Impelmentation of 2-DOF Controller Using Immune Algorithms

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Abstract – In this paper the structure of 2-DOF controller based on artificial immune network algorithms has been suggested for nonlinear system. Up to present time, a number of structures of the 2-DOF controllers are considered as 2-DOF (2-Degrees Of Freedom) control functions. However, A general view is provided that they are the special cases of either the state feedback or the modification of PID controllers. On the other hand, The immune network system possesses a self organizing and distributed memory, also it has an adaptive function by feed back law to its external environment and allows a PDP (parallel distributed processing) network to complete patterns against the environmental situation, since antibody recognizes specific antigens which are the foreign substances that invade living creatures**. Therefore, it can provide optimal solution to external environment. Simulation results by immune based 2-DOF controller reveal that immune algorithm is an** effective approach to search for 2-DOF controller.

I. INTRODUCTION

In recently years, combined learning-based artificial intelligence (AI) such as neural network, fuzzy control, genetic algorithm, immune network structures have been interested in studying much attention for their robustness and flexibility against a dynamically changing system or complex system, since conventional artificial intelligent systems based on a functional decomposition, leading to a so-called "sense-model-plan-action" cycle have been criticized on many grounds over the last decade [1] – [3].

They are used extensively in industry in such diverse applications as fault prediction, fault diagnosis, supervisory control, energy management, production management, software engineering, and among others [3].

It is a challenge in control and computer communities to explore novel control strategies and philosophies for complex industrial processes. In complex processes in practice, the range of uncertainty may be substantially larger than can be tolerated by crisp algorithms of adaptive and robust control. What are known as " intelligent" control techniques [6] are useful here.

The application of intelligent system technologies in industrial control has been developing into an emerging technology, so-called 'Industrial intelligent control'. This technology is highly multi-disciplinary and rooted in systems control, operations research, artificial intelligence, information and signal processing, computer software and production background [8-9].

Chronologically, fuzzy logic was the first technique of intelligent systems. Neural, neuro-fuzzy and evolutionary system and their derivatives followed later. Each technique is offering new possibilities and making intelligent system even more versatile and applicable in an ever-increasing range of industrial applications.

Over the past decade or so, significant advances have been made in two distinct technological area: fuzzy logic (FL) and neural networks (NNs) [1] – [3]. There has been considerable interest in the past few years in exploring the applications of fuzzy neural network (FNN) systems, which combine the capability of fuzzy reasoning to handle uncertain information and the capability of artificial networks to learn from processes, to deal with nonlinearities and uncertainties of control systems.

On the other hand, biological information processing systems such as human beings have many interesting functions and are expected to provide various feasible ideas to engineering fields, especially intelligent control or robotics [1] – [4]. Biological information in living organisms can be mainly classified into the following four systems: brain nervous, genetic system, endocrine system, and immune system. Among this system, brain nervous and genetic systems have already been applied to engineering fields by modeling as neural network and genetic algorithms [8], they have been widely used in various fields. However, Only a little attention has been paid to application of the other systems, not to mention their important characteristics and model. The purpose of this paper is to propose the use of artificial immune algorithms as implementation of 2-DOF (2-Degrees Of Freedom) control system [6] – [8].

II. IMMUNE ALGORITHMS FOR THE PID CONTROLLER

The immune system is interested in data mining, control system application [6] – [10], intelligent system combined with fuzzy or neural network [5], a multi-agent system. It is characterized with a large number and composed of variety of components distributed throughout the body. Individual actions of vast numbers of cells in immune system, and their interactions with even larger numbers of molecular mediators, determine the course of an infection. This distributed collection of agents protects organisms against a wide variety

of attacks. It is important not only for learning to apply for control engineering, but also for understanding control of distributed systems in general.

The characteristics of Cell action are governed largely by molecular signals. Each cell represents on its surface an enormous number of receptors for a variety of different chemicals. These receptors bind to extracellular molecules, or molecules on the surfaces of other cells. Which subsets of receptors are bound determines whether cells die, divide, move, differentiate, or produce molecules for secretion or expression determines whether a cell is listening for a specific kind of information [8].

Intracellular signaling mechanisms connected to these receptors determine the response to each such signal. In addition, interactions between intracellular signaling pathways cause the cell's response to be a function of combinations of external signals.

Some paper explained how certain kinds of molecular signals can provide feedback to tune the immune system response. In addition to eliminating an invading pathogen, an immune response often causes incidental damage to the host. Recruitment of immune system effectors to an infected area results in inflammation, with negative effects on blood circulation and local tissue integrity. Toxins required to kill certain pathogens may also damage host cells.

Antibody in the immune system should kill dangerous antigens but should not harm the host. They showed how chemical signals indicating when antigens were being killed and when host cells were being damaged could be used to adjust the response so as to minimize both kinds of damage. Here, we expand on this earlier work by using genetic algorithms to explore what forms of feedback information are most useful in the model system.

One of modeling the immune system is to derive a set of differential equations that describe the changes in concentrations of the relevant cell and molecule types over time. These equations describe the average behavior of the system, assuming ideal mixing.

Minimal model includes one kind of antigen P and one kind of immune system effector F, which kills antigens by secreting a toxic chemical T (such as nitric oxide). T damages host cells as well as killing antigens. This is a simplified model of the dual nature of antigen responses. If antigen cause damage at rate α, and the noxious chemical causes damage at rate β, then the total damage done during an immune response is given as the following equation:

$$\Gamma = \int \alpha P + \beta T \qquad (1)$$

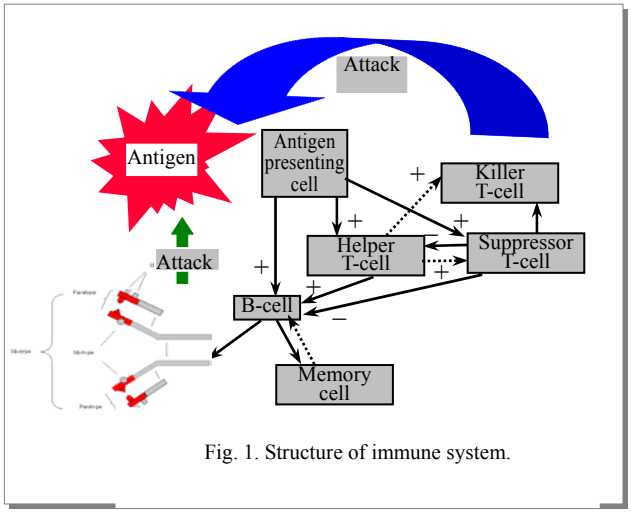

Fig. 1. Structure of immune system.

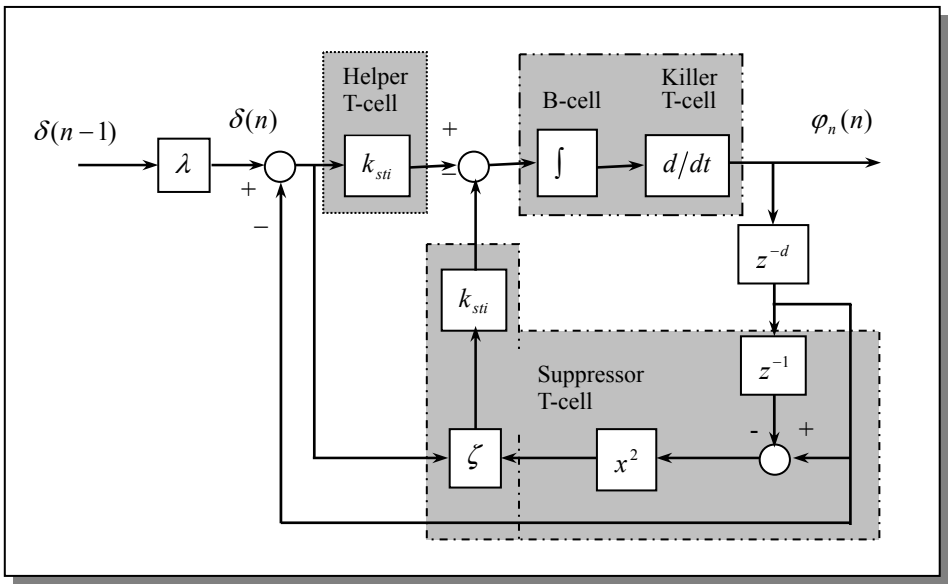

Fig.2. Block diagram for immune based feedback system.

The concentration of effectors grows in proportion to antigen levels (with coefficient η) up to some saturation limit $F_{\max}$ and decays at a fixed rate μ:

$$\frac{dF}{dt} = \eta PF\left(1 - \frac{F}{F_{\max}}\right) - \mu F \qquad (2)$$

T is secreted by effectors at rate ζ and decays at rate λ

$$\frac{dT}{dt} = \zeta F - \lambda T \qquad (3)$$

Antigens reproduce at fixed rate δ. For antigen killing, a "mass action" encounter rate *PF* is assumed and the killing effectiveness of an encounter is taken proportional to *T*, with coefficient σ.

$$\frac{dP}{dt} = \delta P - \sigma PFT \qquad (4)$$

If the secretion rate ζ is too low, the antigen will not be controlled and will do too much damage; if it is too high, the amount of incidental damage by the immune response will be high. An optimal value of ζ is one resulting in the minimum damage to the system. Since this optimal value is dependent on antigen virulence and susceptibility to effectors, adaptive secretion rate will perform well in all situations.

Reference [11] represented that the immune response, and in particular the secretion rate of *T*, should be controlled by feedback indicating whether damages is occurring to the host, and whether effectors are successful in eliminating antigens.

This information could be represented by two chemicals: Φ, created during antigens killing, and Ψ, created during host damage. ξ_Φ and ξ_Ψ are the respective rates of production of these chemicals.

Each chemical also has a fixed decay rate, λ_1 and λ_2:

$$\frac{d\Phi}{dt} = \xi_\Phi(\sigma PFN) - \lambda_1 \Phi \qquad (5)$$

$$\frac{d\Psi}{dt} = \xi_\Psi(\alpha P + \beta T) - \lambda_2 \Psi \qquad (6)$$

Ψ is composed of damage done by both pathogens and the immune response. An estimation concentration of antibody for immune response is given by:

$$\Phi_i(t+1) = \left[\frac{\sum_{j=1}^{N}\{m_{ji}\delta_i(t)\}}{N} - \frac{\sum_{k=1}^{N}\{m_{ik}\delta_i(t)\}}{N} + k_i\right]\delta_i \qquad (7)$$

$$\delta_i(t) = \frac{1}{1+\exp(0.5-\Phi_i(t+1))} \qquad (8)$$

Fig. 3 shows the Eq. (6).

- Antibody concentration: δ_i

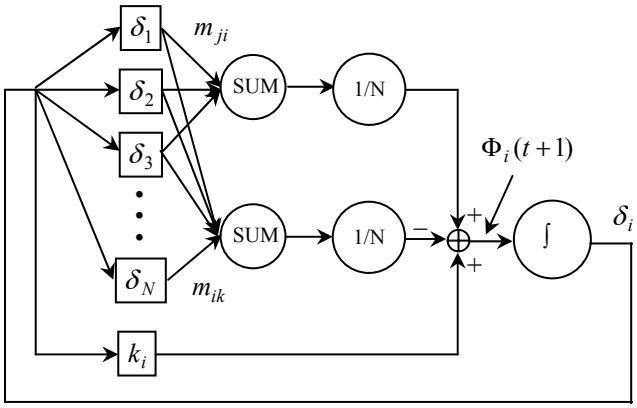

Fig. 3. Block diagram of antibody concentration.

- Stimulii constant : $m_{ji} = \sum_{k}^{L} P_j(k) \oplus Q_i(k)$

- Suppression constant: $m_{ik} = \sum_{k=1}^{L} P_i(k) \oplus Q_k(k)$

- L: bit range in antibody
- $P_j(k)$: k*th* ideotope value in j*th* antibody
- $Q_i(k)$: k*th* bit value of i*th* paratope
- stimulation constant by antigen: $m_i = \sum_{k=1}^{L} R(k) \oplus Q_i(k)$
- $R(k)$: k*th* bit value of epitope in antibody
- $\oplus$: exclusive sum ("1" or "0")

Antibody concentration is computed by the Eq.(8) or the Eq (9):

$$\Delta_i = (1-\eta)\delta_i^{obstacle} + \eta\delta_i^{goal} \qquad (9)$$

Hence, antibody's concentration is calculated by the user based on the control requirement condition of the given plant. The problem at hand is then of a combinatorial nature, with optimization phases. The degree of match between the molecules is termed affinity. The better the match, the higher the affinity, and thus the stronger the binding.

III. EVAIUATION FOR CONTROL SYSTEM

A. Antibody calculation procedure

Procedure for antibody concentration and antigen are represented by the Fig. 4 and Fig. 5.

Gain is computed by prosecure *A, B.* The fitness is given by the following.

$$PI = \frac{1}{m_1 \times rise\ time + m_2 \times settling\ time + m_3} \times \frac{1}{(T_n / T_f)} \quad (10)$$

- m_1, m_2, m_3 : weight constant (+)
- T_f : Overshoot value (1; overshoot < the requirement value, real overshoot value; overshoot value >requirement overshoot)
- T_n : Delay time constant (no delay time plant; T_f, delay time; real delay time value)

Hence, PI controller is designed by learning of editope, paratope.

IV. SIMULATION AND DISCUSSION

Fig. 6 shows how the secretion rate and its contributing terms vary over the course of the simulation for control system. The exact values and forms of the above equations are not as important as the understanding of which kinds of feedback signals have some evolutionary advantage and why. These examples show us how feedback in the immune system could work, and the kinds of effects different signals might have on the developing response. They suggest certain mechanisms to look for in the immune systems of real organisms.

The above tests are just a beginning; they were all performed with a single set of parameters describing the characteristics of the pathogen and effectors.

In other words, our model immune system was only tested against a single kind of antigen, under one set of initial conditions. To evaluate whether the adaptive secretion strategies described above are truly adaptive, a wider range of antigen parameters and initial conditions must be explored. Ideally, individuals in the GA would be challenged with multiple antigens of varying virulence. The fitness measure would then be a composite of results from each individual 'infection'; this would ensure that the best individuals used broadly applicable feedback strategies.

Another important area for future research is in applying the results of such a survey to spatial models.

Differential equations only approximate the dynamics of a spatially distributed system of discrete agents. It is unlikely that the exact parameter values will map directly to agent-based systems. However, they do provide a measure of the relative importance of different signals and interactions.

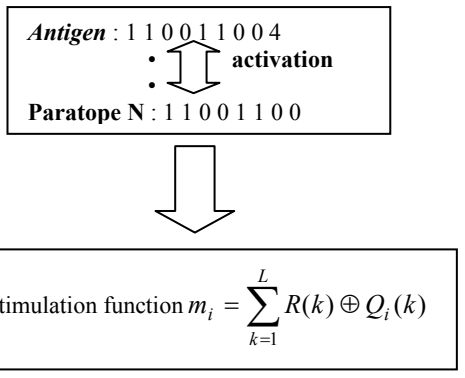

Fig. 4. Procedure of antigen concentration.

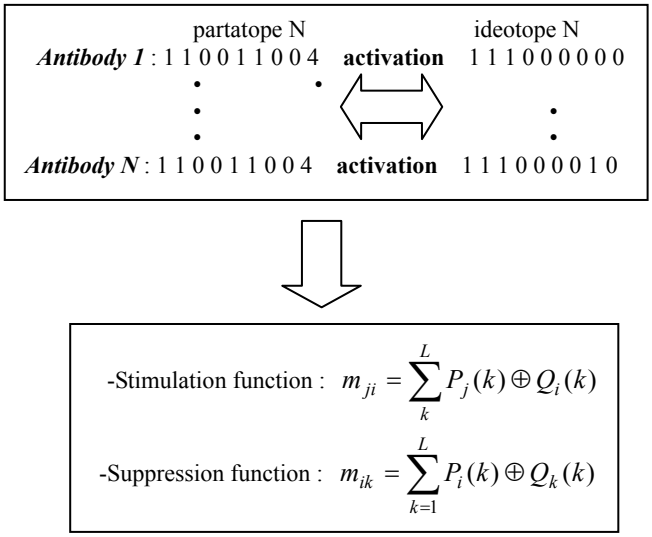

Fig. 5. Procedure of antibody concentration.

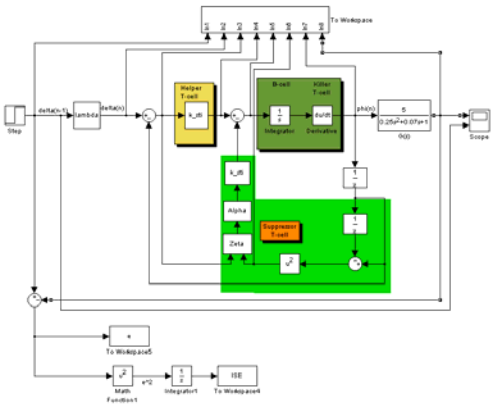

Fig. 6. Simunk model for immune based 2-DOF feedback control.

Figs. 7-14 shows response to variation of each parameter. Fig. 7 is response of lambda=0, alpha=1, k_sti=1, k_sup=0.1 and Fig. 8 is shows response on lambda=1, alpha=1, k_sti=1, k_sup=0.1.

CONCLUSION

This paper suggested the feasibility design of 2-DOF controller by immune network algorithms and represented response to the variation of parameter in immune network. If this parameter is more verified in each case of plant, the results of simulation shows it can be used for the 2-DOF PID controller. Since the structure of feedack immune network is the similar a type of 2-DOF, it will be used for the nonlinear

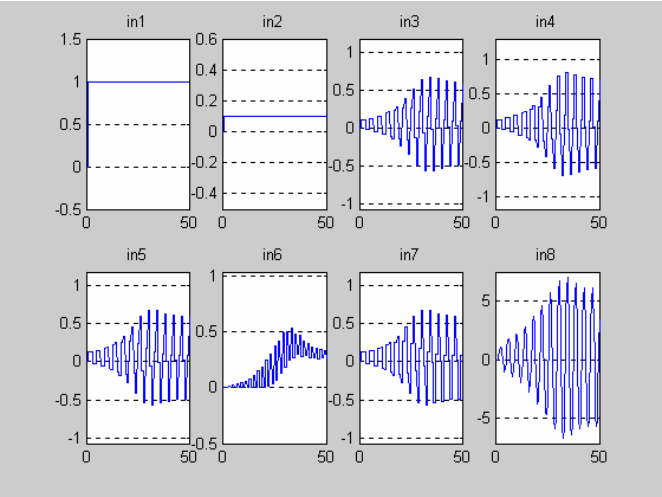

Fig. 7. Reference=10;lambda=.5;alpha=1;ksti=1;ksup=0.1; zeta=ksup/ksti;d=0.5.

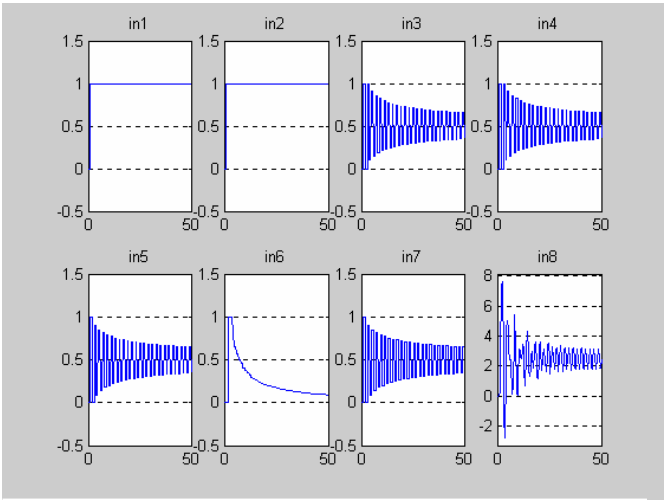

Fig. 8. Reference=10;lambda=1;alpha=1;ksti=1;ksup=0.1; zeta=ksup/ksti;d=0.5.

system if tuning problem is proven.

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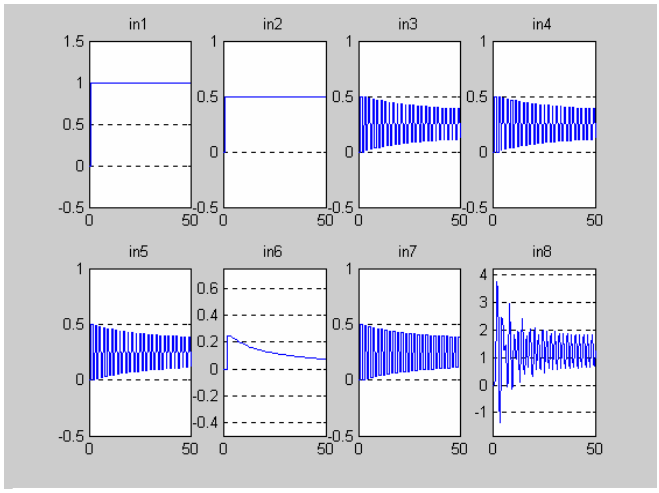
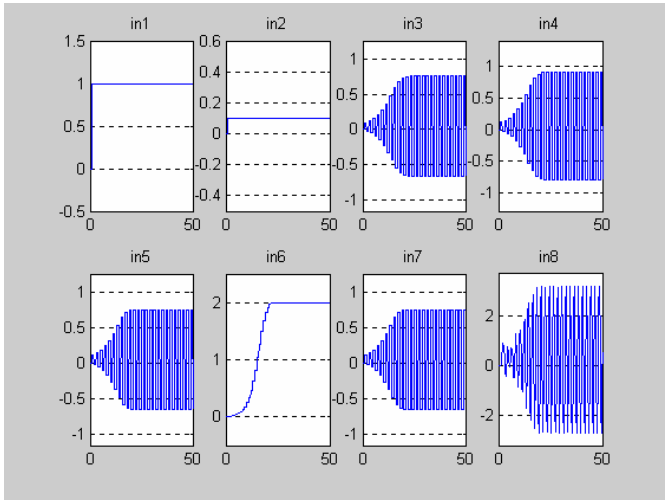


Fig. 9. Reference=10;lambda=.5;alpha=1;ksti=1;ksup=0.1; zeta=ksup/ksti;d=0.5.



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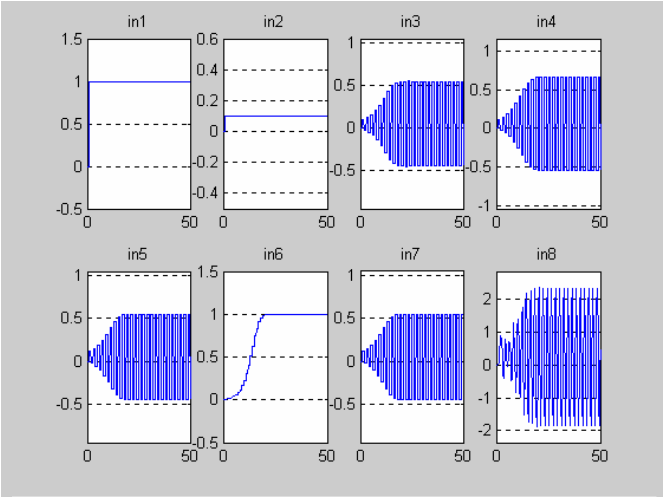

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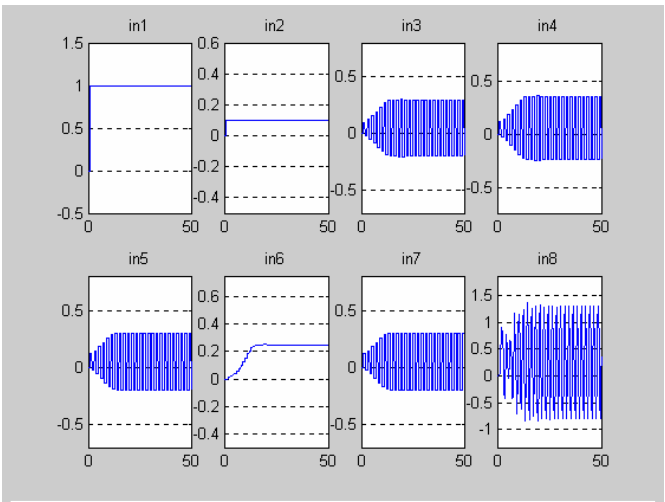
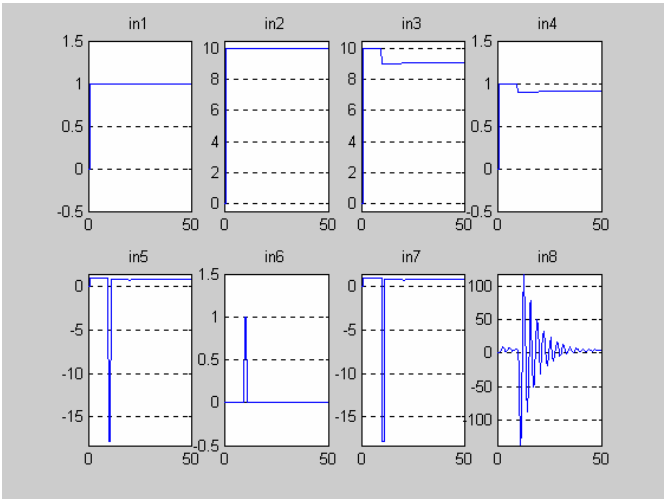


Fig. 12. Reference=10;lambda=.5;alpha=2;ksti=1.2;ksup=0.4; zeta=ksup/ksti;d=0.5.



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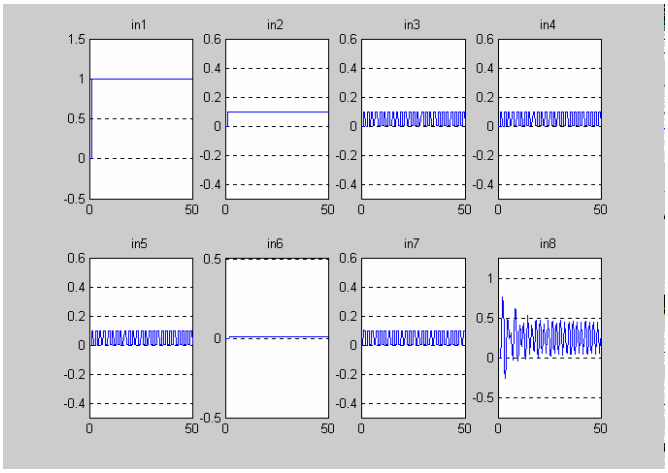

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