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Pareto optimality based multi-objective genetic algorithm: Application for livestock building system using an independent PID controller

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Abstract

The aim of this research is to stabilize the indoor relative humidity and temperature for the poultry house system. The control of these parameters appears as a big challenge due to the mutual interaction existing between the variables affecting the climate livestock building. To achieve this purpose, a developed independent PID controller based on Pareto optimality is proposed in conjunction with a multi-criterion genetic algorithm (MOGA). The broiler house model is decomposed into two independent single input single output (SISO) model using a static output feedback technique (SOF). Then, a multi-criterion genetic algorithm based on Pareto optimality is used to separately design the optimal parameters of the PID controller. The effectiveness of the developed controller is tested very successfully trough numerical simulations and comparison with the Ant Colony Optimization (ACO) and Ziegler Nichols (ZN) method.

Keywords: Pareto front, Independent controller, Climate management, Livestock building

1. Introduction

At present, the climate management of the livestock building stays a perplexing task in light of the nonlinear behavior of psychrometric mechanisms required on both psychological and physiological components. One of the benefits of the livestock building system is the ability to control all aspects of the growing animals. Broiler house system mirrors the development direction of modern control. With the persistent improvement of facilities for agriculture, the requirements of the poultry house control are likewise expanding. The poultry house controlling system can monitor many environmental factors such as relative humidity, temperature, and noxious gas concentration (CO_2, NH_3). Therefore, the adjustment of these parameters is a multi-tasking due to the strong-coupled variables characterized the system.

In fact, high or low humidity may cause hinder development, increase the potential for spreading noxious gases, or advance the dropping of weight. Also, when the temperature is high, this will affect the heat stress [1, 2], high dust levels and respiratory disorders of the chicken [3]. On the other hand, high humidity will increase the potential for spreading diseases. Thusly, a hygrometry and temperature controllers ought to be utilized for maintaining a strategic distance from the beforehand harmful impacts.

In the last decades, numerous researches on domesticated animals building concerning climate management have been discussed in the literature such as predictive control in a naturally ventilated building [4], adaptive control for housed animals [5], fuzzy-PID controller proposed for poultry house [6], modern supervisory control [7]. Therefore, all these control methods have demonstrated their similarity to be applied to an application for a livestock building. Nonetheless, the greater part of these strategies are clearly confusing to be well prepared in the instrumentation of the poultry house system.

Recently, a PID/multi-loop controller has been proposed with the integration of the Ant Colony Optimization (ACO) algorithm [8] and a State-PID feedback controller designed for winter climate has been reported in [9]. These strategies have been tested favorably attributable to the great performance as far as stabilizing the poultry house system, particularly with the genetic algorithm. However, a restriction exists in the significant conflicting nature of the objectives' performances indices, which confuses a simultaneous improvement.

For this reason, earlier works have been extended by utilizing Pareto optimality [10] based on Multi-Objective Genetic Algorithms (MOGA). Subsequently, the aim of this study consists to design an optimal strategy of control to ensure nominal stability and transient performance of the poultry house model.

In this paper, the control design is conducted in the first by decoupling the multivariable state-space model based on the static output feedback (SOF) technique due to its advantage [11], [12] and simplicity to be integrated into a study depends on the control design. Then, the MOGA method was applied to select the optimal values of the PID parameters of each designed PID controller. The multi-objective minimization solution is done based on the adoption of the Pareto concept, since the intention behind this study is to act on the criteria of overshoot, settling time and rise time that are commonly conflicting. The analysis of the Pareto optimality has been well used to highlight the tradeoffs between the dynamic performance indices. Accordingly, the current contributions of this work are as follows:

(a) Concentrate on the control of the simultaneous hygro-thermal parameters control problem for the poultry house

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Table 1 Parameters definitions of poultry house system

Symbol	Parameters definitions
ρ_{air}	Air density (kg/m^3)
C_p	Specific heat of air (J/kg.K)
N_c, M_i	Number and weight of the chickens
ϑ	Velocity of the wind (m/s)
r	Heat of vaporization of the water (0,68Wh/g)
K_g	Global heat transfer coefficient of the poultry house system (W/°C)
$\overline{R_{coat}}$	Thermal resistance of the hair-coat layer of the chickens (s.cm^{-1})

model by combining the genetic algorithms (GA) and output feedback concept.

(b) Reduce the oscillations resulting from the variation of the set-point parameters by the PID controller optimized by the MOGA.

(c) Discuss the efficiency of the proposal controller with a comparison study with the ZN and ACO tuning approach.

The remainder of the paper is structured as follows: the second section is dedicated to presenting the mathematical model and preliminaries. Section 3 describes the genetic algorithm optimization and Pareto optimality. The fourth section presents the results. Finally, some discussions are given to show the performance of the proposed control strategy.

2. Model formulation and preliminaries

2.1 Mathematical model

In order to derive the hygro-thermal regime for poultry house based on control theory, this model is given by the nonlinear dynamic system:

$$\dot{x}_1 = \frac{u_1}{a} - \frac{r}{a}u_2 + R_{cb}(T_b - x_1) - \left(\frac{K_g}{a} + \frac{u_3}{V_b}\right)(x_1 - T_{ext})$$
$$\dot{x}_2 = \frac{u_2}{b} + R_{ev}(0.26x_1^2 - 6.46x_1 + 81.6) - \frac{u_3}{V_e}(x_2 - H_{ext}) \quad (1)$$

where $\dot{x_1}$ is the state of the internal temperature, $\dot{x_2}$ is the state of the internal relative humidity, T_b is the deep temperature body, V_b is the volume air inside the livestock building, Ve is the effective volume for humidity. u_1 is the controller related to the electric heating system. u_2 is the controller input related to the evaporative cooling system (PAD-cooling), it consists to humidify the internal air through the recirculation of the water in the cellulose panels of the PAD-cooling system. u_3 is the actuator related to the ventilation system by commanding the fans at different speed. For a given simplification, the parameters a, b, R_{ev} and R_{cb} are as:

$$a = \rho_{air}V_bC_p \qquad b = \rho_{air}V_e \quad (2)$$

$$R_{ev} = \frac{N_c.0,001}{3600.b}$$
$$R_{cb} = \frac{N_c.0,081.M_i^{0,67}}{a\left(\overline{R_{coat(i)}} + \dfrac{1}{5,4 + \dfrac{0,052 + 1,55.\vartheta_i^{0,48}.M_i^{0,16}}{0,13.M_i^{0,33}}}\right)} \quad (3)$$

Table 1 defines the different meaning of the parameters used in the mathematical model of the poultry house system. For more details, the reader can consult the previous work [13].

It is assumed that this study is conducted during the cold climates where (U_2=0), and where the building is well isolated (not affected by the outside environmental condition).

We can obtain the linearized state space version of (1) as:

$$\begin{bmatrix} \delta\dot{x}_1 \\ \delta\dot{x}_2 \end{bmatrix} = A\begin{bmatrix} \delta x_1 \\ \delta x_2 \end{bmatrix} + B\begin{bmatrix} \delta u_1 \\ \delta u_3 \end{bmatrix}$$
$$\begin{bmatrix} \delta y_1 \\ \delta y_2 \end{bmatrix} = C\begin{bmatrix} \delta x_1 \\ \delta x_2 \end{bmatrix} \quad (4)$$

where:

$$A = \begin{bmatrix} -(R_{cb} + \frac{K_g}{a} + \frac{\overline{u_{3e}}}{V_b}) & 0 \\ R_{ev}(0.52\overline{x_{1e}} - 6.46) & \frac{-\overline{u_{3e}}}{V_e} \end{bmatrix}, B = \begin{bmatrix} \frac{1}{a} & -\frac{\overline{x_{1e}}}{V_b} \\ 0 & -\frac{\overline{x_{2e}}}{V_e} \end{bmatrix},$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

2.2 Static output feedback control

The decoupling control is implemented as a static output feedback, which has this form:

$$u(t) = K_y y(t) + K_r r(t) \quad (5)$$

r(t) is the command signal and y(t) is the output of the plant.

The principle of this technique consists is determining the matrix gains K_r and K_y which leads to modify the dynamics of the system. Let's consider the following structure in Figure 1.

Comparing the terms of (4), (5) and the dimensions of the matrix Kr and Ky, the simplification yields to:

$$\dot{x} = \begin{bmatrix} -(R_{cb} + \frac{K_g}{a} + \frac{\overline{u_{3e}}}{V_b} - \frac{K_{y1}}{a} + \frac{\overline{x_{1e}}}{V_b}K_{y3}) & \frac{K_{y2}}{a}K_{y2} - \frac{\overline{x_{1e}}}{V_b}K_{y4} \\ R_{ev}(0.52\overline{x_{1e}} - 6.46) - \frac{\overline{x_{2e}}}{V_e}K_{y3} & -\frac{\overline{x_{2e}}}{V_e}K_{y4} - \frac{\overline{u_{3e}}}{V_b} \end{bmatrix}x +$$
$$\begin{bmatrix} \frac{K_{r1}}{a} - \frac{\overline{x_{1e}}}{V_b}K_{r3} & \frac{K_{r2}}{a} - \frac{\overline{x_{1e}}}{V_b}K_{r4} \\ -\frac{\overline{x_{2e}}}{V_e}K_{r3} & -\frac{\overline{x_{2e}}}{V_e}K_{r4} \end{bmatrix}r \quad (6)$$

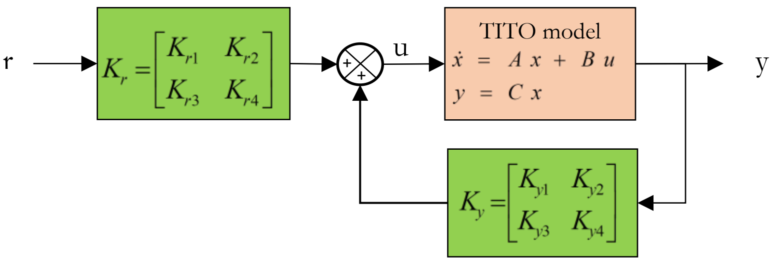

Figure 1 Representation of the Static output feedback technique.

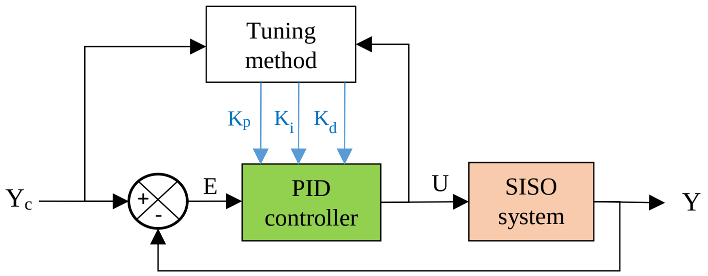

Figure 2 Tuning method of the PID controller.

The matrix of the system (6) is diagonal if:

$$K_{y2} = \frac{a.\overline{x_{1e}}}{V_b} K_{y4} \qquad K_{y3} = \frac{V_e R_{ev}(0.52\overline{x_{1e}} - 6.46)}{\overline{x_{2e}}}$$

$$K_{r2} = \frac{a.\overline{x_{1e}}}{V_b} K_{r4} \qquad K_{r3} = 0 \tag{7}$$

By using the conditions (7), the system (6) can be rewritten in the following:

$$\dot{x} = \begin{bmatrix} -(R_{cb} + \frac{K_g}{a} + \frac{\overline{u_{3e}}}{V_b} - \frac{K_{y1}}{a} + \frac{\overline{x_{1e}}}{V_b} K_{y3}) & 0 \\ 0 & -\frac{\overline{x_{2e}}}{V_e} K_{y4} \end{bmatrix} x + \begin{bmatrix} \frac{K_{r1}}{a} & 0 \\ 0 & -\frac{\overline{x_{2e}}}{V_e} K_{r4} \end{bmatrix} r \tag{8}$$

Furthermore, by applying the Laplace form, the system (8) leads to the two independent subsystems:

$$x_1(s) = \frac{\frac{K_{r1}}{a}}{s + R_{cb} + \frac{K_g}{a} + \frac{\overline{u_{3e}}}{V_b} - \frac{K_{y1}}{a} + \frac{\overline{x_{1e}} V_e R_{ev}(0.52\overline{x_{1e}} - 6.46)}{\overline{x_{2e}} V_b}} r_1(s)$$

$$x_2(s) = \frac{-\overline{x_{2e}} K_{r4}}{sV_e + \overline{x_{2e}} K_{y4} + \overline{U_{2e}}} r_2(s) \tag{9}$$

The generated system obtained are for the first order, its means that the constant time of the systems can be expressed as:

$$\tau_1 = \frac{T_{s1}}{3} \qquad \tau_2 = \frac{T_{s2}}{3} \tag{10}$$

with: T_{s1}, T_{s2} define the settling time related for the first and second systems respectively.

3. MOGA-PID based Pareto optimality

3.1 PID controller

The Proportional-Integral-Derivative (PID) controller is one of the most utilized regulatory controllers in a widespread application covering about 95% in the process industry. This preponderance is due to its straightforwardness and efficiency (Figure 2).

Where E is the error of system, U is the command signal, Y is the output of the plant, Y_c is the desired set-point parameter, K_p, K_i and K_d are the proportional, the integral and the derivative gains respectively.

The control law of the PID controller has the form:

$$\frac{U(s)}{E(s)} = \frac{K_p s + K_i + K_d s^2}{s} \tag{11}$$

In the ensuing section, we will focus on to adjust the parameters [K_p, K_i, K_d] by using the MOGA method.

3.2 Multi-Objective genetic algorithm optimization

GA are well-appropriate to solve multi-objective optimization problems, and it was considered as the most popular heuristic approach to multi-objective design [14]. Therefore, It has been reported that 70% of all meta-heuristics technique were based on evolutionary approach [15]. Many researches have been published on evolutionary algorithm that used the GA such as: MOGA [16], Weight Based Genetic Algorithm (WBGA) [17], Niched Pareto Genetic Algorithm (NPGA) [18], Non-dominated Sorting Genetic Algorithm (NSGA) [19] and others optimization methods detailed in [20, 21]. Generally, all these algorithms optimization have proven their performance via different test simulations and comparative studies. However, there are some

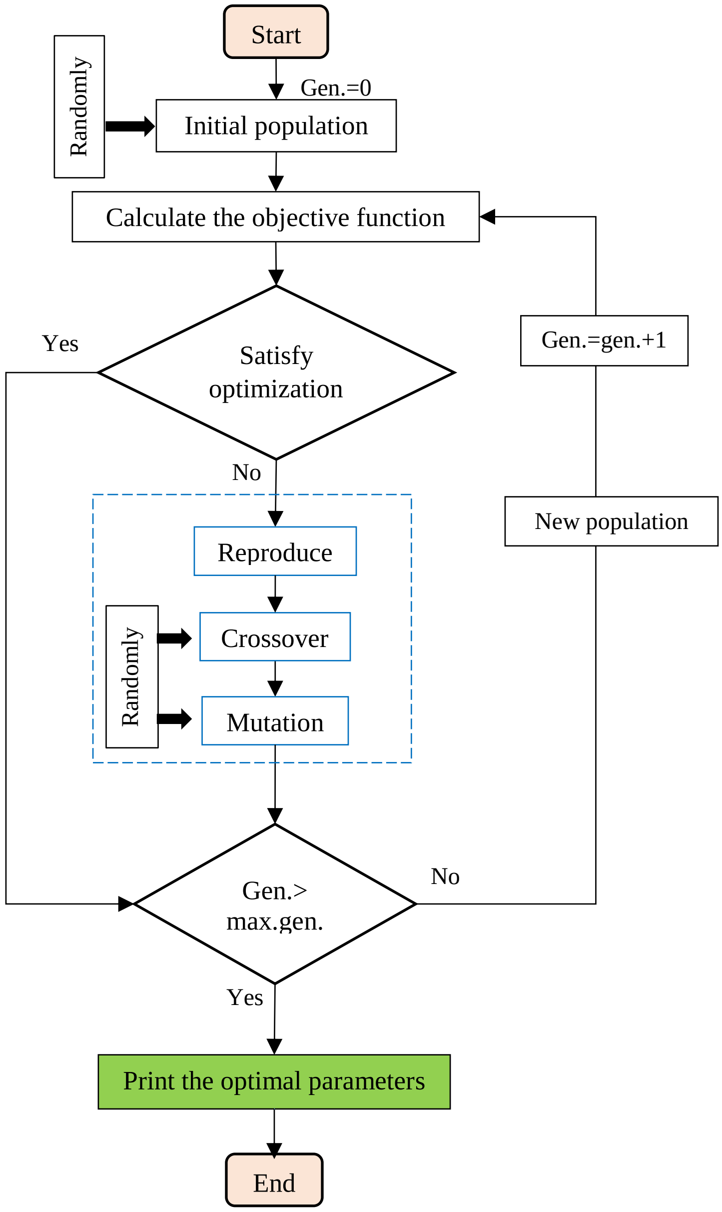

Figure 3 Functional scheme of the genetic algorithm.

required computational effort to be defined with several options conditions like: boundary settings and estimation parameters. Although the MOGA still presents the most efficient and promising optimization technique due to its flexibility to be applied in a variety fields of engineering applications. The Figure 3 above outlines the functional steps of the Genetic algorithm (Goldberg et al [22]).

As can see, the main idea of the GA, repose in three parts noted selection, crossover, and mutation. The first step is the selection of the initial population (chromosome), it depends to reconstruct some random solutions (chromosome). The second part is the crossover operator that consists of recombining the fits solutions with a crossover probability P_c. The last step is the mutation, which consists to alter the gene(s) in a chromosome with a mutation probability P_m.

3.3 Pareto optimality based MOGA

The MOGA method presented here was proposed by Fonseca et al [16] and it is based on Pareto dominance which is an idea suggested by Goldberg. The core of this approach is to use the Pareto optimality concept [18] to keep all the criteria intact, avoiding a priori comparison of the values of different criteria. The performance of the control is measured by the integral time multiplied by absolute error (ITAE) represented as:

$$ITAE = \sum_{0}^{T} t\left|e(t)\right| \ ; \ e(t) = Y_c(t) - Y(t) \qquad (12)$$

The main constrained optimization problem presented in the controller design are the maximum rise time (T_r), settling time (T_s) and overshoot (O(%)).

In this work, the problem of multi-objectivity optimization (MO) is considered in the association relations occurred between the generated solutions of the three optimal parameters referenced above. In this situation, it is appropriate to use the Pareto front equivalent to the all non-dominated solutions based on GA, and more particularly the solutions that represent a compromise between the distinctive targets considered.

Figure 4 Commercial poultry house system.

Table 2 Parameters used in the mathematical model

Parameters	*Values*	*Parameters*	*Values*
ρ_{air}	1.2kg/m^3	T_b	41°C
C_p	1006J/kg.K	N_c	24000(birds)
V_b	3033m^3	V_e	3033m^3
M	1.015kg	K_g	3127W/°C
$\overline{R_{coat}}$	0.3 m^2.K/W	ϑ	0.2m/s

Along these lines, picking out one solution over another is not really legitimized since no arrangement is orderly more awful or better than the others in all the destinations.

To overcome the conflicting targets, Pareto optimality is used to convert the MO problem described above into a single weighted objective. Evidently the concept of the optimality has proven its advantages through several researches such as [23] and [24].

For the most part, it is conceivable to reduce the multi-criterion problem to another mono-criterion by associating targets functions into one by the utilization of weights [25], as pursues:

$$J(\vec{k})=\sum_i \gamma_i f_i(\vec{k}) \qquad \sum_i \gamma_i = 1 \tag{13}$$

Where γ_i is the weight of the objective functions f_i and J is the sum objective function.

The set of all Pareto optimal solutions is called Pareto optimal set and denoted by $P=\{\vec{k}_{p1},\vec{k}_{p2},...\vec{k}_{pn}\}$. Given P for the multi-objective optimization problem defined by the objective function $f(\vec{k})$, the Pareto front is defined by:

$$P_f=\begin{Bmatrix} f_1(\vec{k}_{p1}) & f_2(\vec{k}_{p1}) & \cdots & f_j(\vec{k}_{p1}) \\ f_1(\vec{k}_{p2}) & f_2(\vec{k}_{p2}) & \cdots & f_j(\vec{k}_{p2}) \\ \cdots & \cdots & \cdots & \cdots \\ f_1(\vec{k}_{p_n}) & f_2(\vec{k}_{p_n}) & \cdots & f_j(\vec{k}_{p_n}) \end{Bmatrix} \tag{14}$$

The main objective optimization described here is to search the best solution that combine the individual objectives values.

4. Simulation results

In this section, the MOGA-PID controller is applied to test the performance of the closed-loop step response. The Pareto front is represented too. The optimal solutions will be compared with those given by the application of the Ant Colony optimization (ACO) method and Ziegler-Nichols (ZN) approach. It has been chosen to utilize the ZN method due to its effectiveness and effortlessness [26]. Moreover, the ACO has been utilized for its equivalence to the GA optimization as it a meta-heuristic approach that select the entire acceptable space to find through the optimal parameters.

For the poultry house system modeled by (1) and (4), it is considered to use the experimental measures related to the commercial poultry house system given in Figure 4 and detailed in [13].

The livestock building dimensions were 120 m x 12.4m x 3.85 m. The Table 2 illustrates the different parameters used in the simulation of the proposal controller.

These measured data have been collected during the cold climates and where the chickens are raised of 22 ages.

For the static output feedback (SOF) technique, we consider $T_{s1}\le 10s, T_{s2}\le 10s$ and the static gain should be equal 1 in order to guarantee a stability in the steady state.

Furthermore, by using the terms of (5), (7) and (8), the matrix K_y and K_r are founded as:

$$K_y=\begin{bmatrix} -2,1.10^6 & 2,53.10^5 \\ 3,62.10^{-4} & 5.4 \end{bmatrix},$$

$$K_r=\begin{bmatrix} 1,01.10^6 & -2,36.10^5 \\ 0 & -5.49 \end{bmatrix} \tag{15}$$

By applying the terms (7), the independent two subsystems equivalents for the poultry house system are:

$$x_1(s)=\frac{0.34}{s+0.301}U_1(s)$$

$$x_2(s)=\frac{454.74}{3033s+448.74}U_2(s) \tag{16}$$

Table 3 Parameters settings for the optimization algorithms.

GA		ACO	
Size of population	100	Number of ant	100
Number of generation	50	Number of iteration	50
Crossover probability (Pc)	0.8	Evaporation rate	$\mu = 0.7$
Mutation probability (Pm)	0.03	Constant values	$\alpha = 0.8 \quad \beta = 0.3$

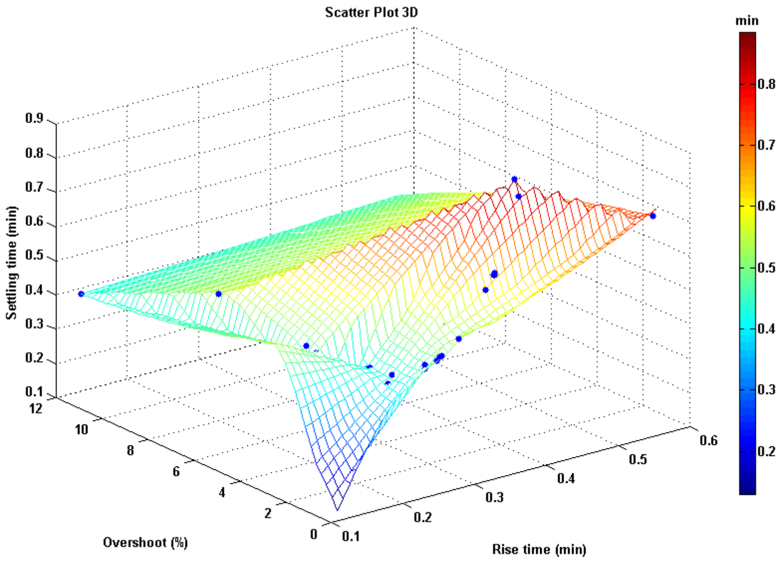

Figure 5 Scatter plot of average Pareto front for temperature control.

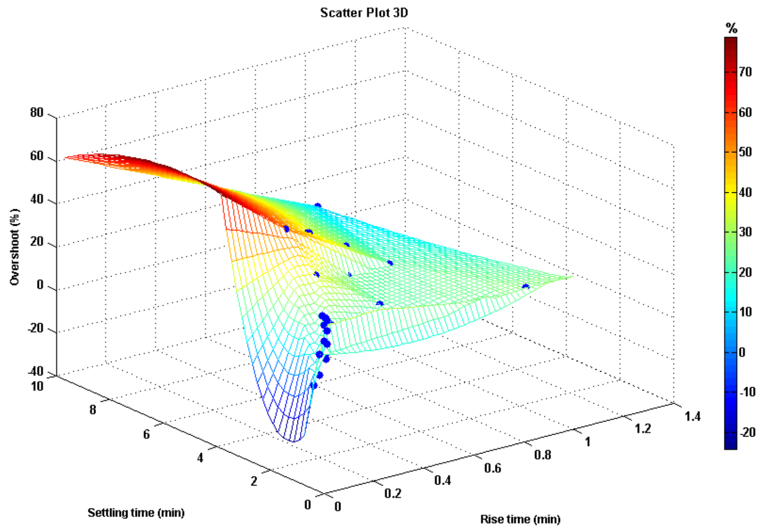

Figure 6 Scatter plot of average Pareto front for relative humidity control.

The optimization algorithms (GA and ACO) have been characterized by the following parameters represented in Table 3.

On the other hand, the parameters [K_p, K_i, K_d] for the ZN method have been formulated and calculated according to the tuning formula given in [27] for the PID controller.

To fill the hole with the problem of multi-objectivity clarified before, the three dimensional scatter plots are used due to its simplicity, robustness and computational low cost. A multivariable interpolation method was adopted [28] with the non-uniform data produced during the simulations test.

Figures 5 and 6 visualize the scatter plots of the Pareto front bounded by the three objective functions: settling time, rise time and overshoot for the performance index ITAE.

Table 4 exposes some of optimal solutions recorded from the scatter plots of Pareto.

It can be clearly seen from Table 4 the conflict between the performance indices calculated using the ITAE criteria. The improvement of an objective cannot be done without deteriorating more or less the other dynamic performances. It is presumed that the issue of improving the parameters of the dynamic response of the poultry house system handled in this manuscript is surely a Pareto-optimality problem. In this case, the minimization of the overshoot rate followed by the settling time and the rise time seems the most crucial objectives that should be optimized in the control of the temperature and relative humidity inside the poultry house. The cost maintenance can be increasing relatively due to the pics (overshoot) of the response of the system [29].

Hence, it can be noted from Figure 5 and 6 that all the solutions disposed of in the Pareto surface (blue marking point) are equivalent to the optimal solutions. The corresponding

Table 4 Optimal solutions supplied by Pareto optimality based GA.

	Rise time	Settling time	Overshoot (%)
Loop 1	0.216	0.414	1.0119
	0.108	0.424	11.1576
Loop 2	0.0869	0.5585	26.9535
	0.0172	0.3281	22.5791

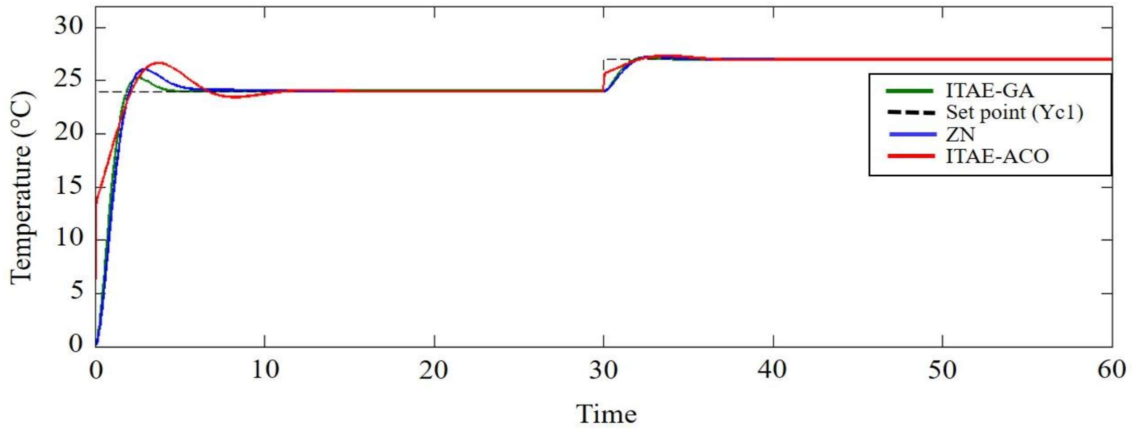

Figure 7 Temperature response for the poultry house system (Loop 1).

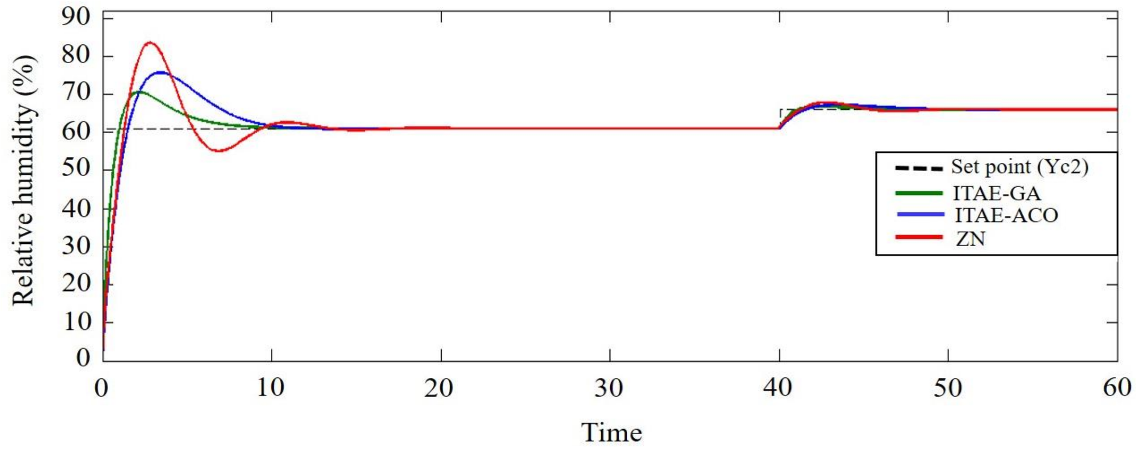

Figure 8 Relative humidity response for the poultry house system (Loop 2).

Table 5 Numerical performances measured of the closed loop step response

Loop	Criterion	*Settling time*	*Rise time*	*Overshoot (%)*
Loop 1	ITAE_MOGA	3.58	1.22	5.24
	ITAE_ACO	4.88	1.35	8.49
	ZN	11.2	2.04	16.1
Loop 2	ITAE_GA	6.9	0.739	15.7
	ITAE_ACO	9.29	1.16	24
	ZN	11.8	1.06	36.9

parameters K_p, K_i, K_d equivalent of the optimal solutions generated by the Pareto front interpolation will be used for a closed-loop response test.

Figures 7 and 8 represent the closed-loop step response tuned by the different controller. The set point of the loop 1 is varied from 24°C to 26°C in t=30. The set point of the loop 2 is varied from 61% to 66% in t=40.

Table 5 illustrates the comparison of the indices performance measures of the different methods.

It can be observed from Figures 7, 8 and Table 5 that the temperature and relative humidity response effectively stabilize toward the set point applied with the different controller. However, the MOGA provides a faster response estimated in (3.58s; 6.9s) a small overshoot (5.24%; 15.7%) for temperature and hygrometry respectively. Moreover, the ZN approach produces poor results particularly for the overshoot (16.1%; 36.9%) for the temperature and relative humidity respectively; these oscillations increase the cost of maintenance and the energy consumption of the actuators. In others hands, the Static output feedback (SOF) technique has improved their capability in the elimination of the interaction between the variables of the system, so when the set point of loop 1 is varied, the response of the loop 2 is not affected and vice-versa. It is very important to emphasize that the model does not perfectly describe the real behavior of the system. Indeed, the parameters uncertainties of the model, the nonlinear phenomena neglected and the assumptions established

Table 6 Numerical performances measured of the closed loop step response

Method	Temperature (°C)			Relative humidity (%)			Fitness function	
	RMSE	RMS	Mean $\|error\|$	RMSE	RMS	Mean $\|error\|$	Ave (μ)	Std. (σ)
MOGA	2.4481	23.8866	0.9528	3.8982	61.1900	5.239	1.08e-03	2.508e-03
ACO	2.6320	23.7773	1.3841	5.7538	61.5988	8.134	2.9437e-02	7.74e-02
ZN	2.0113	23.7524	1.4383	6.0927	61.3506	8.021	——	——

for modeling the system as noted in [13], make that the theoretical parameters achieved during the simulations, will not be the same to use or produce to control the system in real time. Moreover, these results are valid around the working point; also, the parametric variations are often linked to changes in operating conditions of the system. Another important remark is that the SOF controller is designed not only to decouple the TITO model but also to reduce the settling time of the system to a small value less than 10s, then to further optimize the index performance by adding an improved PID controller. Thus, the objective of this study is to act on the criteria of settling time, rise time and overshoot that are commonly conflicting without taking into account the energy consumed by the actuators. Practically, this methodology can be applied in a real poultry house, and we can achieve satisfactory results but not the same as the theoretical results due to the error of the system, noise of measurement, and the aforementioned issues.

For making a quantitative comparison between the controllers, the following variables were calculated and analyzed: root mean square error (RMSE) and root mean square (RMS) values were calculated during the first set points tracking and the mean absolute error in which temperature and hygrometry stay outside the range of ±2% from the set points, respectively. In addition, to compare the accuracy of the optimization algorithms, the MOGA and ACO were repeated 40 times, and both the mean (μ) and standard deviation (σ) are computed. All the statistical results are reported in Table 6.

Results from the quantitative comparisons show that the MOGA controller has the lowest mean absolute error in which temperature and relative humidity are outside $\pm$2% from the set points (0.9528 °C and 5.239 % for temperature and relative humidity, respectively), and the littlest RMSE estimated at 3.8982 % for the relative humidity control. While, the corresponding mean error for the ACO and ZN showed higher values estimated in (1.3841 °C, 1.4383 °C for temperature) and (8.134 %, 8.021 % for relative humidity) and high RMSE values (5.7538 %, 6.0927 % for relative humidity). Likewise, there was no significant difference between the controllers in the RMSE of the control of temperature. In other hands, MOGA controlling system has the closest value (23.8866 °C and 61.19 %) to set point (24°C and 61%) compared to ACO and ZN methods. Moreover, an interesting remark which can be noted from Table 6 is the statistical parameters of the average and standard deviation of the fitness function of the algorithms, where these values optimized using MOGA are far less than that ACO, which proves that the MOGA based Pareto optimality can result in better consistent performance.

It can be concluded from the comparison of the overall performance that the Pareto optimality based GA achieves better stabilization and performance in tracking the desired set point, which illustrates that the proposed method in this manuscript is more efficient. However, it is important to notice that other intersting algorithms such as Grey Wolf Optimizer (GWO) [30] and Ant Lion Optimizer (ALO) [31] exist in the literature. These recent algorithms will be studied and developed deeply in our future works.

5. Conclusions

In this paper, an optimal and flexible tuning method based on the MOGA is created for obtaining good efficiency and performance for the poultry house system. Based on the simulations results, the proposed controller was progressively adaptable and the Pareto optimality was proven their relevance as it offers the best arrangement of the minimum overshoot, littlest settling time and the quick rise time. Additionally, the independent PID controller was capable to maintain the set point value in the desired parameters. Then, the static output feedback control was capable of decoupling the TITO process without deteriorating the dynamics of the system.

Thus, this new proposed approach may give numerous advantages in the climate control of the poultry farming sector. The approach is not limited to the livestock building and could without a doubt be applied with different applications. The result performed in this manuscript allows us in the future work to test and apply other different search algorithms such as GWO and ALO in the regulation of the parameters required for the livestock building.

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7. References

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