies do not fully leverage zone temperature response models to determine an optimal control strategy. This paper presents a model-based predictive control algorithm for TABS that incorporates temperature response models of the zone and concrete core, a temperature and load dependent chiller efficiency model, and optimization of chiller compressor and condenser fan control to minimize energy consumption of the cooling system.

LOW-LIFT PREDICTIVE PRE-COOLING CONTROL FOR THERMO-ACTIVE BUILDING SYSTEMS

A framework for optimal control of low-lift chillers to pre-cool TABS will be developed that determines an optimal chiller control schedule for each hour, looking 24 hours-ahead. The goal of the control algorithm is to minimize cooling energy consumption (or cost) over a 24-hour period by controlling chiller compressor speed and condenser fan speed in a near optimal way. This near-optimal control function incorporates a model of variable-capacity chiller power consumption, presented in Gayeski et al (2010), to account for the temperature and load, or control variable, dependent chiller power consumption and cooling rate. It also incorporates a CRTF temperature response model (Seem 1987, Armstrong et al 2006b) to predict zone temperature response, and a transfer function model of concrete-core temperature response. The optimization function can be described mathematically as follows:

$$\operatorname{argmin}_{\omega} J = \sum_{t=1}^{24} (r_t P_t \cdot 1 + \varphi PO_t + PE_t) \quad (1)$$

In equation (1), the objective function J is the sum over 24 hours of the cooling system energy consumption (or cost), a penalty for operative temperatures outside of a comfort range, and a penalty for chiller evaporating temperatures below a low temperature threshold. The variables are as follows:

- r_t is a weighting factor for system energy consumption. r_t can be set to one to minimize energy consumption or to a utility pricing schedule to minimize cost,
- P_t is the power consumption of the cooling system during the hour t , which is multiplied by one hour to calculate energy consumption over the hour,
- φ is a weighting factor that penalizes excursions from an allowable operative temperature region,
- PO_t is a penalty as a function of zone operative temperatures relative to comfortable operative temperatures at time t ,
- PE_t is a penalty as a function of chiller evaporating temperature relative to a low temperature threshold, which has been included to prevent control predictions that would cause the chiller to freeze.

Chiller performance model

The cooling system energy consumption P_t includes the energy consumption of the water circulation pump and the low-lift chiller serving the TABS and is given by the following equation:

$$P_t = P_{\text{pump},t} + P_{\text{chiller},t}(T_{x,t}, T_{e,t}, \omega_t, f(T_{x,t}, T_{e,t}, \omega_t)) \quad (2)$$

- $P_{\text{pump},t}$ is the energy consumption of the chilled water pump over the hour t . For this research, the chilled water pump is assumed to be operated at constant speed while the chiller is operating and off otherwise. Thus, its power consumption is either zero if the chiller is off or a constant while running.
- $P_{\text{chiller},t}$ is a regression-based curve-fit model of the power consumption of a low-lift chiller as a function of outdoor air temperature T_x , evaporation temperature T_e , compressor speed ω , and fan speed f at hour t .

The chiller power consumption, $P_{\text{chiller},t}$, is shown in equation (3). It is a function of evaporating temperature T_e , outdoor air temperature T_x , compressor speed ω , and fan speed f .

$$P_{\text{chiller},t} = \left(\begin{array}{l} c_1 + c_2 T_e + c_3 T_x + c_4 \omega + c_5 T_e^2 + c_6 T_x^2 + c_7 \omega^2 + c_8 T_e \cdot T_x + c_9 T_e \omega + c_{10} T_x \omega + \\ c_{11} T_e^3 + c_{12} T_x^3 + c_{13} \omega^3 + c_{14} T_e^2 T_x + c_{15} T_e^2 \omega + c_{16} T_x^2 T_e + c_{17} T_x^2 \omega + \\ c_{18} \omega^2 T_e + c_{19} \omega^2 T_x + c_{20} T_e \cdot T_x \omega + c_{21} f + c_{22} f^2 + c_{23} f \cdot T_e + c_{24} f \cdot T_x + c_{25} f \omega \end{array} \right)_t \quad (3)$$

The coefficients of this model can be determined for variable capacity chillers through regression based on physics-based performance simulations or based on measurements of actual chiller performance. Methods for developing empirical curve-fit models from measured data for this type of chiller performance

model are presented by Gayeski et al (2010). Models of the same form as equation (3), but with different coefficients, can be identified to represent cooling capacity $QC_{\text{chiller},t}$ and electric input ratio $EIR_{\text{chiller},t}$ as a function of T_e , T_x , ω , and f (Gayeski et al 2010). Only two of these three curves, one for cooling rate $QC_{\text{chiller},t}$ and for power consumption $P_{\text{chiller},t}$ are needed in the pre-cooling optimization algorithm presented in this paper. This will be explained in more detail below.

The fan speed variable can be eliminated from equations (2-3) by choosing the optimal fan speed at a given T_e , T_x , and ω . By taking a partial derivative of the $EIR_{\text{chiller},t}$ curve with respect to f , the optimal fan speed f_{opt} can be determined that provides the greatest chiller efficiency for a given set of T_e , T_x , and ω . This optimal fan speed is given by the following equation:

$$f_{\text{opt}} = (c_{21} + c_{23}T_e + c_{24}T_x + c_{25}\omega) / 2c_{22} \quad (4)$$

Zone and concrete core temperature response models

The presence of T_e in equations (2-4) requires that evaporating temperature be predicted at each time step of the 24-hour optimization. The prediction of T_e may be based on engineering calculations or data-driven models relating the chilled water supply or return temperatures and the chilled water flow rate to chiller evaporating temperature at specific operating conditions. For a given chiller with a fixed evaporator water flow rate, a fixed compressor speed, and a fixed closed loop superheat control algorithm, T_e is directly related to chilled water return temperature T_{chwr} . Thus, evaporating temperature and chiller power consumption can be predicted if T_{chwr} can be predicted and the operating state of the chiller is known.

In Gayeski (2010) it was shown that T_{chwr} can be predicted based on past cooling rates, return water temperatures, and concrete-core temperature T_{cc} using a simple N^{th} order model for T_{chwr} as a function of cooling rate QC_{chiller} and concrete-core temperature T_{cc} as shown in equation (5):

$$T_{\text{chwr},T} = \sum_{t=T-N}^T a_t T_{\text{chwr},t} + \sum_{t=T-N}^T b_t T_{\text{cc},t} + \sum_{t=T-N}^T c_t QC_{\text{chiller},t} \quad (5)$$

This N^{th} order transfer function model is equivalent to an N^{th} order thermal RC model.

Temperature CRTF models (Seem 1987, Armstrong et al 2006b) of zone temperature response can be used to predict both the zone operative temperature and concrete-core temperature (Gayeski 2010). These models are discrete-time transfer function representations of the one-dimensional heat diffusion equation governing heat transfer through each surface of a zone. Physical constraints on the coefficients of temperature CRTF models have been presented by Armstrong et al (2006b) that provide causal, stable and more physical models. For use in the low-lift cooling predictive pre-cooling of TABS, the operative temperature T_o is predicted from the following temperature CRTF model:

$$T_{o,T} = \sum_{t=T-M}^{T-1} m_t T_{o,t} + \sum_{t=T-M}^T n_t T_{x,t} + \sum_{t=T-M}^T o_t T_{a,t} + \sum_{t=T-M}^T p_t QI_t + \sum_{t=T-M}^T q_t QC_{\text{chiller},t} \quad (6)$$

The temperature of the concrete-core T_{cc} can be predicted from a similar temperature CRTF model:

$$T_{\text{cc},T} = \sum_{t=T-M}^{T-1} d_t T_{\text{cc},t} + \sum_{t=T-M}^T e_t T_{x,t} + \sum_{t=T-M}^T f_t T_{a,t} + \sum_{t=T-M}^T g_t QI_t + \sum_{t=T-M}^T h_t QC_{\text{chiller},t} \quad (7)$$

In equations (6-7), T_o is the zone operative temperature, T_{cc} is the concrete-core temperature, T_x is the outdoor air temperature, T_a is an adjacent zone temperature (in this case only one adjacent zone has been considered), QI is the internal heat load, and QC_{chiller} is the cooling rate delivered by the low-lift chiller. The lower case letters are weighting coefficients for each variable at each time step into the past which determine the temperature response.

The operative temperature $T_{o,T}$ and concrete-core temperature $T_{\text{cc},T}$ at the next hour T are predicted from measurements of each variable at the previous hours $T-M$ to $T-1$, in addition to forecasts at hour T of

outdoor air temperature T_x , adjacent zone air temperature T_a , internal heat rate QI , and chiller cooling rate QI_{chiller} . The optimization determines the chiller cooling rate which minimizes power consumption but maintains thermal comfort conditions. The choice of chiller compressor speed at each hour of a 24 hour look ahead control schedule, along with the historic data and predicted data up to a given hour in the schedule, determines the zone operative temperature, concrete-core temperature, chilled water temperature, evaporating temperature and chiller power consumption and cooling rate at each hour of the next day. The chiller power consumption along with the operative temperature and evaporating temperature penalties in the objective function are minimized to determine the optimal compressor speed and condenser fan speed control schedule.

Operative temperature comfort penalty

The second term in equation (1) accounts for zone operative temperature constraints. Without this term the minimal power consumption would equal zero at all times, but thermal comfort conditions would not be maintained. The operative temperature penalty is given by the following equation:

$$\phi PO_t = \begin{cases} \varphi((T_{o,\min} + 0.5) - T_{o,t})^2 & T_{o,t} \leq T_{o,\min} + 0.5 \\ 0 & T_{o,\min} + 0.5 < T_{o,t} < T_{o,\max} - 0.5 \\ \varphi(T_{o,t} - (T_{o,\max} - 0.5))^2 & T_{o,t} \geq T_{o,\max} - 0.5 \end{cases} \quad (8)$$

In equation (8), $T_{o,\min}$ and $T_{o,\max}$ are the minimum and maximum allowable operative temperatures and $T_{o,t}$ is the operative temperature at the current time t . Operative temperatures within half a degree Celsius of the comfort bounds are penalized, with a quadratically increasing penalty moving away from the comfort bounds. The quadratic dependence is a convenient choice, because the derivative of the function is continuous, however other comfort penalty functions are possible.

The weight φ in the operative temperature penalty function equates operative temperature excursions outside of a comfort range to power consumption. For example, a choice for φ greater than $P_{\min,\text{chiller}}/1^\circ\text{C}$, where $P_{\min,\text{chiller}}$ is the chiller power consumption at its lowest speed, will cause an operative temperature penalty greater than the cost of running the chiller that hour when operative temperature exceeds comfort bounds by one half of a degree Celsius. The operative temperature range can be chosen to reflect thermal comfort conditions in ASHRAE 55 (ASHRAE 2007a), with allowable operative temperatures of about 19.4 to 25°C (67 to 77°F) based on the summer (or 0.5 clo) operative temperature comfort range.

Chiller operational constraint penalty

The last term in the objective function, PE_t is a constraint on the evaporating temperature T_e of the refrigerant. T_e is constrained to prevent freezing of the chiller, or more precisely to prevent *predictions* of infeasible cooling rates at future time steps that would cause the chiller to freeze. The constraint on T_e can be chosen conservatively to prevent T_e below one degree Celsius, with an infinite penalty for evaporating temperatures below the threshold (or replaced by a very high penalty value in computer code). This choice was made to prevent any freezing, even if just locally on a heat exchanger surface, on the water-side of the chiller. The resulting evaporating temperature penalty function is as follows:

$$PE_t = \begin{cases} 0 & T_e(T_{\text{chwr},t}) > T_{e,\min} \\ \text{INF} & T_e(T_{\text{chwr},t}) \leq T_{e,\min} \end{cases} \quad (9)$$

An alternative approach would be to apply the evaporating temperature constraint as a limitation on system operation. Penalizing the evaporating temperature in the objective function is convenient, because it eliminates the need to include additional constraints to the curve-fit chiller model shown in equation (3). Similarly, the T_o penalty function could have been incorporated as a constraint on operative temperatures. However, this approach does not allow for a simple tradeoff between comfortable temperatures and power

consumption, which is useful for allowing some overheating as the optimization searches for the best chiller control schedule.

Predictive pre-cooling control optimization method

In the previous section, an objective function was defined for the pre-cooling control algorithm which contains penalties for power consumption of the cooling system, operative temperatures outside of a comfort region, and low evaporating temperatures. The goal of this section is describe how the objective function, equation (1) is minimized to optimize the chiller control over a 24 hour look ahead schedule.

Each hourly cost component of the objective function must be evaluated sequentially from hour one to 24. This is a result of the fact that P_t , PO_t , and PE_t all depend on past values of both the independent and dependent variables in equations (2-9). As the simulation for each optimization evaluation moves from current time to the next time step, t_{sim} , the choice of compressor speed at time t_{sim} depends on previous values of compressor speeds at times $t < t_{sim}$ and will affect the choice of future compressor speeds at times $t > t_{sim}$. A given compressor speed at time step t_{sim} will determine $QC_{chiller}$. Along with predicted outdoor air temperature T_x , adjacent zone air temperature T_a , and internal loads QI at time t_{sim} , and their histories, it will also determine f_{opt} , T_o , T_{cc} , T_{chwr} , and T_e at the next time step in the simulation which are required to evaluate the t_{sim} term of the objective function and to calculate the required variables for the next time step.

The power consumption and cooling rate of the chiller are non-linear functions of T_x , T_e , and ω (with fan speed f_{opt} determined by these three variables). Consequently, the power consumption of the chiller at the current simulation time depends non-linearly both on the choice of compressor speed at the current time t_{sim} and previous choices of compressor speeds which determine the concrete-core temperature T_{cc} and ultimately evaporating temperature T_e at t_{sim} . Furthermore, when the compressor speed is zero the cooling system is off and the power consumption and cooling rate become zero discontinuously, because the compressor cannot run at arbitrary speeds down to zero Hertz.

As a result of these discontinuities and non-linearities in the objective function, an optimization method suitable for non-linear objective functions is used. A simple form of direct search, called a generalized pattern search was elected as an optimization method (Torczon 1997, Lewis et al 1999, Lewis et al 2000, Audit and Dennis 2003). Pattern search is essentially a grid search on the independent variable, compressor speed, where an initial guess is made and points in a grid around that guess are evaluated for a more optimal solution. Pattern search continues to search the grid until no more optimal solutions can be found, at which point it reduces the size of the grid and searches locally around the current most optimal solution identified by the larger grid.

The pattern search seeks optimal compressor speeds for every hour t in a 24-hour-ahead schedule of chiller operation. The search space is a 24-dimensional space, where each dimension represents a possible chiller compressor speed at each hour of the next 24-hours. The compressor speed at each hour can take the values of 0 Hz, or off, and anywhere within its range of operation. For a given set of forecast outdoor conditions and internal loads, a choice of compressor speed determines $P_{chiller}$, $QC_{chiller}$, T_o , T_e , T_{cc} , and T_o at the current predicted hour. Some speeds will cause infinite penalties if the temperature-CRTF models determine that they will cause operative temperatures outside of comfort bounds or too low evaporating temperatures, and the risk of freezing the chiller.

Beginning with a guess at an initial point in the 24-dimensional grid of compressor speeds, pattern search evaluates the objective function at all of the grid points surrounding the initial guess. This is called a poll. All of these grid points are compared to identify the most optimal solution relative to each other and to the initial guess. If a more optimal grid point is identified, the pattern search continues by polling a grid around the new optimal solution. The grid size is increased, up to maximum compressor speed step size, each time a more optimal point in the grid is identified. If a more optimal grid point is not found, the pattern search continues around the current point with a smaller grid size, down to a minimum grid size. The pattern search continues searching the grid until no more optimal points can be found at the smallest grid size.

An optional step in a pattern search is the execution of a secondary optimization on the current grid point each time a new optimal solution is found around that point. Instead of immediately polling the grid around the new optimal solution, a search of the other dimensions of the grid (not the dimension in which a new optimal point has been found) is conducted to identify whether an even more optimal solution can be found. This allows the pattern search to perform faster, by moving in more than one-dimension of the grid at each iteration. A complete explanation of the pattern search algorithm is included Matlab's Global Optimization Toolbox: User's Guide (Mathworks 2010) and more information can be found in (Torczon 1997, Lewis et al 1999, Lewis et al 2000, Audit and Dennis 2003).

A flow chart of the pattern search implemented for optimizing the daily schedule of compressor speeds, w , of a low-lift chiller serving a concrete-core TABS is shown in Figure 1. An initial guess of 24 compressor speeds $\bar{\omega}_i$ is made at each hour, which may be based on the previous hour's guess. The pattern search algorithm is performed to identify an optimal schedule of compressor speeds $\bar{\omega}_{opt}$ for the next 24 hours. At each iteration of the pattern search, equations (2) through (9) are applied to calculate the P_t , $QC_{chiller}$, T_o , T_{cc} , and T_{chwr} sequentially for each time step because they depend on past-predicted values.

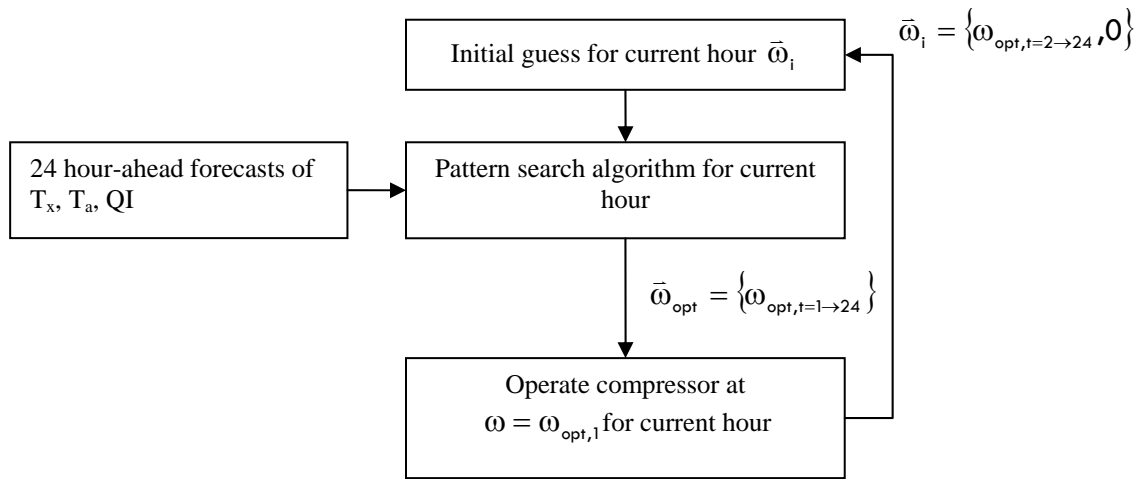


Figure 1 Closed loop optimization of compressor speed for low-lift cooling of TABS with pattern search

For operation of a TABS system pre-cooled with a low-lift chiller, the pattern search algorithm may be employed at every hour to calculate a new set of optimal compressor speeds for the next 24 hours. This allows for the use of updated forecasts of outdoor air temperature T_x , adjacent zone air temperature T_a , and internal loads QI at each hour. Only the first compressor speed computed by the pattern search is then used to set the compressor speed for the following hour. A new pattern search may be performed at the next hour to identify a new optimal set of 24 hour compressor speeds for the following 24 hours. Henze et al (2004) refers to this approach as closed loop optimization, where feedback from the previous time step (hour) and updated forecasts are used to determine a new optimal control schedule.

An alternative approach is consecutive time block optimization Henze et al (2004), in which compressor speeds are predicted once at the beginning of a 24 hour time block. This approach is identical to closed loop optimization only in the case where model predictions and exogenous variable forecasts are perfect.

Example pre-cooling optimization from an experimental implementation

A sample result of the low-lift pre-cooling optimization for TABS from an experimental implementation in a test chamber is shown in Figure 2. The details of this experiment, including the test chamber, the low-lift chiller, and implementation of the control algorithm are described in part 2 of this paper. Figure 2 illustrates an example predicted optimal compressor speed schedule and the resulting predicted temperature response over 24 hours, chiller power and energy consumption. A compressor speed schedule for each of 24 hours into the future, is shown at the top left. For this schedule, the operative temperature T_o , concrete-core temperature T_{cc} , return water temperature T_{chwr} , evaporating temperature T_e , cooling rate $QC_{chiller}$, and chiller power consumption $P_{chiller}$ are predicted for each hour of the 24 hours ahead. At the top right of Figure 2, the predicted T_o , T_{cc} , T_{chwr} , T_e for the 24 hour ahead period are shown along with the outdoor temperature T_x and the comfort constraint $T_{o,max}$ and $T_{o,min}$. The chiller power at each time step and the cumulative energy consumption over the 24 hour period are shown at the bottom. For the hour following this optimization, a low-lift chiller would be operated at the first predicted optimal compressor speed, which is 0 Hz, or off, in the case below.

The example in Figure 2 demonstrates certain important aspects of predictive control for low-lift cooling with TABS. First, the best time to perform most of the cooling is over night and during the early morning hours. The outdoor air temperature T_x is low and the chiller can run more efficiently. Second, the chiller runs at relatively low speed (19 Hz is its minimum) most of the time, and thus at low pressure ratios, because it is most efficient at low part load. These are consistent with expected control in low-lift cooling (Armstrong et al 2009a, Armstrong et al 2009b). Third, near the beginning of the scheduled operation of the compressor, at hours six, seven and eight, the compressor is scheduled to cycle on for an hour, then off for an hour, and then turn back on. The optimization has determined that it is more efficient not to run the compressor continuously for those three hours because doing so would result in a decrease in T_{cc} , T_{chwr} , and most importantly T_e causing the chiller to run less efficiently at lower evaporating temperatures. Lastly, at the end of the scheduled pre-cooling the compressor turns off for an hour and then back on. This is the result of the evaporating temperature T_e approaching the low temperature threshold of one degree Celsius. The compressor is not allowed to run at hour 16 to prevent the chiller from freezing. This freezing constraint can be avoided by improving the design of the concrete-core TABS so that the difference between chilled water temperatures T_{chwr} and the concrete-core temperature T_{cc} is less. This low-temperature constraint is largely an artifact of the system as implemented in the experimental test chamber described in part 2 of this paper.

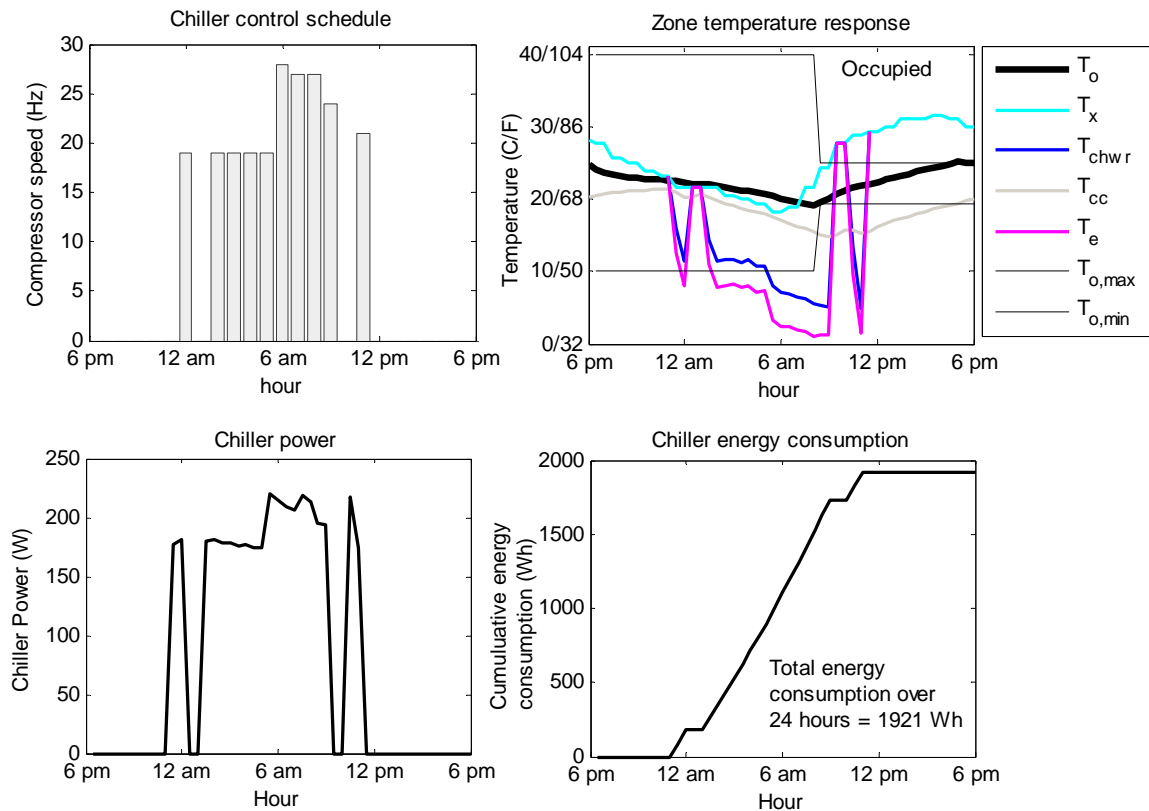


Figure 2 Sample low-lift pre-cooling optimization for TABS from an experimental test chamber

SUMMARY

This paper describes a data-driven, model-based predictive control algorithm for low-lift, variable capacity chillers serving concrete-core TABS. Curve-fit chiller performance models and zone operative temperature and concrete-core temperature response models are incorporated into a chiller control optimization algorithm. This algorithm predicts optimal compressor and condenser fan speeds for a 24 hour period based on the predicted chiller performance and zone and concrete-core temperature response. The optimal schedule minimizes cooling system energy consumption, including temperature and load dependent chiller performance, while maintaining zone comfort conditions during occupied periods over a 24 hour period. For operational implementation, a closed loop optimization is proposed in which the optimal chiller control schedule is determined at every hour based on new forecasts and the latest measured building data.

DISCUSSION

The control algorithm developed in this paper has been applied to a room-sized experimental test chamber with a radiant concrete slab served by a variable capacity chiller operated at low pressure ratios. Experimental results from applying this control algorithm are described in part 2 of this paper. The results showed 25 percent cooling energy consumption for a typical Atlanta summer week with standard efficiency internal loads relative to a high efficiency split-system variable capacity air conditioner.

The predictive control strategy presented here has been developed primarily for the purposes of experimentally testing low-lift cooling with TABS in a test chamber. A number of important additions and revisions must be made to this control strategy for implementation at full-scale. First, the algorithm must be revised to include solar loads in the temperature CRTF models. Furthermore, multi-zone temperature

predictions must be included for TABS systems serving multiple, distinct zones. The inclusion of a variable speed chilled water pump serving the TABS and the chiller will also be important, as it may allow for further improvements in chiller efficiency and control.

Another important revision that must be made is incorporating the possibility for direct cooling into the optimization algorithm, not through TABS but through conventional air conditioner evaporators, large heat exchanger fan coil units, or radiant cooling systems. A strategy that combines pre-cooling of thermal storage, such as TABS, with direct cooling of zones is likely to achieve the best balance of system efficiency and comfort control. This will help deal with another consideration, error in forecasts of exogenous variables, such as outdoor temperature, and error in predictions by the data-driven models.

Lastly, optimization methods other than pattern search may be applicable to the predictive pre-cooling control problem and further research is necessary to evaluate other options. For this research, however, pattern search was found to identify near-optimal solutions within a few minutes, whereas applying genetic algorithms or simulated annealing required hours of optimization time and did not always converge to a solution. Thus, pattern search was suitable for implementation of the control algorithm in the room-size experimental test chamber described in part 2 of this paper.

ACKNOWLEDGEMENTS

The authors wish to acknowledge the Masdar Institute of Science and Technology for support of this research. The authors are also grateful for the support and advice of members of the Mitsubishi Electric Research Laboratory and the Pacific Northwest National Laboratory. Nicholas Gayeski is also thankful for the support of the Martin Family Society of Fellows for Sustainability.

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Figure captions:

- Figure 2. Closed loop optimization of compressor speed for low-lift cooling of TABS with pattern search
- Figure 2. Sample low-lift pre-cooling optimization for TABS from an experimental test chamber