An advanced control of hybrid cooling technology for telecommunication base stations

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Abstract:

Inefficient cooling systems and rudimentary control methods are accountable for the significant cooling energy consumption in telecommunication base stations (TBSs). To address this issue, our study explores the performance of model predictive control (MPC) technology over a hybrid cooling system with ventilation and air-conditioning cooling. Specifically, a discrete particle swarm optimization (DPSO) algorithm is adopted in the MPC to handle the discontinuity and nonlinearity involved in the model built upon a state-space structure. Simulations are performed for a typical week during a cooling season. Moreover, we observe that a model mismatch could hinder the actual performance of MPC; thus, this study initiatively quantifies the impact of model mismatch by setting different coefficients of performance (COP) on the air-conditioner. The results show that the structured MPC has a better performance over conventional control methods, with an average reduction of 34% daily cooling energy consumption, while increasing the control accuracy in terms of maximum deviation from the desired temperature range. It is also found that a higher degree of model mismatch can lead to a higher performance degradation, either on the total energy consumption or on the room temperature deviation.

1 Key words: Telecommunication base stations; Model predictive control; Free cooling; Energy
2 saving; Discrete Particle Swarm Optimization (DPSO); Model mismatch
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1 Nomenclature

c_p	specific heat capacity, J/(kg·K)	Subscripts	
Δx	discretized thickness, m	i, j, k	indices of mass nodes or surfaces
T	temperature, K	g	indices of data
Q	heat gain, W	$mass, E, I$	mass, external or internal nodes
V	volume of zone, m ³	in, out	inside or outside
h	heat transfer coefficient, W/(m ² ·K)	SR, LWR	solar or long-wave radiation
f	area, m ²	IHG, Vet	internal or ventilation heat gain
Fo	Fourier number	AC, fan	air-conditioner or fan
a	thermal diffusivity, m ² /s	bl, ex, fr	blower, exhaust fan or infiltration
K	cloud height coefficient ($K=0.34$)	$SR_E, SR_S, SR_W, SR_N, SR_L$	east, south, west, north, level solar radiation
C_c	cloud coverage coefficient ($C_c=0.34$)	air	air node
C	heat capacity, J/(kg·K)	r	radiation
W	comprehensive coefficient	$env, sky, soil, grd$	environment, sky, soil or ground
RH	air relative humidity	sum	the sum area
F	angle factor	st	set point
a_0, a_1, a_2, a_3	coefficient of polynomial curve	up, low	upper or lower limit
y	data of air-conditioner	$penalty$	parameters of penalty
R, R^2	multiple correlation coefficient and square	$daily$	daily energy consumption
COP	the performance of air-conditioner	mis, non	mismatch or non-mismatch
J	optimization objective function	$real, MPC$	real-time or model predictive controller
E	energy consumption, J	Greek symbols	
m	mass flow rate, kg/s	ρ	density, kg/m ³
u	input vector of state-space form	$\Delta\tau$	sampling time, s
X	state vector of state-space form	λ	thermal conductivity, J/(m·s·K)
Y	output vector of state-space form	ε	emissivity
A, B, C, D	coefficient matrices of state-space form	α	absorptivity
G	penalty value (10 ⁴)	σ	black body radiation constant, W/(m ² ·K ⁴)
I	total performance index	δ	degree of mismatch
P	power consumption, W		

1 **Introduction**

2 Telecommunication base stations (TBSs) are the basis of the telecommunication network
3 with high internal heat density. In China, the quantity of TBSs has been increasing with the
4 continuing development of communication technology and electronic industry. The energy use
5 intensity increases with continuous communication. To remove the heat generated by electronic
6 devices, air conditioning systems are equipped and account for 30-50% of the total energy
7 consumption of TBSs [1]. This large energy consumption presents a significant energy saving
8 potential and makes TBSs a primary target for energy conservation measures in China. Alternative
9 free cooling technologies, including airside free cooling (e.g. ventilation cooling), waterside free
10 cooling (utilizing natural cold water to remove indoor heat) and heat pipe could supplement the
11 cooling and save energy for TBSs [2]. Ventilation cooling is the most effective and simplest
12 among the proposed energy saving technologies, which draws the cold outside air directly into the
13 TBSs when the outside air conditions are favorable [3]. It has been widely used for the cooling of
14 TBSs in China in recent years and occupies 40% of the total number utilizing free cooling source
15 [4].

16 However, ventilation cooling is only intermittently available and affected by the outdoor air
17 humidity and cleanness. It needs to couple with a mechanical cooling unit to function well as a
18 hybrid cooling system. Currently, there is very limited research on the control strategy for a hybrid
19 cooling system in TBSs. In practice, the existing control and application strategies for ventilation
20 cooling are dominantly traditional rule-based [5-8]. For example, the rules turn on ventilation
21 cooling (via fans) when the outdoor temperature is below a preset point and off when the outdoor
22 temperature is higher than a preset point [6]. Obviously, due to ignoring the useful information,
23 such as local weather, internal heat gains, fan type, air-conditioning type, thermal properties of the

1 envelope etc., a traditional rule-based control method is inefficient to guarantee the indoor
2 environment with minimum energy consumption. Improvement of the energy efficiency of this
3 technology is needed in an attempt to achieve energy and environment sustainability. The focus of
4 the present work is to demonstrate the potential energy efficiency achievable through the use of
5 advanced control methods, which can fully exploit the benefits of hybrid cooling systems.

6 Model predictive control (MPC) technology as one advanced control algorithm has been
7 suggested as an effective means to reduce energy consumption for heating, ventilation and air
8 conditioning (HVAC) systems within the indoor air temperature and humidity constraints. With
9 the information on the local weather, internal heat gains and occupancy schedule, MPC has been
10 reported applicable to different kinds of building HVAC systems to seek the optimal control input
11 sequences, providing potential cooling energy saving of 5-70% and 10-45% peak electrical
12 demand in comparison with the conventional control technology with rule-based controllers or
13 proportional integral derivative (PID) controllers. Examples of the building HVAC systems
14 application of MPC in the literature include passive energy storage systems within building
15 structures of an office building [9-10], ice thermal storage systems of a commercial building
16 [11-13], chilled water thermal energy storage systems of university buildings [14], hydronic
17 heating systems of a university office building [15], radiant slab systems with evaporative cooling
18 sources [16], pre-cooling systems with natural ventilation technology of an office building [17-18].
19 It can be seen from the literature that MPC is a promising control technology with many good
20 traits; it can improve energy efficiency and indoor environmental control accuracy for building
21 HVAC systems. However, the performance of MPC could be affected by many factors, such as the
22 prediction model, process type, optimization solver, cost function, planning and sampling horizons,

1 type of control variables (continuous/discrete in the decision space) and constraints [19].

2 Upon the literature review and to the best of authors' knowledge, application of MPC to a
3 hybrid cooling system with mechanical ventilation in TBSs has not been reported. In the
4 meantime, the quality of models, i.e. the degree of similarity with the actual system, is the key
5 importance in the evaluation since it has strong impact on the reliability and accuracy of the
6 optimization results. However, an air conditioner is generally modelled with a constant coefficient
7 of performance (COP) in the previous studies of MPC [8, 17-18, 22]. Therefore, it is very
8 necessary to study the quantitative effect of model mismatch on the MPC performance. There are
9 three types of models developed in MPC for the dynamic thermal process of buildings: a)
10 Physics-based model [17, 20-21] is based on the knowledge of the heat transfer process, analogous
11 to electrical RC (resistance and capacitance) networks; b) Data-driven model [18, 22-25] fits
12 linear and nonlinear mathematical functions to measure data, including ANN (artificial neural
13 network), time delay model and statistical model; c) Comprehensive model, using simulation
14 programs such as EnergyPlus [26]. The latter two have some limitations as follows: The quality of
15 data-driven model relies on the accuracy of measurement data; besides, data-driven models only
16 can apply within the range of experimental conditions; a comprehensive model is more likely to
17 produce accurate results, but it is computationally expansive as simulation-based optimization
18 techniques often require hundreds or thousands of simulation runs which may make it infeasible to
19 used in practice [27]. In general, the choice of optimization algorithm is based on the intrinsic
20 properties of predicted model and control variables. For example, if the modelling of the
21 optimization problem is a non-linear model or the control variables contain discrete control
22 variables, then the linear programming technique will not perform well to generate an optimum

1 solution. Therefore, stochastic global search strategies, such as particle swarm optimization (PSO),
2 genetic algorithm (GA), simulated annealing (SA), etc., are suitable to identify the optimums.
3 Yuce B et al. [28] addressed appliance schedules (discrete control variables) with ANN–GA for
4 optimised energy management in the domestic sector. A review on the theory and applications of
5 computational intelligence techniques for prediction, optimization, control and diagnosis of HVAC
6 system can be found in [27] by Ahmad M. et al.

7 Motivated by the above, the research presented herein aims to demonstrate the potential
8 performance bounds of MPC for TBSs with a hybrid cooling system. We adopted a physics-based
9 method with state-space form to model the building dynamic thermal process, a non-linear
10 regression model for COP of the air-conditioner and analyzed the impact of model-plant mismatch
11 coordinated with the constant COP model and non-linear regression COP model for MPC. On the
12 other hand, we applied the intelligent optimization algorithm, termed discrete particle swarm
13 optimization (DPSO), to handle the optimization problems of MPC with discrete control variables
14 and nonlinearity predicted model..

15 The rest of the paper is organized as follows: First, we present the system description and
16 modelling in Section 2, consisting of building dynamic thermal process, long-wave radiation,
17 air-conditioner and air exchange models. Then, the formulation of MPC is presented, including the
18 objective function, constraints and DPSO as the optimization algorithm. In Section 4, the
19 performance of this method is illustrated by simulations in comparison with other conventional
20 control methods. And impacts of COP model on the performance of MPC are also discussed.
21 Conclusions are presented in Section 5.

22 23 **2. System description and modelling**

1 Telecommunication base stations are centers of receiving and switching signals in the
2 telecommunications network and have higher cooling energy intensity than most public buildings
3 due to their large internal heat density. Depending on the applications and functions, the indoor
4 environmental requirements are divided into four levels, as shown in Table 1. This work focuses
5 on the third level, with the indoor temperature between 10-30°C and the relative humidity 20-85%,
6 which is widely adopted by small size TBSs. Examples are a local telephone communication room
7 with less than 50,000 telephones, long-distance transmission relay station and metropolitan area
8 network (MAN) convergence layer data room etc. Fig. 1 and Fig.2 show the outside view and
9 inside layout of general TBSs, respectively. The building has dimensions of 4.1m x 3.6m x 3.5m,
10 with a door (0.9m x 2m), and no window. Table 2 and Table 3 provide the detail materials thermal
11 and structural parameters of the envelope, floor and roof. The cooling system contains a split-type
12 air-conditioner, a supply fan installed in the west wall and an exhaust fan installed in the east wall.

Fig.1 Outside view of the TBS building

Fig.2 Inside layout of the TBS building

Table 1

Classification and environmental requirements of TBSs ^[26]

Classification	Temperature (°C)	Relative humidity (%)	Type
First level	10-26	40-70	Toll switch data room etc.
Second level	10-28	20-80	Tandem office, Internet Data Center (IDC) data room etc.
Third level	10-30	20-85	MAN convergence layer data room etc.
Fourth level	5-35	15-85	MAN access layer devices room etc.

Table 2

Materials of building structure ^[1, 29]

Component	Materials
Wall	20mm cement mortar+240mm ordinary clay+20mm cement mortar
Roof	20mm cement mortar+100mm reinforced concrete+120mm foam concrete +20mm cement mortar
Door	40mm wood
Ground	40mm foam concrete+(800mm sand for thermal resistance to $1.5 \text{ m}^2 \cdot \text{K/W}$)

Table 3

Thermal parameters of building materials ^[30]

Materials	Density (ρ) kg/m ³	Thermal conductivity (λ) J/(m·s·K)	Specific heat capacity (c_p) kJ/(kg·K)	Thermal diffusivity (a) $\times 10^{-7}$ (m ² /s)
Cement mortar	1800	0.93	0.84	6.15
Ordinary clay	1800	0.81	0.88	5.11
Reinforced concrete	2400	1.54	0.84	7.64
Foam concrete	232	0.077	0.88	3.77
Wood	500	0.14	2.51	1.51
Sand	1420	0.59	1.51	2.75

2.1 Model development

2.1.1 Dynamic thermal process modelling

1 The thermal dynamic of a building is determined mainly by the thermal mass of the building
 2 envelope. Since most of the building envelope materials have a large time constant, building heat
 3 and mass transfer is a slow response process. Therefore, to predict the future evolution of indoor
 4 air conditions, the dynamics need to be represented accurately in the model.

5 In this paper, the dynamics of this building are modelled by applying the heat balance method
 6 based on the first law of thermodynamics. The thermal network approach discretizes a building
 7 thermal system into a network of space temperature nodes. Fig. 3 depicts the schematic diagram of
 8 structure temperature nodes. Each node is modelled by heat balance to determine the node
 9 temperature with interconnecting paths through heat flux by convection, conduction and radiation.
 10 Heat gains, such as solar radiation, internal source and auxiliary heat supply from air-conditioner,
 11 can be regarded as current source acting on the inside or outside capacitance.

Fig.3 Schematic diagram of structure temperature node

14 Basically, there are two types of nodes in building network: envelope nodes and indoor air
 15 node. We denote the indoor air temperature with T_{in} . The surface nodes are denoted as $T_{E,k}$ and $T_{I,k}$
 16 and mass nodes of envelope structure as $T_{mass,k,j}$. The modelling method to be presented here

1 requires several assumptions as follows [1,4-5]:

- 2 1. The heat transfer through the envelope is one-dimension perpendicular to the surface.
- 3 2. The air inside of the TBS is uniformly mixed.
- 4 3. Thermal parameters of building materials and air are constant and not influenced by the
- 5 temperature change.
- 6 4. The solar radiation heat gain for node is a fixed value during a sampling time.

7 Based on the above assumptions, heat transfer through the envelope of the building can be
 8 represented with the following equations for external surface nodes (Eq. (1)), mass nodes in
 9 envelope structure (Eq. (2)), internal surface nodes (Eq. (3)) and indoor air node in the room (Eq.
 10 (4)):

$$11 \quad \frac{1}{2} c_{p,E,k} \rho_{E,k} \Delta x_{E,k} \frac{dT_{E,k}}{dt} = h_{out} (T_{out} - T_{E,k}) + \frac{\lambda_{E,k}}{\Delta x_{E,k}} (T_{mass,k,j} - T_{E,k}) + Q_{SR,k} + Q_{ELWR,k} \quad (1)$$

$$12 \quad \left(\frac{1}{2} c_{p,mass,k,j-1} \rho_{mass,k,j-1} \Delta x_{mass,k,j-1} + \frac{1}{2} c_{p,mass,k,j} \rho_{mass,k,j} \Delta x_{mass,k,j} \right) \frac{dT_{mass,k,j}}{dt} = \frac{\lambda_{mass,k,j-1}}{\Delta x_{mass,k,j-1}} (T_{mass,k,j-1} - T_{mass,k,j}) + \frac{\lambda_{mass,k,j}}{\Delta x_{mass,k,j}} (T_{mass,k,j+1} - T_{mass,k,j}) \quad (2)$$

$$13 \quad \frac{1}{2} c_{p,I,k} \rho_{I,k} \Delta x_{I,k} \frac{dT_{I,k}}{dt} = h_{in} (T_{in} - T_{I,k}) + \frac{\lambda_{I,k}}{\Delta x_{I,k}} (T_{mass,k,j} - T_{I,k}) + \sum_j Q_{ILWR,k} \quad (3)$$

$$14 \quad c_{p,air} \rho_{air} V_{air} \frac{dT_{in}}{dt} = \sum_{k=1}^n f_k h_{in} (T_{I,k} - T_{in}) + Q_{IHG} + Q_{AC} + Q_{Vet} \quad (4)$$

15 where $c_{p,mass,k,j}$, $\rho_{mass,k,j}$, $\lambda_{mass,k,j}$, $\Delta x_{mass,k,j}$ are the specific heat capacity, density, thermal
 16 conductivity and thickness in node (j) of envelope (k), respectively; h_{out} and h_{in} are the convective
 17 heat transfer coefficient of external and internal surface with the value of $23\text{W}/(\text{m}^2 \text{K})$ and
 18 $8.7\text{W}/(\text{m}^2 \text{K})$, respectively [30]; $c_{p,air}$, ρ_{air} , and V_{air} are the specific heat capacity, density and
 19 volume of indoor air, respectively; f_k is the area of internal surface (k); Q_{IHG} , Q_{AC} , and Q_{Vet} are the
 20 internal heat gain, auxiliary heat extraction rate (e.g. air-conditioner) and infiltration or ventilation
 21 to the indoor air node, respectively; $Q_{SR,k}$ is the solar radiation heat gain for external surface nodes
 22 heat balance; $Q_{ELWR,k}$ and $Q_{ILWR,k}$ are the long wave radiation heat flux on the external surface and

1 internal surface nodes, respectively.

2 Since the space interval does affect the accuracy of calculations, in this study we determine
3 the appropriate discrete spacing according to the Fourier number (Fo) [31]:

$$4 \quad Fo = \frac{a\Delta\tau}{\Delta x^2} \quad (5)$$

5 where a is the thermal diffusivity; $\Delta\tau$ is the sampling time of thermal disturbance, which is 1
6 hour in this study. Thus, the space interval is dependent on Fourier number (Fo), envelope thermal
7 diffusivity (a) and sampling time of thermal disturbance ($\Delta\tau$). For instance, in this paper, Fo is
8 set to greater than 0.2, then the wall was divided into four layers with five nodes and the roof was
9 divided into five layers with six nodes.

10 2.1.2 Long wave radiation modelling

11 We model the long wave heat transfer between building external surfaces and ambient
12 environment for external surface nodes heat balance as proposed in [32]. The amount of heat
13 transferred from the building to the environment is given by Stefan-Boltzmann law:

$$14 \quad Q_{env,k} = \varepsilon\sigma T_{E,k}^4 \quad (6)$$

15 where ε and $T_{E,k}$ are the emissivity and the average temperature of external surface for
16 envelope (k), respectively; σ is the black body radiation constant with the value of $5.67 \times 10^{-8} \text{W/m}^2$
17 K^4 . We also take into account the sky thermal radiation to the building, based on the proposed
18 relation in [32]:

$$19 \quad Q_{sky} = (1 + KC_c^2) 8.78 \times 10^{-13} T_{out}^{5.852} RH^{0.07195} \quad (7)$$

20 where K is the coefficient related to the cloud height and C_c is a function of cloud coverage.
21 We use $K = 0.34$ and $C_c = 0.8$ for simulations, based on the study of [32]. RH is the air relative
22 humidity percentage. The total radiation exchange between building external surfaces and ambient
23 environment for external surface nodes heat balance is then given by:

$$Q_{ELWR,k} = Q_{env,k} - Q_{sky} \quad (8)$$

Although the long wave radiation heat transfer between internal surfaces is complicated, it can be simplified with some assumptions (details as following derivation) as the following equation:

$$Q_{ILWR,i} = \sum_{j, j \neq i} h_{r,i,j} (T_j - T_i) \quad (9)$$

where T_i and T_j are the temperature of the internal surface node (i) and (j), respectively; $h_{r,i,j}$ is the radiation heat transfer coefficient between internal surface (i) and (j), defined as following:

$$h_{r,i,j} = W_{ij} \sigma (T_i^2 + T_j^2) (T_i + T_j) \quad (10)$$

where T_i and T_j can be approximated by a fixed value 20°C (293K) for this simulation, since the annual average temperature inside the building surfaces remain the range of 10°C (283K) to 30°C (303K); W_{ij} is a comprehensive coefficient, considering emissivity and angle factor etc., defined as follows:

$$W_{ij} = F_{ij} \varepsilon_j f_i \alpha_i \quad (11)$$

where α_i is the absorptivity of surface (i). F_{ij} is the angle factor from internal surface (j) to internal surface (i), given by:

$$F_{ij} = \frac{f_j}{f_{sum}} \quad (12)$$

where f_{sum} is the sum area of all internal surfaces of the zone, including walls, roof and ground.

Therefore, the radiation heat transfer coefficient $h_{r,i,j}$ between internal surfaces can be calculated using the above derivation of equations with the known thermal properties and geometric parameters. In this way, $h_{r,i,j}$ is a constant at the current time-step for this simulation.

The full description and details of radiation heat transfer estimation is available in [31].

2.1.3 Air-conditioner modelling

The investigated building is a typical third category TBS building. A split air-conditioner (A/C) and mechanical ventilation fans (e.g. a blower and an exhaust fan) are used to maintain the indoor air temperature within a safe range operated by the controller. The COP represents the ratio between a cooling rate and consumed power. Actually, the COP of A/C is a function of evaporator and condenser air inlet conditions. However, upon the literature review, it is found that a constant COP was generally used [8, 17-18, 22]. MPC as a smart control strategy, based on local weather forecasts, can seek optimal control sequences to minimize the energy consumption within a future time horizon. A constant COP, which is not real, would not capture the dependence of performance on operating conditions therefore might lead the MPC to a wrong decision. As the main mechanical device in TBSs, a suitable COP model for it is extraordinary essential. In this paper, the dominant dynamic mode is the slow dynamics (hours) of building thermal transfer process since analyzing issues of energy use and indoor environment is our purpose. But the refrigerant circuit is a fast dynamic process (seconds or minutes), which is virtually instantaneous and no dynamics is needed to consider. Thus, we develop an empirical static model for A/C to characterize the COP using nonlinear regression method as follows:

$$\begin{aligned} COP &= a_0 + a_1 T_{in} + a_2 T_{out} + a_3 T_{in} T_{out} \\ Q_{AC} &= P_{AC} \times COP \end{aligned} \quad (13)$$

where a_0, a_1, a_2 and a_3 are the coefficients for the polynomial curve and they are identified by a nonlinear least squares algorithm using manufacturer's data. T_{in} , T_{out} are the inside air dry temperature and outside air dry temperature, respectively. P_{AC} is the power consumption of the A/C (W) using a constant value for simulation. The performance of the model is evaluated by the multiple correlation coefficients (R) and R square (R^2):

$$R = \frac{\sum_{g=1}^n (y_g - \bar{y})(\hat{y}_g - \bar{y})}{\sqrt{\sum_{g=1}^n (y_g - \bar{y})^2 \sum_{g=1}^n (\hat{y}_g - \bar{y})^2}} \quad (14)$$

in which y is the actual output, $\hat{y}$ is the predicted output and $\bar{y}$ is the average of the actual output. The identified parameters for the empirical static model are listed in Table 4. Fig.4 shows the COP as a function of evaporator inlet air dry temperature and condenser inlet air dry temperature. The results show that the non-regression model for COP has a good prediction accuracy with the R and R^2 equal to 0.993 and 0.985 respectively.

Fig.4 COP of a split air conditioner as a function of working conditions

Table 4

Parameter identified results for COP model

Parameter	Value	Parameter	Value
a_0	1.287	a_2	-4.58×10^{-3}
a_1	0.117	a_3	0.84×10^{-3}
R^2	0.985	R	0.993

2.1.4 Air exchange modelling

When the ventilation cooling is on, the energy input to the building model is different. The heat transfer associated with air flow Q_{vet} , includes infiltration Q_{fr} and mechanical ventilation Q_{fan} is determined by the air flow rate and outdoor air temperature. The infiltration is considered

1 constant with 0.3h^{-1} air change rate as simplifying assumption and the fans are fixed speed with
 2 constant supply volume air in the present study. And they can be computed from the following
 3 equations:

$$\begin{aligned}
 Q_{fr} &= 0.3 \times V_{air} \times \rho_{air} \times c_{air} (T_{in} - T_{out}) \\
 Q_{fan} &= m_{fan} c_{air} (T_{in} - T_{out}) \\
 Q_{vet} &= Q_{fr} + Q_{fan} \\
 P_{fan} &= P_{bl} + P_{ex}
 \end{aligned}
 \tag{15}$$

5 where m_{fan} is the air mass flow rate of the fan. P_{fan} is the fans power (W) includes the blower
 6 (P_{bl}) and exhaust fan (P_{ex}), which is a constant value from manufacturer's data.

7 According to the above derivation, the dynamic thermal system consists of the envelope and
 8 indoor air nodes Eqs. (1) - (4), which can be formulated using the state-space representation as
 9 follows:

$$\begin{aligned}
 C\dot{X} &= A_t X + B_t u + f(X, u) \\
 Y &= DX
 \end{aligned}
 \tag{16}$$

11 in which, A , B , C , D are coefficient matrices and subscript t means time-varying. X is the
 12 state vector containing the temperature of each node. u is the controllable input variable (e.g.
 13 auxiliary heat extraction rate) and uncontrollable variables (e.g. outside air temperature, air
 14 relative humidity, soil temperature, internal heat gain and each direction solar heat gain) and Y is
 15 the output vector (e.g. indoor air temperature in this paper).

16 Obviously, the **dynamic** thermal process model is nonlinear and time-varying. Values of A_t , B_t
 17 coefficient matrices are time-varying affected by the operation of fans and A/C. The nature of
 18 nonlinearity is due to the term $f(X, u)$ that represents the long wave heat transfer between
 19 building external surfaces and ambient environment mentioned Eq.(6). Furthermore, the control
 20 variables are the binary state (on/off) of A/C and fans, which introduces the discontinuity to the
 21 optimization problem. Thus, a classical MPC formulation can't be applied in this proposed system.

In order to solve above mentioned problems and take advantage of MPC strategy, the formulation of MPC relative to nonlinear time-varying model and discrete control variables problem is described in next section.

3. MPC formulation

3.1 Optimization of the objective function

An MPC uses the future information and building dynamic thermal process model to predict the temperature profile of the building and generates optimal operation sequences to minimize energy consumption over a future planning horizon. In the present study, the primary control objective is to maintain the indoor temperature of TBS, T_{in} , within a given band in the presence of disturbances brought by varying ambient conditions and internal heat gains. The secondary control objective is to maximize the energy efficiency by minimizing the energy consumption of HVAC equipment. Thus, the objective function of MPC strategy can be defined as a sum of the A/C and fans energy consumption over the future 24h planning horizon as well as the temperature penalty related to indoor temperature constraints. The 24h planning horizon begins from 1:00am to 24:00pm and the optimization problem can be formulated mathematically as follows:

$$\text{Min: } J(\vec{u}_i) = \sum_{i=1}^{24} \Delta\tau (P_{fan} + P_{AC}) + T_{penalty} + RH_{penalty} \quad (18)$$

$$\text{s.t: } \vec{u}_i = \{(0,0), (0,1), (1,0), (1,1)\}, i = 1, 2, \dots, 23, 24$$

$$T_{penalty} = \begin{cases} G_{penalty} (T_{low} - T_{in}) & , T_{in} < T_{low} \\ G_{penalty} (T_{in} - T_{up}) & , T_{in} > T_{up} \end{cases}$$

$$RH_{penalty} = \begin{cases} 0 & , 20\% \leq RH \leq 85\% \\ 10^4 & , else \end{cases}$$

in which, i indexes the sampling instant, $\Delta\tau$ is the sampling period (1 hour), $\vec{u}_i$ is the operate vector of fans and A/C. The temperature penalty ensures that the control variable, the indoor temperature in this case, is inside of the safe range. The penalty gain $G_{penalty}$ is set as 10000 in this study. T_{low} , T_{up} are the lower limit and the upper limit, set as 10 °C and 30 °C in this study,

respectively. In order to avoid excessive moisture into inside, the optimal operate vector is also constrained by the relative humidity RH as suggested by [7].

3.2 Optimization algorithm

The optimization procedure is carried out as a moving horizon control strategy [38], at time t an optimal solution for the manipulated variables $U_t = \{\vec{u}_{t|t}, \vec{u}_{t|t+1}, \dots, \vec{u}_{t|t+N-1}, \vec{u}_{t|t+N}\}$ is calculated for the complete horizon. Only the first element $\vec{u}_{t|t}$ is actually applied to the real plant then the optimization procedure is repeated at time $t+1$ with the updated states X_{t+1} . Gradient based optimization techniques are not particularly suitable for this problem since the optimal operation vector in this study contains binary (0/1) control variables which is the states (off/on) of the fans and A/C. Furthermore, the objective function is coupled with the building and the HVAC system. Thus, stochastic global search strategies such as genetic algorithm, simulated annealing, particle swarm optimization (PSO), etc., can be applied to search the decision space and identify the optimum.

PSO is originated from the observation and research of birds' social behavior, first proposed by Kennedy and Eberhart in 1995 [34]. As a global searching method based on swarm intelligence, PSO has many advantages such as simple principle, few parameters, easy to implement, fast convergence, etc. and has been applied successfully in many fields [35]. PSO optimizes a problem by having a swarm of particles (candidate solutions including position, velocity and the objective value), and moving these particles around in the search-space based on simple algorithms. Each particle's movement and update is decided not only by its local best known solutions, but also by the best known solutions in the search-space. This process is repeated until all of particles converge to the best known solution.

1 In the present study, a discrete particle swarm optimization (DPSO) algorithm is used to
2 search the optimal operation vector for fans and A/C combination with the building dynamic
3 thermal model and the objective function. The parameters and neighborhood topological structure
4 have a large impact on the performance of PSO. In view of analysis and recommendation by [17,
5 34-37], star topology is applied. The flow chart of DPSO-MPC is presented in Fig.5. And related
6 parameters are shown in table 5, which can yield good performance and work well for the problem
7 considered here. In one generation, DPSO algorithm generates a series of potential operation
8 schedules $U_t = \{\bar{u}_{t|t}, \bar{u}_{t|t+1}, \dots, \bar{u}_{t|t+N-1}, \bar{u}_{t|t+N}\}$ included in the particles. The *pbest* represents the best
9 position of each particle among its historical records and the *gbest* is the group's best particle
10 position by comparing the objective function.

11 The steps for each particle are as follows:

12 (a) with the temperature field X_t and the states (0/1) of the fans and A/C, the auxiliary heat
13 extraction rate (negative) and energy consumption from ventilation and A/C transferred to indoor
14 space can be evaluated by Eq.(13) and Eq.(15) during each sampling period, respectively;

15 (b) with the auxiliary heat extraction rate as known controllable input variables in dynamic
16 thermal process Eq.(16), the temperature field can be calculated and updated as X_{t+1} with
17 MATLAB 'ode45' solver which is found suitable in terms of speed and robustness [33];

18 (c) repeat steps (a) and (b) until the last time stamp, N . Then energy consumption for each
19 sampling time and penalty value (punishing beyond set range for conditions) are known and
20 Eq.(18) can be used to estimate the objective function of this particle. The DPSO algorithm
21 compares the results of each particle and decides how to promote the next generation particles.

22 The iteration continues until the desired criteria are reached, i.e. obtaining the same cost in the

1 final 10 iterations [17] or reaching the set number of generations.

2 In a word, the DPSO-MPC framework consists of three parts, predicted models (a building
3 dynamic thermal process model and a static HVAC model), objective function and an optimizer
4 based on DPSO algorithm.

Fig.5 The flow chart of DPSO-MPC strategy

Table 5 Main parameters for DPSO algorithm

Parameter	Value	Parameter	Value
Cognition parameter	2	Particles	500
Social parameter	2	Generations	200
Inertia weight	Linear varying from 0.9 to 0.5		

4. Simulation results and analysis

In the present study, taking a typical week during cooling season from June 20 to June 26 in Changsha city (China) for instance, Fig.6 depicts the ambient dry temperature T_{dry} , dew temperature T_{dew} and total horizontal radiation intensity. The ambient conditions are obtained from historical data (in a data profile) consisting of hourly measurement of dry temperature, dew temperature, relative humidity, radiation intensity in all directions

Fig.6. Weather conditions used in the simulation study

In this study, we demonstrate the potential performance bound of MPC applied for hybrid-mode cooling technology in TBS building through its comparison with:

(a) baseline cooling system only using air conditioner with simple rules control (if $T_{in} > 30^{\circ}\text{C}$ turn on and if $T_{in} < 20^{\circ}\text{C}$ turn down) to maintain a given set temperature and humidity;

(b) hybrid-mode cooling system coupling with mechanical ventilation and air conditioner operated based on a heuristic rule control method. Fig.7 shows the control flow chart of this control strategy.

Under MPC strategy, the planning horizon (the time interval over which the objective function is evaluated) and the execution horizon (the time interval over which the control strategy is applied) are all set to 24h. The performance of control strategies is evaluated by daily cooling energy consumption and the control accuracy in terms of the maximum deviation from the desired temperature range. The daily energy consumption is summed over the 24 hours, yielded by fans and A/C E_{daily} :

$$E_{daily} = \Delta\tau \sum_{i=1}^{24} (P_{fan} + P_{AC}) \quad (19)$$

1 5 and 6. The reason is that when the cooling capacity of A/C is close to the cooling load, it is
2 unable to quickly reduce the indoor air temperature to below 20°C (rule to turn off A/C). The
3 consequence is that the running time of A/C greatly increases. Fig. 8 (d) presents the maximum
4 deviation of indoor temperature from the temperature control range which indicates the control
5 accuracy of each control strategy in meeting the primary control objective. As shown, the
6 proposed MPC design is able to provide better temperature accuracy control performance than
7 conventional control method, 0.8°C with respect to 0.38°C within the simulation period. With
8 regard to the secondary control objective, Fig. 8 (e) and Table 7 summarize the daily cooling
9 performance for each control method. As shown, compared to baseline case (42.87×10^4 kJ) and
10 rule-based controller case (33.45×10^4 kJ), the cooling energy of MPC is 21.97×10^4 kJ over the
11 simulation period, achieving 48.75% and 34.32% cooling energy saving, respectively.

12 Notice that during some ambient conditions when the refrigerating efficiency of fan is lower
13 than that of A/C unit, the MPC can find the better one to execute, but rule-based controller always
14 takes precedence of free cooling due to ignoring the comparative efficiency between A/C cooling
15 and ventilation cooling. It also explains why the energy consumption of hybrid cooling system
16 under rule-based controller is higher than that of baseline cooling system during the simulation
17 period June 25 (Table 7). As mentioned above, the MPC can take much information into
18 consideration, such as the cooling efficiency, energy storage in the building structure, future
19 weather, etc.; therefore, it can fully exploit free cooling and always demonstrates better
20 performance relative to conventional control methods during different weather conditions. We
21 discuss how the quality of plant impact on the MPC performance in next part.

(a) Operation schedule of fans

(b) Operation schedule of A/C

(c) Indoor temperature

(d) The control accuracy in terms of the maximum deviation

(e) Daily cooling energy consumption

Fig.8. Results comparison: baseline (without free cooling), rule-based control and MPC

Table 6

Daily operation conditions for fans and A/C

		Baseline (h)	Rule-based (h)	MPC (h)
20/6	Fans	--	21	13
	A/C	7	0	0
21/6	Fans	--	21	15
	A/C	10	0	0
22/6	Fans	--	20	16
	A/C	8	0	0
23/6	Fans	--	10	10
	A/C	13	9	4
24/6	Fans	--	4	7
	A/C	18	16	10
25/6	Fans	--	1	10
	A/C	16	15	7
26/6	Fans	--	22	19
	A/C	9	0	0

Note: '--' means not available.

Table 7

Daily cooling performance for three control strategies

Date	Baseline ×10 ⁴ (kJ)	Rule-based ×10 ⁴ (kJ)	MPC ×10 ⁴ (kJ)	Savings(1) (%)	Savings(2) (%)
20/6	3.70	2.27	1.51	59.19	33.48
21/6	5.29	2.27	1.62	69.38	28.63

22/6	4.23	2.16	1.73	59.10	19.91
23/6	6.88	6.37	3.20	53.49	49.76
24/6	9.53	8.90	6.05	36.52	32.02
25/6	8.47	9.10	4.78	43.57	47.47
26/6	4.76	2.38	2.05	56.93	13.87
Total	42.87	33.45	21.97	48.75	34.32

Note: Savings (1) = (Baseline - MPC) / Baseline; and Savings (2) = (Rule-based - MPC) / Rule-based

4.2 Impact of COP model mismatch

As mentioned above, the COP does impact the MPC performance in the current system and the quality of model plays an important role in the performance of MPC [37]. A model can never be a true representative of the system and model-plant mismatch is inevitable. A desired model is simple and easy to implement and has the mismatch as small as possible. Thus, a pertinent question to ask is: what is the quantitative effect of model mismatch on the MPC performance?

Fig.9 The block diagram of MPC simulation for mismatch analysis

In order to answer this question, a simple approach is proposed to investigate the effects of model-plant mismatch shown in Fig. 9. In this paper, we focus on analyzing the mismatch of COP model; the building dynamic thermal process model mismatch as well as weather conditions prediction uncertainty are beyond the scope of this paper. As shown in this figure, we set the variable COP model introduced in Section 2 as a real plant and use a COP model with different constant values as the inner plant model for the MPC.

The degree of model mismatch is defined as the following equation:

$$\bar{\delta} = \frac{1}{n} \sum_n \frac{|COP_{real} - COP_{MPC}|}{COP_{real}} \times 100\%$$

(20)

where $\bar{\delta}$ is the average degree of model-plant mismatch; n is the planning horizon;

Subscripts *MPC* and *real* represent COP value from constant COP model and variable COP model in real-time, respectively.

As mentioned above, the control objective is to maintain the TBS indoor temperature within a safe range, and at the same time minimize the energy consumption of HVAC system. Therefore, to illustrate the performance of the MPC, we use energy consumption and the maximum deviation of temperature to generate the total performance evaluation index I_{total} .

I_{total} is defined as:

$$I_{total} = \frac{J_{mis} - J_{non}}{J_{non}} \times 100\% \quad (21)$$

where J is the optimization objective function (described in Section 3), which considers above two control objectives. Subscripts *mis* and *non*, are on behalf of mismatch and non-mismatch model, respectively.

Cases with June 24 weather data were selected to demonstrate and quantify the impact of model mismatch on the model predictive controller. During that day, the A/C needs to be operated long to maintain the space temperature as shown in Table 6 and in Fig.8 (d). The operation schedules of fans and A/C from each MPC with different COP model are presented in Table 8. As shown in the last row of Table 8, the total running time of the fans decreases while that of the A/C increases with the rising COP constant value. Fig.10 depicts the COP values for MPC, as the straight horizontal solid line, and the real-time COP with scatters. From the subplots it can be seen that in general the real COP marked with scatters is different from the COP regarded in the MPC and leads to model mismatch. The real COP in each controller is close to the one given in the non-mismatch MPC as shown in the last subplot. Since MPCs with different COP value generates different input and yields different temperature field and real-time COP is dependent on value of temperature, the scatter for COP in each sub-plot is not the same.

1 It is observed from Table 8 that during 1:00am - 7:00am with low outdoor temperature, the
2 control signals from all controllers are the same since the mechanical ventilation is effective and
3 more efficient than the A/C for cooling the space. However, as the outside temperature rises after
4 the period, using fans may no longer be effective to maintain the space temperature. The choice of
5 running the fans or A/C will be affected by the COP model in the MPC and starts to show the
6 discrepancy. Very likely, the MPC with a higher COP value model prefers the A/C cooling. For
7 example, under the same conditions at 8:00, the MPC with 2.5, 3.0 COP value selects fan while
8 the one with 3.5 and 4.0 COP value selects A/C. The exception from the MPC with 4.5 COP is due
9 to the stochastic feature of the intelligent optimization algorithm.

10 Fig. 11 depicts the variation of energy objective, temperature objective and total performance
11 index versus the degree of average mismatch. The MPC with variable COP model is considered to
12 be non-mismatch ($\bar{\delta} = 0\%$) controller as a reference. The extent of average mismatch in different
13 MPCs can be calculated using Eq.(20), and the sequence is 2.5>4.5>3.0>4.0>3.5>Variable. It
14 seems to be non-regular when we analyze separately the energy consumption and deviation
15 temperature with the model mismatch. In general, a high model mismatch leads to a high
16 performance degradation as illustrated by the performance index. Taking COP with 4.5 for
17 instance, its energy consumption is 58,320kJ and control deviation of temperature is 0.27°C with
18 $\bar{\delta} = 27\%$ while the corresponding results of non-mismatch controller ($\bar{\delta} = 0\%$) are 56,268 kJ and
19 0.24°C respectively. The [degradation](#) of performance because of model mismatch could be
20 affected by the formulation of the cost function. But it is clear that the total performance decreases
21 significantly as the degree of mismatch ($\bar{\delta}$) increases, either with more deviation on the air
22 temperature or more energy consumption as demonstrated in the second plot of Fig. 11.

1

2

Table 8 Operation schedule of fan and A/C for model mismatch analysis

	time	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800	1900	2000	2100	2200	2300	000	total
2.5	Fan	0	0	0	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	9
	A/C	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	0	0	0	9
3	Fan	0	0	0	1	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	7
	A/C	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	1	1	1	1	0	0	0	10
3.5	Fan	0	0	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	6
	A/C	0	0	0	0	0	0	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	10
4	Fan	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	5
	A/C	0	0	0	0	0	0	0	1	0	1	0	1	0	1	1	1	1	1	1	1	0	1	0	0	10
4.5	Fan	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	5
	A/C	0	0	0	0	0	0	0	0	1	1	0	1	1	0	1	0	1	1	1	1	0	1	1	0	10
variable	Fan	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	8
	A/C	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	1	1	0	1	0	0	9

1 means on and 0 means off)

3

4

5

6

7

Fig.10 The real time COP value during simulation

8

Fig.11 The performance index of MPC versus model mismatch

5. Conclusions and future work

In this work, we present a model predictive control (MPC) strategy of hybrid cooling system, i.e. ventilation cooling and air conditioner cooling, for telecommunication base stations. The purpose is to explore the energy saving potential with this advanced control. To handle the discontinuity and nonlinearity involved with the hybrid cooling system model, a discrete particle swarm optimization algorithm is adopted. The variable COP model is obtained by regressing the manufacturer data. The building dynamic thermal process and HVAC system models as well as optimization algorithm are presented. Simulations were conducted for a typical week during cooling season to evaluate the performance of MPC. Meanwhile, the performance due to model mismatch is also investigated by using various COP values.

The following conclusions are made based on the results:

(1) For the simulation period considered in this study, ventilation cooling technology is an effective solution in TBS building for energy saving. When the outdoor weather conditions are appropriate, the maximum daily energy saving can be up to 57% compared with baseline cooling system.

(2) The MPC can take much information into consideration, such as the cooling efficiency, energy storage in the building structure, future weather, etc., therefore, it can exploit free cooling and demonstrates better performance overall preset rules. Meanwhile, it also increases the control performance in terms of the maximum deviation from the desired temperature range (model predictive controller 0.3°C versus rule-based controller 0.8°C).

(3) The quality of model has a great impact on the performance and control outcome of MPC. In general, the higher model mismatch leads to the higher performance degradation as

illustrated by the performance index. During the hottest day, MPCs with a constant COP either consume more energy or lead to a higher deviation on the air temperature compared to the MPC with a real and variable COP. However, in general, it still has better performance than rule-based controller's.

(4) The discrete particle swarm optimization algorithm is an effective method to handle the optimization problems of MPC with discrete control variables and nonlinearity predicted model.

In this study, we also observe that, although DPSO-MPC can optimize the control sequence of fan and A/C and obtain good performance for hybrid cooling system, this approach is computationally expensive. Thus, a more efficient optimization algorithm, which can make the MPC applications in practical project, is worth exploring. In the meantime, model mismatch with the building dynamic thermal process model as well as weather conditions prediction uncertainty considered and the consequences should be further investigated and discussed in the future. A more quantitative criterion is needed as well in this direction.

Acknowledgements

The authors gratefully acknowledge the support of this study by the National Science Foundation under Grant No. EPS-10004094 and University of Nebraska-Lincoln Faculty Start-up Fund.

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