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A global optimized operation strategy for energy savings in liquid desiccant air conditioning using self-adaptive differential evolutionary algorithm

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Abstract: This study proposes a global optimized operation strategy to reduce energy consumption of a liquid desiccant air conditioning (LDAC) driven by chiller and electric heater. Energy models of chiller, electric heater, pumps and fans are developed to predict their energy consumptions under different operating conditions with different control settings. Heat transfer models of cooling heat exchanger, heating heat exchanger and recovery heat exchanger are established to analyze the heat transfer processes in these components. An optimization problem considering system constraints and interactions between components is built to optimize the energy usage of the whole liquid desiccant air conditioning and simultaneously maintaining the required indoor air quality (IAQ) level. Nine controllable variables related to the performance and energy usage of LDAC are selected as control settings. Self-adaptive differential evolutionary (SADE) algorithm with fast convergence rate is employed to solve the optimization problem to obtain optimal control settings and to develop optimal operation strategies. Compare study is carried out on a fabricated testing facility to show the energy saving performance of the proposed global optimized operation strategy. Compared with the conventional strategy, 18.5% energy saving can be achieved by using the proposed global optimized operation strategy. The proposed global optimized operation strategy is a valid operation strategy that is suitable for application in energy reduction of the existing LDAC system in building.

Keywords: Liquid desiccant air conditioner, Energy conservation, Component models, Optimization, Evolutionary algorithm.

1. Introduction

In recent years, there have been extensive interests on liquid desiccant air conditioning (LDAC) as an alternative method to achieve air temperature and humidity control in occupied space due to its benefits of high energy efficiency and better Indoor Air Quality (IAQ). Compared with conventional cooling based method, LDAC can dehumidify the air energy efficiently by adopting low-grade thermal energy and natural substances with high affinity of water without cooling air below its dew point and reheating again to desired temperature, and can provide high quality air by better air humidity control and prevention of virus and bacteria breeding.

Currently, the main research topics of LDAC include the development of heat and mass transfer model [1-5], experimental investigation [6, 7] and designing new types of system such as inner cooled/heated dehumidifier/regenerator[8, 9], solar energy integrated dehumidification

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systems[10-13] and membrane based dehumidification systems[14-17]. Among these schemes, LDAC driven by chiller and hot water is one of the typical applications used in building air cooling and dehumidification[18]. Experimental and theoretical studies were carried out by Bouzenada et al [19] to analyze performance of LDAC driven by evacuated-tube (ETC), flat-plate (FPC) and hybrid solar thermal arrays under different climates. They concluded that cost savings and design flexibility can be improved by adopting a ratio of 30% FPCs and 70% ETCs. Zhao et al. [20] developed a LDAC system driven by heat pumps and chilled water to be implemented in an office building to achieve air temperature and humidity independent control. Compared with the conventional air conditioning system, the testing results demonstrated big energy saving potential with accepted comfortable indoor environment as well. Qi et al focused on the energy performance of solar-assisted LDAC systems in commercial buildings for four main climate regions[21]. Simulation results showed that building sensible and latent load ratio seriously impacts energy performance of solar assisted LDAC and best performance can be achieved in humid areas.

There is no doubt that LDAC is with the benefits of high energy efficiency compared with conventional air conditioning system. However there is still considerable space to improve the system control, efficiency, capacity, and economics of LDAC by suitable system optimal control and energy management [22]. Optimal control technologies have been widely studied for Heating, Ventilation and Air Conditioning (HVAC) systems based on Genetic Algorithm (GA)[23], Particle Swarm Optimization (PSO)[24, 25] and evolutionary computation algorithm[26]. To further explore the energy saving potential of LDAC systems, more and more attentions have been paid on the research of optimization technologies for LDAC systems to get a better application in building HVAC area with improved comfort and economic benefits. Ge et al. [15] developed an optimal control strategy for liquid desiccant based Dedicated Outdoor Air-Chilled Ceiling system (DOAS-CC) by employing Genetic Algorithm to improve the system energy performance and indoor thermal comfort. Qi et al.[27] optimized system control parameters of a solar assisted LDAC system for buildings in different climates with multi-population GA to obtain maximum energy savings with a minimum cost payback year. Audah et al. [28] indicated the feasibility of supplying both building cooling capacity and fresh water needs with minimal energy cost in Beirut by formulating an optimization problem for a LDAC integrated with solar energy. Multi-objective optimization strategy based on PSO algorithm was

presented by Wang et al. [29] to minimize the energy usage of a liquid desiccant regenerator while maintaining the regeneration rate within an accepted level. Simulation study carried out by Ge et al. reported the development of optimal control strategy for LDAC systems to minimize total energy consumption and keep the multi-zone space thermal comfort as well [30]. Zhang et al. [31] investigated the method for removing extra heat from a heat pump driven LDAC system to improve and optimize the performance of the proposed system. Most of previous studies on optimization of LDAC systems focused on system optimal design, i.e. how to effectively balancing internal load with reduced system initial cost; however rarely concerned about performance optimization to reduce operating cost with optimized control settings. This may be attributed to the lack of simplified models in real-time performance prediction and evaluation for entire LDAC system even though heat and mass transfer process in LDAC is well understood. Even though optimization strategies have been widely investigated for chiller system to improve its energy efficiency based on PSO [24], dynamic neural network [32] and model predictive control [33], the study on global optimized operation strategy for LDAC to reduce the energy cost from the whole system in which all the components including dehumidifier, regenerator and chiller etc. are still missing. Considering that reliable heat and mass transfer models for both dehumidifier and regenerator to be suitable in system performance monitoring and optimization were reported in previous studies[5, 34], this study develops a global optimized operation strategy for energy savings in LDAC and maintaining the required IAQ level based on Evolutionary Algorithm (EA). Energy models of components, such as chiller, electric heater, heat exchangers, as well as the interactions between them are derived to evaluate the system performance and energy usage. Then Self-Adaptive Differential Evolutionary (SADE) algorithm is adopted to search the optimal control settings. Finally, proposed global optimized operation strategy is implemented on an existing LDAC testing facility to show its energy saving potential.

2. System description and problem formulation

The LDAC being investigated in current study is schematically illustrated in Fig 1. Air dehumidification and desiccant solution regeneration are the two processes involved in the dehumidifier and regenerator respectively. The system consists of two main components, namely dehumidifier and regenerator. Some other auxiliary devices, such as pumps, fans, chiller and electric heater, pipes and valves, are equipped with the system to drive these two processes. In

the two processes, coupled heat and mass transfer driven by temperature difference and water vapor pressure difference between the air and desiccant solution performs in opposite directions. During process of air dehumidification, both water vapor pressure (p_a) and temperature (T_a) of air are higher than that of desiccant solution which is cooled in Cooling Heat Exchanger (CHE) by chilled water from chiller. Water vapor from supply air will be absorbed into desiccant solution, and air temperature will decrease as well. As the process of air dehumidification, desiccant solution will be diluted, and need to be concentrated in the regenerator so that it can be reutilized in dehumidifier. In desiccant solution regeneration, diluted desiccant solution from dehumidifier is warmed up through a Recovery Heat Exchanger (RHE) and then further heated by the Heating Heat Exchanger (HHE) equipped in regenerator to increase its water vapor pressure. Sensible heat and water contents will be transferred from the weak desiccant solution with higher temperature and water vapor pressure to the regeneration air. The regenerated strong desiccant solution then will be pumped back to the dehumidifier to be reused in air dehumidification. To prevent the desiccant overflowed during operation, balance pipe connecting dehumidifier and regenerator is installed below the system to keep the level balance of the two units.

From the previous study [5], it can conclude that by adjusting the desiccant solution temperature and flow rate into the dehumidifier, the humidity ratio of supply air can be controlled and regulated to fulfill the IAQ requirements. The lower desiccant solution temperature, the higher desiccant solution flow rate, the drier supply air will be obtained from dehumidifier, meanwhile cooling energy from the chiller and energy consumed by the pump will be increased as well. Same to regenerator, desiccant solution temperature and flow rate together with the regeneration air can affect both the desiccant solution regeneration rate and energy consumption of the regenerator. Conventional operation strategy based on local feedback control may meet the particular performance criteria of subsystem, dehumidifier and regenerator for example, but may not be optimal for the whole system. Global optimized operation strategy which takes into consideration the nature of interactions between subsystems and components, variations of IAQ requirements, outdoor air conditions, overall performance and energy efficiency of the whole system, has the ability to reduce the energy cost and improve the system performance globally by regulating the control settings based on the system perspective.

The energy consumption in LDAC is contributed by the operating equipment, namely pumps and fans in both dehumidifier and regenerator, cooler in dehumidifier and heater in regenerator. Therefore, the total LDAC energy consumption W_{total} can be expressed as follows:

$$E_{total} = E_{F,D} + E_{P,D} + E_C + E_{F,R} + E_{P,R} + E_H \quad (1)$$

where $E_{F,D}$, $E_{P,D}$ and E_C are the energy consumptions of dehumidifier fan, pump and cooler; $E_{F,R}$, $E_{P,R}$ and E_H are the energy consumptions of regenerator fan, pump and heater, respectively. In current study, cooler energy are the sum of energy consumed by the chiller to supply required chilled water to the cooler and energy usage by the chilled water pump to drive the chilled water circulating between the chiller and cooler,

$$E_C = E_{Chiller} + E_{CWP} \quad (2)$$

where $E_{Chiller}$ and E_{CWP} are the energy of chiller and chilled water pump. In the same way, energy consumption of heater can be obtained by Eq. (3):

$$E_H = E_{Electric Heater} + E_{HWP} \quad (3)$$

where $E_{Electric Heater}$ and E_{HWP} are the energy of electric heater and hot water pump.

To develop global optimized operation strategy with minimized energy usage for LDAC, models that can predict the energy consumption of system, and evaluate air dehumidification performance as well as describe the characteristics to the changes of control settings need to be analyzed and established, which will be discussed in next section.

3. System model development

In general, complicated numerical physics-based models are not suitable for real-time optimization applications in this study because it is time-consuming to solve the equations contained in those models. Hybrid models based on theoretical analyses and lumping parameters however can handle the inherent nonlinearity and complexity from the system with acceptable accuracy and less computational burden. Therefore, in this section, hybrid models of chiller, heater, pumps and fans which contribute to the entire energy cost are developed. In addition, performance of heat exchangers together with the heat and mass transfer processes are also

analyzed with hybrid approach to describe the cooling and heating processes in dehumidifier and regenerator. For simplification in model development, some following reasonable assumptions are adopted:

- (1) Steady state operation for LDAC during every optimization time instant;
- (2) Energy loss to environment is neglected;
- (3) Unchanged desiccant solution concentrations in both dehumidifier and regenerator during every optimization time instant;
- (4) Constant thermodynamic properties of the fluids with respect to the temperature.

3.1. Chiller energy model

Chiller supplies chilled water into the CHE in dehumidifier to drive the air dehumidification process, meanwhile electric energy is consumed. The chiller energy consumption can be predicted by introducing the concept of Coefficient of Performance (COP) which is defined as the ratio of cooling energy provided and chiller energy input. From Yao's study[35], COP of chiller can be written as follows, by empirically fitted parameters (a_1 and a_2):

$$COP = \frac{r_c}{\left(\frac{t_c + 273.15}{t_e + 273.15} - 1\right)r_c + a_1 \frac{t_c + 273.15}{t_e + 273.15} + a_2} \quad (4)$$

where r_c is the chiller part load ratio which is defined as the ratio of chiller current capacity $Q_{c,cur}$ and chiller nominal capacity $Q_{c,nom}$,

$$r_c = \frac{Q_{c,cur}}{Q_{c,nom}} \quad (5)$$

In steady operating condition, energy balance between the chiller and CHE in the dehumidifier should be obtained. Thus, current load of chiller is determined by the cooling requirement of CHE in the dehumidifier which can be expressed as follows:

$$Q_{c,cur} = Q_{CHE} = c_s m_{s,D} (T_{s,in,CHE} - T_{s,in,D}) \quad (6)$$

Therefore, chiller energy consumption can be determined by Eq. (7):

$$E_{chiller} = \frac{Q_{c,cur}}{COP} = \frac{c_s m_{s,D} (T_{s,in,CHE} - T_{s,in,D})}{r_c} \left[\left(\frac{t_c + 273.15}{t_e + 273.15} - 1 \right) r_c + a_1 \frac{t_c + 273.15}{t_e + 273.15} + a_2 \right] \quad (7)$$

3.2. Electric heater model

Electric heater is utilized to heat up the weak desiccant solution to increase its water vapor pressure and to enhance the mass transfer process before it is pumped into the regenerator to be concentrated. Insulation materials are well wrapped up outside the electric heater shell as well as along the hot water pipeline so that the heat loss from heater and hot water pipeline to the environment can be reasonably neglected. Therefore the electric heater energy consumption is determined by the heating load from HHE during solution regeneration process, which is presented in Eq. (8):

$$E_{Electric\ Heater} = Q_{HHE} = c_s m_{s,R} (T_{s,in,R} - T_{s,in,HHE}) \quad (8)$$

where Q_{HHE} is the heating load of the electric heater, $m_{s,R}$ is the mass flow rate of desiccant solution in regenerator, $T_{s,in,HHE}$ and $T_{s,in,R}$ are the desiccant solution temperatures of inlet and outlet the HHE, respectively.

3.3. Pump and fan energy model

Pumps and fans are equipped with Variable Speed Drivers (VSDs) so that both the flow rates of liquid fluids (desiccant solutions, chilled water and hot water) and the air (supply air and regeneration air) can be regulated. Energy models of the pumps and fans with VSDs can be developed by following equations:

$$E_j = E_{j,nom} (b_{1,j} + b_{2,j} r_j + b_{3,j} (r_j)^2 + b_{4,j} (r_j)^3) \quad (9)$$

$$r_j = \frac{m_{j,cur}}{m_{j,nom}} \quad (10)$$

where E_j and $E_{j,nom}$ are current energy consumption and nominal energy consumption of pumps or fans, respectively ($j = 1, 2, \dots, 6$ is representing the dehumidifier pump, regenerator pump, chilled water pump, hot water pump, dehumidifier fan and regenerator fan in current study), $m_{j,cur}$ and $m_{j,nom}$ are the current and nominal mass flow rates for the corresponding pump or fan,

respectively; r_j is the part load ratio of pump or fan accordingly, $b_{1,j} \sim b_{4,j}$ are the parameters needs to be determined before using the energy models to predict energy consumptions of pumps or fans.

3.4. Heat exchanger model

Three heat exchangers are equipped in the proposed LDAC system for the purpose of cooling, heating and energy recovery, namely CHE in the dehumidifier, HHE in the regenerator and RHE between them. These heat exchangers are all in counter flow configurations and well thermal insulations are made so that energy losses to the surrounding ambient can be neglected. Under a small working range, it is assumed that the heat transfer coefficients at desiccant solution side or the water side in the heat exchangers remain unchanged and are relevant only to the flow rate of fluid. The heat transfer rate of the heat exchanger can be presented in Eqs. (11) and (12):

$$Q_i = k_{c,i} A_i (T_{wall,i} - T_{c,in,i}) \quad (11)$$

$$Q_i = k_{h,i} A_i (T_{h,in,i} - T_{wall,i}) \quad (12)$$

where Q_i is the heat transfer rate of i th heat exchanger ($i = CHE, HHE, RHE$) with $T_{c,in,i}$ and $T_{h,in,i}$ as inlet temperatures of cooling fluid and heating fluid, respectively, A_i is the heat transfer area, $k_{c,i}$ and $k_{h,i}$ are the heat transfer coefficients for both cool and hot sides, $T_{wall,i}$ is the average wall temperature of heat transfer surface. According to the assumptions mentioned above, heat transfer rate can also be described as follows:

$$Q_i = \lambda_{c,i} (m_{c,i})^{\gamma_{c,i}} (T_{wall,i} - T_{c,in,i}) \quad (13)$$

$$Q_i = \lambda_{h,i} (m_{h,i})^{\gamma_{h,i}} (T_{h,in,i} - T_{wall,i}) \quad (14)$$

where $m_{c,i}$ and $m_{h,i}$ are the mass flow rates of cooling fluid and heating fluid in i th heat exchanger. Combining Eqs. (13) and (14), the heat transfer rate of heat exchanger can be rewritten as,

$$Q_i = \frac{\lambda_{c,i} (m_{c,i})^{\gamma_{c,i}}}{1 + (\lambda_{c,i} / \lambda_{h,i}) (m_{c,i})^{\gamma_{c,i}} (m_{h,i})^{-\gamma_{h,i}}} (T_{h,in,i} - T_{c,in,i}) \quad (15)$$

The parameters in Eq. (15) $\lambda_{c,i}$, $\lambda_{h,i}$, $\gamma_{c,i}$ and $\gamma_{h,i}$, reflecting the heat transfer performance of heat exchangers, can be identified by historical operating data from heat exchangers using recursive least-squares (RLS) method [36].

3.5. Heat and mass transfer models

In addition to energy models of components in LDAC, heat and mass transfer processes in both dehumidifier and regenerator have significant impacts on system energy utilization, stable operation as well as the performance of LDAC system. Theoretical analysis and model development of the heat and mass transfer in LDAC has attracted attentions in last decades [37, 38]. Models with complex parameters and iterative computations cannot have a proper application in developing real-time optimization operation strategy for LDAC. Previous studies have reported and expounded hybrid models with little parameters and eased computational burden to predict heat and mass transfer processes appropriately in both dehumidifier and regenerator. By considering desiccant flow rate $\dot{m}_s$, temperature $T_{s,in}$, concentration ω_s and air flow rate $\dot{m}_a$, temperature $T_{a,in}$, relative humidity $RH_{a,in}$ as model input variables, the heat and mass transfer rates during air dehumidification and desiccant solution regeneration processes can be predicted by Eqs. (16) and (17) [5, 34]:

$$Q_{D/R} = \frac{c_{1,D/R} (m_{s,D/R})^{c_{3,D/R}}}{1 + c_{2,D/R} \left(\frac{m_{s,D/R}}{m_{a,D/R}} \right)^{c_{3,D/R}}} | (T_{a,in,D/R} - T_{s,in,D/R}) | \quad (16)$$

$$N_{D/R} = \frac{c_{4,D/R} (m_{s,D/R})^{c_{6,D/R}}}{1 + c_{5,D/R} T_{a,in,D/R} (m_{s,D/R})^{c_{6,D/R}} (m_{a,D/R})^{c_{7,D/R}}} | (p_{a,in,D/R} - p_{s,in,D/R}^*) | \quad (17)$$

where $c_{1,D/R} \sim c_{7,D/R}$ are the identified parameters related to the above models.

4. Global optimized operation strategy

To get the global optimization of LDAC in the study, optimized operation strategy is developed to minimize energy usage of whole system and simultaneously maintaining the required IAQ level in which indoor air temperature and relative humidity are considered, as shown in Fig. 2. System input and output data will be communicated via building automation local network. System components models periodically updated by system input-output data are integrated with given operational conditions such as outdoor environments, IAQ requirements and interaction

relationships between components to evaluate energy consumption and system performance under different operating strategies. In every optimization time instant, Optimizer based on SADE algorithm will be adopted to seek the optimal control settings in response to the change of outdoor conditions and IAQ requirements. Optimized control setting will be implemented to LDAC system via building automation local network. Cost function, system variables together with their constraints and the adopted SADE algorithm should be addressed to develop the proposed global optimized operation strategy.

4.1. Cost function

By using the above presented energy models from Eqs. (4)-(10), the overall energy consumption of the system can be evaluated in response to the changes of control settings. The aim of this study is to minimize the energy consumption of proposed LDAC, therefore the total energy consumption which has been explained in Eq. (1) is considered as the cost function J to be optimized. The cost function can be denoted by Eq. (19),

$$J = E_{total} = E_{Chiller} + E_{Electric\ Heater} + \sum_{j=1}^6 E_j \quad (18)$$

4.2. System variables

The variables from the LDAC system can be classified into three different sets namely control settings, uncontrollable variables and dependent variables. Variables that can affect both the system energy consumption and performance and can be controlled independently are considered as the control settings. During optimization process, control settings will be adjusted in the feasible range to search the optimal control settings that can obtain the feasible minimal value of energy cost for the LDAC system. According to the features of LDAC in this study, the following control settings are included:

- Dehumidifier desiccant solution inlet temperature, $T_{s,in,D}$
- Dehumidifier desiccant solution mass flow rate, $m_{s,D}$
- Regenerator desiccant solution inlet temperature, $T_{s,in,R}$
- Regenerator desiccant solution mass flow rate, $m_{s,R}$
- Regenerator air mass flow rate, $m_{a,R}$

- 277 • Chilled water supply temperature, T_{chws}
- 278 • Chilled water supply mass flow rate, m_{chws}
- 279 • Hot water supply temperature, T_{hws}
- 280 • Hot water supply mass flow rate, m_{hws}

281 Uncontrollable variables cannot be adjusted during optimization process, such as outdoor air
 282 temperature and relative humidity ($T_{a,out}$ and $RH_{a,out}$), indoor required air flow rate, temperature
 283 and relative humidity ($m_{a,req}$, $T_{a,req}$ and $RH_{a,req}$) which are determined by occupants' thermal
 284 comfort, desiccant solution temperatures and concentrations in bottom tanks from dehumidifier
 285 and regenerator ($T_{s,bot,D}$, $T_{s,bot,R}$ and $\omega_{s,bot,D}$, $\omega_{s,bot,R}$) which rely on system operating conditions. It
 286 should be noted that the mass flow rate of supply air in dehumidifier is considered as
 287 uncontrollable variable and ignored from the control settings since it is generally determined by
 288 requirements from indoor occupants. All the uncontrolled variables should be fixed based on
 289 real-time weather data, indoor thermal comfort requirements and the system measurements
 290 before the optimization process starts.

291 Dependent variables are the variables that can be expressed by control settings or uncontrollable
 292 variables, for example chiller evaporating temperature, condensing temperature and chiller part
 293 load ratio (t_e , t_c and r_c), pumps and fans part load ratios (r_j , $j = 1, 2 \dots 6$), desiccant solution
 294 temperatures of inlet and outlet of CHE and RHE ($T_{s,in,CHE}$ and $T_{s,in,HHE}$), water vapor pressures
 295 of desiccant solution and air in both dehumidifier and regenerator ($p_{s,in,D}^*$, $p_{s,in,R}^*$ and $p_{a,in,D}$,
 296 $p_{a,in,R}$).

297 4.3. Constraints

298 To ensure the feasibility of the solution generated from proposed global optimized operation
 299 strategy, some constraint limitations should be satisfied for control settings and dependent
 300 variables. These values of upper and lower limitations are determined based on physical
 301 constraints, capacities of operating components and some safety issues to avoid extreme working
 302 conditions that would cause damages to system. For example, operating frequencies of pumps,
 303 fans and chiller compressor that equipped with VSDs should never be larger than the nominal

frequency, but be more than 30Hz in order to avoid poor motor heat dissipation under too lower rotating speeds. Therefore, the flow rates of fluids among control settings should vary between the maximum values and minimum values. Evaporating temperature and condensing temperature for chiller are also recommended within appropriate range to offer enough cooling energy efficiently to CHE and keep energy balance of chiller sub-system. Chiller part load ratio should also be some values between minimal value and one. Table 1 summarizes the bounded limitations for the variables.

Besides the bounded limitations, some interaction relationships between variables and components should be adopted for establishing this optimization problem so that indoor thermal comfort requirements can be fulfilled correspondingly.

Temperature and relative humidity of supply air are considered as the two indexes that related with the IAQ, therefore dehumidified air conditions from LDAC should be kept within the accepted range of the required conditions so that the requirements of the indoor occupants can be met, which can be described as follows:

$$T_{a,req,min} \leq T_{a,out} \leq T_{a,req,max} \quad (19)$$

$$RH_{req,min} \leq RH_{a,out} \leq RH_{req,max} \quad (20)$$

To maintain the material balance in the system, there should have the same mass transfer rates in both dehumidifier and regenerator. Furthermore, the solution temperatures of inlet CHE and HHE depend on the energy recovery performance of RHE which can be calculated by Eq. (15). From energy and material balance, these constraints can be determined by the following Eqs,

$$N_D = N_R \quad (21)$$

$$T_{s,in,CHE} = T_{s,bot,R} - \frac{Q_{RHE}}{c_s m_{s,D}} \quad (22)$$

$$T_{s,in,HHE} = T_{s,bot,D} + \frac{Q_{RHE}}{c_s m_{s,R}} \quad (23)$$

where $Q_{RHE} = \frac{\lambda_{c,RHE} (m_{s,R})^{\gamma_{c,RHE}}}{1 + (\lambda_{c,RHE} / \lambda_{h,RHE}) (m_{s,R})^{\gamma_{c,RHE}} (m_{s,D})^{-\gamma_{h,RHE}}} (T_{s,bot,R} - T_{s,bot,D})$. Meanwhile, cooling and

heating energies supplied to CHE and HHE should be equal to the desiccant solution energies

changes through the CHE and HHE, respectively. That means following equality constraints should be met between some system variables,

$$c_s m_{s,D} (T_{s,in,CHE} - T_{s,in,D}) = \frac{\lambda_{c,CHE} (m_{cws})^{\gamma_{c,CHE}}}{1 + (\lambda_{c,CHE} / \lambda_{h,CHE}) (m_{cws})^{\gamma_{c,CHE}} (m_{s,D})^{-\gamma_{h,CHE}}} (T_{s,in,CHE} - T_{cws}) \quad (24)$$

$$c_s m_{s,R} (T_{s,in,R} - T_{s,in,HHE}) = \frac{\lambda_{c,HHE} (m_{s,R})^{\gamma_{c,HHE}}}{1 + (\lambda_{c,HHE} / \lambda_{h,HHE}) (m_{s,R})^{\gamma_{c,HHE}} (m_{hws})^{-\gamma_{h,HHE}}} (T_{hws} - T_{s,in,HHE}) \quad (25)$$

Consequently, the optimization problem to be optimized in global optimized operation strategy can be formulated as follows:

$$\begin{aligned} \min \quad & J = E_{Chiller} + E_{Electric Heater} + \sum_{j=1}^6 E_j \\ \text{subject to: } & \mathbf{X}_{\min} \leq \mathbf{X} \leq \mathbf{X}_{\max} \\ & T_{a,req,min} \leq T_{a,out} \leq T_{a,req,max} \\ & RH_{req,min} \leq RH_{a,out} \leq RH_{req,max} \\ & T_{s,in,CHE} = T_{s,bot,R} - \frac{Q_{RHE}}{c_s m_{s,D}} \\ & T_{s,in,HHE} = T_{s,bot,D} + \frac{Q_{RHE}}{c_s m_{s,R}} \\ & c_s m_{s,D} (T_{s,in,CHE} - T_{s,in,D}) = \frac{\lambda_{c,CHE} (m_{cws})^{\gamma_{c,CHE}}}{1 + (\lambda_{c,CHE} / \lambda_{h,CHE}) (m_{cws})^{\gamma_{c,CHE}} (m_{s,D})^{-\gamma_{h,CHE}}} (T_{s,in,CHE} - T_{cws}) \\ & c_s m_{s,R} (T_{s,in,R} - T_{s,in,HHE}) = \frac{\lambda_{c,HHE} (m_{s,R})^{\gamma_{c,HHE}}}{1 + (\lambda_{c,HHE} / \lambda_{h,HHE}) (m_{s,R})^{\gamma_{c,HHE}} (m_{hws})^{-\gamma_{h,HHE}}} (T_{hws} - T_{s,in,HHE}) \end{aligned} \quad (26)$$

where $\mathbf{X}$, $\mathbf{X}_{\min}$ and $\mathbf{X}_{\max}$ are the vectors of control settings and dependent variables listed in Table 1, and their lower and upper limitations, respectively.

4.4. Self-adaptive differential evolutionary algorithm

In every optimization time instant, system components models developed in section 3 are integrated with the given operational conditions such as outdoor air conditions, IAQ requirements and interaction relationships between components to calculate the energy consumption and system performance under different operation strategies. In this study, a self-adaptive differential evolution (SADE) algorithm which is a simple and powerful population-based stochastic tool in global optimization will be employed to solve the optimization problem in Eq. (26) and to seek the optimal control settings in response to the changes of outdoor air

conditions and IAQ requirements. Four following operations are involved in proposed SADE algorithm:

Initialization: At the beginning of the SADE algorithm, the initial population denoted as $\{\mathbf{x}(0) | x_j^L \leq x_{j,i}(0) \leq x_j^U, i = 1, 2, \dots, NP; j = 1, 2, \dots, N\}$ is generated randomly by applying Eq. (27) to select candidate solutions from N -dimensional search space. N is determined by the dimension of the control settings and NP is the size of population.

$$x_{j,i}(0) = x_j^L + rand(0,1)(x_j^U - x_j^L) \quad (27)$$

where $x_{j,i}(0)$ is values of the j th control variable from the i th individual in initial population sized NP , x_j^L and x_j^U are the lower and upper bounds of the j th control variable of the individual, respectively.

Mutation: As the vital operation of SADE algorithm, in g th generation, for each individual $\mathbf{x}_i(g)$ denoted as $\{\mathbf{x}_i(g) | x_j^L \leq x_{j,i}(g) \leq x_j^U, j = 1, 2, \dots, N\}$, three distinct individuals are randomly selected from the current generation to generate the mutant individual $\mathbf{v}_i(g+1)$, $i = 1, 2, \dots, NP$ for the next generation. The mutation operation is described as follows,

$$\mathbf{v}_i(g+1) = \mathbf{x}_{r_1}(g) + F \cdot (\mathbf{x}_{r_2}(g) - \mathbf{x}_{r_3}(g)) \quad (28)$$

where F is the differential weight for scaling the differential of vectors. r_1 , r_2 and r_3 are different integers randomly generated in the range $[1, NP]$. After the mutation operation, a mutant population denoted as $\{\mathbf{v}(g+1) | x_j^L \leq v_{j,i}(g+1) \leq x_j^U, i = 1, 2, \dots, NP; j = 1, 2, \dots, N\}$ is generated.

Crossover: After the mutant population is produced, crossover operation is applied to generated recombinant population based on the crossover rate,

$$u_{j,i}(g+1) = \begin{cases} v_{j,i}(g+1) & \text{if } rand(0,1) < Cr \in [0,1] \text{ or } j = j_{rand} \\ x_{j,i}(g) & \text{otherwise} \end{cases} \quad (29)$$

where Cr is the crossover rate, j_{rand} is a integer randomly selected from $[1, 2, \dots, N]$ (here N is the number of control variables) to make sure every individual from the recombinant population will at least differ from its target parent $x_{j,i}(g)$ by one variable. If the value of some variable from the recombinant population exceeds lower or upper limitations, a new and random value within feasible range will be assigned to this variable to ensure feasibility of the optimal solution.

Selection: Values of cost function will be evaluated and compared between recombinant individual and its parent. The one with better cost value will survive and be remained in the final offspring. The selection operation can be expressed as follows:

$$\mathbf{x}_i(g+1) = \begin{cases} \mathbf{u}_i(g+1), & \text{if } f(\mathbf{u}_i(g+1)) \leq f(\mathbf{x}_i(g)) \\ \mathbf{x}_i(g), & \text{otherwise} \end{cases} \quad (30)$$

In original Differential Evolution (DE) algorithm, NP , F and Cr are three parameters that with close relationship to its performance. Larger NP can improve the robustness of the algorithm. In addition, F and Cr are considered as the parameters that are more sensitive to the problem's property and convergence speed. Higher values of F and Cr can result in a faster convergence with more diverse populations. On the other hand, larger F may lead to over exploration. In current study, NP will be determined by the users and kept unchanged during the iterations. Other two tuning parameters, differential weight and crossover rate, will be varying adaptively in each generation to achieve a faster, robust convergence and to avoid degeneration and local minimum[39]. In the initialization operation, F and Cr are initialed randomly between their lower and upper limitations. For each individual in every population, F and Cr are updated as follows:

$$F = 1 - (f(\mathbf{x}_{best}(g)) / f(\mathbf{x}_i(g))) \quad (31)$$

$$Cr = \frac{2f(\mathbf{x}_i(g))}{f(\mathbf{x}_{worst}(g)) + f(\mathbf{x}_{avg}(g))} \cdot rand(0.5,1) \quad (32)$$

where $f(\mathbf{x}_{best}(g))$, $f(\mathbf{x}_{worst}(g))$ and $f(\mathbf{x}_{avg}(g))$ are the best, worst and average cost values in gth generation, respectively. $rand(0.5,1)$ is the random number between 0.5 and 1. By this adaptive updating procedure, individuals with better cost values will be more likely to be remained in next generation. The mutation, crossover and selection operations will be repeated generation after generation until maximum generation is reached or some specific stopping criteria are satisfied. Flowchart of the proposed SADE algorithm is illustrated in Fig. 3.

5. Results and discussion

5.1. Experimental test facility

To test the energy saving performance of proposed global optimized operation strategy, an experimental test facility using LiCl-H₂O solution as the desiccant material is developed and fabricated in Process Instrumentation Lab at Nanyang Technological University, Singapore,

which is illustrated in Fig. 4. The test facility consists of a chiller, an electric heater, two packed columns (a dehumidifier and a regenerator). The chiller and electric heater are employed to provide chilled water and hot water respectively to dehumidifier and regenerator. Desiccant solutions come into contacting with the air in counter-flow configuration within the packed columns filled with $\varnothing 500\text{mm} \times 600\text{mm}$ structure packing material where heat and mass transfer processes occur. All the equipment and pipelines are well thermal insulated to prevent the energy loss to environment. Sensors and transmitters such as flow meter, PT1000 RTD and air humidity sensors are installed in the facility to monitor and evaluate the performance of proposed LDAC system. Control settings described in Section 4.2 can be adjusted and controlled by the inverters or controllers equipped in chiller, heater, fans and pumps. Power meters are utilized to measure and monitor the energy consumption of the whole LDAC system. All these system measurements and readings are collected by data acquisition system based on NI cRIO 9023 with 1-min sampling intervals.

5.2. Model validation

To validate the developed models in section 3, testing was conducted to adjust the controlled variables within feasible operating ranges; meanwhile energy consumptions of the components, for instance chiller, electric heater, pumps and fans, are monitored by power meters. After filtering some abnormal data, the dataset were used to identify the developed energy models with methods introduced in study of [40]. Then some data points are randomly selected from the dataset to verify the identified models. It is worthwhile to note that previous study [29] has already presented and reported the models of heat and mass transfer, pumps and fans therefore only chiller model and heat exchanger models are verified and discussed in this study. Table 2 lists the identified parameters for chiller, heat transfer models of CHE, HHE and RHE, respectively. Mean Absolute Error (MAE), Standard deviation of Absolute Error (Std_AE), Mean Relative Error (MRE) and Standard deviation of Relative Error (Std_RE) described in Eqs. (33) - (36) are employed as the statistical metrics to evaluate the prediction performance in energy consumption or heat exchange rate of proposed models for corresponding components.

$$MAE = \frac{\sum_{k=1}^n |\tilde{y}_k - y_k|}{n} \quad (33)$$

$$Std_AE = \sqrt{\frac{\sum_{k=1}^n (|\tilde{y}_k - y_k| - MAE)^2}{n-1}} \quad (34)$$

$$MRE = \frac{\sum_{k=1}^n \left| \frac{\tilde{y}_k - y_k}{y_k} \right| \times 100\%}{n} \quad (35)$$

$$Std_RE = \sqrt{\frac{\sum_{k=1}^n \left(\left| \frac{\tilde{y}_k - y_k}{y_k} \right| \times 100\% - MRE \right)^2}{n-1}} \quad (36)$$

where y_k and $\tilde{y}_k$ are the k th actual measure value and predicted value from n data points for model performance evaluation respectively. The predicted results by developed energy models and corresponding measured energy consumptions are compared along with standard derivation error bar, as illustrated in Figs. 5-8. In these figures, red line and green line stand for the +8% and -8% relative errors, respectively. It can be drawn from the figures that energy consumptions of chiller, cooling energy from CHE, heat energy from HHE and energy recovery rate of RHE can be predicted accurately by the proposed models with the maximum relative errors less than 8% (within space between the red line and green line in the figures). The errors may come from the assumptions during model development and accumulation errors from sensors measuring. The prediction performances for the proposed models are summarized in Table 3. From the table, acceptable statistical metrics can be obtained from these four energy models with MRE less than 5% and Std_APE less than 2.5%. It indicates that the developed models are accurate enough to predict power consumption of components or to evaluate the performance of different strategies during the optimization process.

5.3. Optimization results and discussion

To demonstrate the effectiveness of proposed global optimized operation strategy, one day's evaluations were carried out on a typical day of March 2016 to supply dehumidified and cooled air to the lab cubic space with about area 100m². The outdoor air temperature and relative humidity during the experiment time are derived from the weather forecast data available from National Environment Agency of Singapore. And the supply air rate of this space is determined according to the number of occupants. Outdoor air conditions and fresh air requirements are presented in Fig. 9. The supply air temperature and relative humidity is fixed around 17°C and 50% respectively which is lower than required indoor settings (normally 25°C and 50% based on ASHRAE Standard [41]) to cover the internal sensible and latent loads. It should be noted that

evaluations are only discussed during the working hours from 6:00 to 22:00 because of no cooling and dehumidification requirements for the lab space during the night. From the figure, three segments are divided from the testing period, namely morning (6:00-9:00), noon and afternoon (9:00-18:00) and evening (18:00-22:00), respectively. Lower air supply rates are applied (300m³/h to 600m³/h) to the space during the first and third segments due to fewer occupants, while higher air flow rate in the second segment because the space is fully occupied. Firstly, one case study is carried out under condition at 12:00 with air temperature 32°C, relative humidity 66% and 900m³/h fresh air. Uncontrollable variables described in Section 4.2 are fixed based on the weather condition, indoor thermal requirement and system operation data. For comparison study, the proposed SADE algorithm and original DE algorithms (DE1, DE2 and DE3) with different parameter settings listed in Table 4 are then employed to solve the optimization problem of Eq. (26) to find the optimal solution of control settings by using Matlab 2014a on a computer with Intel CORE i50-4300U @1.90Ghz and 8.00GB memory. Fig. 10 shows the values of cost functions against the generation during the optimization for algorithms with different parameter settings. It indicates that by introducing adaptive mechanism, the proposed SADE algorithm performs better in terms of convergence and the cost function value reaches convergence before the first 50 generations with 10.9s total computation time. The computation time is competitive with that used by original DE algorithms. The optimal control settings and energy consumption of LDAC under the selected outdoor air condition are listed in Table 5.

Secondly, the proposed global optimized operation strategy and conventional operation strategy are applied to the testing facility at beginning of each hour from 6:00 to 22:00 on that typical day to demonstrate its energy saving performance. In conventional strategy, flow rates such as desiccant solution in dehumidifier and regenerator, regeneration air, chilled water and hot water are kept as constant ratings, 0.4kg/s, 0.4kg/s, 0.2kg/s, 0.66kg/s and 0.66kg/s, respectively. Meanwhile chilled water and hot water temperatures are set as 7°C and 66°C. These setting values are determined by commissioning operation to make the system be operating stably and supply required air condition. Control settings of solution desiccant inlet temperatures of dehumidifier and of regenerator are varying to meet the sensible and latent loads of occupied space under different conditions as black and red lines indicated in Fig. 11. In proposed global optimized strategy, for each hour, control settings introduced in Section 4.2 are optimized by

proposed SADE algorithm through solve the optimization problem with constraints and then implemented to the LDAC by adjusting the inverters and controllers installed in the system. The average computation time to obtain optimal control settings by proposed operation strategy on the testing day is 9.38s, which is acceptable and feasible for real implementation compared with the optimization interval (one hour in current study). Hourly optimized control settings of temperatures and flow rates from proposed operation strategy are shown in Figs. 11 and 12, respectively. As known from Fig. 11, in optimized operation strategy, the desiccant solution temperature of inlet regenerator keeps almost the same with that in original strategy, and desiccant solution flow rate increases with the rising of cooling and dehumidification loads demands. It should be noticed that hot water from heater hardly changes around the upper limit value (68°C) throughout the testing day. That is because hot water temperature has little impact on energy efficiency of electric heater but higher hot water temperature will result in energy savings for hot water pump with reduced hot water flow rate. Moreover, optimized operation strategy employs higher regeneration air flow rates during noon and afternoon, lower rates in morning and evening. The reason is that outdoor air with higher temperature and lower relative humidity during noon and afternoon can enhance the desiccant regeneration process and improve the energy efficiency of regenerator.

For the dehumidifier, inlet desiccant temperature of dehumidifier and chilled water temperature are decreasing with the rising cooling and dehumidification loads, shown in Fig. 11. Desiccant and chilled water flow rates are increasing with the trend, as illustrated in Fig. 12. Furthermore tradeoff between pumps and chiller is obtained from optimized control settings of proposed operation strategy. Higher inlet desiccant solution temperature of dehumidifier from 13 to 15°C (12 - 14°C in original strategy) and chilled water temperature from 10 to 12°C (7°C in original strategy) is recommended by optimized strategy, simultaneously higher desiccant and chilled water flow rates are selected to cover the loads. Though higher energy consumptions for dehumidifier pump and chilled water pump, higher chilled water temperature means higher evaporating temperature of chiller which will be in favor of chiller's COP improvement. Moreover, chiller and heater energy consumptions are analyzed and compared individually between the two strategies during the testing day, as shown in Figs. 13 and 14 in which energy compares in black color with left axis and energy saving percentage in red color with right axis. From the figures, more energy is consumed for both chiller and heater during the noon and

afternoon (9:00-18:00) due to higher sensible and latent load. And considerable energy savings can be achieved from both chiller and heater after the proposed optimized operation strategy is implemented. From the analysis above, chiller energy consumption can be reduced because higher chilled water temperature is adopted. Meanwhile, higher hot air flow rates in the noon and afternoon and reduced lower air flow rates in the morning and evening for regenerator can contribute to the reduction the energy consumption of heater. Fig. 15 illustrated the total energy consumptions of LDAC system under the two operation strategies through the testing day. It can be drawn from the results that energy consumption of the whole LDAC system under proposed global optimized operation strategy is obviously lower than that under original strategy. Particularly, the gap between the two strategies during the morning and evening is bigger than that during the noon and afternoon (the biggest gap occurs at about 8:00 am). It reveals that more significant energy savings can be achieved by the proposed global optimized operation strategy when LDAC system is running under partial load conditions. The lower cooling and dehumidification loads are, the more energy savings can be obtained. Energy savings performances during the three different testing segments are also analyzed and compared, as listed in Table 6. It confirms this deduction with about 22% energy savings in morning and evening, and 16% in noon and afternoon.

The energy consumptions of related components under the two operation strategies are analyzed in Figs. 16 and 17. From Fig. 16, a little bit more energy is consumed for dehumidifier pump and chilled water pump in proposed strategy due to the higher flow rates adopted. It should be also noted that no energy saving is gained from dehumidifier fan since supply air is restrained by occupants' indoor thermal comforts. However energy of hot water pump would drop obviously if the proposed strategy is implemented. That is due to the optimization of hot water temperature and flow rate which has been analyzed above. After comparing the results from Figs. 16 and 17, we can figure out that chiller and electric heater are the two key energy consuming components which account for up to 90% of the total system energy consumption. Any improvements of energy efficiency on the two components would have remarkable results on the energy savings of the whole LDAC system. It should be noted that chiller based on vapor compression refrigerant cycle can achieved several times of cooling energy because of its high COP. That's the reason that 43.1kWh ($208.3-165.2=43.1\text{kWh}$) is saved for electric heater while only 14.6kWh ($68.5-53.9=14.6\text{kWh}$) after the proposed optimized operation strategy is implemented. The

proposed global optimized operating strategy demonstrates that significant energy savings up to 18.5% can be achieved on the testing day.

6. Conclusion

In this study, a global optimized operation strategy for liquid desiccant air conditioning system has been presented to achieve the optimal performance in terms of energy consumption and fulfilling required IAQ by considering dehumidifier, regenerator, chiller, heater, pumps and fans. Reliable predictive models developed based on parameters lumping method for energy consumptions of components, heat and mass transfer processes and heat exchangers were identified by operation data gained from system measurements. Optimal control settings were produced by solving the optimization problem considering system constraints and interactions between components via adopting SADE algorithm. The optimization results on a testing facility show that the proposed global optimized operation strategy can reduce the energy consumption of LDAC i.e. save around 22% in the morning and evening, 16% in the noon and afternoon. It reveals that more significant energy savings can be achieved by the proposed global optimized operation strategy when LDAC system is running under partial load conditions. For regenerator side, higher hot water temperature was selected to obtain the energy savings from pumps and more regeneration air was employed during the noon and afternoon to improve the energy efficiency. For dehumidifier side, there is a tradeoff between chiller and pumps, higher chilled water and desiccant solution temperatures were recommended by proposed optimized operation strategy to achieve system energy savings by improve chiller COP though a little more pump energy consumed. Experiment results also show that chiller and electric heater account for a major proportion of system energy consumption, and in result any improvements of energy efficiency on these two components would have significant effect on the energy savings of the whole LDAC system. Comparison results illustrated about 18.5% energy can be saved by the proposed global optimized operation strategy. The proposed global optimized operation strategy is a valid operation strategy that is suitable for application in energy reduction of the existing LDAC system in building.

Nomenclature

A_i heat transfer area of CHE, HHE or RHE (m²)

$b_{1,j} - b_{4,j}$ parameters for energy models of pumps or fans

578	$c_{1,D/R} - c_{3,D/R}$	parameters for heat transfer models in dehumidifier or regenerator
579	$c_{4,D/R} - c_{7,D/R}$	parameters for mass transfer models in dehumidifier or regenerator
580	COP	coefficient of performance
581	c_s	specific heat of desiccant solution (kJ/(kg°C))
582	E_{total}	total energy consumption by LDAC (kW)
583	E_C	energy consumption of cooler (kW)
584	$E_{Chiller}$	energy consumption of chiller (kW)
585	E_{CWP}	energy consumption of chilled water pump (kW)
586	$E_{Electric\ Heater}$	energy consumption of electric heater (kW)
587	$E_{F,D}$	energy consumption of dehumidifier fan (kW)
588	$E_{F,R}$	energy consumption of regenerator fan (kW)
589	E_H	energy consumption of heater (kW)
590	E_{HWP}	energy consumption of hot water pump (kW)
591	E_j	energy consumption of pumps or fans (kW)
592	$E_{j,nom}$	nominal energy consumption of pumps or fans (kW)
593	$E_{P,D}$	energy consumption of dehumidifier pump (kW)
594	$E_{P,R}$	energy consumption of regenerator pump (kW)
595	J	cost function to be optimized (kW)
596	$k_{c,i}$	heat transfer coefficient for cool side of CHE, HHE or RHE (kW/(m ² °C))
597	$k_{h,i}$	heat transfer coefficient for hot side of CHE, HHE or RHE (kW/(m ² °C))
598	$m_{a,D/R}$	mass flow rate of air in dehumidifier or regenerator (kg/s)

599	$m_{a,req}$	indoor required supply air flow rate (kg/s)
600	$m_{c,i}$	mass flow rate of cooling fluid in CHE, HHE or RHE (kg/s)
601	$m_{h,i}$	mass flow rate of hot fluid in CHE, HHE or RHE (kg/s)
602	$m_{j,cur}$	current mass flow rate of pumps or fans (kg/s)
603	$m_{j,nom}$	nominal mass flow rate of pumps or fans (kg/s)
604	$m_{s,D}$	desiccant solution flow rate in dehumidifier (kg/s)
605	$m_{s,D/R}$	mass flow rate of desiccant solution in dehumidifier or regenerator (kg/s)
606	$m_{s,R}$	desiccant solution flow rate in regenerator (kg/s)
607	$N_{D/R}$	mass transfer rate in dehumidifier or regenerator (kg/s)
608	p_a	water vapor pressure of air (kPa)
609	$p_{a,in,D/R}$	water vapor pressure of inlet air in dehumidifier or regenerator (kpa)
610	$p_{s,in,D/R}^*$	equilibrium water vapor pressure of inlet desiccant solution in dehumidifier or
611		regenerator (kpa)
612	$Q_{c,cur}$	chiller current cooling capacity (kW)
613	Q_{CHE}	cooling requirement of CHE in dehumidifier (kW)
614	$Q_{c,nom}$	chiller nominal cooling capacity (kW)
615	$Q_{D/R}$	heat transfer rate in dehumidifier or regenerator (kW)
616	Q_{HHE}	heating load of heater in regenerator (kW)
617	Q_i	heat transfer rate of CHE, HHE or RHE (kW)
618	r_c	chiller part load ratio

619	$RH_{a,out}$	outdoor air relative humidity (%)
620	$RH_{a,req}$	indoor required air relative humidity (%)
621	r_j	part load ratio of pumps or fans
622	T_a	temperature of air (°C)
623	$T_{a,in,D/R}$	inlet temperature of air in dehumidifier or regenerator (°C)
624	$T_{a,out}$	outdoor air temperature (°C)
625	$T_{a,req}$	indoor required air temperature (°C)
626	t_c	condensing temperature of chiller (°C)
627	$T_{c,in,i}$	inlet temperature of cooling fluid for CHE, HHE or RHE (°C)
628	t_e	evaporating temperature of chiller (°C)
629	$T_{h,in,i}$	inlet temperature of hot fluid for CHE, HHE or RHE (°C)
630	$T_{s,bot,D}$	temperature of desiccant solution in bottom of dehumidifier (°C)
631	$T_{s,bot,R}$	temperature of desiccant solution in bottom of regenerator (°C)
632	$T_{s,in,CHE}$	desiccant solution temperature of inlet CHE in dehumidifier (°C)
633	$T_{s,in,D}$	desiccant solution temperature of inlet dehumidifier (°C)
634	$T_{s,in,D/R}$	inlet temperature of desiccant solution in dehumidifier or regenerator (°C)
635	$T_{s,in,HHE}$	desiccant solution temperature of inlet HHE in regenerator (°C)
636	$T_{s,in,R}$	desiccant solution temperature of inlet regenerator (°C)
637	$T_{wall,i}$	average wall temperature of heat transfer surface for CHE, HHE or RHE (°C)
638	Greek symbols	

639 λ, γ parameters for heat transfer models of CHE, HHE or RHE

640 $\omega_{s,bot,D}$ concentration of desiccant solution in bottom of dehumidifier (%)

641 $\omega_{s,bot,R}$ concentration of desiccant solution in bottom of regenerator (%)

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645 **Reference**

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Fig. 1. Schematic diagram of the proposed LDAC

Fig. 2. Scheme of proposed global optimized operation strategy of LDAC

Fig. 3. The flowchart of the proposed SADE algorithm

Fig. 4. Photograph of developed experimental test facility

Fig. 5. Comparison results between the measured and predicted energy consumption of chiller

Fig. 6. Comparison results between the measured and predicted cooling rate of CHE

Fig. 7. Comparison results between the measured and predicted heating rate of HHE

Fig. 8. Comparison results between the measured and predicted energy recovery rate of RHE

Fig. 9. Outdoor air conditions and fresh air requirements during the day

Fig. 10. Cost function against the generation

Fig. 11. Hourly control settings of fluids temperature in both operation strategies

Fig. 12. Hourly control settings of fluids flow rates in proposed optimized operation strategy

Fig. 13. Comparisons of chiller energy consumptions between both operation strategies

Fig. 14. Comparisons of heater energy consumptions between both operation strategies

Fig. 15. Comparisons of whole system energy consumptions between both operation strategies

Fig. 16. Comparisons of pumps and fans energy consumptions between both operation strategies

Fig. 17. Comparisons of heater, chiller and total energy consumptions between both operation strategies

786 Table 1. Bounded limitations for control settings and dependent variables

Variables	Units	Lower	Upper	Variables	Units	Lower	Upper
$T_{s,in,D}$	°C	11	17	m_{chws}	kg/s	0.4	0.82
$m_{s,D}$	kg/s	0.2	0.7	T_{hws}	°C	60	68
$T_{s,in,R}$	°C	52	60	m_{hws}	kg/s	0.4	0.82
$m_{s,R}$	kg/s	0.3	0.9	t_e	°C	4	9
$m_{a,R}$	kg/s	0.1	0.3	t_c	°C	35	40
T_{chws}	°C	7	12	r_c	--	0.3	1

787

788 Table 2. Identified parameters for proposed models

Model name	Identified parameters
Chiller	$a_1 = 0.0575$, $a_2 = 0.0937$
CHE Model	$\lambda_{c,CHE} = 1.3367$, $\lambda_{h,CHE} = 5.3145$, $\gamma_{c,CHE} = -0.3134$, $\gamma_{h,CHE} = 1.2482$
HHE Model	$\lambda_{c,HHE} = -1.5272$, $\lambda_{h,HHE} = -14.4569$, $\gamma_{c,HHE} = 0.1056$, $\gamma_{h,HHE} = -4.8393$
RHE Model	$\lambda_{c,RHE} = -0.1478$, $\lambda_{h,RHE} = 1.0235$, $\gamma_{c,RHE} = -1.0319$, $\gamma_{h,RHE} = 0.1061$

789

790 Table 3. The prediction performances for proposed models

Model name	MAE (kW)	Std_AE (kW)	MRE (%)	Std_APE (%)
Chiller	0.1477	0.0903	3.66%	2.18%

CHE Model	0.3794	0.2027	4.25%	2.09%
HHE Model	0.3607	0.1872	4.01%	1.95%
RHE Model	0.8007	0.4050	4.96%	2.48%

Table 4. Parameter settings of DE algorithms and proposed SADE algorithm

Parameters	DE1	DE2	DE3	Proposed SADE
Differential weight (F)	1.5	1.0	1.5	Adaptive
Crossover rate (Cr)	0.6	0.6	0.8	Adaptive
Population size	200	200	200	200
Maximum generation	300	300	300	300

Table 5. Optimal control setting and energy consumption under selected typical condition

Variables	Units	Lower	Variables	Units	Lower
$T_{s,in,D}$	°C	13.3	T_{cws}	°C	10.4
$m_{s,D}$	kg/s	0.54	m_{cws}	kg/s	0.84
$T_{s,in,R}$	°C	55.3	T_{hws}	°C	67.5
$m_{s,R}$	kg/s	0.42	m_{hws}	kg/s	0.67
$m_{a,R}$	kg/s	0.28	J	kW	16.1

Table 6. Comparison of energy savings of the optimized strategy in different segments

Energy consumption	Original strategy (kWh)	Optimized strategy (kWh)	Energy savings (%)
Morning	61.5	48.3	21.5%
Noon and afternoon	175.0	147.1	16.0%
Evening	63.1	48.8	22.7%