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COMPARATIVE STUDY OF DIFFERENT PARADIGMS OF EVOLUTIONARY ALGORITHM IN THE CONTEXT OF SYSTEM OPTIMIZATION FOR SOLAR DESICCANT COOLING

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ABSTRACT

Solar desiccant cooling is new air-conditioning approach that can make use of solar energy to provide the conditioned air directly, together with full outdoor air provision. This system can handle the space loads and achieve good indoor air quality simultaneously. It is necessary to have system optimization for the overall year-round performance according to the local climatic and loading changes. The objective of optimization is to maximize the solar fraction against the involvement of auxiliary electric heating. This is a constrained optimization problem since the room temperature should be maintained within a comfortable range. Evolutionary algorithm (EA) is effective in handling the constrained, nonlinear and multidimensional engineering problems like this case. In this paper, comparative study among the three major paradigms of EA was carried out, in order to evaluate a suitable approach for the current engineering application with demanding computational function calls.

INTRODUCTION

Global warming and climate change are the current headlines both globally and locally, it is urgent to explore sustainable and low-carbon technology to minimize the use of fossil fuels. To utilize solar energy instead of electricity from power plant is a hot topic in the field of air-conditioning and refrigeration. Feasibility studies in applying solar cooling are getting popular in these recent years (Wang 2001, Henning 2004, Chow 2006). The passive solar cooling is mainly about the strategic design of building façades and thermal mass control, while the active solar cooling would provide the required refrigeration effect or cooling capacity by appropriate mechanical means and solar thermal technology. Solar desiccant cooling system is the one that can provide the conditioned air for indoor space directly, together with the bonus of using full outdoor air. This system can handle the space sensible and latent loads on one hand, and achieve a good indoor air quality on the other. In the subtropical modern cities like Hong Kong, provision of air-conditioning is indispensable in buildings, and it is technically feasible to apply solar cooling system in Hong Kong (Fong *et al.* 2007). With suitable considerations of system design and operation, the solar energy would be fully utilized and the involvement of auxiliary electric heating minimized. In this paper, effective optimization method was suggested for a solar desiccant cooling system developed by simulation model, and the parameters for suitable operation and control would be determined.

METHODOLOGY

The solar desiccant cooling system model was developed by a component-based plant simulation software (Fong and Chow 2007). The model was used for system optimization of the overall performance throughout the annual climatic and loading changes. It is obvious that the solar irradiation is not always sufficient to provide the required regeneration temperature for the desiccant wheel, so auxiliary heater was installed, but inevitably energized by electricity. This optimization problem is to maximize the solar fraction against the operation of auxiliary electric heater. This is a constrained optimization problem since the room temperature should not exceed the required indoor comfortable range.

Evolutionary algorithm (EA) is effective in handling the constrained, nonlinear and multidimensional engineering problems (Michalewicz and Fogel 2004), like this solar desiccant cooling system. Owing to the possible existence of a number of local optima in a nonlinear problem, the stochastic and multi-searching nature of EA would enhance the optimization and prevent from being trapped at local optimum. There are three major paradigms of EA, they are genetic algorithm, evolutionary programming and evolution strategy. The ruggedness of a search landscape is problem-dependent, a good paradigm of EA should have a balance in deep exploitation and wide exploration, in order to find the global optimum eventually. Comparative study among these three paradigms of EA was carried out, so as to advise the most suitable paradigm in handling the current solar cooling problem, which is a plant simulation model featured with high computational cost in function evaluation.

SIMULATION MODEL OF SOLAR DESICCANT COOLING SYSTEM

By using TRNSYS (2000) and its component library (TESS 2004), the plant simulation model of a typical desiccant cooling system with solar air collectors were built. The schematic diagram of different components of the system is shown in Fig. 1.

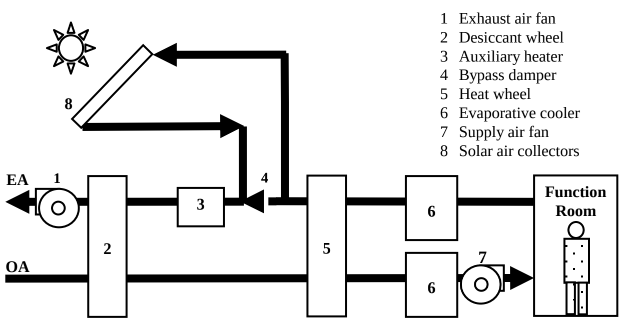

Fig. 1. Schematic diagram of solar desiccant cooling system.

The major components of a typical desiccant cooling system include the desiccant wheel, heat wheel, evaporative coolers and fans. Auxiliary heater is also commonly included for it would have moment of insufficient solar irradiation. In a desiccant cooling system, the latent cooling load is handled by desiccant wheel, while the sensible cooling by heat wheel. The two evaporative coolers are used to facilitate the heat recovery effectiveness of heat wheel. By using the solar air collectors, the room air that has already captured the sensible heat from heat wheel would be further heated up by the solar irradiation received. This leaving air stream of the collectors would provide the required regeneration temperature for the desiccant wheel. If the regeneration temperature was not enough, the electric auxiliary heater would be used to supplement the thermal energy. This solar desiccant cooling system was designed to serve a function room located on the top floor.

To implement a year-round simulation in response to different climatic and loading conditions, a number of air-conditioning modes of the solar desiccant cooling system were included in this simulation model. In order to maximize its merit of energy efficiency, a practical control and operation scheme was formulated. There were altogether four operation modes of this solar desiccant cooling system:

a. Desiccant cooling mode: All the components of the solar desiccant cooling system are in full operation, with minimum but necessary involvement of auxiliary electric heater. The speed of both supply or exhaust air fan was variable to cater for the changing cooling load.

b. Free air cooling mode: Since 100% outdoor air was designed for the desiccant cooling system, free air cooling mode, or economizer mode, could be used. This mode was activated when the room temperature could be maintained at the design level solely by the appropriate enthalpy of the outdoor air during the occupying period, otherwise the 'desiccant cooling mode' would be called in. In this mode, the fan speed could also be adjusted in order to minimize the energy consumption.

c. Full auxiliary heating mode: Between the heat wheel and auxiliary heater at the exhaust air stream, a bypass air damper was included. This damper would be activated when there was no thermal gain from the solar air collectors in case of insufficient solar irradiation at the day time. The regeneration air for the desiccant wheel would then be boosted up to the required temperature fully by the auxiliary heater, so that the desiccant wheel could function properly and the latent load would be handled.

d. No cooling mode: In this mode, the entire system would be off. This was mainly dictated by the occupying period of the function room, or the outdoor temperature was below a very low temperature. In this model, this temperature was set at 5°C.

In this optimization study, the design parameters of different components of the simulation model for the solar desiccant cooling system are summarized in Table 1. The operation of this system would be coincident with the availability of solar irradiation in the day time generally.

MAJOR PARADIGMS OF EA

A detailed component simulation model would be constructed with a set of implicit differential-algebraic equations. In order to closely mimic the design, operation and interaction among different components should also be incorporated into the system model. As a result, even for a single run of the mathematical model, the function evaluation would be computationally expensive. To carry out optimization for this kind of models, classical and traditional numerical methods are not feasible. The metaheuristic EA that is a population-based stochastic search optimization method has been proven effective for these engineering problems (Hanby *et al.* 2005, Giraud-Moreau and Lafon 2002, Fong *et al.* 2006a).

Table 1. Design parameters of different components of the simulation model for solar desiccant cooling system.

Component	Design parameter
Desiccant wheel	- Set point of humidity ratio of desiccant dehumidification: 0.01 kg/kg
Solar air collectors	- Area: 100 m^2 - 22°C tilt angle and facing south - Un-glazed type - Absorptance: 0.947 - Emissivity: 0.85
Heat wheel	- Sensible effectiveness: 0.8 - Power: 0.19 kW
Evaporative coolers	- Saturation efficiency: 0 – 100% - Power: 0.034 kW
Supply / exhaust air fan	- Variable speed (30 – 100%) - Rated mass flow rate: 14976 kg/hr - Rated power: 4.63 kW
Auxiliary heater	- Electric type - Capacity: 100 kW - Efficiency: 1
Operation mode	- Desiccant cooling mode Set point of SA temperature: 13°C Set point of room temperature: 24°C Offset temperature differential (for calling in this mode during free air cooling mode): 0°C Adjustable speed for fans - Free air cooling mode OA temp > 5°C Adjustable speed for fans - Full auxiliary heating mode Bypass control during no thermal gain at solar air collectors
Weather data	- Hong Kong TMY
Function room	- Floor area: 210 m^2 - Wall-fenestration ratio: 0.4 to 0.6 - 120 persons - 13 W/m^2 artificial lighting - Occupying period: 08:00 – 18:00

There are three main paradigms of EA, they are genetic algorithm, evolutionary programming and evolution strategy (Bäck and Schwefel 1993). The engineering practitioners may have confusion on these three paradigms, some people suppose EA and generic algorithm the same, in fact the latter is just a paradigm of EA. It is important to distinguish the features among the three paradigms and identify the most suitable one according to the problem characteristics. Like this study, the optimal solutions should be determined at a limited number of evaluation function calls due to the expensive computational cost, a robust paradigm can respond to such condition effectively.

The general evolutionary operators of these three paradigms are crossover, mutation, selection and evaluation, but their role and importance may be deviated according to the paradigm. The evolutionary loop of these three paradigms are shown in Fig. 2, and briefly described as follows.

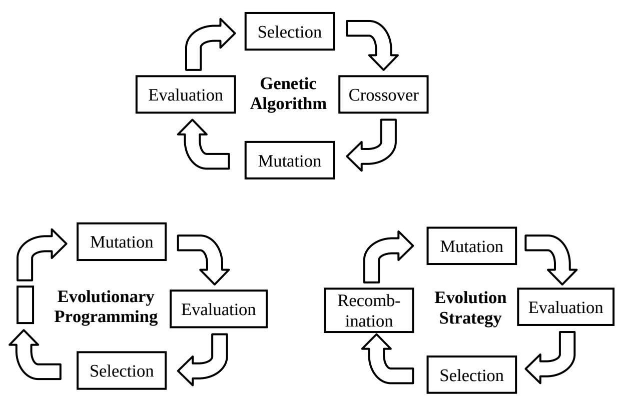

Fig. 2. Evolutionary loop of genetic algorithm, evolutionary programming and evolution strategy.

a. *Genetic algorithm* has an evolutionary loop and sequence formed by selection, crossover, mutation and evaluation. A population of the optimized individuals would be continuously evolved in this loop up to the epoch of termination. Parents would be firstly selected from the population by the selection operator, offspring would be born by the crossover operator (with crossover probability above 0.5), then transformed by the mutation operator (with small mutation probability). In this study, the proportional selection, single-point crossover and single-bit-flip mutation were used, which are typical for a simple genetic algorithm. The crossover probability was set at 0.8, while the mutation probability was the reciprocal of the chromosome length of the optimized variable.

b. *Evolutionary programming* has an evolutionary loop and sequence formed by mutation, evaluation and selection. The parent population would undergo Gaussian mutation first. After evaluation of the fitness, an offspring population would be formed by tournament selection. This is a typical arrangement of a classical evolutionary programming. As compared to genetic algorithm, no crossover is involved. In addition, the role of selection is different in the two paradigms. In genetic algorithm, selection is used to find the parents for mating purpose. But selection is applied to build up an offspring population from the mutated individuals in evolutionary programming.

c. *Evolution strategy* has the evolutionary loop similar to that of evolutionary programming, but the recombination (or called crossover) operator is also involved, and used before mutation. In general, the optimization approach of evolution strategy and evolutionary programming is near. In evolution strategy, both recombination and mutation would be certainly applied in the parent population, without probability being used in genetic algorithm. In this study, the arithmetic recombination was used together with the Gaussian mutation and tournament selection, which is typical for a classical evolution strategy.

Owing to the respective features of genetic algorithm, evolutionary programming and evolution strategy, it cannot simply adopt a certain paradigm due to its popularity or by chance. It is necessary to carry out a comparative study among these three EA paradigms, so that the most effective and efficient method could be identified under the condition of limited number of evaluation function calls of a complex system model.

SYSTEM OPTIMIZATION BY EA

This was a single optimization problem. In order to achieve the optimal performance of energy saving, the optimization objective was to maximize the solar fraction of the solar desiccant cooling system against the involvement of auxiliary electric heating. According to the system parameters mentioned in Table 1 before, there were five optimization variables with the corresponding bounds as follows:

i. the set point of supply air temperature, $T_{SA,sp} \in [11,15]$;

ii. the set point of room temperature, $T_{RA,sp} \in [23, 27]$;

iii. the set point of humidity ratio of desiccant dehumidification, $\omega_{dd,sp} \in [0.008, 0.012]$;

iv. the rated mass flow rate of supply air fan (or that of exhaust air fan), $m_{SAF} \in [10000, 20000]$; and

v. the offset temperature differential (as compared to the room temperature) for calling in desiccant cooling mode, $T_{offset} \in [0, 4]$.

This optimization problem is a constrained one because the room temperature should be maintained below the upper comfortable limit at 27°C. If this constraint was not prescribed, the optimization search would tend to determine a scenario of high solar fraction but insufficient involvement of auxiliary electric heating, this would lead to the room temperature exceeding the upper comfortable limit easily.

Since the computational time of a yearly (8760 hours) simulation run of the detailed model of solar desiccant cooling system was substantial, the number of population and epoch was limited at a relatively small but sufficient for stochastic search purpose. In this study, the population size was set at ten and the epoch of termination fifty, which was commonly adopted for EA optimization for plant simulation model (Hanby *et al.* 2005). The suitability of this setting would be verified from the validity and convergence of the optimization results.

OPTIMIZATION RESULTS AND DISCUSSIONS

The optimization results of generic algorithm, evolutionary programming and evolution strategy are summarized in Table 2.

Table 2. Optimization results of the three EA paradigms.

	Genetic algorithm	Evolutionary programming	Evolution strategy
Solar fraction	7.85%	12.28%	13.11%
$T_{SA,sp}$ (°C)	11.81	11.25	11.34
$T_{RA,sp}$ (°C)	23.77	23	23
$\omega_{dd,sp}$ (kg/kg)	0.0080	0.0099	0.0099
m_{SAF} (kg/hr)	18294	17379	17228
T_{offset} (°C)	1.97	1.71	4
Constr. value	15	0	0

From Table 2, evolution strategy could find the best optimal solution for the solar desiccant cooling system in this study, with the highest solar fraction of 13.11%. Evolutionary programming could also find a close but lower optimal solar fraction of 12.28%. However, genetic algorithm could not determine a feasible solution, since the result at the epoch of termination still had a constraint value of 15, implying that fifteen air-conditioning hours would be above the acceptable indoor comfortable limit in a year. In addition, the solar fraction was the lowest at 7.85%.

To have a better understanding to the optimization performances of the three EA paradigms, the searching profiles along the fifty epochs were also studied. Figs. 3 to 5 show the searching profiles of the best fitness, mean fitness and constraint value respectively, while Figs. 6 to 10 correspond to the five optimized variables for the solar desiccant cooling system. At each epoch, the best fitness was the maximum evaluation value (for this maximization problem) with the least constraint violation among the population, so it was the fitness value of the elite. The mean fitness was the average fitness value of the entire population, this reflected the uniformity or diversity of the population at a certain epoch.

In Figs. 3 to 5, evolution strategy could continually search better optimal solution, and the solution became feasible since the fifth epoch, as shown in Fig. 5. Although evolutionary programming could find a feasible and optimal solution, it firstly occurred in the sixteenth epoch. For the profiles of genetic algorithm, its 'best' solution was identified from the fifth epoch as shown in Fig. 3, but it was infeasible and had no further improvement thereafter. In fact, the search of genetic algorithm was still ongoing along the epoch, as reflected in Fig. 4, since the mean fitness value was still changing along the epoch. The optimization search of genetic algorithm was not as effective as the other two paradigms, even a feasible solution could not be identified within the epoch of termination. From the searching profiles of genetic algorithm in Figs. 3 to 5, there was no idea how far the epoch should be prolonged in order to determine a feasible solution.

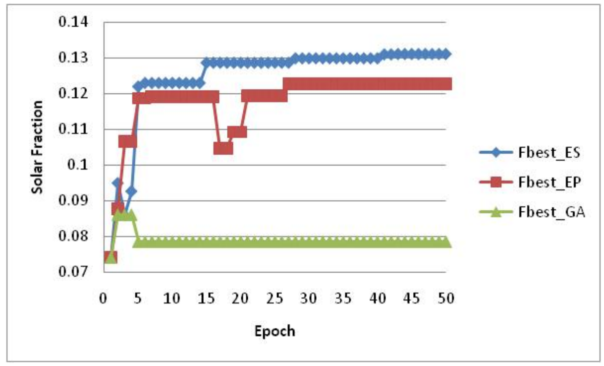

Fig. 3. Searching profile of best fitness (solar fraction) vs. epoch.

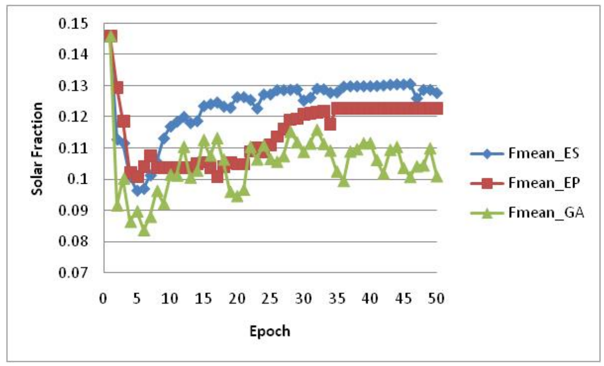

Fig. 4. Searching profile of mean fitness (solar fraction) vs. epoch.

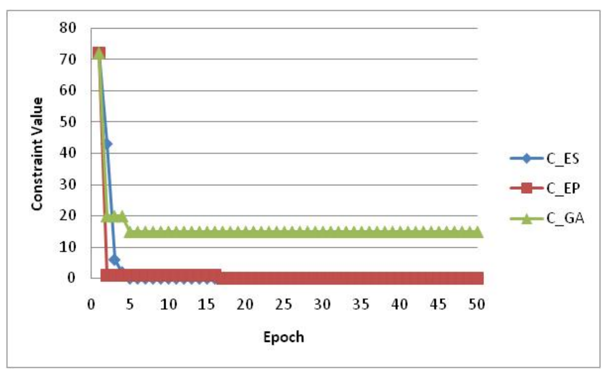

Fig. 5. Searching profile of constraint value vs. epoch.

From the searching profiles of the five optimized variables in Figs. 6 to 10, more observations about the performances of the three EA paradigms can be obtained. The ineffectiveness of the genetic algorithm was due to the stagnant evolution of certain optimized variables, particularly the second and third ones as shown in Figs. 7 and 8. These two optimal values were deviated much from those found by evolution strategy or evolutionary programming. The genetic algorithm could not help to effectively evolve a feasible and better optimal solution through its crossover and mutation operators. The superiority of evolution strategy among the three paradigms can be observed from its search for the fifth optimized variable, as shown in Fig. 10. The searching results of evolutionary programming and genetic algorithm for this optimized variable were close, while that of evolution strategy was at another possible value. This helped that the ultimate solution determined by evolution strategy was the best among the three paradigms.

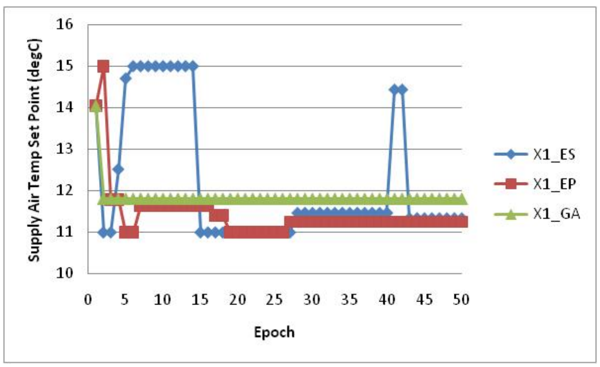

Fig. 6. Searching profile of optimal supply air temperature set point vs. epoch.

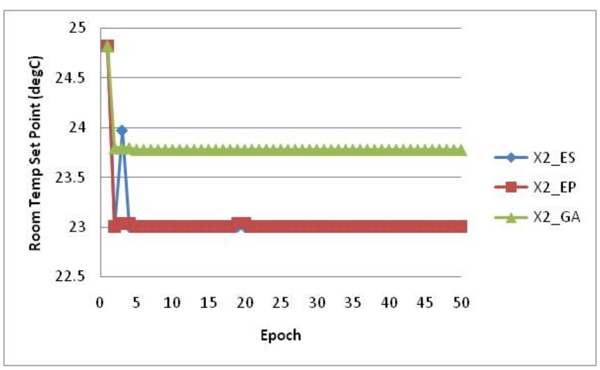

Fig. 7. Searching profile of optimal room temperature set point vs. epoch.

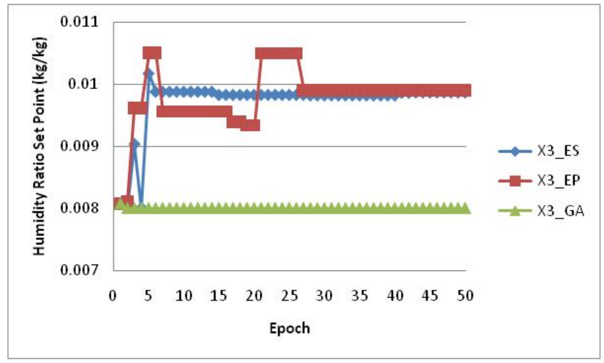

Fig. 8. Searching profile of optimal humidity ratio set point of desiccant dehumidification vs. epoch.

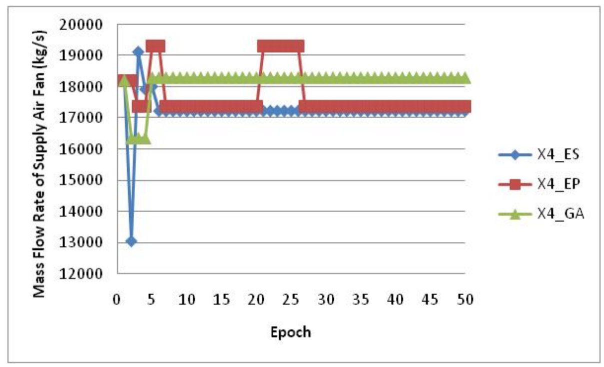

Fig. 9. Searching profile of optimal mass flow rate of supply/exhaust air fan vs. epoch.

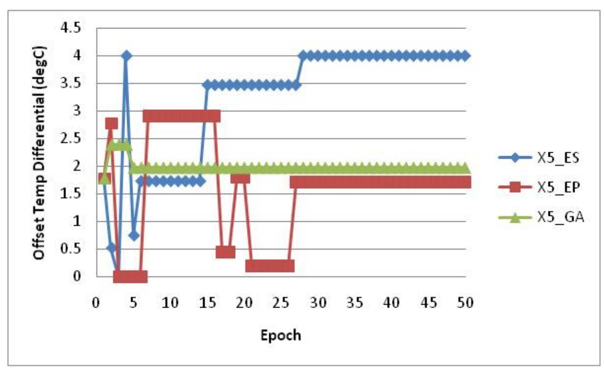

Fig. 10. Searching profile of optimal offset temperature differential vs. epoch.

Although the genetic algorithm has been widely used as an optimization method of EA in handling the HVAC engineering problems (Asiedu *et al.* 2000, Angelov *et al.* 2003, Lu *et al.* 2004), satisfactory results would be acquired with the population and epoch both in an order of hundreds, and it is commonly used to handle the empirical mathematical models that require a relatively inexpensive computational cost. However, the other two paradigms – evolution strategy and evolutionary programming – could perform more robust at a limited number of population and epoch in this complex model. With the continual advancement of the computer hardware, it is getting more popular to handle the optimization problems for computationally demanding function evaluation. It would be found in the mathematical models developed by a complex set of system equations, no matter the component-based plant simulation or computational fluid dynamics. Evolution strategy and evolutionary programming would therefore provide a more guaranteed and reliable results at a limited number of function evaluation, as compared to genetic algorithm. In fact, similar finding was reported in another study (Fong *et al.* 2006b), in which the optimization problem was also related to a plant simulation model of solar energy system.

CONCLUSIONS

To study a novel HVAC system, component-based plant simulation model is useful to develop a complete model with the required operation and control strategy. The model would be expressed by a complex nonlinear and implicit equation set that is computationally intensive to solve. In this regard, the traditional numerical optimization method cannot be applied. With the help of evolutionary algorithm (EA), such problem can be handled by this population-based stochastic searching approach without the need of derivative information. In this study, a model of solar desiccant cooling system was built, and its year-round performance was maximized. Since it took time to have a single simulation run, the optimization search should be achieved in a limited population and within a specified epoch. A comparative study of the three major paradigms of EA – genetic algorithm, evolutionary programming and evolution strategy – was therefore carried out, in order to identify the most appropriate paradigm in terms of both effectiveness and efficiency of optimization.

Among the three EA paradigms, both evolution strategy and evolutionary programming could determine a feasible and optimal solution within the prescribed epoch of termination, and evolution strategy had a more superior performance. However the genetic algorithm could not provide a feasible result in this constrained problem. Larger population size and longer epoch for the genetic algorithm might help, but it was unlikely applied in this case due to a more extensive computational time. From this study, the evolution strategy and evolutionary programming, particularly the former, are robust in handling a constrained optimization problem, in which the simulation model is developed by complex mathematical expressions or built on a component-based simulation platform. These are the scenarios where expensive computational cost is commonly encountered. Through this type of problems, the exploitation and exploration of evolution strategy, has been demonstrated effective among the EA paradigms.

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