Dynamic Optimization of commercial greenhouse in Middle East climatic condition using particle optimization (PSO) and Genetic Algorithm (GA) with an error comparison.

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Abstract

Dynamic modeling is the most feasible platform to study agronomical precision level details. In the normal scenario, we are optimizing the temperature, relative humidity, and air velocity values to maintain the microclimate. However, in order to maintain a high level of precision, we shall optimize the uncertain parameters in the conditioned system. Particle swarm optimization (PSO) and Genetic algorithm (GA) were used to predict the unpredictable parameters for the energy optimization process. **Keywords**: Greenhouse HVAC, Covering material, Greenhouse climate control, Optimization , Energy prediction.

1.Introduction

Dynamic modeling of the greenhouse climate is generally used for the optimization of the uncertain parameters using various dynamic equations directly related to the greenhouse indoor climate. Greenhouse operational cost in terms of commercial energy spent is the major milestone in terms of yield management. In some cases, due to the anti-seasonal nature of the greenhouse operations, energy consumption cost may reach almost 50% of the operational cost of commercial greenhouses. Therefore, it is important to predict the energy consumptions in the greenhouses. Parameter optimization-based algorithms based on energy conservation principle can provide a stronger platform in developing energy-based greenhouse optimization models (Yongato Shen et al., (2018)) [1]. In order to utilize the energy prediction in an efficient approach, the growers can implement intelligent system (Korner et al., (2008)) [2].

In the present study, the uncertain parameters for the upgraded greenhouse model for energy consumption are optimized using particle swarm optimization and genetic algorithm. The dynamic model with optimized parameters is used for energy prediction and compared with the experimental results with respect to both the optimization models used.

2. Optimization Methodology

Indoor parameters of the greenhouse are closely related to changes in the various heat and mass transfer processes. In order to establish an accurate greenhouse model with optimal indoor parameters, it is important to study the details of this heat and mass transfer mechanism. This is a dynamic process with energy exchange between the inside and outside of the greenhouse. The energy exchange process of the upgraded greenhouse with 2mm polyethylene sheet and box type evaporative cooler is shown in Figure 1.

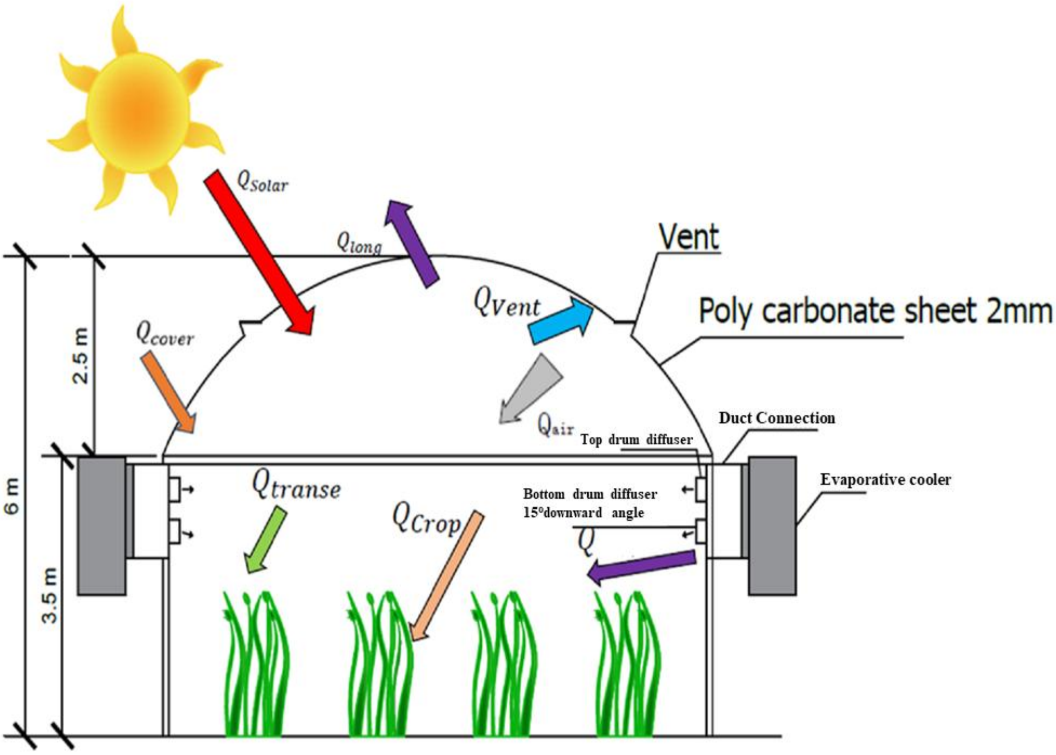


Figure 1. : Greenhouse Energy Exchange Between Indoor and Out Door

Energy exchange between the greenhouse and outside system involves various factors and Figure 1 shown above highlighted the major factors which are influencing the greenhouse indoor climatic condition in Middle East countries. Energy transferred, Q (in Watts) through the heating or cooling of the greenhouse is the sum of seven individual components as given below. List of parameters involved in the dynamic model for optimization process has been listed in the Table 1.

Table 1. : List of parameters involved in optimization

Parameter	Description	Units
$\boldsymbol{Q_{heat}}$	Net heat transfer per unit time to/from the greenhouse	Js^{-1} or W
$\boldsymbol{Q_{rad}}$	Radiative heat transfer from air at $T_{air}(t)$ to outside air at $T_{out}(t)$	Js^{-1} or W
$\boldsymbol{Q_{vent}}$	Heat energy lost from greenhouse to outside due to ventilation	Js^{-1} or W
$\boldsymbol{Q_{cover}}$	Heat exchange between the cover to outside air	Js^{-1} or W
$\boldsymbol{Q_{trans}}$	Heat exchange between plants and inside air	Js^{-1} or W
$\boldsymbol{Q_{air}}$	Heat required to raise the temperature of air	Js^{-1} or W
$\boldsymbol{Q_{crop}}$	Heat transfer from plant to greenhouse air	Js^{-1} or W
$\boldsymbol{Q_{solar}}$	Heat transfer to the greenhouse air due to solar radiation	Js^{-1} or W
$\boldsymbol{\rho_{water}}$	Density of water	$kg\ m^{-3}$
$\boldsymbol{c_{p_{water}}}$	Specific heat capacity of water	$J\ kg^{-1}C^{-1}$
$\boldsymbol{v_{water}}$	Flow rate of water in the pipeline	m^3s^{-1}
$\boldsymbol{T_{in}(t)}$	Temperature of supply water which can change with time t	°C
$\boldsymbol{T_{opt}(t)}$	Optimal temperature of return water	°C
$\boldsymbol{\epsilon}$	Emissivity of the greenhouse covering material (polyethylene or polycarbonate)	No units
$\boldsymbol{A_{cover}}$	Greenhouse cover surface area	m^2
$\boldsymbol{\sigma}$	Universal Stefan-Boltzmann constant = $5.67\ x\ 10^{-8}$	$Wm^{-2}K^{-4}$
$\boldsymbol{T_{air}(t)}$	Air temperature inside greenhouse, varies with time	°C
$\boldsymbol{T_{out}(t)}$	Outside air temperature, varies with time	°C
$\boldsymbol{X_{cover}}$	Influence coefficient of glass/ Transmittance of glass including spectral variation	Depends on cover material
$\boldsymbol{A_{gw}}$	Greenhouse ground surface area	m^2
$\boldsymbol{C_d}$	Vent discharge coefficient	No units

$\boldsymbol{g}$	Acceleration due to gravity	ms^{-2}
$\boldsymbol{A_{roof}}$	Area ratio of top windows to ground	No units
$\boldsymbol{A_{side}}$	Area ratio of side windows to ground	No units
$\boldsymbol{C_w}$	Wind pressure coefficient	No units
$\boldsymbol{V_{wind}}$	Outdoor wind speed	ms^{-1}
$\boldsymbol{\rho_{air}}$	Density of air	kgm^{-3}
$\boldsymbol{c_{P_{air}}}$	Specific heat capacity of air	$Jkg^{-1}C^{-1}$
$\boldsymbol{A_{N,side}}$	Total area of the side windows	m^2
$\boldsymbol{A_{N,roof}}$	Total area of the roof windows	m^2
$\boldsymbol{U_{vent}}$	Open percentage of top windows	No units
$\boldsymbol{X_{screen}}$	Coefficient of internal thermal curtain infiltration	No units
$\boldsymbol{LAI}$	Leaf area index (denotes surface area of leaves to ground area)	$m^2\ m^{-2}$
$\boldsymbol{\Delta H}$	Enthalpy of vaporization of water (treated as a constant)	$J\ kg^{-1}$
$\boldsymbol{\gamma}$	Psychometric constant (= 65.8)	$Pa\ K$
$\boldsymbol{VP_{can}}$	Crop canopy saturated vapor pressure	Pa
$\boldsymbol{VP_{air}}$	Saturated vapor pressure of air inside greenhouse	Pa
$\boldsymbol{L_{water}}$	Latent heat of evaporation of water from the leaf surface	$J\ kg^{-1}$
$\boldsymbol{r_b}$	Somatic resistances of leaves (Depends on canopy temperature, air temperature, concentration of air and solar radiation)	$s\ m^{-1}$
$\boldsymbol{r_s}$	Aerodynamic resistances of leaves (Depends on canopy temperature, air temperature, concentration of air and solar radiation)	$s\ m^{-1}$
$\boldsymbol{r_{s,min}}$	Minimum somatic resistances of leaves	$s\ m^{-1}$
$\boldsymbol{R_{can}}$	Solar radiation on the canopy per unit time per unit area	$J\ s^{-1}\ m^{-2}\ \ or\ Wm^{-2}$
$\boldsymbol{X_{CO_2}}$	Influence coefficient of CO_2 on stomatal opening	No units
$\boldsymbol{\rho'_{CO_2}}$	CO_2 concentration in the greenhouse	ppm
$\boldsymbol{\tau_{cover}}$	Transition coefficient of covering material	No units
$\boldsymbol{\tau_{scr}}$	Influence coefficient of shading net	No units
$\boldsymbol{U_{scr}}$	Open percentage of shading net	No units
$\boldsymbol{I_{glob}}$	Outdoor solar radiation flux (location & time dependent)	$J\ s^{-1}\ m^{-2}\ \ or\ Wm^{-2}$
$\boldsymbol{T_{can}}$	Temperature of crop canopy	℃
$\boldsymbol{H_{air}}$	Relative humidity of air	No units
$\boldsymbol{R_u}$	Universal gas constant (= 8314)	$J\ kg^{-1}\ K^{-1}$

M_{H_2O}	Molecular mass of water $(= 18)$	$kg\ kmol^{-1}$
v_g	Greenhouse volume	m^3
Δt	Difference in time between t and $t-1$ $(= 300)$	s
$T_{leaf}(t)$	Leaf temperature, varies with time	°C

$$Q_{heat} = Q_{rad} + Q_{vent} + Q_{cover} + Q_{trans} + Q_{air} + Q_{crop} + Q_{solar} \tag{1}$$

Individual components on LHS of equation (7-1)

$$Q_{heat} = \rho_{water}\, c_{p_{water}}\, v_{water}\, [T_{in}(t) - T_{opt}(t)] \tag{2}$$

Individual components on RHS of equation (7-2)

$$Q_{rad} = \epsilon A_{cover} \sigma [(T_{air}(t) + 273.15)^4 - 2(T_{out}(t) + 273.15)^4] X_{cover} \tag{3}$$

$$Q_{vent} = A_{gw} C_d \left[2g \frac{\Delta T_{air}}{T_{out}} \left(\frac{A_{roof}^2\, A_{side}^2}{A_{roof}^2 + A_{side}^2}\right) + \left(\frac{A_{roof} + A_{side}}{2}\right)^2 C_w V_{wind}^2\right]^{\frac{1}{2}} [T_{in}(t) - T_{out}(t)]\, \rho_{air} c_{p_{air}} \tag{4}$$

$$A_{\ side} = U_{vent}\, A_{N,side} \tag{5}$$

$$A_{roof} = U_{vent}\, A_{N,roof} \tag{6}$$

$$Q_{cover} = A_{cover} X_{screen} [T_{in}(t) - T_{out}(t)] \tag{7}$$

$$Q_{trans} = \frac{2\rho_{air}\, c_{p_{air}}\, LAI}{\Delta H\, \gamma\, (r_b + r_s)} \quad (VP_{can} - VP_{air}) A_{gw} L_{water} \tag{8}$$

$$r_s = r_{s,min} \frac{R_{can} + 4.3}{R_{can} + 0.6} \left[1 + X_{CO_2}\left(\rho'_{CO_2} - 200\right)^2\right] \left[1 + X_P (VP_{can} - VP_{air})^2\right] \tag{9}$$

(X_p is neglected since the value is not significant)

$$R_{can} = 0.9 \tau_{cover} [1 - (1 - \tau_{scr}) U_{scr}] I_{glob} \tag{10}$$

$$VP_{can} = 2.229\ x\ 10^{11}\ exp \left[\frac{5385}{T_{can} + 273.15}\right] \tag{11}$$

$$VP_{air} = \frac{H_{air}\, R_U\, (T_{air} + 273.15)}{M_{H_2O}}\ x\ 10^{-3} \tag{12}$$

$$Q_{air} = \rho_{air} v_g c_{P_{air}} \left[\frac{T_{air}\,(t) - T_{air}(t-1)}{\Delta t}\right] \tag{13}$$

$$Q_{crop} = 2\, A_{gw}\, (LAI) \left[\frac{\rho_{air}\, c_{P_{air}}\, [(T_{air}(t) - T_{leaf}(t)]}{r_b}\right] \tag{14}$$

$$\mathrm{Q_{solar}} = 0.9\ \mathrm{A_{gw}} \tau_{\mathrm{cover}} [1 - (1 - \tau_{\mathrm{scr}}) \mathrm{U_{scr}}] \mathrm{I_{glob}} \tag{15}$$

3. Optimization

According to the principle of conservation of energy, physical sub-models of all the sub-models energy flow analysis have concurred. As shown in Figure 1., greenhouse's major operations have been divided into various sub-models and an energy prediction model has been established. Major physical parameters were measured with the help of field sensors and controlled accordingly. Major parameters inside the greenhouse like temperature, relative humidity, air velocity; daylight integral have been input into the model along with external disturbances. However, there are some uncertain parameters to be optimized in order to improve the efficiency of the design. Two optimization algorithms- particle swarm optimization and genetic algorithm were used. There are 7 uncertain parameters that have been optimized with the help of the above-said algorithms. Constant input parameters for the algorithm have been listed in Table 2.

Table 2. : Constant Physical Parameters Used in the Optimization Program

Sl. No.	Symbol	Physical description	Numerical value	Units
1	LAI	Leaf area index	3.21	$m^2\ m^{-2}$
2	$\mathrm{A_{cover}}$	Greenhouse cover surface area	677.19	m^2
3	σ	Stefan-Boltzmann constant	$5.67\ x\ 10^{-8}$	$Wm^{-2}K^{-4}$
4	g	Gravity acceleration.	9.8	ms^{-2}
5	$\mathrm{A_{N,side}}$	Maximum area side wall windows.	0.16	m^2s^{-2}
6	$\mathrm{A_{N,roof}}$	Maximum area top wall windows.	0.48	m^2s^{-2}
7	ρ_{air}	Air density	1.2	kgm^{-3}
8	$\mathrm{cp_{air}}$	Specific heat capacity of the air	1008	$Jkg^{-1}K^{-1}$
9	ΔH	Water evaporation latent heat constant.	$2.45\ x\ 10^6$	Jkg^{-1}
10	γ	Psychometric constant	65.8	PaK
11	$\mathrm{A_{gw}}$	Greenhouse ground surface area	272	m^2
12	$\mathrm{r_{s,min}}$	Minimum somatic resistance of the leaves	79	sm^{-1}
13	$\mathrm{L_{water}}$	Latent heat of evaporation for the leaf surface	$2.45\ x\ 10^6$	Jkg^{-1}
14	$\mathrm{M_{H_2O}}$	The molar mass of water	18	$kgkmol^{-1}$
15	$\mathrm{R_u}$	Molar gas constant	8314	$Jkmol^{-1}K^{-1}$
16	ν_g	Greenhouse volume	1486	m^3
17	$\mathrm{r_b}$	Aerodynamic resistance of leaves.	195	sm^{-1}

18	ρ_{water}	Water density	1000	$kg\ m\hat{}-3$
19	c_{water}	Specific heat capacity of water	4200	$J\ kg^{-1}C^{-1}$

4. Genetic Algorithm

A genetic algorithm is widely used to evaluate the natural selections by mutations in various genetic evolution experiments. Genetic algorithm is widely used in mutation experiments for the precise and accurate selection. In this process, the end-user can get various identical groups of similar behavior for multiple results and therefore can select the optimal result out of these.

According to the current model, Q is the heat consumption prediction from the equation (1) stated previously, Q_{actual} is actual energy consumption and the objective function for the algorithm can be defined as shown below in equation (16).

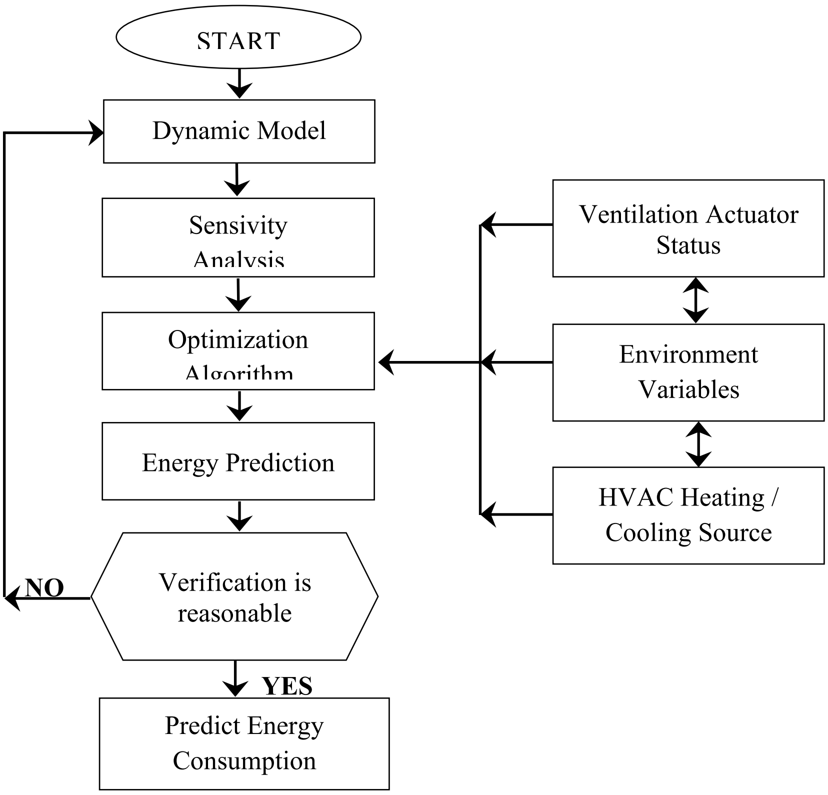


Figure 2. : Energy Prediction Model Flow Chart

Objective function:

$$\mathrm{OBJ} = \sqrt{\frac{1}{n}\sum_{t=1}^{t=n}[Q_{heat}\ (t) - Q_{actual}(t)]^2} \tag{16}$$

Where, objective function represents the root mean square value of the error between theoretical and actual values of Q and each individual parameter used for optimizing the objective function is represented in terms of vector X.

Where, $X = [\epsilon,\ X_{cover},\ C_d,\ C_w,\ X_{screen},\ \tau_{cov},\ \tau_{screen}]$

A pseudocode for the Genetic algorithm provided by Saemi Behzad et al., (2017) [3] has shown below.

```
Begin
        For each topic from a topics set
        begin
        generate a population
        while not terminated condition
        For each chromosome from population
        compute the fitness functions
        make next population:
        select parents
        recombine pairs of parents
        apply mutation to offspring
        End while.
        Store the chromosome that obtain the best fitness
        End for.
        Take all stored chromosomes
End.
```

Figure 3. : Pseudo Code for Genetic Algorithm (Saemi Behzad et al., (2018)) [3]

5. Particle Swarm Optimization Algorithm

A particle swarm optimization (PSO) algorithm is working based on the principle that individuals can determine the characteristics in such a way that each and every particle in the system can contribute towards the entire results and thereby optimize the whole system accurately. According to this algorithm, each particle should have two characteristics, such as velocity and position. The equation of each particle in the optimization process has shown been below.

$$vi^{k+1} = w.vi^{k} + b_1.r_1.(pi^{k} - xi^{k}) + b_2.r_2.(g^{select} - xi^{k}) \tag{17}$$

$$yi^{k+1} = yi^{k} + vi^{k+1} \tag{18}$$

Where “vi^{k+1}” stands for the speed of i^{th} particle in the k^{th} population evolution with an inertia weight of “w”. b_1 and b_2 are the learning and social factor respectively. r_1 and r_2 are the random numbers between (0,1). pi^{k} is the local optimal solution of the i^{th} particle after k^{th} development and g^{select} is the global optimal selected position. PSO got the advantage that this will avoid the conversion to binary field and backward, this can save the time for selection. . In this research, also the complex uncertain parameter characteristics have been identified with the help of PSO. Psuedo code for the PSO optimization provided by Lucian et al., (2012) [4] has shown in the Figure 4.

```
Function: PSO-Clustering
    Input: $Algorithm_{parameters}, K_{dusters}, Data_{count}$
    Output: Sbest Clustering
    Initialize a Population of particles with random positions and
    velocities, throught the input space
    While ~ StopCondition () do
    For each particle i do
    $f_p = f(X_i)$
    if $f_p > pbest$ then
    $pbest_i = f_p$
    $p_i = x_i$
    end
    $g = \{g \mid f(p_i) = max(f(p_x), k \varepsilon N(x_i))\}$
    Update velocity
    Update velocity
    End
```

```
End
Return Sbest Clustering
```

Figure 4. : Pseudo Code for Particle Swarm Algorithm (Lucian et al., (2014))

6. Optimization Results

An Intel SSD processor with 10GB RAM capacity computer has been used to perform the MATLAB process for the optimization process.

GA parameters: Population size N = 50 and Generations = 700 respectively, Cross over and mutation probabilities are 0.8 and 0.1; Function tolerance = 1e-6; Elite count = 2.5.

PSO parameters: Max. iterations = 1400; Max. stall iterations =20; Min Neighbours Fraction = 0.25; Self Adjustment Weight = 1.49; Social Adjustment Weight = 1.49; Swarm Size = 70.

Results obtained in both algorithms with respect to the predicted range have been comprehended in the Table 3.

Table 3. : Optimized Parameters Comparison with Desired Range

Parameter	Range	GA	PSO
$\boldsymbol{\epsilon}$	$[0.5, 0.8]$	0.86	0.90
$\boldsymbol{X_{cover}}$	$[0.1, 0.9]$	0.89	0.90
$\boldsymbol{C_d}$	$[0.3, 0.5]$	0.41	0.42
$\boldsymbol{C_w}$	$[0.05, 0.2]$	0.08	0.05
$\boldsymbol{X_{screen}}$	$[0.3, 0.9]$	0.32	0.30
$\boldsymbol{\tau_{cov}}$	$[0.05, 0.2]$	0.075	0.075
$\boldsymbol{\tau_{screen}}$	$[0.3, 1.0]$	0.33	0.33

The optimum paramters obtained from both the algorithms vary slighlty. The computation required for GA was more than that of PSO. Based on the optimized parameters listed above a maximised energy prediction was carried for the summer climate in Middle East using PSO and GA and the same was listed in the Figures 5 and 6 shown below. Maximum value of energy is in the range of 1.8x10^4 W [18kW] in both PSO and GA prediction results but the actual power consumptions for the experimental study was 1.85x10^4W which is little higher than the optimized maximum value for the power consumption. However, the power consumption reduction in the optimized scenario is following the same pattern of the actul power consumption. Similar synchronisation results obtained for the optimization for winter climate conditons by Chen et al., (2005) [5] but the same was in the opposite cocnept such as increasing the heat inside the green house instead of cooling in summer climates. In Middle East climate, the peak summer is very crucial to control the temperature, eventhough the average energy consumption for the greenhouse observed between 14-18kW per day therefore, peak summer requires a high power consumption, therfore the total load requirement for the greenhouse energy prediction was designed into meet this challenge which is 6 to 7 times more than the actual avaerge power consumption in the winter season in the Middle East.

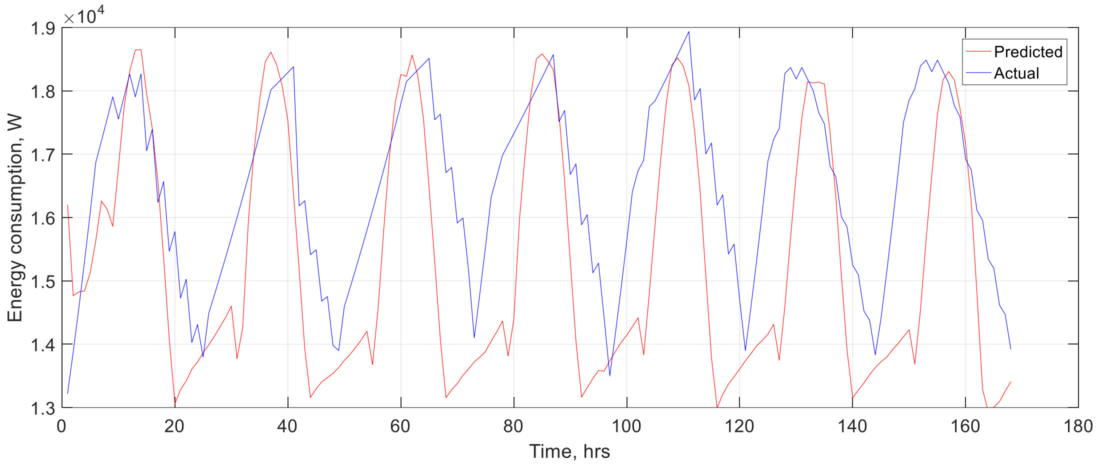


Figure 5. : Predicted Power Consumption with PSO optimization

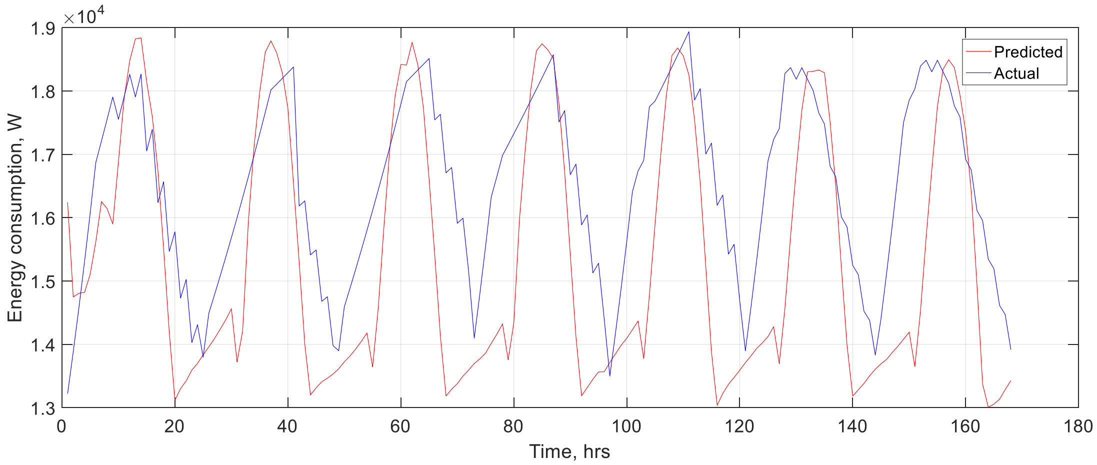


Figure 6. : Predicted Power Consumption with GA Optimization

Present study carried out based on the optimization platforms such as PSO and GA and validated the same with pilot run experimental results. Results obtained has been plotted, from figures 5 and 6, actual power consumption meets the prediction in general with an average error of 8.26%. Relative error between the predicted and actual energy consumption has been verified for the 7 days' cycle from 1st July 2017 till 7th July 2017, outdoor temperature was 35 to 42°C with a relative humidity of 55 to 85%.

Error prediction for the average energy consumption has been done with respect to the temperature and day lighting level (day light integral). When the greenhouse average solar radiation is between 250 ($W.m^{-2}$) and 350 ($W.m^{-2}$) the outdoor average temperature is in a moderate level the indoor parameters observed as good as predicted results. Table 7.4 shows the error computed between the actual values and predicted values using PSO and GA optimized power consumption. The error ranges from 2.78% to 9.66% for PSO and for GA it is in the range of 2.37% to 9.27%. Hence the optimized uncertain parameters can be used for energy consumption model for reasonable prediction.

Table 4. : Relative error calculation between actual and predicted model

Date(dd-mm-yy)	Outdoor Average light ($W.m^{-2}$)	Outdoor average temperature in °C	Average power in kW	Relative error (%)	
				PSO	**GA**
01/07/2024	196.2	33.5	16.21	2.78	2.37
02/07/2024	329.5	34.0	16.16	5.24	4.91
03/07/2024	316.1	34.5	16.62	8.25	7.94
04/07/2024	315.9	35.0	16.69	8.21	7.96
05/07/2024	320.3	35.5	16.79	9.07	8.80
06/07/2024	275.2	36.0	16.43	7.56	7.26
07/07/2024	307.1	36.5	16.67	9.66	9.27

During the summer season, commercial greenhouse requires an efficient energy management portfolio. According to the past studies by Hemming et al., (2015) [6], HVAC system cost in the peak summer and winter conditions is reaching 30 -50% of the total energy cost element.

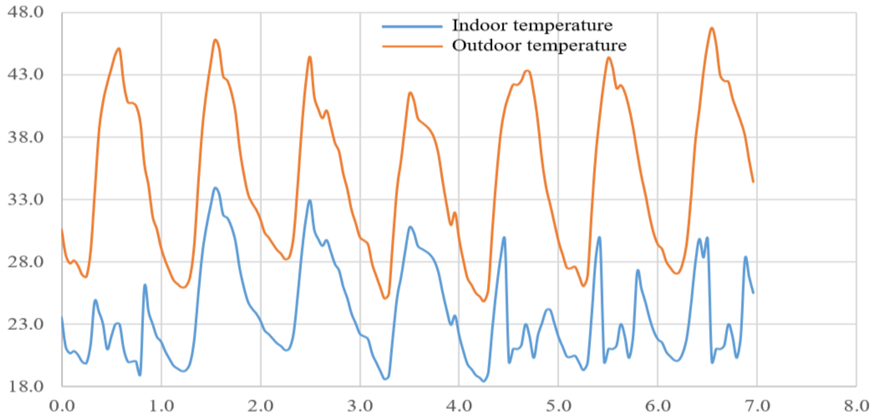


Figure 7. : Temperature Trends over Time

Figure 8 representing the predicted temperature synchronization with respect to the outdoor temperature. Temperature difference between the actual and predicted after optimization has shown in Figure 7.8. During the peak summer at 12.00 noon, the green house grill openings will close and circulation fans and evaporative coolers will be in operation to cool the indoor climate condition. When the greenhouse reached into the adequate energy the grills will open again and the excess energy will banish.

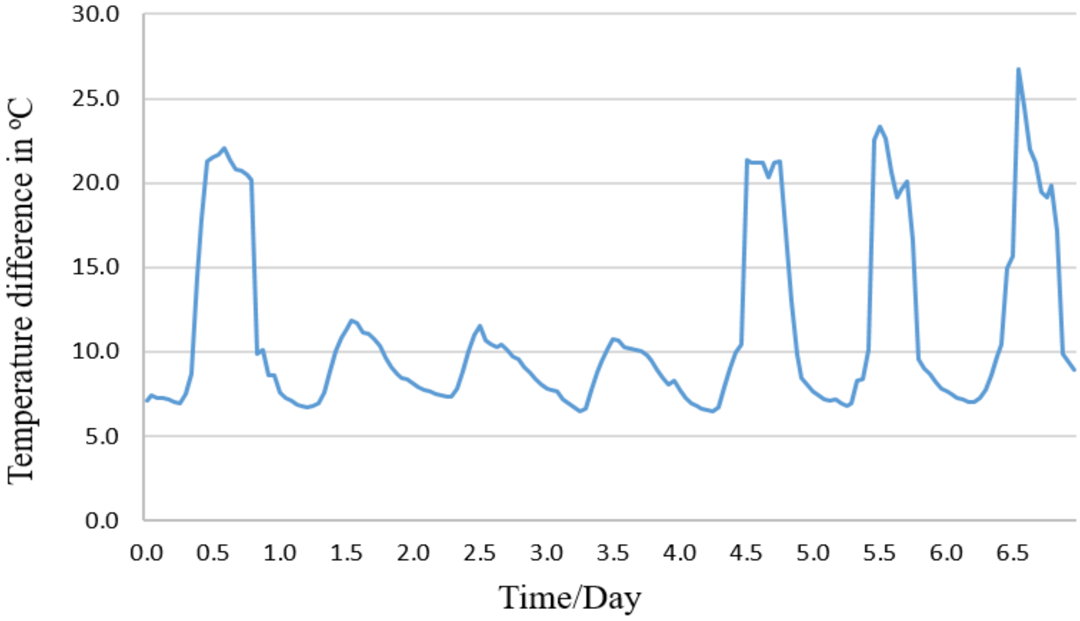


Figure 8. : Temperature Difference Graph between Outdoor and Indoor

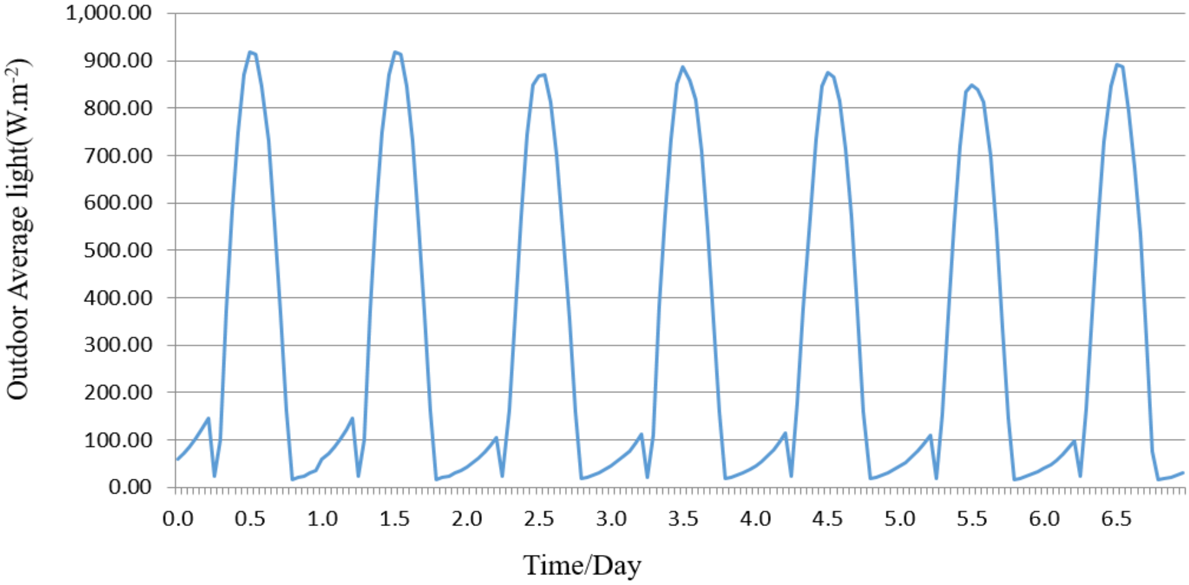
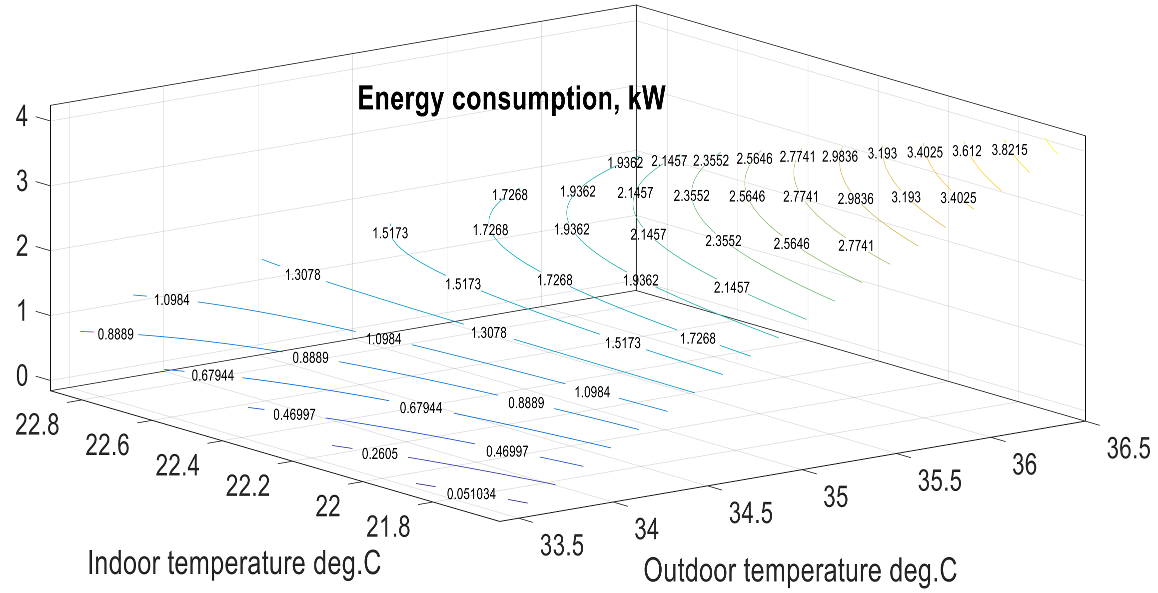


Figure 9. : Outdoor Average Light Variation over Time



Outdoor average light parameters are closely related to the plant growth indoor lighting and also in maintaining the indoor temperature. High outside solar level causes the rise in indoor temperature. Average light trends over the time has been shown in Figure 9 for the seven days' time period from 1st July 2024 to 7th July 2024

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Figure 10. : Energy Prediction for Different Outdoor Average Temperature and Solar Radiation

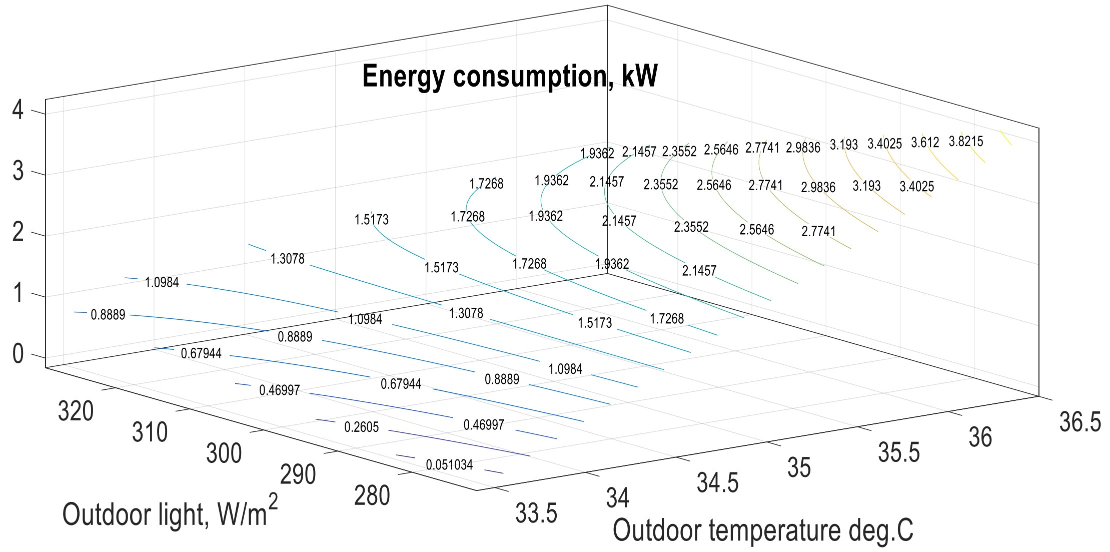

Figure 11. : Energy Prediction for Different Outdoor and Indoor Average Temperature

Daily management of the greenhouse is based on the day outdoor temperature and indoor temperature trends. As shown in the Figure 10 and Figure 11, from July 1st to July 7th 2024, actual indoor and outdoor temperature and light in the greenhouse located in the greenhouse in UAE is changing gradually, and following a synchronization trend during the day. Based on the predicted model temperature inside the greenhouse has fixed as 22°C, and daily energy consumption was predicted with different outdoor temperature and light as shown in Figure 7.10. While we fixed the daily outdoor solar as 200W/m^2, daily energy consumption is predicted for the different indoor temperature and outdoor temperature as shown in Figure 7.11.

8.Conclusion

In the present study, the greenhouse located in Middle East climate was taken as an example to predict the energy for real scenario using two major optimization algorithms. Based on the optimized seven parameters obtained, energy consumption prediction carried out in between 1st July 2025 to 7th July 2025 for 7 days cycle in a summer period in United Arab Emirates. Predicted energy trend followed the same modularity as of actual energy consumption but with an optimized result. Exclusively in the present study an energy prediction model has been established in line with the real time energy production for a period of time using the PSO and GA.

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