A Novel GA-based Fuzzy Extended State Observer for Fault Detection of Nonlinear Systems

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ABSTRACT
This paper presents a novel Genetic Algorithm based Fuzzy Extended State Observer (GA-FESO) to improve the estimation performance and reduce the peaking phenomenon of the classical Linear Extended State Observer (LESO). The proposed GA-FESO consists of a LESO integrated with a fuzzy supervisor designed to automatically adjust the observer bandwidth based on real-time estimation errors. The parameters of the fuzzy supervisor, including membership functions and scaling factors, are optimized by a real-coded genetic algorithm (GA). The integration of fuzzy logic and genetic algorithms into the classical LESO allows the observer to exhibit good transient response and accurate state estimation. As an illustrative application, the GA-FESO is applied to fault detection of the Van Der Pol process, a well-known nonlinear system exhibiting oscillatory behavior. Simulation results demonstrate that the GA-FESO significantly improves state estimation accuracy and fault detection effectiveness, and reduces the peaking phenomenon compared to traditional observer designs.

Keywords
Fuzzy extended state observer, genetic algorithm, fault detection

1. INTRODUCTION
Extended State Observers (ESOs) are an essential tool in modern control systems, especially within the framework of Active Disturbance Rejection Control (ADRC). The concept of ESO was first introduced by Han Jingqing in the 1990s [1]. The primary role of ESOs is to estimate system states and total disturbances encompassing unmodeled dynamics and external disturbances in real-time, allowing for more robust and accurate control, even in systems with unknown dynamics or uncertainties. Over the years, many studies have explored how ESO can enhance the robustness and performance of control systems, making it applicable to various fields, including robotics and industrial applications ([2], [3], [4]). ESO can also be employed in fault detection and identification ([5]). An overview of the development of extended state observers for uncertain systems is presented in [6].

There are two primary types of ESOs: linear and nonlinear. The Linear ESO (LESO) is derived from a linear system model and is simpler to design and implement. While effective in some applications, LESOs may not perform well when faced with significant nonlinearities or large disturbances. The Nonlinear ESO (NESO), on the other hand, extends this approach to nonlinear systems, offering improved performance in systems with significant uncertainties or time-varying disturbances. Many studies focusing on increasing the observer performance have been done recently; these techniques can be divided into three categories related to the observer structure, observer tuning, or observer working conditions [7].

The Fuzzy Extended State Observer (FESO) is a variant of the traditional Extended State Observer (ESO), integrating fuzzy logic into the observer framework to improve its performance and robustness. Fuzzy logic, with its capacity to handle uncertainty and approximate human reasoning, has been introduced to enhance ESO's performance in systems with strong nonlinearities, high levels of uncertainty, or complex time-varying disturbances. The FESO focuses on the observer tuning in an intelligent manner. It can dynamically adjust observer parameters, such as observer gains, in response to varying system conditions based on expert experiences. This adaptability improves the observer's ability to reject disturbances and estimate system states more accurately in nonlinear and uncertain environments. One of the simplest FESO designs is to develop a fuzzy system to adjust the bandwidth of a LESO, in which the estimated error is considered as the fuzzy system input, and the observer bandwidth is regarded as the fuzzy system output ([8]). The fuzzy rules are derived based on the principle that the larger the absolute value of the error is, the lower the bandwidth of the observer should be. An improvement of FESO is to consider the linear combination of estimated error and its derivative as the fuzzy system input ([9], [10]). This approach reduces the number of fuzzy rules and simplifies the calculation. However, it also decreases the flexibility to adjust the observer bandwidth. To increase the flexibility in observer design, the Takagi–Sugeno fuzzy extended state observer (TSFESO) was developed ([11], [12]), in which the nonlinear functions of the ESO are approximated by several local linear models weighted by membership functions.

The Fuzzy Extended State Observer (FESO) has a major drawback: its membership function parameters are typically tuned through a tedious and time-consuming trial-and-error process, often resulting in suboptimal performance. One approach to overcome this limitation is to design the adaptive fuzzy extended state observer ([13]), in which the Takagi–Sugeno fuzzy system was employed to model nonlinear systems, and the observer gains were adjusted using an adaptation law.

Motivated by the aforementioned literature reviews, this work proposes a new approach employing a genetic algorithm (GA) to overcome the drawback of FESO. By evolutionary searching the parameter space, the GA can find optimal membership functions and scaling factors, significantly improving FESO performance and substantially reducing the time required for manual tuning. This combination enhances the accuracy and efficiency of the observer, making it more robust and practical for real-world applications.

The rest of the paper is organized as follows: Section 2 briefly reviews the background of extended state observers. Section 3 details the design of the GA-based Fuzzy Extended State Observer for nonlinear systems. An application of the proposed GA-FESO in fault detection is presented in Section 4. Finally, the conclusion and future work are discussed in Section 5.

2. PRELIMINARY

2.1 Linear Extended State Observer

Consider an n-order nonlinear system with the input $u(t)$ and the output $y(t)$ described by the following differential equation:

$$y^{(n)} = h(y, \dot{y}, ..., y^{(n-1)}) + g(y, \dot{y}, ..., y^{(n-1)}, u, w) + bu \tag{1}$$

where $h(.)$ is the known system function, b is a constant value, and $w(t)$ is the external disturbance. The function $g(.)$ is the unknown system function named the total disturbance. Denote the state variables as $x_1 = y, x_2 = \dot{y}, ..., x_n = y^{(n-1)}$. The state equation of the system (1) is:

$$\begin{cases} \dot{x}_1 = x_2 \\ \vdots \\ \dot{x}_n = h(x_1, x_2, ..., x_n) + g(x_1, x_2, ..., x_n, u, w) + bu \\ y = x_1 \end{cases} \tag{2}$$

Denote $x_{n+1} = g(.)$ as an extended state of the system (1), and $\varphi(t) = \dot{g}(.)$ is a bounded unknown function, then the extended state equation of the system is:

$$\begin{cases} \dot{x}_1 = x_2 \\ \vdots \\ \dot{x}_n = x_{n+1} + h(x_1, x_2, ..., x_n) + bu \\ \dot{x}_{n+1} = \varphi(t) \\ y = x_1 \end{cases} \tag{3}$$

Suppose that only the state x_1 is measurable, the linear extended state observer (LESO) is designed as:

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 - \beta_1 e_1 \\ \vdots \\ \dot{\hat{x}}_n = \hat{x}_{n+1} + h(\hat{x}_1, \hat{x}_2, ..., \hat{x}_n) + bu(t) - \beta_n e_1 \\ \dot{\hat{x}}_{n+1} = -\beta_{n+1} e_1 \\ e_1 = \hat{x}_1 - x_1 \end{cases} \tag{4}$$

where $\hat{x}_1, \hat{x}_2, ..., \hat{x}_{n+1}$ are the estimated states, and $\beta_1, \beta_2, ..., \beta_{n+1}$ are the observer gains. The characteristic equation of the observer is:

$$s^{n+1} + \beta_1 s^n + ... + \beta_{n+1} = 0 \tag{5}$$

Using the bandwidth parameterization approach, the observer gains $\beta_1, \beta_2, ..., \beta_{n+1}$ are chosen such that all the poles of (5) are placed at $-\omega_O$, where ω_O is the observer bandwidth:

$$s^{n+1} + \beta_1 s^n + ... + \beta_{n+1} = (s + \omega_O)^{n+1} \tag{6}$$

The binomial expansion of the right-hand side of (6) yields the observer gains as:

$$\beta_k = \frac{(n+1)!}{(n-k+1)!k!}\omega_o^k \quad (k = 1, ..., n+1) \tag{7}$$

The bandwidth parameterization is one of the most widely used methods among various analytical LESO tuning techniques. The convergence of the above LESO is presented in [9]. It is noted that the observer bandwidth plays a significant role in determining the LESO performance. A proper selection of the observer bandwidth is necessary to achieve a reasonable trade-off between the convergence rate and the peaking value, and obtain an acceptable performance in the inevitable presence of measurement noise. However, because the observer bandwidth is the only tunable parameter, this approach limits the design flexibility of LESO.

2.2 Nonlinear Extended State Observer

LESOs can achieve rapid convergence with high observer gains but suffer from the peaking phenomenon. To overcome this issue, Nonlinear Extended State Observers (NESOs) utilize nonlinear functions, enabling fast convergence without the undesirable peaking effect. By replacing the observer error e_1 with the nonlinear function $fal(.)$, the NESO is designed as:

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 - \beta_1 fal(e_1, a_1, \delta_1) \\ \vdots \\ \dot{\hat{x}}_n = \hat{x}_{n+1} + h(\hat{x}_1, \hat{x}_2, ..., \hat{x}_n) + bu(t) - \beta_n fal(e_1, a_n, \delta_n) \\ \dot{\hat{x}}_{n+1} = -\beta_{n+1} fal(e_1, a_{n+1}, \delta_{n+1}) \\ e_1 = \hat{x}_1 - x_1 \end{cases} \tag{8}$$

The function $fal(.)$ proposed by Han ([1]) as follow:

$$fal(e, a, \delta) = \begin{cases} |e|^a \, sign(e) & if \ |e| > \delta \\ \dfrac{e}{\delta^{1-a}} & if \ |e| \le \delta \end{cases} \tag{9}$$

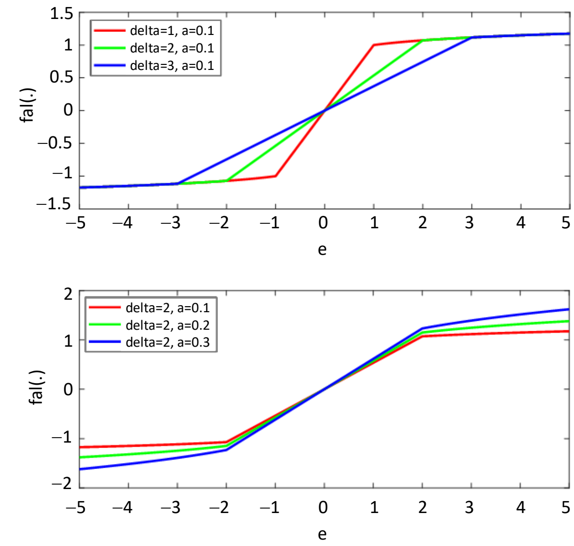

Fig 1: The nonlinear function fal(.)

The nonlinear function $fal(.)$ helps to improve accuracy and reduce the peaking phenomenon because it generates a high gain when the error is smaller than δ, and vice versa. The constants $0 < a < 1$ and $\delta > 0$ are the shaping parameters of the nonlinear function. Figure 1 illustrates the $fal(.)$ function with different value of δ and a. The appropriate selection of the parameters δ and a plays an important role in ensuring the performance of the NESO.

3. GA-BASED FUZZY EXTENDED STATE OBSERVER DESIGN

3.1 Fuzzy Extended State Observer

The block diagram of the proposed GA-FESO is presented in Figure 2. The GA-FESO is based on a LESO integrated with a fuzzy supervisor to adjust its bandwidth corresponding to the estimation error, and the fuzzy supervisor's parameters are optimally tuned by a genetic algorithm.

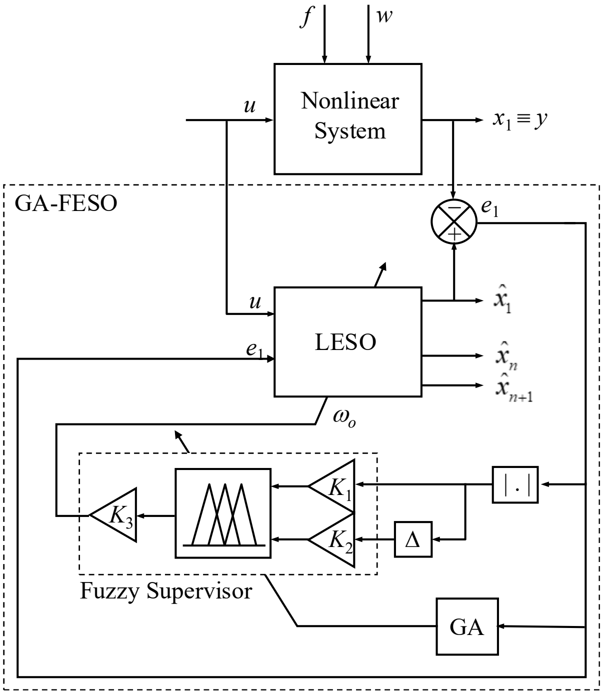

Fig 2: Block diagram of the proposed GA-FESO

The fuzzy supervisor has two inputs: the absolute value of the estimation error $|e_1|$ and the change of the absolute value of the estimation error $\Delta|e_1|$ in 1 sampling cycle, and its output is the observer's bandwidth ω_o. The linguistic values of the input and output variables of the fuzzy supervisor are respectively defined in normalized ranges of [0, 1] or [−1, 1], as presented in Figure 3 and Figure 4. The input $|e_1|$ has 5 linguistic values Very Low (VL), Low (LO), Medium (ME), High (HI), and Very High (VH); the input $\Delta|e_1|$ has 3 linguistic values Negative (NE), Zero (ZE) and Possitive (PO); and the output ω_o has 15 linguistic values W1, W2,..W15. To reduce the calculation load in fuzzy reasoning, piece-wise membership functions and singleton membership functions are employed for the input and output linguistic values, respectively. The parameters $P_1, P_2, \ldots, P_{20}$ of the membership functions qualifying the linguistic values, and the scaling constants K_1, K_2, and K_3 normalizing the inputs and output of the fuzzy supervisor are optimized by a genetic algorithm presented in section 3.2.

The fuzzy supervisor's rules are derived based on knowledge and experience about the relationship between the estimation error, the observer's bandwidth and performance. If the absolute value of the estimation error $|e_1|$ is very low (VL) and the change of the absolute value of the estimation error $\Delta|e_1|$ is negative (NE), the observer' bandwidth should be very high (W15) to maintain the estimation error around zero. If the absolute value of the estimation error is larger (LO, ME, HI…), the observer bandwidth should be lower (W14, W13, W12,…) to prevent the peaking phenomenon. If the absolute value of the estimation error $|e_1|$ is very high (VH) and the change of the absolute value of the estimation error $\Delta|e_1|$ is possitive (PO), the observer' bandwidth should be very low (W1). Based on these basic ideas, the complete fuzzy rules are developed as presented in Table 1.

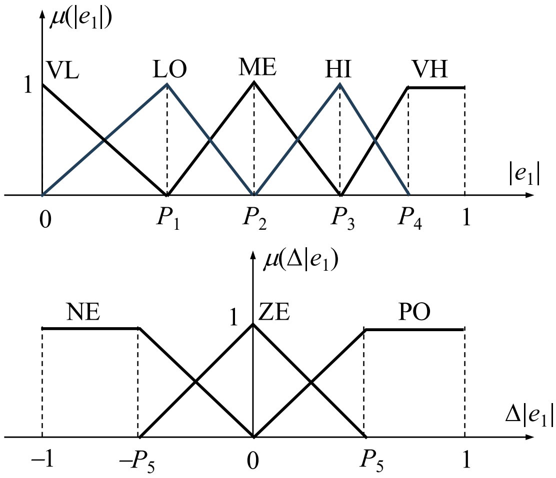

Fig 3: Linguistic values of the fuzzy supervisor's inputs

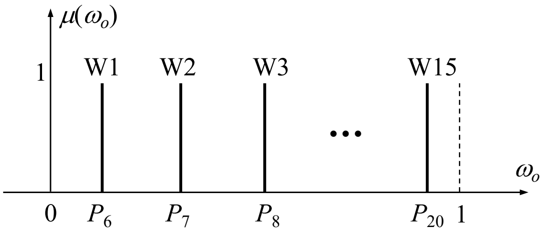

Fig 4: Linguistic values of the fuzzy supervisor's outputs

Table 1. Fuzzy supervisor's rules

ω_o		$\|e_1\|$				
		VL	LO	ME	HI	VH
$\Delta\|e_1\|$	NE	W15	W14	W13	W12	W11
	ZE	W10	W9	W8	W7	W6
	PO	W5	W4	W3	W2	W1

The fuzzy supervisor utilizes the product operation (PROD) to calculate the degree of truth of the fuzzy rule's antecedents and employs the weighted average defuzzification method to calculate the bandwidth of the LESO according to the defuzzification formula:

$$\omega_o = \frac{\sum_{k=1}^{15} \gamma_k \omega_{ok}}{\sum_{k=1}^{15} \gamma_k} \tag{10}$$

where γ_k is the degree of truth of the antecedent, and ω_{ok} is the constant corresponding to the singleton membership function of the conclusion of the k^{th} fuzzy rule (k=1..15).

The performance of the FESO depends on the parameters of the membership functions of the fuzzy supervisor. The trial-and-error process to select these parameters often takes a long time, and the estimation results are not optimal due to the subjective nature of human tuning. To overcome this drawback, the parameters of the fuzzy membership functions are optimally adjusted using a genetic algorithm.

3.2 Genetic algorithm design

The genetic algorithm (GA) is a powerful meta-heuristic optimization technique inspired by the natural biological evolution process [13]. In this research, a genetic algorithm is proposed to optimize the FESO, as illustrated in the general algorithm flowchart in Figure 5.

GA iteratively applies the genetic operators, namely natural selection, crossover, and mutation, to a population of solutions. which together drive the population towards optimal solutions. Natural selection favors the best-performing individuals, crossover combines genetic material from these individuals to create new offspring, and mutation introduces random variations to maintain diversity and explore new possibilities.

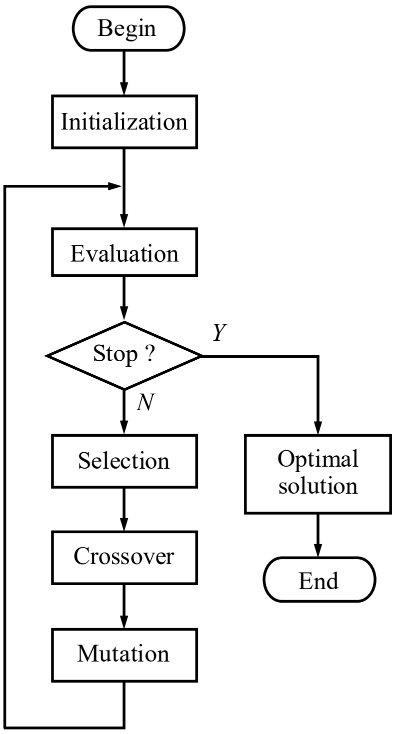

Fig 5: Genetic algorithm

The objective of the genetic algorithm is to optimize the parameters of the membership functions of the input and output variables of the fuzzy supervisor in order to minimize the cost function:

$$J = \sum_{k=1}^{K} e_1^2(k) + \rho \sum_{k=1}^{K} (\Delta | e_1(k) |)^2 \to \min \tag{11}$$

in which ρ is the optional weighting factor, and K is the total number of samples collected to evaluate the cost function. The fitness function of the GA is defined as:

$$fitness = 1/J \tag{12}$$

The real-value encoding method is applied to encode the parameters of the membership functions qualifying the linguistic values of the input and output variables of the fuzzy controller and the input and output scaling constants into genes on the chromosome as presented in Figure 6.

P_1	P_2	P_3	P_4	P_5	P_6	...	P_{20}	K_1	K_2	K_3

Fig 6: Encoding fuzzy supervisor's parameters into chromosomes

To preserve the linguistic meaning of the membership functions, it is necessary to ensure that the parameters satisfy the following conditions during GA optimization:

$$0 < P_1 < P_2 < P_3 < P_4 < 1 \tag{13}$$

This research employs the linear ranking selection method, where individuals (or chromosomes) are ranked from 1 to N in ascending order of fitness calculated by the equations (11) and (12). The selection probability of an individual ranked k^{th} is determined as follows:

$$p_k = \frac{1}{N}\left[\eta + 2(1-\eta)\frac{k-1}{N-1}\right] \tag{14}$$

The BLX-α crossover method [14] is used to generate offspring from two parent individuals selected through linear ranking selection described above. Each gene c_i ($1 \le i \le L$, L is the length of the chromosome) of the offspring will be created from the corresponding genes a_i and b_i of the two parent individuals. At the crossover probability p_c, the gene c_i is randomly assigned a value within the range [$c_{i\min}$, $c_{i\max}$] determined as follows:

$$\begin{cases} c_{i\min} = \min(a_i, b_i) - \alpha |a_i - b_i| \\ c_{i\max} = \min(a_i, b_i) + \alpha |a_i - b_i| \end{cases} \tag{15}$$

Mutation is the process of altering one or more genes of the individuals in the population, creating genetic diversity within the population, which helps the genetic algorithm to find a global optimal solution. In this study, random mutation is employed. At the mutation probability p_m the gene c_i ($1 \le i \le L$) is changed to a random value according to the formula (17):

$$c_i = \underline{c}_i + r(\bar{c}_i - \underline{c}_i) \tag{16}$$

where $0 \le r \le 1$ is a random value, and $[\underline{c}_i, \bar{c}_i]$ is the range of c_i.

Due to the randomness of the genetic algorithm, after crossover and mutation, there is a possibility that the offspring may not satisfy the constraints (13) to preserve the linguistic meaning of the fuzzy sets. In this case, such offspring are rejected, and one of the two parent individuals is retained to continue evolving in the next generation.

After the genetic algorithm finishes, the parameters of the best individual from the final generation will be used to configure the fuzzy supervisor of the FESO.

4. FAULT DETECTION APPLICATION

Consider the Van Der Pol process described by the following differential equation ([9]):

$$\ddot{y} + 2\omega\xi(\mu y^2 - 1)\dot{y} + \omega^2 y = u + \beta(t - T_0) f(y) \tag{17}$$

where ω, ξ, μ are the positive constants, $\beta(t-T_0)$ represents the fault time properties, and $f(y)$ is the fault occurring in the system, T_0 represents the time of fault occurrence. The parameters and control input of the Van Der Pol process are set as $\omega = 0.9$, $\xi = 0.6$, $\mu = 0.95$, and $u = 0$ ([9]).

Assume that the fault occurs in the period from 5 to 10 seconds. Two fault functions, $f(y) = 1$ and $f(y) = \cos(y)$, are used to evaluate the performance of the FESO.

Denote the states of the system as $x_1 = y$ and $x_2 = \dot{y}$. To detect the fault, consider $x_3 = \beta(t-T_0) f(y)$ as the extended state of the system. The extended state space equation of the Van Der Pol process is:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 - 2\omega\xi(\mu x_1^2 - 1)x_2 - \omega^2 x_1 + u \\ \dot{x}_3 = \varphi(t) \\ y = x_1 \end{cases} \tag{18}$$

The FESO is designed as follows:

$$\begin{cases} \dot{\hat{x}}_1 = \hat{x}_2 - \beta_1 e \\ \dot{\hat{x}}_2 = \hat{x}_3 - 2\omega\xi(\mu \hat{x}_1^2 - 1)\hat{x}_2 - \omega^2 \hat{x}_1 + u - \beta_2 e \\ \dot{\hat{x}}_3 = -\beta_3 e \\ e = \hat{x}_1 - x_1 \end{cases} \tag{19}$$

The observer gains β_1, β_2 and β_3 are calculated using the pole placement method as $\beta_1 = 3\omega_o, \beta_2 = 3\omega_o^2, \beta_3 = \omega_o^3$ where the observer bandwidth ω_o is adjusted by the fuzzy supervisor. The fuzzy supervisor is optimized by the GA with the parameters presented in Table 2. To investigate the peaking phenomenon, the initial states of the Van Der Pol are set as $x_1(0) = x_2(0) = 1$, while the intial states of the observer are set as $\hat{x}_1(0) = \hat{x}_2(0) = \hat{x}_3(0) = 0$.

Table 2. Parameters of the genetic algorithm

Parameter	Symbol	Value
Population size	N	20
Weighting constant of the cost function	ρ	0.02
Linear ranking selection parameter	η	0.5
BLX-α crossover parameter	α	0.1
Crossover probability	p_c	0.9
Mutation probability	p_m	0.1

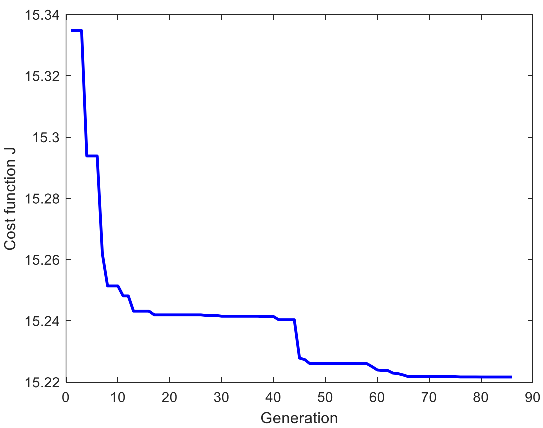

Fig 7: GA optimization result

Figure 7 shows a typical GA optimization result. The parameters of the fuzzy supervisor are optimized during the evolution process, and the cost function is minimized.

Figure 8 presents the input-output characteristic of the fuzzy supervisor optimized by the GA. It can be seen that this characteristic is highly nonlinear and difficult to achieve by manual tuning. Thanks to this nonlinearity, the performance of FESO is better than that of LESO and NESO, as demonstrated below.

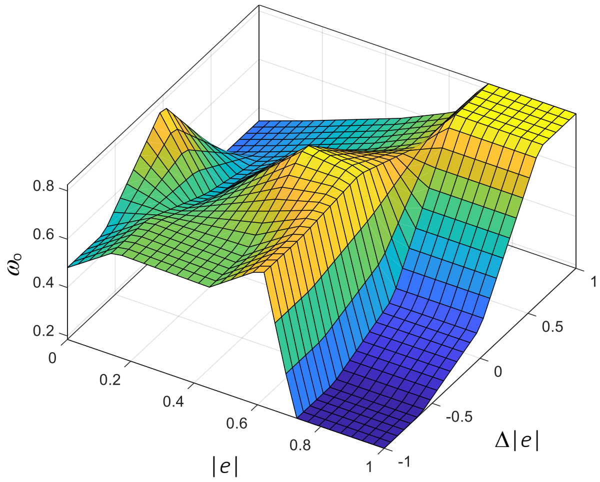

Fig 8: Fuzzy supervisor characteristic surface

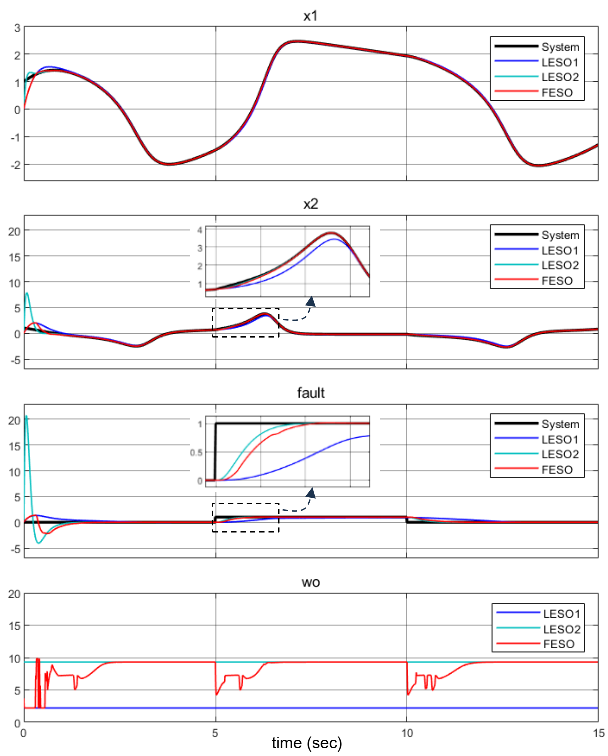

Fig 9: Fault detection result of FESO and LESO (fault $f(y)$= 1)

Figure 9 and Figure 10 compare the responses of the GA-based FESO and the LESO in two scenarios of the fault. Two LESOs are considered, in which LESO1 has a low bandwidth ($\omega_o = 2.2$ rad/sec) and LESO2 has a high bandwidth ($\omega_o = 9.3$ rad/sec). Because of its low bandwidth, LESO1 does not have the peaking phenomenon, but the state estimation is not good, and the fault detection response time is slow. On the other hand, the LESO2 with the high bandwidth responds faster to the fault, but it suffers from very high peaking values. The GA-FESO with varying bandwidth outperforms the LESOs in both peaking phenomenon and fault detection performances.

Figure 11 and Figure 12 evaluate the GA-optimized FESO and the NESO with parameters chosen as $\delta = 0.01$, $a = 0.2$, $\beta_1 = 2$, $\beta_2 = 4$, $\beta_3 = 6$ ([9]). It can be seen that the peaking phenomenon occurring in FESO and NESO is the same, but the state estimation and fault detection accuracy of FESO is better than that of NESO.

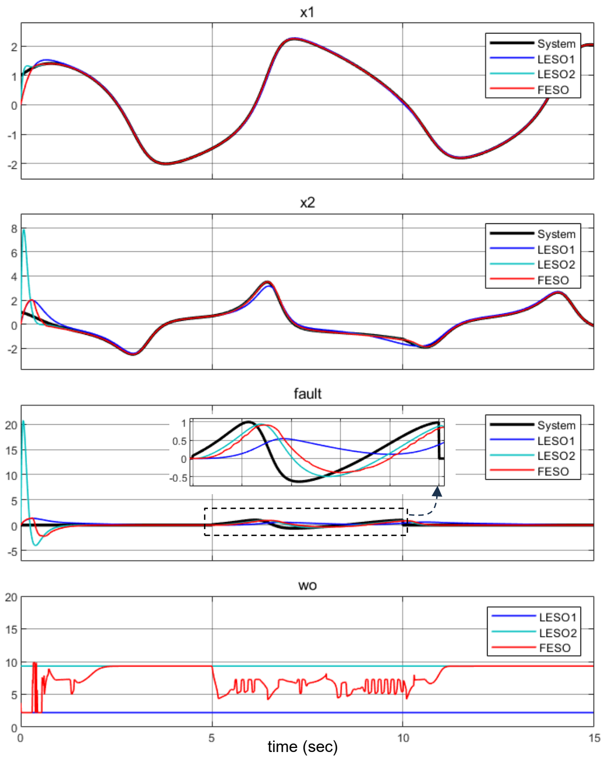

Fig 10: Fault detection result of FESO and LESO (fault $f(y) = \cos(y)$)

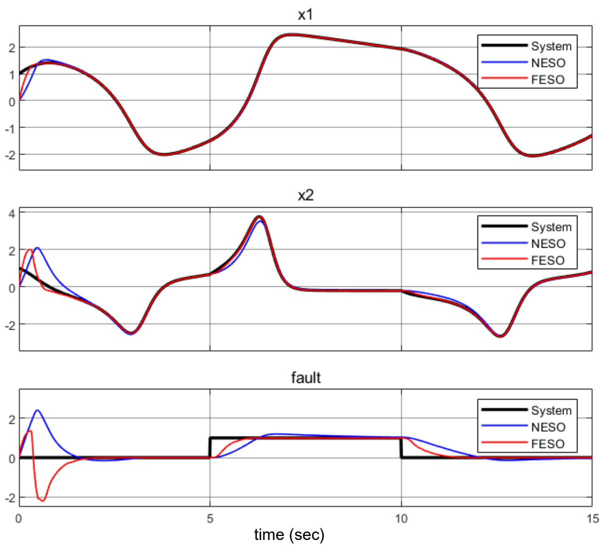

Fig 11: Fault detection result of FESO and NESO (fault $f(y) = 1$)

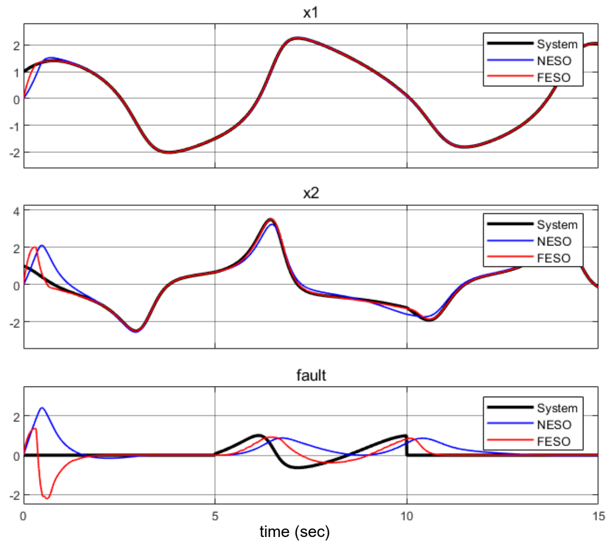

Fig 12: Fault detection result of FESO and NESO (fault $f(y) = \cos(y)$)

5. CONCLUSION

The paper presented a practical and effective approach to improving the performance of extended state observers through the development of a novel GA-FESO. The fuzzy supervisor is designed to dynamically adjust the bandwidth of the LESO according to the estimation error and its rate of change, thereby mitigating the peaking phenomenon often encountered in traditional observers. To optimize the fuzzy supervisor, a real-coded genetic algorithm is employed to fine-tune its membership function's parameters, ensuring optimal estimation results and eliminating the need for manual tuning of the observer bandwidth. The proposed GA-FESO is applied to detect the fault that could happen in a Van Der Pol process. Simulation results demonstrated that it significantly improves state estimation and fault detection quality and reduces the peaking phenomenon compared to conventional LESO. Future research could focus on applying the GA-FESO approach to active disturbance rejection control systems or exploring other evolutionary algorithms to further enhance the performance of FESO.

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