An Observer based Backstepping control for a Greenhouse

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Abstract- In this paper we use the backstepping approach to control climate parameters of greenhouse. To get realistic simulation, we use real weather data collected in the south region of Algeria (Biskra). We control temperature, relative humidity and CO2 concentration by acting on four variables such as heating, ventilation, CO2 injection and water injection. However as the CO2 sensors is not available, we use an nonlinear observer based on temperature and steam density measurements, To get an optimal controller, the multi- objective genetic algorithms based on Non dominated Sorting Genetic Algorithms (NSGA) techniques and Multi-Criteria Decision Analysis (MCDA) approach are introduced.

Keywords:* *Backstepping method, Lyapounov stability, nonlinear observers, Multi-Criteria Decision Analysis, Non dominated, Sorting Genetic Algorithms

I. INTRODUCTION

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 [1], [2]. 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 [3]-[4].

Another approach based on optimal theory is proposed by Ooteghem [5]. Furthermore, the application of fuzzy control is introduced by Lafont and Balmat [6]-[7]. Neural networks control has been applied by Ferreira et al [8].

This work presents a non linear control with an implementation of observer, the control strategy is based on the backstepping theory, so the design of an optimal controller is through the Non Dominated Sorting Algorithms (NSGA) and 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 on nonlinear systems, is introduced in the second section, and 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.

II. BACKGROUND

This section presents some preliminaries related to the system class we are interested in, and its properties..

A. Class of non linear Systems

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

$$\Sigma : \begin{cases} \dot{x} = f_i(x,v) + g(x,v)u, \text{ if } \sigma_i(x) \text{ is verified} \\ \zeta = h(x) \end{cases} \qquad (1)$$
$$x \in \Re^n, \varepsilon \in \Re^p \;,\; \zeta, u \in \Re^q \text{ and } v \in \Re^l$$

x denotes the state vector, ζ is the output vector, u is the direct input vector and v is the exogenous perturbation vector.

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

B. 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:

$$J = \min(J_1, J_2, ..., J_q) \qquad (2)$$
$$\varphi_i(x) \geq 0$$

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.

III. 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 Lyapounov 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 [9].

IV. 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[10]. NPGA method introduced by Horn and Napfliotis[11] and NSGA treated by Deb et Srivinas[12]. 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 simple genetic algorithms flowchart

V. 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.

Table I
Scale for pairwise comparison

Intensity of importance	Definition
1	Equal importance
2	Equal to moderately importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance

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[13]. 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[14].

Any decision problem can be structured into three major phases[15] (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:

$$D = \begin{bmatrix} a_{11} & a_{12} & a_{13} & .... & a_{1n} \\ . & . & . & . & . \\ a_{m1} & . & . & . & a_{mn} \end{bmatrix}$$

The M alternatives represent the solution in pareto set and the aij 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 [16]. 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 (table1), *(ii)* Computation of the weights, *(iii)* Estimation of the consistency ratio, in order to determine if the comparisons are consistent or not.

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[13],[17]. $A_{iSAW} = \sum_{j=1}^{n} w_j a_{ij}$, then the best alternative is defined by:

$$A^* = \max_i (A_{iSAW})$$

VI. APPLICATION FOR A GREENHOUSE SYSTEM

A. Mathematical model

The greenhouse is a nonlinear hybrid system described by six nonlinear differential equations such as [18-19]:

Steam density, indoor temperature and condensation

$$\begin{cases} \dot{x}_1 = \beta_1\left[-x_1 f_1^1(x,v) + \varphi_1^1(x,v) + g_1(x)u_1 + g_2(x)u_2\right] \\ \dot{x}_2 = -x_2 f_2^1(x) + \varphi_2^1(x) + \bar{g}_1(x)u_1 + \bar{g}_2(x)u_2 + u_3 \\ \dot{x}_6 = -x_1 f_6^1(x,v) + \varphi_6^1(x,v) \\ \quad if{:}\sigma_1(x) > 0 \; ou \;\; \sigma_1(x) < 0 \;\; et\, x_6 > 0 \end{cases}$$

$$\begin{cases} \dot{x}_1 = \beta_1\left[-x_1 f_1^2(x,v) + \varphi_1^2(x,v) + g_1(x)u_1 + g_2(x)u_2\right] \\ \dot{x}_2 = -x_2 f_2^2(x) + \varphi_2^2(x) + \bar{g}_1(x)u_1 + \bar{g}_2(x)u_2 + u_3 \\ \dot{x}_6 = 0 \\ \quad if{:}\;\sigma_1(x) < 0 \;\; et\, x_6 = 0 \end{cases}$$

CO2 concentration, profit and biomass

$$\begin{cases} \dot{x}_3 = \beta_3\left[-x_3 f_3^1(x) + \varphi_3^1(x) + g_4(x)u_2 + u_4\right] \\ \dot{x}_4 = \beta_4\left[f_4^1(x) + \alpha_{16}u_3 + \alpha_{17}u_4\right] \\ \dot{x}_5 = \beta_5\left[f_5^1(x)\right] \\ \quad if{:}\;\sigma_2(x) \le 0 \; ou \; \sigma_2(x) > 0 \; et \; d_1 \le \sigma_3(x) \le d_2 \end{cases}$$

$$\begin{cases} \dot{x}_3 = \beta_3\left[-x_3 f_3^2(x) + \varphi_3^2(x) + g_4(x)u_2 + u_4\right] \\ \dot{x}_4 = \beta_4\left[f_4^2(x) + \alpha_{16}u_3 + \alpha_{17}u_4\right] \\ \dot{x}_5 = \beta_5\left[f_5^2(x)\right] \\ \quad if{:}\;\sigma_2(x) > 0 \;\; et \; \sigma_3(x) < d_1 \end{cases}$$

$$\begin{cases} \dot{x}_3 = \beta_3\left[-x_3 f_3^3(x) + \varphi_3^3(x) + g_4(x)u_2 + u_4\right] \\ \dot{x}_4 = \beta_4\left[f_4^3(x) + \alpha_{16}u_3 + \alpha_{17}u_4\right] \\ \dot{x}_5 = \beta_5\left[f_5^3(x)\right] \\ \quad if{:}\;\sigma_2(x) > 0 \;\; et \; \sigma_3(x) > d_2 \end{cases}$$

All functions are defined in appendix.

$x(t) = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5 \quad x_6]$ is the greenhouse state vector with x_1 is the indoor steam density, x_2 is the indoor air temperature, x_3 is the indoor CO2 concentration, x_4 is the accumulated profit), x_5 is the accumulated biomass and x_6 is the condensation on glass.

$u(t) = [u_1 \quad u_2 \quad u_3 \quad u_4]$ represents the control variable vector with u_1 is the water injection command , u_2 is the ventilation command u_3 is the heating command and u_4 id the CO2 injection command.

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

B. Constraints

Three constraints should be considered for this process, they can be defined by:

$\varphi_1(x) = w_2(x) \ge 0$,

$\varphi_2(x) = -x_6 + 25 \ge 0$

$\varphi_3(x) = x_6 \ge 0$

C. Observer design

In this paragraph we consider the design of our observer, we consider only measurable the steam density and indoor temperature.

Assumptions

1. We assume that the reduced system defined by x1, x2 and x3 is observable :
2. $(dh \quad dL_f h \quad dL_f^2 h)$ has a rank 3
3. For a good crop we consider :

$$\begin{cases} S_{\min} \le x_1 \le S_{\max} \\ T_{\min} \le x_2 \le T_{\max} \\ C_{\min} \le x_3 \le C_{\max} \end{cases}$$

This constraints allow to create intervals for all functions f_i^j :

$$F_{1:3,\min}^i \le f_{1:3}^i(x) \le F_{1:3,\max}^i$$

Observer dynamic

Our proposed observer is governed by the fellow dynamic:

$$\begin{cases} \dot{\hat{x}}_1 = \beta_1\left[-\hat{x}_1 F_{10}^i + g_1(x_1,x_2)u_1 + g_2(x_1)u_2\right] + \gamma_1 sign(\tilde{x}_1) + \gamma_2 sign(\tilde{x}_2) \\ \dot{\hat{x}}_2 = -\hat{x}_2 F_{20}^i + \bar{g}_1(x_1,x_2)u_1 + \bar{g}_2(x_1)u_2 + u_3 + \gamma_3 sign(\tilde{x}_1) + \gamma_4 sign(\tilde{x}_2) \\ \dot{\hat{x}}_3 = \beta_3\left[-\hat{x}_3 F_{30}^i + \hat{g}_4(\hat{x}_3)u_2 + u_4\right] + \gamma_5 sign(\tilde{x}_1) + \gamma_6 sign(\tilde{x}_2) \\ \tilde{x}_i = x_i - \hat{x}_i \end{cases}$$

So, the error dynamic is:

$$\begin{cases} \dot{\tilde{x}}_1 = -\beta_1 \tilde{x}_1 F_{10}^i + \eta_1 - \gamma_1 sign(\tilde{x}_1) - \gamma_2 sign(\tilde{x}_2) \\ \dot{\tilde{x}}_2 = -\tilde{x}_2 F_{20}^i + \eta_2 - \gamma_3 sign(\tilde{x}_1) - \gamma_4 sign(\tilde{x}_2) \\ \dot{\tilde{x}}_3 = -\beta_3 \tilde{x}_3 F_{30}^i + \eta_3 - \gamma_5 sign(\tilde{x}_1) - \gamma_6 sign(\tilde{x}_2) \end{cases}$$

With:

$$\begin{cases} \eta_1 = \beta_1\left[x_1(f_1^i - F_{10}^i) + \varphi_1^i(x_1,x_3)\right] \\ \eta_2 = x_2(f_2^i - F_{20}^i) + \varphi_2^i(x_1,x_2) \\ \eta_3 = \beta_3\left[x_3(f_3^i - F_{30}^i) + \varphi_3^i(x_1,x_2) + \tilde{g}_4(\hat{x}_3)u_2\right] \end{cases}$$

Gains identification

Theorem1:

For the observer described above, the gains γ_i allowed the convergence of errors to zero is given by:

$$\gamma_1 sign(\tilde{x}_1) - \gamma_2 sign(\tilde{x}_2) > \|\eta_1\|_\infty$$
$$\gamma_3 sign(\tilde{x}_1) - \gamma_4 sign(\tilde{x}_2) > \|\eta_2\|_\infty$$
$$\gamma_5 sign(\tilde{x}_1) - \gamma_6 sign(\tilde{x}_2) > \|\eta_3\|_\infty$$

Proof

Let the Lyapunov function: $V = 0.5\sum_{i=1}^{3} \tilde{x}_i^2$

$$\Rightarrow \dot{V} = \sum_{i=1}^{3} \tilde{x}_1 \dot{\tilde{x}}_1 = \tilde{x}_1(-\beta_1 \tilde{x}_1 F_{10}^i + \eta_1 - \gamma_1 sign(\tilde{x}_1) - \gamma_2 sign(\tilde{x}_2))$$
$$+ \tilde{x}_2(-\tilde{x}_2 F_{20}^i \eta_2 - \gamma_3 sign(\tilde{x}_1) - \gamma_4 sign(\tilde{x}_2))$$
$$+ \tilde{x}_3(-\beta_3 \tilde{x}_1 F_{30}^i + \eta_3 - \gamma_5 sign(\tilde{x}_1) - \gamma_6 sign(\tilde{x}_2))$$
$$\Rightarrow \dot{V} = -\beta_1 \tilde{x}_1^2 F_{10}^i + \tilde{x}_1(\eta_1 - \gamma_1 sign(\tilde{x}_1) - \gamma_2 sign(\tilde{x}_2))$$
$$- \tilde{x}_2^2 F_{20}^i + \tilde{x}_2(\eta_2 - \gamma_3 sign(\tilde{x}_1) - \gamma_4 sign(\tilde{x}_2))$$
$$- \beta_3 \tilde{x}_3^2 F_{30}^i + \tilde{x}_3(\eta_3 - \gamma_5 sign(\tilde{x}_1) - \gamma_6 sign(\tilde{x}_2)) \le 0$$

To get the negativity we should have:

$$\gamma_1 sign(\tilde{x}_1) - \gamma_2 sign(\tilde{x}_2) > \|\eta_1\|_\infty$$
$$\gamma_3 sign(\tilde{x}_1) - \gamma_4 sign(\tilde{x}_2) > \|\eta_2\|_\infty$$
$$\gamma_5 sign(\tilde{x}_1) - \gamma_6 sign(\tilde{x}_2) > \|\eta_3\|_\infty$$

D. Controller design

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

$$relative\ humidity : RH_d = 75\%$$
$$x_{1d} = RH_d * \frac{e^{-\psi_1(x_{2d})}}{x_{atempd} * RWS}$$
$$x_{2d} = 20°$$
$$x_{3d} = 800$$
$$x_{4d} = 50.v_{pr}$$

***Theorem 2* [20]**: We consider the system (1) with the set point defined above and let:

$$\begin{cases} z_1 = x_1 - x_{1d} \\ z_2 = x_2 - x_{2d} \\ z_3 = x_3 - x_{3d} \\ z_4 = x_4 - x_{4d} \end{cases}$$

To be the errors between the actual states and the desired values, then the control laws stabilize the system (1) is given by:

$$u = A^{-1}B \qquad (4)$$

Where A and B are defined in [20]

Proof: for proof and stability analysis see [20]

E. Identification of gain matrix K and gains observer

To identify the gain matrix and gain observer, 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 $i = 1,2,3,4$.

By using NSGA the minimization problem should be transformed to a maximization problem; In this order the set of criteria is :

$$J = \max imize\left(\frac{1}{\sum_{t_0}^{t_1} z_1(t)}, \frac{1}{\sum_{t_0}^{t_1} z_2(t)}, \frac{1}{\sum_{t_0}^{t_1} z_3(t)}, \frac{1}{\sum_{t_0}^{t_1} z_4(t)}\right) \qquad (6)$$

So, the NSGA is used to identify 10 parameters, it is introduced with:

popsize=50, maxgen =50, Pcros=0.85, Pmut=0.01, Lchrom=200, σ_{share}=10, $k_{1,23,,4} \in [0\ 10]$, $\eta_{1:6} \in [0\ \ 1]$.

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:

	x_{atemp}	x_{steam}	x_{CO_2}	x_{profit}
x_{atemp}	1	2	4	9
x_{steam}	1/2	1	3	9
x_{CO_2}	1/4	1/3	1	9
x_{profit}	1/9	1/9	1/9	1

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

VII. Results of Simulation

The real weather data is obtained from the station sited in south of Algeria (Biskra), excepted v_{CO2} and v_{sun} which they can be kept constant at 340 ppm and 600w/m^2 respectively. The Other quantities are:

$$\begin{cases} v_{pr} = 35DA \\ v_{pheat} = 2DA \\ v_{pCO_2} = 4DA \end{cases}$$

The simulation is used through:

- 10 min for sample time
- 1 sec for integration time,
- 5 days for simulation, so we have 432000 iterations

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

$K = [9.28 \quad 9.74 \quad 9.98 \quad 1.10]^T$

$\eta = [0.51 \quad 0.11 \quad 0.22 \quad 0.36 \quad 0.82 \quad 0.89]T$

After training, pareto front contains 45 individuals, which can be explained by the convergence of algorithm to the optimal solutions.

For weather data, showed by figure (1), we have take samples for 30 days; however, to clarify the graph, the training is treated for 5 days.

Figure (2) shows the evolution of different greenhouse quantities, for the temperature, a good tracking is reached, however, for CO_2 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 with static tracking. For the relative humidity, it is obvious that the objective is realized, the indoor steam density is deduced from the relative humidity.

Also, we see the profit is reached; it represents the gain of crop minus the price of both heating and CO_2 injection. The biomass is the dry weight of the crop.

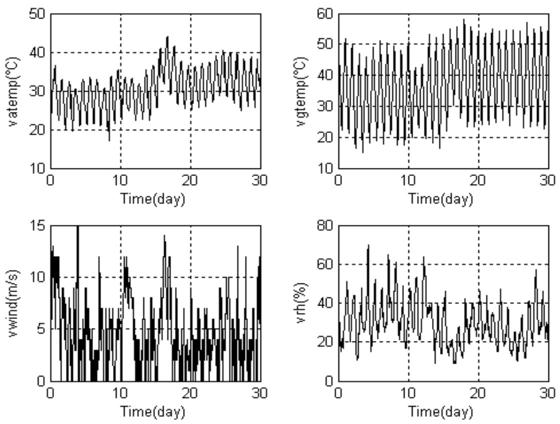

Figure 1: Real weather data for 30 days

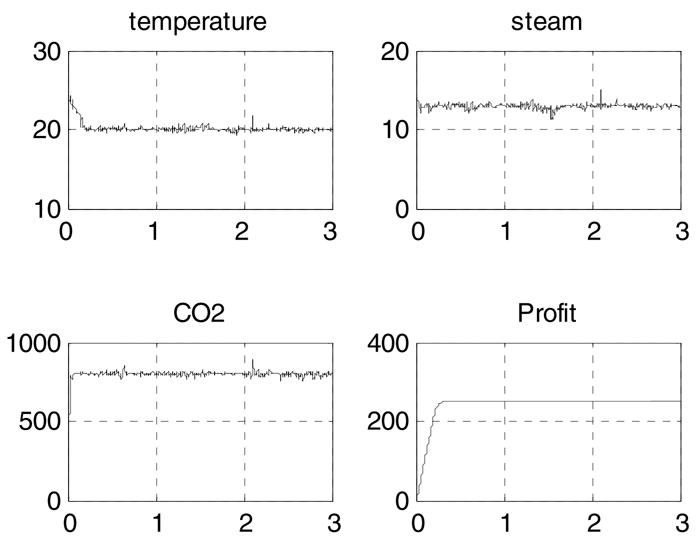

Figure 2: Greenhouse climate for 3 days

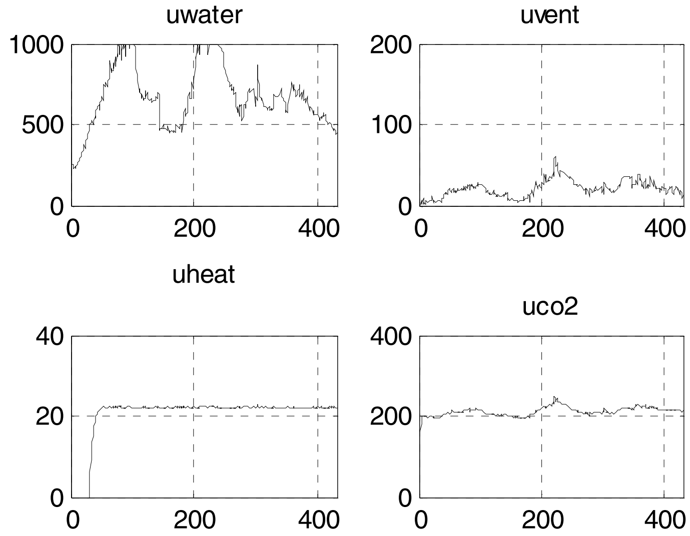

Figure 3: control signals for 3 days (sample time 10min)

VIII. CONCLUSION

In this paper a greenhouse system control is considered,. 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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APPENDIX

$$
\begin{cases}
f_2(x_1) = -w_8(x_1)(\alpha_4\alpha_7\lambda_2 + \alpha_4\alpha_7\lambda_3 x_1 + \alpha_8 + \alpha_9) \\
\varphi_2^1(x_2) = w_8(x_1)(Hsun - \alpha_4\alpha_7\lambda_1(x_1 - v_{atemp}) + \alpha_4\alpha_7\lambda_2 v_{steam} + \alpha_4\alpha_7 v_{atemp} v_{steam} + \alpha_8 v_{gtemp+} \\
\qquad + \alpha_9 v_{atemp} - \alpha_{10}\alpha_6(w_3(x_2) + w_4(x_2))) \\
\varphi_2^2(x_2) = w_8(x_1)(Hsun - \alpha_4\alpha_7\lambda_1(x_1 - v_{atemp}) + \alpha_4\alpha_7\lambda_2 v_{steam} + \alpha_4\alpha_7 v_{atemp} v_{steam} + \alpha_8 v_{gtemp+} \\
\qquad + \alpha_9 v_{atemp} \\
w_5(x_2) = x_{2A} - v_{gtempA} = x_2 - v_{gtemp} \\
w_6(x_2) = x_{2A} - v_{atempA} = x_2 - v_{atemp} \\
w_7(x_2) = GH(\lambda_2 + \lambda_3 x_2) \\
w_8(x_1) = (\alpha_{11} + \alpha_{12} x_1)^{-1} \\
\overline{g}_1(x_1, x_2) = -w_7(x_2) w_8(x_1) g_1(x_1, x_2) \\
\overline{g}_2(x_1) = w_8(x_1)(w_7(x_2) g_2(x_1) - \alpha_7 g_3(x_1, x_2)) \\
g_3(x_1, x_2) = \lambda_1(x_1 - v_{atemp}) + \lambda_2(x_2 - v_{steam}) + \lambda_3(x_1 x_2 - v_{atemp} v_{steam})
\end{cases}
$$

$$
\begin{cases}
f_3^1(x_1, x_2, x_3) = \alpha_{13}(\alpha_{14} w_9(x_2, x_3) + w_{10}(x_2)) - \alpha_4 \alpha_{15} g_4(x_3) \\
f_3^2(x_1, x_2, x_3) = \alpha_{13}(\alpha_{14} w_9(x_2, x_3) + w_{10}(x_2)) w_{11}(x_1, x_2) - \alpha_4 \alpha_{15} g_4(x_3) \\
f_3^3(x_1, x_2, x_3) = \alpha_{13}(\alpha_{14} w_9(x_2, x_3) + w_{10}(x_2)) w_{12}(x_1, x_2) - \alpha_4 \alpha_{15} g_4(x_3) \\
w_9(x_2, x_3) = (1 - e^{-c_3 x_3})(x_2 + c_4 x_2^2) \\
w_{10}(x_2) = -c_5(x_2 + c_6 x_2^2) \\
w_{11}(x_2) = e^{-c_7(d_1 - \sigma_3(x))^2} \\
w_{12}(x_2) = e^{-c_8(d_2 - \sigma_3(x))^2} \\
\sigma_2(x) = \alpha_{14} w_9(x_2, x_3) + w_{10}(x_2) \\
\sigma_3(x) = \dfrac{e^{\psi_1(x_1)} - x_1 x_{2A} RWS}{100} \\
g_4(x_3) = -\alpha_{14}(x_3 - v_{CO2})
\end{cases}
$$

$$
\begin{cases}
f_4^1(x_1, x_2, x_3) = f_3^1(x_1, x_2, x_3) + \alpha_4 \alpha_{15} g_4(x_3) \\
f_4^2(x_1, x_2, x_3) = f_3^2(x_1, x_2, x_3) + \alpha_4 \alpha_{15} g_4(x_3) \\
f_4^3(x_1, x_2, x_3) = f_3^3(x_1, x_2, x_3) + \alpha_4 \alpha_{15} g_4(x_3)
\end{cases}
$$

$$
\begin{cases}
f_5^1(x_1, x_2, x_3) = f_4^1(x_1, x_2, x_3) \\
f_5^2(x_1, x_2, x_3) = f_4^2(x_1, x_2, x_3) \\
f_5^3(x_1, x_2, x_3) = f_4^3(x_1, x_2, x_3)
\end{cases}
$$