Backstepping-Based Non dominated Sorting Genetic Algorithms
NSGA for Greenhouse Control with Real Weather Data

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Abstract:
In this paper we use the backstepping approach to control climate parameters of greenhouse simulated trough effect of real weather data collected in the south region of Algeria (Biskra) for the period of June 2008.
The greenhouse model is a sixth order nonlinear multivariable system. We consider the control of both temperature, relative humidity, CO2 concentration by acting on four control variables such as heating, ventilation, CO2 injection and water injection.
To get an optimal controller, we try to solve a multi-objective problem. The multi-objective genetic algorithms based on NSGA (define le sigle ici) technique are used to get a set of optimal controllers. To choose one controller from the above set, we take into account the application of the Multi-Criteria Decision Analysis (MCDA) approach.

Keywords
Greenhouse climate model, Lyapunov stability, Backstepping method, Genetic Algorithms, NSGA, MCDA.

1. Introduction
A good greenhouse crop requires an appropriate climate in order to maintain the agricultural environment in appropriate conditions that satisfy the agronomic and economic objectives of the farmer. In this order many parameters must be controlled and supervised such as the temperature, the relative humidity and the CO2 concentration by acting on the heat system, ventilation, water injection and CO2 injection (Ursem et al., 2001).
The control of climatic environment inside greenhouse has received considerable attention these last years in order to satisfy objectives like: (i) to extend the growing season and the potential yield; (ii) to manage the climate in order to reach higher standards of quality; (iii) to develop low-cost production systems, compatible with the scarcity of resources and the low investment capacity of growers (Bennis et al., 2008). Many approaches are developed for this problem, Ursem and al have developed an approach based on the evolutionary algorithms, a set of controllers is proliferated randomly and, by using genetic operators, this set converges to an optimal controller(Ursem et al., 2002).

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Another approach based on optimal theory is proposed by Ooteghem (Ooteghem, 2007), Bennis and al have proposed an $H_2$ robust control method for the greenhouse (Bennis et al., 2008).

Furthermore, the application of fuzzy control is introduced by Lafont and Balmat (Lafont, and Balmat, 2004), neural networks control has been applied by Ferreira et al (Ferreira et al., 2002).

This work presents a nonlinear control approach using the nonlinear greenhouse model developed by Pohlheim. The backstepping-based Non Dominated Sorting Algorithms (NSGA) method is applied to get a set of optimal controllers, and in order to choose one of these controllers the multi-criteria decision analysis (MCDA) is applied. The proposed approach is tested with real weather data for a region situated in south Algeria.

The paper is organized as follows. Some background, dealing with the control of a class of nonlinear systems, is introduced in the second section, then we present, in the third section, the backstepping control method. In section four, we focus attention on the NSGA. The MCDA is treated in the section five. Section six describes the greenhouse climate model for application of the proposed control method. Finally a conclusion and some perspectives are given.

2. Background

This section presents some preliminaries related to the system class we are interested in, and its properties. Furthermore the control method of this kind of system is developed.

2.1. Class of Non Linear Systems

The system considered belongs to a specific class such as variable structure system with a triangular form. It can be described like the following dynamic system

$$\dot{x} = f(x, v) + g(x, v)u$$

$$\zeta = h(x)$$

(1)

$x$ denotes the state vector, $\zeta$ is the output vector, $u$ is the direct input vector and $v$ is the perturbation vector.

Under this form, the system can be controlled by a backstepping approach described later. A developer

2.2. Objectives, criteria and constraints

Some objectives to ensure must fulfill some criteria and constraints. These objectives can be summarized in the stabilization of the system regardless the exogenous perturbations. In order to reach the desired performance an optimization criterion is introduced and expressed by:

$$J = \min(J_1, J_2, \ldots, J_q)$$

$$\phi_j(x) \geq 0$$

(2)
\[ J_i \] are the minimization criteria and \( \varphi_i(x) \) are the constraints

It is obvious that we are face to a multi-objective problem with constraints. **A developer**

3. **The Backstepping**

The Backstepping is a non-linear approach method based on the Control Lyapunov Function (CLF) scalar design governed by Lasalle-Yoshizawa theorem. It is a recursive design method applied for systems having a triangular form. The controller design has several steps, in the first step, we consider a Lyapunov candidate function for the first error state, and then a corresponding virtual control is calculated in order to guarantee the negativity of the proposed Lyapunov function. Using this virtual control, we can associate a second error state defined as difference between the second state and the virtual control calculated in first step, then, the next objective is to ensure the cancellation of this error. So, we consider then an augmented joint Lyapunov function where, the first Lyapunov function and the second error must appear. The second virtual control is then calculated in the same way, and so on. The exact control will be calculated in the last step by using the virtual control laws defined in the previous steps. We can interpret this method by adding of integrator (Kristic et al., 1995).

4. **Non dominated Sorting Genetic Algorithms (NSGA)**

In several problems, we need to realize the optimization of multiple criteria, in order to reach some performances simultaneously, so, it is necessary to use methods based on multi-objective optimization. The metaheuristics methods are the most known method for the kind of this problem, the most used is the methods based on genetic algorithms. Several approaches have been developed and they are based on the tionnon-dominance concept with introduction of the notion of pareto set. Among these approaches we find the MOGA technique developed by Fonseca and Fleming (Fonseca and Fleming, 1993) NPGA method introduced by Horn and Napfliotis (Horn and Napfliotis, 1994) and NSGA treated by Srivinas and Deb. (Srivinas and Deb., 1994). NSGA is the method used in this paper, it based on the non – dominance concept and it works by adding a classification procedure into the the simple genetic algorithms flowchart

5. **Multi-criteria decision analysis (MCDA)**

After applying the NSGA, the algorithm converges to a pareto front, it is a set of solutions respecting the criteria to optimize and realizing minimum conflicts. So the question is how we can choose one solution among the solution situated in the pareto front? This problem defines the MCDA approach.

Multi-Criteria Decision analysis (MCDA) is the most well known branch of decision making. It is a branch of a general class of operation research model which deal with decision problems under the presence of a number of decision criteria (Triantaphyllou et al., 1998). It is a set of systematic Procedures for analyzing complex decision problems. These procedures include dividing the decision problems into smaller more understandable parts; analyzing each part; and integrating the parts in a logical manner to produce a meaningful solution (Malczewski, 1997)

Any decision problem can be structured into three major phases (Simon, 1960) (i) intelligence which examines the existence of a problem or the opportunity for change, here in systems control the problem is to design the optimal MIMO controller with minimization of a set of criteria to achieve some desired values, (ii) design which determines the alternatives (set of MIMO controllers) by introducing the design matrix notion
which elements indicates the performances of alternative (iii) choice which decides the best alternative. This choice corresponds to the optimal MIMO controller.

To solve such problem, three steps must be ensured, in the first step a decision matrix is generated by using NSGA methods, it has the following expression:

\[ D = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \ldots & a_{1n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & \ldots & \ldots & \ldots & a_{mn} \end{bmatrix} \]

The M alternatives represent the solution in pareto set and the \( a_{ij} \) indicates the performance index attributed by alternative \( i \) to all \( N \) criteria.

In the second step, a weight vector is computed for \( N \) criteria, several methods exist, in this paper The pairwise comparison method is used to compute this vector weights (Saaty, 1960). It takes pairwise comparison as input and produced relative weights as output. The methods involves three steps: (i) Development of pairwise matrix by using a scale with values range from 1 to 9 (table3), (ii) Computation of the weights: The computation of weights involves three steps. First step is the summation of the values in each column of the matrix. Then, each element in the matrix should be divided by its column total (the resulting matrix is referred to as the normalized pairwise comparison matrix). Then, computation of the average of the elements in each row of the normalized matrix should be made which includes dividing the sum of normalized scores for each row by the number of criteria. These averages provide an estimate of the relative weights of the criteria being compared and ensure that \( \sum_{i} w_i = 1 \), (iii) Estimation of the consistency ratio, in order to determine if the comparisons are consistent or not. It involves several operations, the first one is the multiplication of column times its weight and sum these values over the rows, after, we determine the consistency vector by dividing the weighted sum vector by the criterion weights determined previously and calculate lambda \( \lambda \) which is the average value of the consistency vector and Consistency Index \( CI \) which provides a measure of departure from consistency with: \( CI = (\lambda - n)/(n-1) \). The last step operation is to the calculation of the consistency ratio \( CR \) which is defined by \( CR = CI / RI \), Where \( RI \) is the random index and depends on the number of elements being compared (Triantaphyllou et al., 1998) in our case we have \( N=0.90 \). If \( CR < 0.1 \) The ratio indicates a reasonable level of consistency in the pairwise comparison, however, if \( CR \geq 0.10 \), the values of the ratio indicates inconsistent judgments.

The best alternative can be detected by several approaches; we use here the simple additive weighting method (\( SAW \)). The method is based on the weighted average. An evaluation score is calculated for each alternative by (Janssen, 1992; Triantaphyllou et al., 1998).

\[ A_{SAW} = \sum_{j=1}^{n} w_j a_{ij} \]

then the best alternative is defined by:

\[ A^* = \max_{i} (A_{SAW}) \]
6. Application for a greenhouse system

6.1. Mathematical model

The greenhouse is described by six nonlinear differential equations, the model considers interactions with environment as measured perturbations. Figure (1) shows the interaction diagram between the greenhouse, environment and controller.

\[
x(t) = [x_1 \ x_2 \ x_3 \ x_4 \ x_5 \ x_6] \text{ is the greenhouse state vector with } x_1 \text{ is the indoor steam density (} x_{steam} \text{), } x_2 \text{ is the indoor air temperature (} x_{atemp} \text{), } x_3 \text{ is the indoor CO2 concentration (} x_{CO2} \text{), } x_4 \text{ is the accumulated profit (} x_{profit} \text{) is the accumulated biomass (} x_{Biom} \text{), } x_5 \text{ is the accumulated biomass (} x_{biom} \text{) and } x_6 \text{ is the condensation on glass (} x_{cond} \text{).}
\]

\[
u(t) = [u_1 \ u_2 \ u_3 \ u_4] \text{ represents the control variable vector with } u_1 \text{ is the water injection command (} u_{water} \text{), } u_2 \text{ is the ventilation command (} u_{vent} \text{), } u_3 \text{ is the heating command (} u_{heat} \text{) and } u_4 \text{ is the CO2 injection command (} u_{CO2} \text{).}
\]

\[
\nu(t) = [v_{atemp} \ v_{gtemp} \ v_{sun} \ v_{wind} \ v_{rh}] \text{ is the measured perturbation vector contains outdoor air temperature, outdoor ground temperature, outdoor sunlight intensity, wind speed and outdoor relative humidity.}
\]

The mathematical climate model of greenhouse can be described as follow (Pohlheim and Heißner, 1996; Ursem et al., 2002):

\[
\begin{align*}
\dot{x} &= f(x, v) + g(x, v)u \\
\zeta &= h(x)
\end{align*}
\]

With:

\[
\begin{align*}
f_1(x, v) &= \frac{1}{GH} \cdot (Trans - EnvExc - CondEvap) \\
f_2(x, v) &= \frac{1}{HCap} \cdot (HSun - HExVent - HExGround - HExHull - HCondEvap - HHum) \\
f_3(x, v) &= \frac{C_{Photo} + C_{ExVent}}{10^{-6} \cdot DC \cdot GH} \\
f_4(x, v) &= \frac{30}{44} \cdot C_{Photo} \cdot DWF \cdot v_{ph} \cdot 10^{-3} \\
f_5(x, v) &= C_{Photo} \cdot \frac{30}{44} \\
f_6(x, v) &= CondEvap
\end{align*}
\]
\[
g(x, v) = \begin{bmatrix}
\frac{c_w d f_{ssp}}{GH} & -x_1 - v_{steam} & 0 & 0 \\
\frac{1}{(E E W 0 + H C S \cdot x_2) \cdot c_w d f_{ssp}} & \frac{1}{GH} & \frac{1}{(E E W 0 + H C S \cdot x_2) \cdot (x_1 - v_{steam})} & 0 \\
H_{cap} & 0 & 1 & 0 \\
0 & 0 & -v_{pheat} & -10^{-3} v_{pCO2}
\end{bmatrix}
\]

\[
h(x) = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}
\]

Where: \( v_{pr} \) is the price of crop, \( v_{pheat} \) is the price of heat and \( v_{pCO2} \) is the price of \( CO_2 \). All other quantities are defined in appendix 6.2.

6.2. Constraints

More constraints should be considered in this process, they can be defined by:

\[
\varphi_1(x) = f_{SSP}(x_{atempd}) - f_{SP}(x_{steam}, x_{atempd}) \geq 0
\]

\[
\varphi_2(x) = -x_6 + 25 \geq 0
\]

\[
\varphi_3(x) = x_6 + 25 \geq 0
\]

In the end of script, indicate temperature in Kelvin,

7. Controller design

We consider as crop of tomatoes and for the system (3) the set points are:

- **relative humidity** = 75%
- \( x_{atempd} = \begin{cases} 15^\circ \text{ at night} \\ 20^\circ \text{ at day} \end{cases} \)
- \( x_{CO2,d} = \begin{cases} 0^\circ \text{ at night} \\ 800 \text{ppm at day} \end{cases} \)
- \( x_{profitd} = 50 v_{pr} \)

The steam density set point can be computed by using the equation:

\[
x_{steamd} = RH_d \cdot \frac{f_{ssp}(x_{atempd})}{x_{atempd} \cdot RWS}
\]

7.1. Theorem We consider the system (1) with the set point defined above and let:
To be the errors between the actual states and the desired values, then the control laws stabilize the system (1) is given by:

\[ u = A^{-1}B \]  

Where

\[
A = \begin{bmatrix}
    G_H \tilde{g}_1 \\
    H_{cap} \tilde{g}_2 \\
    10^{-6} \cdot D.C.G_H \tilde{g}_3 \\
    \tilde{g}_4
\end{bmatrix},
B = \begin{bmatrix}
    -k_1z_1 + G_H f_1 \\
    -k_1z_2 + H_{cap} f_2 \\
    -k_1z_3 + 10^{-6} D.C.G_H f_3 \\
    -k_1z_4 + f_4
\end{bmatrix}
\]

With: \( \tilde{g}_i = g(x, v)[i, :], i = 1:4 \) (Line \( i \) of matrix \( g(x, v) \))

**Proof**

Let:

\[ V = 0.5GH.z_1^2 + 0.5H_{cap}.z_2^2 + 0.5 \cdot 10^{-6}GH.DC.z_3^2 + 0.5z_4^2, \]

to be the joint Lyapunov function associated to the error signals define above. So:

\[
\frac{dV}{dt} = \frac{\partial V}{\partial z_1} \dot{z}_1 + \frac{\partial V}{\partial z_2} \dot{z}_2 + \frac{\partial V}{\partial z_3} \dot{z}_3 + \frac{\partial V}{\partial z_4} \dot{z}_4 \Rightarrow \frac{dV}{dt} = G_H.z_1 \dot{z}_1 + H_{cap}.z_2 \dot{z}_2 + 10^{-6}D.C.G_H.z_3 \dot{z}_3 + z_4 \dot{z}_4
\]

The negativity of this function must be ensured, so the judicious choice is:

\[
\begin{align*}
G_H \dot{z}_1 &= -k_1z_1 \\
H_{cap} \dot{z}_2 &= -k_2z_2 \\
10^{-6}D.C.G_H \dot{z}_3 &= -k_3z_3 \\
\dot{z}_4 &= -k_4z_4
\end{align*}
\]

\[
\begin{align*}
G_H \dot{x}_1 &= -k_1z_1 \\
H_{cap} \dot{x}_2 &= -k_2z_2 \\
10^{-6}D.C.G_H \dot{x}_3 &= -k_3z_3 \\
\dot{x}_4 &= -k_4z_4
\end{align*}
\]

Under this choice, the derivative of Lyapunov function becomes:

\[ V = -k_1z_1^2 - k_2z_2^2 - k_3z_3^2 - k_4z_4^2 \]

By replacing the equation (1) in the above system, we have: \( AU = B \) and the errors state becomes:

\[
\dot{Z} = -KZ
\]

\[
K = \begin{bmatrix}
    k_1 & 0 & 0 & 0 \\
    0 & k_2 & 0 & 0 \\
    0 & 0 & k_3 & 0 \\
    0 & 0 & 0 & k_4
\end{bmatrix} > 0
\]
7.2. Stability analysis
Since \( V' \leq 0 \) we can deduce that \( V \) is a decreased function, so \( V \leq V(0) \), therefore, \( z_i \in L_{\infty} \) for \( i=1,2,3,4 \).

To check that \( V' \) is uniformly continuous, we should demonstrate that \( \ddot{V} \) is bounded, so:

\[
\ddot{V} = -2(k_1 \dot{z}_1 \dot{z}_1 + k_2 \dot{z}_2 \dot{z}_2 + k_3 \dot{z}_3 \dot{z}_3 + k_4 \dot{z}_4 \dot{z}_4) = 2(k_1^2 z_1^2 + k_2^2 z_2^2 + k_3^2 z_3^2 + k_4^2 z_4^2)
\]

Then since \( z_i \in L_{\infty} \) for \( i=1,2,3,4 \), so \( \ddot{V} \) is bounded and \( V' \) is uniformly continuous.

Using barbalat’s lemma (Slotine Li, 1991), we have \( \lim_{t \to \infty} \dot{V} = 0 \), then indicates that \( \lim_{t \to \infty} z_i = 0 \) for \( i=1,2,3,4 \).

7.3. Identification of gain matrix \( K \)
To identify the gain matrix, a multi-objective genetic algorithm-based NSGA approach is used. The training conduct to a set of optimal controller. The main task is to minimize the error signals \( z_i \) for \( i=1,2,3,4 \). In this order the set of criteria is:

\[
\text{objfunc}_i = \frac{1}{\sum_{i=0}^{\infty} z_i(t)}, i=1,2,3,4
\]

The NSGA is introduced via the parameters such: \( \text{popsize}=50, \text{mlaxgen}=50, \text{Pcr}=0.9, \text{Pmut}=0, \text{Lchrom}=400, \sigma_{\text{share}}=1, c_{1,2,4} \in [0 0.5] \) and \( c_3 \in [0 2] \). The pareto front is a set of optimal controller. To obtain the best controller we proceed by the MCDA approach. The pairwise comparison has the following representation:

\[
\begin{pmatrix}
X_{\text{atemp}} & X_{\text{steam}} & X_{\text{CO}_2} & X_{\text{profit}} \\
X_{\text{atemp}} & 1 & 2 & 4 & 9 \\
X_{\text{steam}} & 1/2 & 1 & 3 & 9 \\
X_{\text{CO}_2} & 1/4 & 1/3 & 1 & 9 \\
X_{\text{profit}} & 1/9 & 1/9 & 1/9 & 1 \\
\end{pmatrix}
\]

Then by applying the algorithm described above, the weight vector is \( W = [0.483 0.312 0.17 0.035]^T \) with CR=0.093

8. Results of simulation
The real weather data is obtained from the station sited in south of Algeria (Biskra), excepted \( v_{\text{CO}_2} \) and \( v_{\text{sun}} \) which they can be kept constant at 340 ppm and 600w/m² respectively. The Other quantities are:

\[
\begin{align*}
\nu_p &= 35DA \\
\nu_{\text{ph}} &= 2DA \\
\nu_pCO_2 &= 480DA
\end{align*}
\]

By using the MCDA, the most optimal controller satisfy the importance degree of criteria is defined by the gain vector:

\[
K = [0.4813 0.4652 0.6208 0.4997]^T
\]

After training, pareto front contains 37 individuals, which can be explained by the convergence of algorithm to the optimal solutions.

For weather data, showed by figure (2), we have take samples for 30 days, however, to clarify the graph, the training is treated for 5 days.

Figure (3) shows the evolution of different greenhouse quantities, for the temperature, a good tracking is reached, however, for CO₂ concentration, at day the controller can satisfy the desired values, but at the night the
controller take more time than day to satisfy the goal. For the relative humidity, it is obvious that the objective is realized, the indoor steam density is deduced from the relative humidity.

In the figure (4) we see the profit is reached, it represents the gain of crop minus the price of both heating and CO₂ injection. The biomass is the dry weight of the crop.

8. Conclusion

In this paper a greenhouse system control is considered, this system is a multivariable and it is described by six non linear equation, it must be controlled by four quantifies. The task is to reach some set points in order to get a good crop. This task is realized by introducing the backstepping method to design a MIMO controller.

The design through Lyapunov function, need some parameters which there numbers depends by the order of system, in this order, the choice of values it can be tedious. To avoid this problem and in order to satisfy all objectives simultaneously, multi-objective genetic algorithms is introduced by using the NSGA approach, after training, a pareto front defines a set of optimal controller is reached, and to get the best one, the MCDA approach is introduced by using the pairwise comparison method.

The simulation is based on real weather data for a region sited in south Algeria (Biskra), a good result are obtained.

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10. Appendix A

\( Trans = 100 \cdot \text{LeafSize}[\text{month}] \cdot \text{PM2} \cdot \text{LeafTrans}[\text{month}] \cdot \text{TrGrow} \)

\( \text{TrGrow} = (1 - b_0 \cdot (x_{\text{CO2}} - 600)) \cdot \frac{\text{TrCur}}{\text{TrStd}} \)

\( \text{TrCur} = b_1 + b_2 \cdot x_{\text{sun}} + b_3 \cdot (x_{\text{sun}})^2 + b_4 \cdot f_{\text{RH}} (x_{\text{steam}}, x_{\text{atempA}}) \cdot f_{\text{SD}} (x_{\text{steam}}, x_{\text{atempA}}) \)

\( \text{TrStd} = (b_1 + b_2 \cdot 300 + b_3 \cdot 300^2 + b_4 \cdot 60) \cdot 10 \)

\( \text{EnvExc} = (VM0 + VM1 \cdot v_{\text{wind}}) \cdot (x_{\text{steam}} - v_{\text{steam}}) \)

\( \text{Cond} = \text{CondEvap} \cdot \begin{cases} \text{Cond if } x_{\text{Cond}} > 0 \\ 0 \text{ if } x_{\text{Cond}} < 0 \end{cases} \)

\( \text{CondEvap} = \begin{cases} \text{Cond if } x_{\text{Cond}} > 0 \text{ and } x_{\text{Cond}} > 0 \\ 0 \text{ if } x_{\text{Cond}} < 0 \text{ and } x_{\text{Cond}} = 0 \end{cases} \)

\( \text{Trpo} = \text{GR} \cdot \frac{f_{\text{SD}} (x_{\text{steam}}, x_{\text{atempA}}) - f_{\text{SSP}} (x_{\text{atempA}})}{0.5 \cdot \text{RWS} (x_{\text{atempA}}, x_{\text{atempA}})} \)

\( \text{Trpo} = \frac{0.33 \cdot x_{\text{atemp}} - x_{\text{hemp}}}{DA \cdot CA} \)

\( x_{\text{hemp}} = \begin{cases} -2.71 + 0.00811 \cdot v_{\text{sun}} + 0.795 \cdot x_{\text{atemp}} + 0.289 \cdot v_{\text{atemp}}, & 5 < n_{\text{month}} < 9 \\ \frac{1}{3} x_{\text{atemp}} + \frac{2}{3} v_{\text{atemp}}, & \text{otherwise} \end{cases} \)

\( \text{HCap} = \text{LeafSize} \cdot LSW \cdot \text{HCW} + \text{GH} \cdot \text{HCA} \cdot DA + \text{GH} \cdot \text{HCS} \cdot x_{\text{steam}} \)

\( \text{HSun} = TS \cdot x_{\text{sun}} \)
\[ H_{\text{ExVent}} = (V_M 0 + V_M 1 \cdot v_{\text{wind}}) \cdot (x_{\text{energy}} - v_{\text{energy}}) \]

\[ x_{\text{energy}} = HCA \cdot D \cdot x_{\text{atemp}} + x_{\text{steam}} \cdot (E W 0 + H C S \cdot x_{\text{atemp}}) \]

\[ v_{\text{energy}} = HCA \cdot D \cdot x_{\text{atemp}} + v_{\text{steam}} \cdot (E W 0 + H C S \cdot x_{\text{atemp}}) \]

\[ H_{\text{ExGround}} = H G \cdot (x_{\text{atemp}} - v_{\text{atemp}}) \]

\[ H_{\text{ExHull}} = G R \cdot (H W 0 + H W 1 \cdot v_{\text{wind}}) \cdot (x_{\text{atemp}} - v_{\text{atemp}}) \]

\[ H_{\text{CondEvap}} = E W \cdot \text{CondEvap} \]

\[ H_{\text{Hum}} = G H \cdot (E W 0 + H C S \cdot x_{\text{atemp}}) \cdot (\text{trans-Evexc-CondEvap}) \]

\[ C_{\text{Photo}} = 100 \cdot \text{LeafSize}_{\text{month}} \cdot \text{PM2.5 CO}_2 \text{Ex}_{\text{month}} \cdot C_{\text{PhGrow}} \]

\[ C_{\text{PhGrow}} = \begin{cases} C_{\text{PhCur}} \cdot C_{\text{PhDec}} & \text{if } C_{\text{PhCur}} > 0 \\ C_{\text{PhCur}} & \text{otherwise} \end{cases} \]

\[ C_{\text{PhCur}} = c_1 \cdot (1 - \exp(-c_2 \cdot 0.5 \cdot x_{\text{sun}})) \cdot (1 - \exp(-c_3 \cdot x_{\text{CO}_2}))(x_{\text{atemp}} + c_4 \cdot x_{\text{atemp}}^2) - c_5(x_{\text{atemp}} + c_5 \cdot x_{\text{atemp}}^2) \cdot \exp(-c_6(d_1 - f_{\text{sd}}(x_{\text{steam}}, x_{\text{atemp}}))^2) \]

\[ C_{\text{PhDec}} = \begin{cases} 1 & \text{if } f_{\text{sd}}(x_{\text{steam}}, x_{\text{atemp}}) < d_1 \\ \exp(-c_6(d_2 - f_{\text{sd}}(x_{\text{steam}}, x_{\text{atemp}}))^2) & \text{if } f_{\text{sd}}(x_{\text{steam}}, x_{\text{atemp}}) > d_2 \end{cases} \]

\[ v_{\text{steam}} = \frac{V_{\text{RH}} \cdot f_{\text{ssp}}(x_{\text{atemp}})}{100 \cdot v_{\text{atemp}} \cdot R_{\text{WS}}} \]

With: \[ b_0 = 5.10^{-4}, \quad b_1 = -2.219.10^{-6}, \quad b_2 = -5.213.10^{-6}, \quad b_3 = -6.22.10^{-9}, \quad b_4 = 8.5.10^{-6}, \quad c_1 = 0.1381, \quad c_2 = 8.687.10^{-6}, \]

\[ c_3 = 3.697.10^{-3}, \quad c_4 = 1.9083.10^{-2}, \quad c_5 = 2.073.10^{-3}, \]

\[ c_6 = 8.7525.10^{-2}, \quad c_7 = 0.0001, \quad c_8 = 0.001, \quad d_1 = 5, \quad d_2 = 10 \]

\[ df_{\text{ssp}} = f_{\text{ssp}}(x_{\text{atemp}}) - f_{\text{ssp}}(x_{\text{steam}}, x_{\text{atemp}}) \]

Table (A.1) shows the constants, table (A.2) shows plants growth variables
11. References


**Table A.1**: greenhouse constants

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Figure 1: interaction diagram between the greenhouse, environment and controller
Figure 2: Real weather data for 30 days
Figure 3: Climatic greenhouse state
Figure 4: profit
Figure 5: Condensation and biomass