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# Energy demand forecasting of the greenhouses using nonlinear models based on model optimized prediction method

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ABSTRACT

Energy demand forecasting is able to improve the energy efficiency and energy savings of the agricultural greenhouses. A model optimized prediction (MOP) methodology is proposed to predict the energy demand of greenhouses with a better performance of accuracy and cost time. The physical model of greenhouses energy demand is built up based on the energy and mass balance. According to the sensitivity analysis of the Sobol' method, the uncertain parameters of greenhouse energy model are sort by the first-order and total order indices. The uncertain parameters greatly affecting the model prediction can be collected from indistinct internal parameters for calibration to save computation time. Adaptive particle swarm optimization and genetic algorithms (APSO-GA) is utilized to calibrate the uncertain parameters of energy model by using the measured data in an experimental greenhouse with surface water source heat pumps system. To speed up the convergence, adaptive operator adjusts the proportion of particles for PSO and GA and changes the weight of the adjust factor during the optimization process. Compared with GA, PSO and conventional PSO-GA, APSO-GA can improve the optimization performance with more accurate of 3.2% and save the optimization time of more than 15.4%. Predicted energy demand by the optimized model is in agreement with measured energy demand with a better accuracy of a 95.6% significant level, which proves that the MOP methodology is reliable to predict energy demand and peak load of greenhouses.



## 1. Introduction

Agricultural greenhouses area has increased greatly worldwide in the last few decades, particularly in China. The large amount of energy input is required to maintain the appropriate temperature for crop growth during the winter and summer seasons. It is necessary for energy demand prediction to enhance energy management and energy savings of the agricultural greenhouses.

In order to predict the energy requirement for energy savings, several numerical models for buildings simulation have been developed over the years [1,2]. However, the microclimate in agricultural greenhouses is a complex and nonlinear system and is affected by crop canopy and bare soil surface significantly. The numerical models of buildings cannot be used to accurately predict the energy requirement of greenhouses. Moreover, it is impossible to be integrated into control system of greenhouses for energy management and energy savings. The greenhouse energy model is quite different from buildings energy model, and has been investigated by some researchers. Bot [3] and Impron et al. [4] proposed a greenhouse physical model based on the experimental measurement of the main physical processes. The model was validated by the comparison of the simulated and measured air temperature. Albright et al. [5] proposed a simple time dependent thermal model of greenhouse under unventilated conditions for heating purposes using the heat balance. Tiwari et al. [6] developed the Albright model to estimate the thermal efficiency by considering the energy balance equations for different components of the greenhouse. Chou et al. [7], Singh et al. [8], Sethi [9], Vadiee and Martin [10], Kıyan et al. [11] and Joudi and Farhan [12] developed and validated these models of greenhouse microclimate describing the energy and mass exchanges between the internal layers and external layers, and applied these models to investigate the thermal performance in the greenhouses.

Jolliet et al. [13] presented a dynamic model based on the static thermal energy balance for predicting the energy consumption of

*Abbreviation:* APSO-GA, adaptive particle swarm optimization and genetic algorithms; CPSO-GA, conventional PSO-GA; GA, genetic algorithms; MOP, model-optimize-predict; PSO, particle swarm optimization; RMSE, root mean square error; SWSHPS, surface water source heat pumps system.

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**Nomenclature**

*Symbols*

| | |
|---|---|
| $\Delta$ | slope of water vapor saturation curve (kPa $^\circ$ C$^{-1}$) |
| $\gamma$ | psychometric constant (0.0646 kPa $^\circ$ C$^{-1}$) |
| $\rho_a$ | air density (kg m$^{-3}$) |
| $\sigma$ | Stefan–Boltzmann constant ($5.67\times10^{-8}$ W m$^{-2}$ K$^{-4}$) |
| $\tau_a$ | cover material transition coefficient |
| $\epsilon_{12}$ | emissivity between the cover and sky |
| $\epsilon_1, \epsilon_2$ | individual emission coefficients of cover and sky |
| $A_g$ | the area of greenhouse ground (m$^2$) |
| $A_s$ | surface area of greenhouse cover material (m$^2$) |
| $c_1, c_2$ | positive constant of accelerate rates |
| $c_a$ | air specific heat (J kg$^{-1}$ K$^{-1}$) |
| $E$ | evaporation rate from the wet canopy (J kg$^{-1}$) |
| $e_a$ | ambient vapor pressure (Pa) |
| $e_o$ | actual air water vapor pressure outside (Pa) |
| $e_s$ | saturated vapor pressure (Pa) |
| $f$ | particle fitness |
| $I_a$ | outside solar radiation (W m$^{-2}$) |
| $K_s$ | sky clearness index |
| $K_c$ | correct coefficient of internal thermal curtain and infiltration (W K$^{-1}$ m$^{-2}$) |
| $K_g$ | heat transfer coefficient (W K$^{-1}$ m$^{-2}$) |
| $LAI$ | leaf area index (m$^2$ m$^{-2}$) |
| $max\_n$ | maximum iteration |
| $P_c$ | crossover probability |
| $P_i$ | memory of personal best position (m) |
| $P_m$ | mutation probability |
| $P_{best}$ | the best position in all particles (m) |
| $q_{con}$ | heat flux through the cover (W) |
| $q_l$ | the energy flux due to the long wave thermal radiation (W) |
| $q_{plant}$ | heat flux due to the convection between greenhouse air with soil and crop leaves (W) |
| $q_s$ | energy input from heating system (W) |
| $q_t$ | net solar radiation into greenhouse (W) |
| $q_{vent}$ | heat flux from ventilation and infiltration (W) |
| $R$ | resolution ratio |
| $r_1, r_2$ | two random variables |
| $r_a$ | stomatic resistances of the leaves (s m$^{-1}$) |
| $r_b$ | aerodynamic resistances of the leaves (s m$^{-1}$) |
| $R_{net}$ | net radiation available to the canopy (W m$^{-2}$) |
| $T_i$ | greenhouse air temperature (K or °C) |
| $T_o$ | outside air temperature (K or °C) |
| $T_{sky}$ | sky temperature (K) |
| $v_a$ | greenhouse volume (m$^3$) |
| $v$ | the velocity of the x (m s$^{-1}$) |
| $V_i$ | particle velocity (m s$^{-1}$) |
| $w$ | inertia weight |
| $X$ | optimized parameters vector |
| $x_i$ | the $i$th of optimized parameters |

a greenhouse, and found that the error in annual energy consumption between simulation and measurement was less than 10% in general. Singh and Tiwari [14] developed a thermal model based on energy balances for each component with respect to the weather data and greenhouse shape parameters, and used the model to estimate the total energy requirement for the greenhouse. Du et al. [15] presented a heat transfer model in the greenhouse to predict the heating power requirement in cold weather. However, the internal distinct parameters of above models are difficult to be measured or are changing in a long term. Moreover, it is not easy for these parameters to be determined from above physical models due to the difference of greenhouse locations, shape, orientation, cover materials, crop and weather conditions.

Owing to the complexity of physical processes, black-box modeling can be used in the greenhouse model with input and output data and without regard to the inside physical and chemical laws of greenhouse. Lpez et al. [16] developed the energy consumption model using the linear regressions between energy consumption and temperature deviation, and found that the model gave satisfactory fits by considering the only input data of outside air temperature. The most used approach of black-box modeling for nonlinear system is neural network, which was applied to develop the greenhouse model by Linker and Seginer [17], Ferreira et al. [18], Frausto and Pieters [19], Patil et al. [20] and Fourati [21]. Trejo-Perea et al. [22] predicted greenhouse energy consumption using neural networks, and found that the model can estimate the energy consumption with a 95% significant level in an experimental greenhouse. However, the black-box modeling needs a large mounts of possible data, otherwise the developed model can be resulted in overfitting and unacceptable reliability. Since the parameters with respect to plant in the energy model of greenhouse can be acted as constant within a few days, it is impossible to generate all possible data to train the accurate energy model in the short term. Compared with the black-box modeling method, physical model-based identification methods require fewer data specimens to match the practical engineering targets [23].

Furthermore, mathematical models for greenhouse energy demand prediction require a suitable calibration of their parameters. The model parameters identification is acted as an optimization problem, and different solution methods have been proposed. Blasco et al. [24] presented genetic algorithm (GA) to adjust the non-linear model parameters of greenhouse obtained from physical processes. Guzmn-Cruza et al. [25] presented a comparison of different evolutionary algorithms to calibrate parameters of a climate model describing the air temperature and relative humidity in the greenhouse, such as GA, evolutionary strategies and evolutionary programming. Hasni et al. [26] proved that the performance of a greenhouse climate model using PSO is better than GA in terms of calculation time and prediction accuracy. Piltan et al. [27] developed a modified approach for PSO and GA in the field of energy forecasting, and found that the performance of real coded GA is better than PSO. However, GA can obtain a solution within excessive computational burden, and PSO is easy to prematurely converge and lead to the undesired local optima [28,29]. Yu et al. [30] proposed that the PSO-GA can fully combine the merits of these two methods to optimize the coefficients better. In order to further improve the accuracy and decrease computation time, it is necessary for an improved PSO-GA technique to adjust the uncertain parameters of greenhouse energy model.

In this study, a model optimized prediction (MOP) methodology is presented to predict greenhouse energy demand with a better performance of accuracy and computation speed. Since the number of parameters is large in the greenhouse physical model, the calibration processes may be computationally intensive and the computational cost may become prohibitive. Sensitivity analysis is necessary for the uncertain parameters of greenhouse physical model to decrease the optimizing parameters number. An improved algorithm with adaptive particle swarm optimization and genetic algorithms (APSO-GA) is utilized to adjust uncertain