INTELLIGENT CONTROL OF HYBRID COOLING FOR TELECOMMUNICATION BASE STATIONS

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ABSTRACT

Telecommunication base stations consume significant amount of energy for heating and cooling the space. This study explores the application of model predictive control (MPC) technology to hybrid cooling systems with ventilation and air-conditioning cooling in TBSs and demonstrates the potential performance of MPC. Discrete particle swarm optimization (DPSO) algorithm is adopted as the optimizer to handle the nonlinearity. Simulations are performed for a typical week during a cooling season. The results show that the MPC controller has better performance over conventional control methods, with a maximum reduction of 50% in terms of daily cooling power requirement, while increasing the control accuracy in terms of the maximum deviation from the desired temperature range. The study also quantifies the impact of model uncertainty on the MPC with different coefficient of performance on the internal model.

INTRODUCTION

Telecommunications base stations (TBSs) are the basis of the telecommunications network with high internal heat density. In China, the quantity of TBSs has been increasing with the continuing development of communication technology and electronic industry. Although the efficiency of electronic devices has greatly improved, the energy use intensity climbes up with more frequent communication. To remove the heat generated by electronic devices, air conditioning systems are equipped and account for 30-50% of the total energy consumption of TBSs [1]. This large energy consumption presents a significant energy saving potential in TBSs. Alternative free cooling technologies, including airside free cooling (e.g ventilation cooling), waterside free cooling (utilizing natural cold water to remove indoor heat) and heat pipe could supplement the cooling and save energy for TBSs [2]. Ventilation cooling is the most effective and simplest one among the proposed energy saving technologies, which draws the cold outside air directly into the TBSs when the outside air conditions are favorable [3]. It gains increasing popularity for the cooling of TBSs in China in recent years and occupies 40% of the total number utilizing free cooling source [4].

However, ventilation cooling is only intermittently available, affected by the outdoor air humidity and cleanness. It needs to couple with a mechanical cooling unit to function well as a hybrid cooling system. Currently, there is very limited research on the control strategy for a hybrid cooling system in TBSs. In practice, the existing control and application strategies for ventilation cooling are dominantly rule-based [5-8]. For example, the rule turns on and off a ventilation cooling (via fans) by checking the outdoor air temperature against a preset value [6]. Obviously, due to the ignorance of useful information, such as local weather, internal heat gains, etc., a traditional rule-based control method is inefficient to maintaint the indoor environment with minimum energy consumption. Improvement of the energy efficiency of this technology is needed in an attempt to achieving energy and environment sustainability. The focus of the present work is to demonstrate the potential energy efficiency achievable through the use of advanced control methods, which can fully exploit the benefits of ventilation cooling technology.

Model predictive control (MPC) technology as one advanced control algorithm has been reported applicable to different kinds of building HVAC systems. 5-70% energy savings and 10-45% peak electrical demand reduction were achieved in comparison with the conventional control technology [9-15]. For example, Henze [9] and Braun [10] simulated a MPC controller for thermal ice storage systems and analyzed the performance by comparison with chiller-priority and storage-priority control strategies. An extensive study of the method with dynamic electric rates was developed in [11]. Based on cooling load and forecasted weather as well as simplified models of HVAC systems (chillers, cooling tower and thermal energy storage tank), Ma [12] studied the performance of MPC in a campus building with an energy storage water tank. The simulation results showed that the daily electricity bill could be reduced by 24.5% compared to the heuristic manual control sequence. In [13] the authors proposed the formulation of MPC algorithm used for a cooling system with ice storage device, developed linear models for building thermal process and cooling plant. Taking the consideration of a time-varying electricity price profile, the MPC leads to 5-30% operational cost reductions. In [14] Yu et al. described a multi-structural fast nonlinear MPC for handling the nonlinearity and non-continuity of models and applied it to a hydronic heating system in a university office building. The optimization of one week operation was achieved in 8 minutes and 6 to 56% of energy savings were reported.

Despite the reported advantages, the performance of MPC is affected by many factors, such as the prediction model, process type, optimization solver, cost function, planning and sampling horizons, type of control variables (continuous/discontinuous in the decision space) and constraints [15]. The quality of models, i.e. the degree of similarity with the actual system, is the most important among them. Models used in a MPC can be developed based on the physics, from trained data, or using existing simulation platform. The latter two have some limitations as follows: The quality of data-driven model relies on the accuracy of measurement data; besides, data-driven models work best within the range of experimental conditions and need re-identification when the conditions change; a comprehensive model is more likely to produce accurate results, but it is generally not used in actual controllers. On the other hand, upon the literature review and to the best of authors' knowledge, the model of an air conditioner is generally set to a constant coefficient of performance (COP) in the previous studies of MPC [8, 16].

Motivated by the above, the research presented herein aims to demonstrate the potential performance bounds of MPC controller for TBSs with hybrid cooling. We adopted a physics-based method with state-space form to model the building dynamic thermal process. As one contribution of this paper, authors proposed a non-linear regression model for COP of the air-conditioner and analyzed the impact of model-plant mismatch coordinated with the constant COP model and non-linear regression COP model for MPC. Another contribution is that we applied the intelligent optimization algorithm, termed discrete particle swarm optimization (DPSO), to handle the nonlinearity of the system dynamics and multi-non-continuity of the control variables. Despite the findings from the aforementioned peers, very few publications considered both non-linear time-varying model and multi-discrete control variables.

DESCRIPTION AND MODELLING

Telecommunication base stations are centers of receiving and switching signals in the telecommunications network and have a higher cooling energy intensity than most public buildings due to their internal heat density. The studied TBS is a small size with 10-30 ^{o}C and the relative humidity 20-85%. Examples are a local telephone communication room with less than 50,000 telephones, long-distance transmission relay station and metropolitan area network (MAN) convergence layer data room etc. Fig. 1 shows the outside view and inside layout of general TBSs, respectively. The building has dimensions of 4.1 m x 3.6 m x 3.5 m, with a door (0.9 m x 2 m), and no window.

Dynamic thermal process modelling

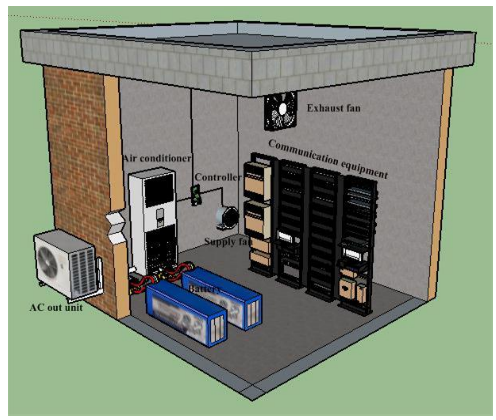

Fig.1 Inside layout of the TBS building

The thermal dynamic of a building is determined mainly by the thermal mass of the building envelope. In this paper, the dynamics of this building is modelled by applying the heat balance method based on the first law of thermodynamics. The thermal network approach discretizes a building thermal system into a network of space temperature nodes. Fig. 2 depicts the schematic diagram of structure temperature nodes. Each node is modelled by heat balance to determine the node temperature with interconnecting paths through heat flux by convection, conduction and radiation. Heat gains, such as solar radiation, internal source and auxiliary heat supply from an air-conditioner, can be regarded as a current source acting on the inside or outside capacitance. Several assumptions are made as follows [1, 4-5]:

1. The heat transfer through the envelope is one-dimension perpendicular to the surface.
2. The air inside of the TBS is uniformly mixed.
3. Thermal parameters of building materials and air

are constant and not influenced by the temperature change.

4. The solar radiation is a fixed value during a sampling time.

The appropriate discrete spacing is determined according to the Fourier number (Fo) [17]. The long wave heat transfer between building external surfaces and ambient environment, sky thermal radiation to the building, and radiation heat transfer between internal surfaces are also modelled in this study.

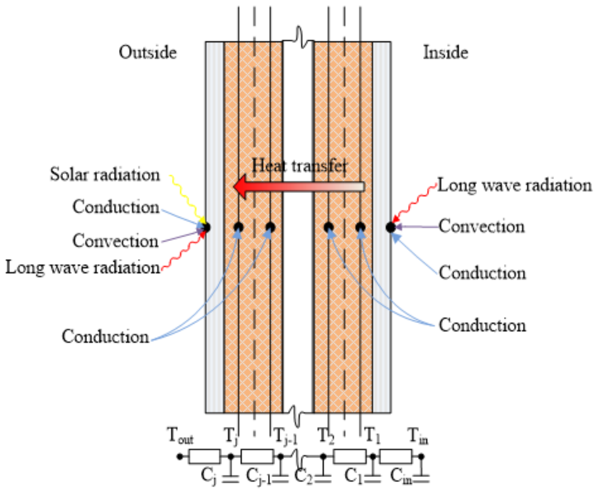

Fig.2 Schematic diagram of structure temperature node

Air-conditioner modelling

The investigated building is a typical third category TBS building. A split air-conditioner (A/C) and ventilation fans are used to maintain the indoor air temperature within a safe range operated by the controller. 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:

$$COP = a_0 + a_1 T_{in} + a_2 T_{out} + a_3 T_{in} T_{out} \quad (1)$$

where, a_0 *to* 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. Fig.3 shows the COP as a function of the 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 correlation coefficients R and R^2 equal to 0.993 and 0.985 respectively.

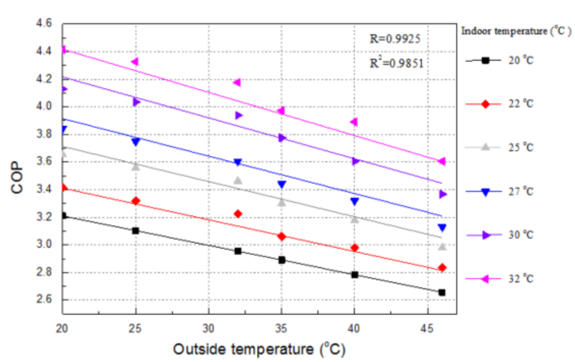

Fig.3 COP measurement of a split A/C

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 includes infiltration and mechanical ventilation. The infiltration is considered constant with 0.3 h^{-1} air change rate and the fans are fixed speed with constant supply volume air in the present study.

Obviously, the resulted thermal dyamic model is nonlinear and time-varying. Values of coefficient matrices are affected by the operation of fans and A/C. The nature of nonlinearity comes from the long wave heat transfer between building external surfaces and ambient environment mentioned. Furthermore, the control variables are the binary state (on/off) of A/C and fans, which introduces the discontinuity to the optimization problem.

MPC FORMULATION

The primary control objective of the porposed MPC is to maintain the TBS's indoor temperature within a given range 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 power consumptions 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:

$$\text{Min:} \quad J(\vec{u}_i) = \sum_{i=1}^{24} \Delta\tau (P_{fan} + P_{ac}) + T_{penalty} + RH_{penalty} \qquad (2)$$

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

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

$$RH = \begin{cases} 0 & , 20\% \le RH \le 85\% \\ 10000 & , else \end{cases}$$

in which, i indicates the sampling instant, $\Delta\tau$ is the sampling period (1 hour), $\vec{u}_i$ is the operate vector of fans and A/C. P_{fan} and P_{AC} are the fans and A/C electrical power consumption per hour (kW), respectively. 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 10^4 in this study. T_{low}, T_{up} are the lower limit and the upper limit, set as 10 ºC and 30 ºC in this study, respectively. In order to avoid excessive moisture into inside, the optimal operate vector is also constrained by the relative humility RH as suggested by [7].

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. 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 optimums.

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 [18]. 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 on the best known solution. In the present study, a discrete particle swarm optimization (DPSO) algorithm is used to search the optimal operation vector for fans and A/C combination with the building dynamic thermal model and the objective function. The parameters and neighborhood topological structure have a large impact on the performance of PSO. In view of analysis and recommendation by [19-21], star topology is applied here. The flow chart of DPSO-MPC is presented in Fig.4.

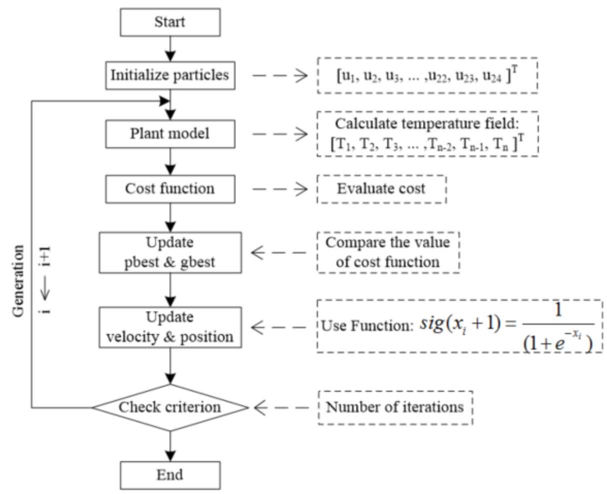

Fig.4 Fow chart of DPSO-MPC

SIMULATION RESULTS AND ANALYSIS

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

(a) baseline building operation only using air conditioner with simple rules control (if T_{in}>30 turn on and if T_{in}<20 turn down) to maintain a given setting temperature and humidity; and
(b) hybrid-mode cooling coupling with mechanical ventilation and air conditioner operated based on heuristic rules control.

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 24h. The performance of control strategies is evaluated by daily cooling power consumption and the control accuracy in terms of the maximum deviation from the desired temperature range.

Evaluation and comparison of control strategies

To quantify the performance of control strategies with respect to each control objective, two measures (temperature deviation and cooling power consumption) were used. Table 1 lists the operating time of fans and A/C. The MPC controller through optimization the operation schedules of fans and A/C can reduce the running time of A/C or fan. For example, when free cooling can meet the indoor cooling load (in June 20, 21, 22, 26), the operating time of fan is reduced by 8, 6, 4, 3 hours, respectively. In June 23, 24, 25, when the cooling load is beyond the free cooling ability and requires the assistance from mechanical cooling, the MPC can reduce the running time of A/C while exploiting the free cooling.

Table 1 Daily operation hours for fan and A/C

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

Note: '--' means not available.

Fig. 5 presents the maximum deviation of indoor temperature from the temperature control range which indicates the control accuracy of each control strategy in meeting the primary control objective. The proposed MPC is able to provide better temperature accuracy control performance than conventional control method, with 0.38 ºC against 0.8 ºC maximum deviation within the simulation period.

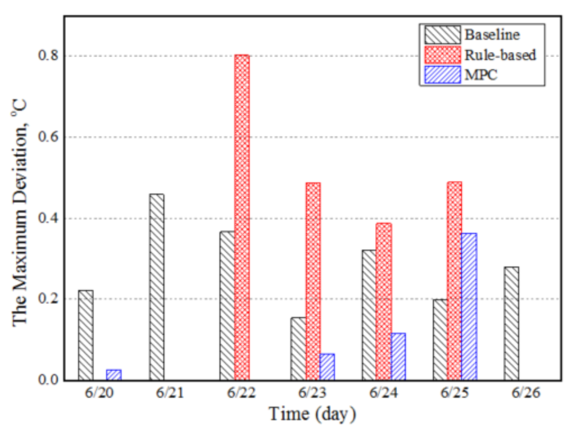

Fig.5 Control accuracy in maximum deviation

With regard to the secondary control objective, As shown in Fig. 6, compared to baseline case (42.87×10^4 kJ) and rule-based controller case (33.45×10^4 kJ), the cooling energy with the MPC controller is 21.97×10^4 kJ over the simulation period, achieving 105% and 37% cooling energy saving, respectively. Notice that during some ambient conditions when the refrigerating efficiency of fan is lower than that of A/C unit, MPC controller can find the better one to execute, but rule-based controller always takes precedence of free cooling due to the ignorance of comparative efficiency between the A/C and the fan. It also explains why the energy consumption of hybrid cooling system under based-rule controller is higher than that of baseline cooling system during the simulation period June 25.

Impact of COP model mismatch

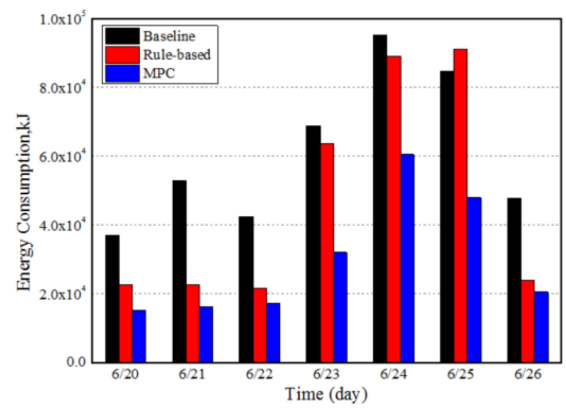

Fig.6 Daily cooling power consumption

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 have 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?

In order to answer this question, a simple approach is proposed to investigate the effects of model-plant mismatch. 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.

The degree of model mismatch is defined as follows equation:

$$\bar{\delta} = \frac{1}{n}\sum_{n}\frac{|COP_{real} - COP_{MPC}|}{COP_{real}} \times 100\% \qquad (3)$$

where $\bar{\delta}$ is the average degree of model-plant mismatch; n is the planning horizon; Subscript *MPC* and *real* reprensent COP value from constant COP model and variable COP model in real-time, respectively.

To illustrate the performance of the MPC controller, we use energy consumption and the maximum deviation of temperature to generate the total performance evaluation index I_{total}, defined as:

$$Itotal = \frac{J_{mis} - J_{non}}{J_{non}} \times 100\% \qquad (4)$$

where J is the optimization objective function, which considers above two control objectives. Subscript *mis* and *non,* are on behalf of mismatch and non-mismatch model, respectively.

	time	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	0:00	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	1	0	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	0	1	1	1	0	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	0	1	0	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	0	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	1	1	1	8
	A/C	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	0	1	0	0	0	9

1 means on and 0 means off)

Fig. 7 Operation hours of fan and AC with model mismatch

Cases with June 24 weather data were selected to demonstrate and quantify the impact of model mismatch on the MPC. During that day, the A/C needs to be operated long to maintain the space temperature as shown above. The operation schedule of fan and A/C from each MPC controller with different COP model is present in Fig. 7. As shown in the last row, the total running time of the fan decreases while that of the A/C increases with the rising constant COP value.

Fig.8 depicts the COP values for MPC controllers, 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 are different from the COP regarded in the MPCs and lead to model mis-match. The real COP in each controller is close to the one given in the non-mismatch MPC as sown in the last subplot. Since MPC with different COP values generates different input and yields different temperature field, real-time COP depends on the value of temperature; hence, the scatter for each sub-plot is not the same.

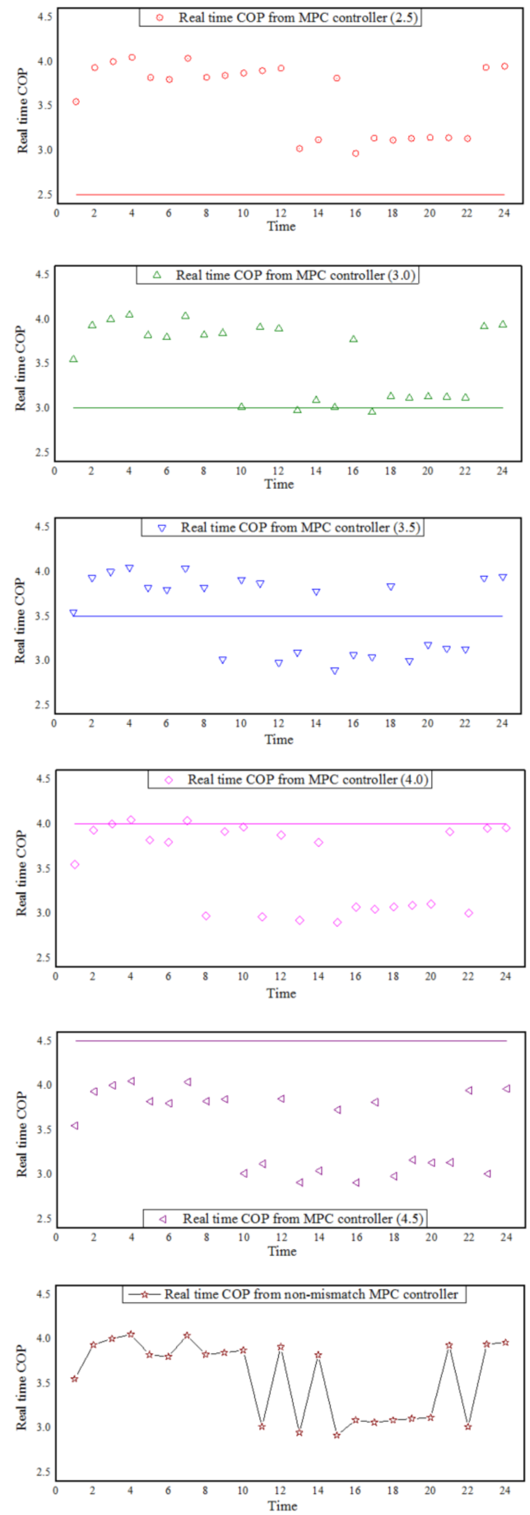

Fig.8 Real time COP value during

It is observed from Fig. 7 that during 1:00am - 7:00am with low outdoor temperature, the control signals from all controllers are the same since the fan is effective and more efficient than the A/C for cooling the space. However, as the outside temperature rises after the period, using the fan may no longer be effective to maintain the space temperature. The selection to run the fan or A/C by the MPCs will be affected by the COP models and start to show the descrepancy. Very likely, an MPC with a higher COP value model prefers the A/C. For example, under the same conditions at 8:00, MPCs with 2.5, 3.0 COP value select fan while MPCs with 3.5 and 4.0 COP value select A/C. The exception from MPC with 4.5 COP is due to the stochastic feature of the intelligent optimization algorithm.

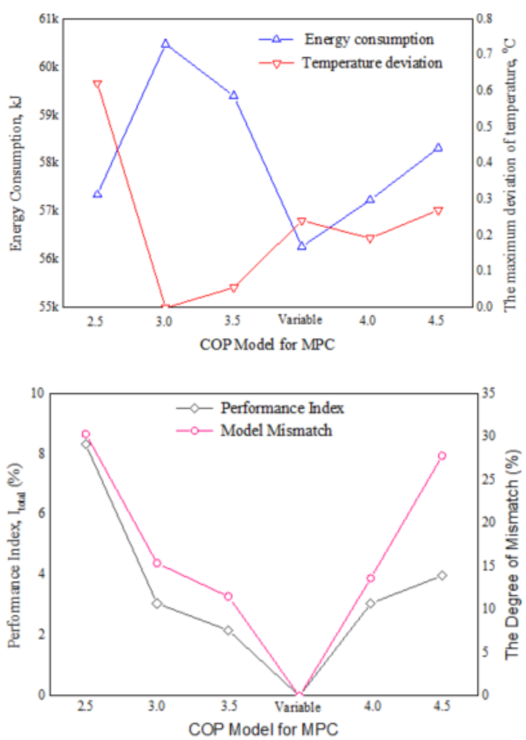

Fig.9 Performance of MPC vs model mismatch

Fig. 9 depicts the variation of energy objective, temperature objective and total performance index versus the degree of average mismatch. The MPC controller with variable COP model is considered to be non-mismatch ($\bar{\delta} = 0\%$) as a reference. The extent of average mismatch in different MPC controllers can be calculated using Eq. (3), and the sequence is 2.5>4.5>3.0>4.0>3.5>Variable. It seems to be non-regular when we analyze separately the energy consumption and deviation temperature with the model mismatch. In general, a high model mismatch leads to a high performance degredation as illustrated by the performance index. Taking COP = 4.5 for instance, its power consumption is 58,320 kJ and control deviation of temperature is 0.27 °C with $\bar{\delta} = 27\%$ while the corresponding results of non-mismatch controller ($\bar{\delta} = 0\%$) are 56,268 kJ and 0.24 °C respectively. The degradation of performance because of model mis-match could be affected by the formulation of the cost function. But it is clear that the total performance decreases significantly as the degree of mismatch ($\bar{\delta}$) increases, either with more deviation on the air temperature or more energy consumption as demonstrated in the second plot of Fig. 9.

CONCLUSIONS

In this work, we present a model predictive control (MPC) strategy with hybrid cooling, i.e. ventilation cooling and mechanical cooling, for telecommunication base stations. The purpose is to explore the energy saving potentials with advanced control. To handle the discontinuity and nonlinearity involved with the multi-mode system, a discrete particle swarm optimization algorithm is adopted. The variable COP model is obtained using the manufacturer data. The building and system models and optimization algorithms are presented. Simulations were conducted for a typical week during the cooling season to evaluate the performance of MPC. Meanwhile, the performance due to model mis-match 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 power saving can be up to 57% compared with baseline cooling system.

(2) The MPC controller demonstrates better performance by reducing cooling power consumption up to 50% relative to conventional control methods. Meanwhile, it also increases the control performance in terms of the maximum deviation from the desired temperature range (MPC controller 0.3 °C versus based-rules controller 0.8 °C).

(3) The quality of model has a great impact on the performance and control outcome of MPC. In general, a high model mismatch leads to a high performance degredation as illustrated by the performance index. During the hottest day, MPC controllers with a constant COP either consumes more energy or lead to a higher deviation on the air temperature compared to the MPC with a real and variable COP.

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