World Automation Congress

Fifth International Symposium on Soft Computing for Industry

Seville, Spain
June 28th-July 1st, 2004

Soft Computing Optimizer For Robust KB Design Processes: The Structure And Applications

L.V. Litvintseva and T. Hagiwara

SOFT COMPUTING OPTIMIZER FOR ROBUST KB DESIGN PROCESSES: THE STRUCTURE AND APPLICATIONS

L.V. LITVINTSEVA, YAMAHA Motor Europe N.V. R&D Office, Italy,
llitvintseva@crema.unimi.it
T. HAGIWARA, YAMAHA Motor Co., LTD, Japan,
hagiwarat@yamaha-motor.co.jp

ABSTRACT

We demonstrate robust intelligent control systems design technology based on new types of computing such as advanced soft computing (SC) and stochastic simulation (as a first step). To avoid disadvantages of traditional SC approach, we developed a new tool - *Soft Computing Optimizer*. We describe SC Optimizer structure and demonstrate its efficiency and robustness for design of new types of *self-organizing intelligent control systems* adapted to control of essentially nonlinear stable and unstable plants under different kinds of stochastic excitations. Examples of robust KB design for P(I)D-fuzzy controllers are demonstrated as Benchmarks. Comparison of simulation results in three cases of control design (classical PD, SC Optimizer control and traditional FNN control) is demonstrated.

Keywords: Soft Computing, Optimization, Robust Intelligent Control

1. INTRODUCTION

Traditional Soft Computing approaches based on Genetic Algorithms (GA) with fitness function as a minimum control error and Knowledge Base refine methods based on Fuzzy Neural Networks (FNN) tuning with error back propagation algorithm cannot guarantee a robust and stable control achievement in the case of globally unstable essentially nonlinear dynamic control objects (CO). Main disadvantage of FNN-based approaches is that the FNN structure must be given *a priori* (i.e., the number and type of MF must be introduced by a user), but in the abovementioned cases of CO it is difficult to define optimal FNN structure manually. To avoid these disadvantages we developed a new tool - *Soft Computing Optimizer*. We describe SC Optimizer structure and demonstrate its efficiency and robustness for design of new types of *self-organizing intelligent control systems* adapted to control of essentially nonlinear stable and unstable plants under different kinds of stochastic excitations. SC Optimizer is considered as a new flexible tool for design of optimal structure and robust Knowledge Base of Fuzzy Controller based on a chain of GAs with information-thermodynamic criteria of optimization.

2. BRIEF HISTORY OF SC TECHNOLOGY OF INTELLIGENT CONTROL SYSTEMS DESIGN

The current situation of intelligent control systems design technology is introduced by a historical flow chart in Figure 1. This picture shows main steps of our technology [1, 2]. We have investigated possibilities and limitations of classical (advanced) control theory for the cases of globally unstable and essentially non-linear control objects (CO) in the presence of stochastic noises with different probability distribution densities. By using a set of non-linear CO benchmarks and by using our stochastic simulation system we found limitations of classical control approach. Classical control system is based on PID regulator (with constant gain coefficients) and principle of global negative feedback. Experimental and benchmark simulation results show that a classical control system doesn't work well, if we have globally unstable or essentially non-linear CO in the presence of Rayleigh noises (with non-symmetric probability distribution densities), or if we have random noises in sensor's measurement system in control channel loops. The control criterion based only on a minimum of control error cannot guarantee a robust and stable control achievement in these cases. How can we introduce into control system more complicated control quality criteria such as a minimum of entropy production in a plant and in control system, or a minimum of energy loss in plant and controller, etc.? Limitations of classical PID control pushed researchers to develop new types of control systems based on ideas of human intelligent control strategies. For this aim SC approaches are developed. SC applied to design of intelligent control systems represents a combination of fuzzy systems theory for a fuzzy control, GA for global optimization of control laws, and FNN for physical realization of optimal control laws and knowledge base (KB) design of FC using error back propagation learning algorithm. Our benchmarks simulation results shows that by using traditional GA-FNN tuning we can design KB of FC only for limited control conditions such as: fixed initial conditions, fixed reference signals, fixed model parameters and in the presence of fixed noises. A change of these conditions results in incapability of designed FC to control new situation (see example below).

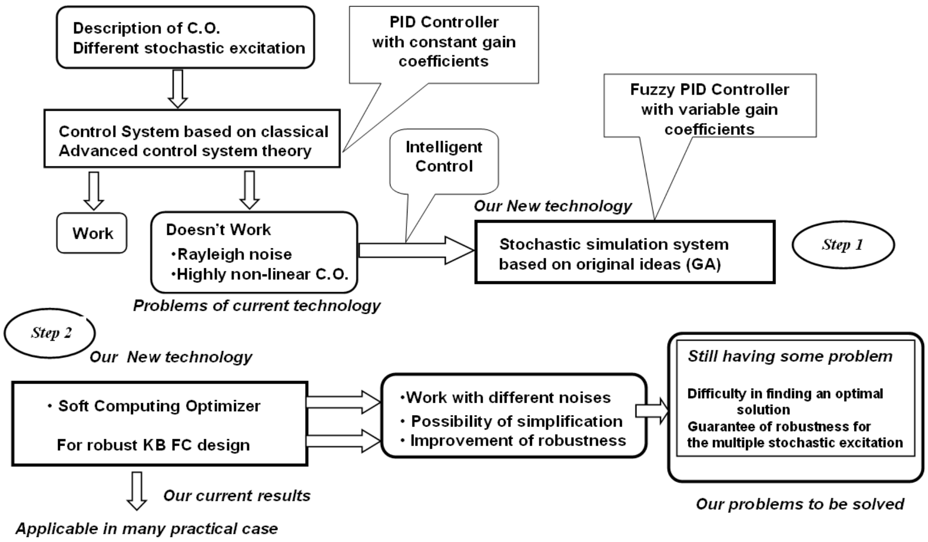

Figure 1: Main steps of intelligent control systems design technology.

Thus, limitations of classical PID control and traditional SC approaches based on FNN error back propagation learning algorithm inspired us to develop new types of control systems based on new types of computations such as advanced SC technology.

3. SC OPTIMIZER MACRO-LEVEL STRUCTURE

In Figure 2 the general structure of intelligent control system design based on *SC Optimizer* (step2 technology) is shown. Here the following designations are used: GA - Genetic Algorithm; ε - Error; u*- Optimal Control Signal; m(t) – stochastic disturbance; FC - Fuzzy Controller.
SC Optimizer is considered as a new flexible tool for design of optimal structure and robust KB FC. SC Optimizer is based on a chain of GAs with information-thermodynamic criteria of optimization [3]. Input to SC Optimizer can be some measured or simulated data (called as 'teaching signal" (TS)) about the modeled system. For TS design we use stochastic simulation system based on the model of control object. Random trajectories of the chaotic behavior of stochastic excitations with appropriate probability density function are generated by the noise stochastic simulation according to the solution of Fokker-Planck-Kolmogorov equations [4]. Then by using stochastic simulation system and new control quality criteria we generate trajectory of control object behavior under the given stochastic noise and chosen structure of FC-P(I)D.

Design of KB for robust FC is based on the extraction of the value information about random dynamic behavior of control object using GA fitness functions in stochastic and fuzzy simulation subsystems.

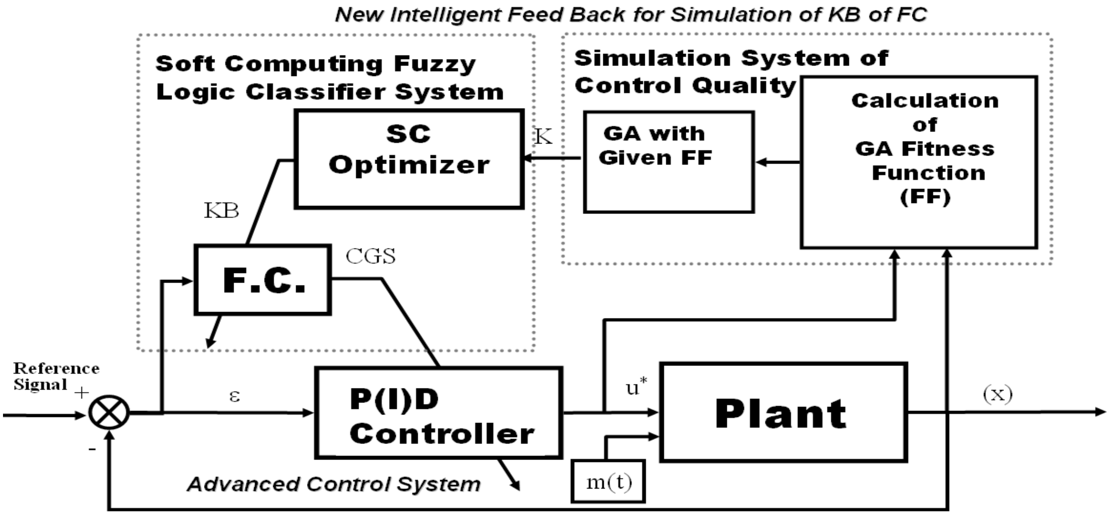

Figure 2: Structure of self-organizing robust intelligent control system based on SC Optimizer

The basic peculiarities of our step 2 technology are: (1) SC Optimizer uses the chain of GAs to solve optimization problems connected with the optimal choice of number of membership functions (MFs) for input variables values description, their shapes and parameters and with optimal choice of fuzzy rules; (2) To design GA fitness functions we use an information-thermodynamic approach based on the analysis of dynamic behavior of control object and FC; (3) SC Optimizer works as a universal approximator, which extracts information from simulated (or measured) data about the modeled CO.

SC Optimizer guarantees the robustness of FC, i.e. successful control performance in wide range of plant's parameters, reference signals, and external disturbances.

On macro level SC Optimizer operations is divided into several stages.

Stage 1: *Fuzzy Inference System* (*FIS*) *Selection*. The user makes the selection of fuzzy inference model with the featuring of the following initial parameters: number of input and output variables; type of fuzzy inference model (Mamdani, Sugeno, Tsukamoto, etc.); preliminary type of membership functions (MF).

Stage 2: *Linguistic values creation*. By using information obtained on Stage 1, GA_1 optimizes a number of MFs and their shapes, approximating TS, obtained from the 'in-out' tables, or from dynamic response of CO (real or simulated in Matlab).

Stage 3: At this stage we use the rule-rating algorithm for selection of certain number of rules and of their structure prior to the selection of the index of the output MF corresponding to the rules. For this case two criteria based on a rule's activation parameter called as a "manual threshold level" (*TL*). This parameter is given at user (or it can be done automatically).

At this stage the *total firing strength of each rule* is calculated as

$$R^l_{total\_fs} = \sum_{k=1}^{N} R^l_{fs}(t_k), \text{ and } R^l_{fs}(t_k) = \prod \left[\mu^l_{j1}(x_1(t_k)), \mu^l_{j2}(x_1(t_k)), ..., \mu^l_{jn}(x_n(t_k)) \right],$$

where t_k is a time moment, $k = 1,...,N$, N is a number of temporal points in TS, and l is a rule index. The following criteria are used for the selection of KB:

(1) "*Sum of firing strength*" criterion: select KB, where rules satisfy the following condition: $R^{l}_{total\_fs} \geq TL$; (2) "*Max of firing strength*" criterion: select KB, where rules satisfy the following condition: $\max_{t} R^{l}_{fs}(t) \geq TL$.

Output of this stage is KB designed according to the chosen criterion and the given threshold level *TL*.

Stage 4: *Rule base optimization*. GA_2 optimizes the rule base obtained on the Stage 3, using the fuzzy model obtained on Stage 1, optimal linguistic variables, obtained on Stage 2, and the same teaching signal as it was used on Stage 1.

Stage 5: *Refine KB*. On this stage, the structure of KB is already specified and close to global optimum. In order to reach the optimal structure, a few methods can be used. The first method is based on GA_3 with fitness function as minimum of approximation error, and in this case KB refining is similar to classical derivative based optimization procedures (like error back propagation (BP) algorithm for FNN tuning). The second method is also based on GA_3 with fitness function as a maximum of mutual information entropy. The third method is realized as a pure BP algorithm. BP algorithm may provide further improvement of output after genetic optimization.

As output results of the Stages 3, 4 and 5, we have a set of KB corresponding to chosen KB optimization criteria. Finally, we must test all developed KB FC by using the model of the control object and choose the best KB from control quality point of view.

4. EXAMPLES OF SC OPTIMIZER APPLICATIONS

We compare the results of fuzzy control obtained with presented approach (FC_SCO), with traditional SC approaches based on back-propagation FNN-tuning (FC_FNN) (for comparison we have used the Adaptive Fuzzy Modeler developed by ST Microelectronics [5]) and with classical PD control. We will consider two control situations: TS control situation (for which KB FC is designed) and new control situation different from TS (for robustness property investigation of designed KB).

Example 1: *Coupled non-linear oscillators control problem*. The nonlinear equations of CO motion and entropy production rate are as follows:

$$\begin{cases} \ddot{x} + 2\beta_1 \dot{x} + \omega_1^2 \left[1 - k \cdot y\right] x = \xi_1(t) + u_1(t) \\ \ddot{y} + 2\beta_2 \dot{y} + \omega_2^2 y + \dfrac{\pi^2}{2l}\left[x\ddot{x} + \dot{x}^2\right] = \dfrac{1}{m}\left\{\xi_2(t) + u(t)\right\} \end{cases}; \quad \frac{dS_x}{dt} = 2\beta_1 \dot{x} \cdot \dot{x}; \frac{dS_y}{dt} = 2\beta_2 \dot{y} \cdot \dot{y},$$

where $\xi_{1,2}(t)$ are given stochastic excitations with appropriate probability density functions.

TS control situation	**New control situation**
Model parameters: $\beta_1 = 0.03$; $\beta_2 = 0.3$; $\omega_1 = 1.5$; $\omega_2 = 4$; $k = 5$; $l = 1$; $M = 5$ Initial conditions: [0.5 0.1] [0.01 0.1] Reference signals: $x = 0$, $y = 0$; Noise along *x*-axis: *Gaussian* noise (max amplitude A = 4); Noise along *y*-axis: *Rayleigh* noise: (max amplitude A = 10)	New model parameters: $\beta_1 = 0.5$; $\beta_2 = 0.05$; $\omega_1 = 5$; $\omega_2 = 1$; $k = 3$; $l = 1$; $M = 5$ New initial conditions: [1 1] [0.01 0.01] New reference signals: $x = 0.1$, $y = 0.05$; Noise along *x*-axis: *no noise* Noise along *y*-axis: *Rayleigh* noise: (max amplitude A = 15)

Table 1. Two different control situations

Description of TS and new control situation for example 1 is given in Table 1. In TS control situation the system is disturbed by two different noises acting along x (*Gaussian* noise) and y-axes (*Rayleigh* noise).

Stochastic simulation of random excitations with appropriate probability density functions is based on non-linear forming filters methodology developed in [4]. Consider excited motion of the coupled non-linear oscillator under fuzzy control (with 4 inputs and 4 outputs) designed for two PD-controllers along x-axis and along y-axes.

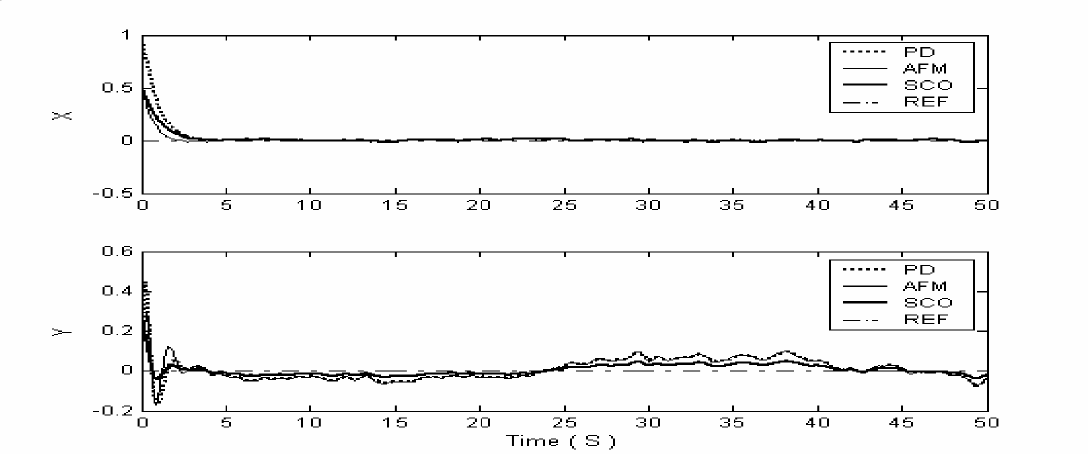

Figure 3: Comparison of motion under SCO, FNN and PD in TS control situation

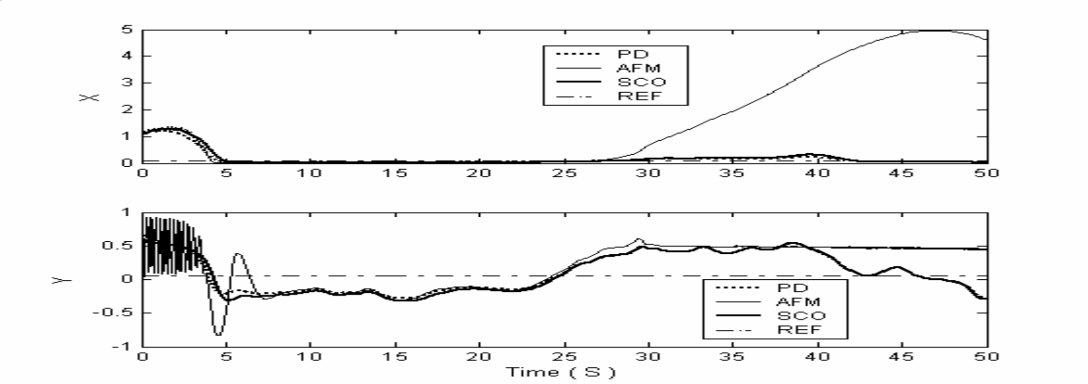

Figure 4: Comparison of motion under SCO, FNN and PD in new control situation

Results of comparison of control performance of FC_SCO with **34 rules**, FC_FNN with **625 rules** and two PD controllers in two control situations are shown in Figure 3 and 4 (K-gains ranging area is [0,20]). Simulation results show *that FC_SCO control is robust*, and *FC_FNN control is failed (unstable)*, i.e. it is *not robust* when new control conditions (as shown in Table 1) are considered**.**

Remark. In FNN-based KB FC design tools, the number and the type of MF must be introduced at user. But in the case of globally unstable or essentially non-linear (as shown in Figure4) it is difficult to define optimal FNN structure *manually*. This is a week point of many KB design tools based on traditional SC approach.

Example 2. *Semi-active suspension control system for passenger cars*. The behavior of the car body is often discussed from views of acceleration and jerk. However, they are not well suited to control both vehicle stability and riding comfort. The stability is dominated mainly by a low frequency component around 1Hz and the comfort by above 4 or 5Hz. Three axes of heave, pitch and roll also have to be considered. A globally optimized teaching signal for damper control was generated by genetic algorithm, the fitness function of which is set to satisfy conflicting requirements such as riding comfort and stability of the car body. Running condition was also varied between flat and undulated surface. The control performance of optimized KB base for different fitness functions were evaluated and compared by computer simulations and by field tests. The road signals and damping coefficients for four dampers being supplied, the Matlab-Simulink model calculates the motion of the car and suspension based on the equations of motion [6]. GA searches and finds out the best damping coefficients for the dampers that minimize the fitness function every 7.5ms. A series of such damping coefficients are stored as TS. At the next step, by using SC Optimizer we design optimal KB FC for the given TS. The experimental results show that the low frequency components of pitch movement are well controlled by the chosen fitness function. High frequency components of heave movement are also kept at a low level. Even though the road condition is very different from the one, which was used for off-line tuning, obtained knowledge base seems to be working effectively. And using only one single accelerometer for vertical heave movement detection as a signal source, the system is controlling the body behavior well as mentioned above. This is explained by the fact that good KB were created, during off-line tuning, with properly arranged fuzzy input signals extracting necessary information to detect the state of the vehicle and consequently providing useful information to the fuzzy controller to control the body movement.

5. CONCLUSIONS

By using SC Optimizer tools, based on stochastic simulation and GA randomized search of optimal robust control, we can model different versions of KBs of FC and choose best KB from control quality point of view. SC Optimizer allows to design smart robust control of essentially non-linear stable and, especially, of unstable CO in the presence of uncertainty information about external excitations, model parameters, and with changing reference signals and initial conditions. The robustness of control laws is achieved by the introduction of vector fitness function of GA, one of its components contains physical principle of minimum entropy production rate in controlled object and in control system. The robust intelligent control system designed on the basis of such approach needs the minimum of initial information about the behavior of controlled object and about external random excitations.

6. REFERENCES

[1] *US Patent N 6,411,944 B1*, "Self-organizing control system" (Inventor: S.V.Ulyanov), Filed Date: March 17, 1998; Date of Patent: June 25, 2002.

[2] *US Patent N 6,415,272 B1*, "System for intelligent control based on soft computing" (Inventor: S.V. Ulyanov), Filed Date: Oct 22, 1998; Date of Patent: July 2, 2002.

[3] S.A. Panfilov, L.V. Litvintseva, I.S. Ulyanov, K. Takahashi, "Soft Computing Optimizer: Structure and SW for simulation of Universal Fuzzy Approximators", *Proc. ICSCCW-2003, 2nd International Conference on Soft Computing with Words in System Analysis, Decision and Control*, September 9-11, Antalya,Turkey, 2003, pp.112-123.

[4] S.V. Ulyanov, M. Feng, K. Yamafuji, I. Kurawaki *et all*, "Stochastic analysis of time-variant nonlinear systems. Pts 1, 2", *Intern. J. Probabilistic Engineering Mechanics,* Vol. 13, No 3, 1998, pp. 183-226.

[5] http://eu.st.com/stonline/index.shtml**.**

[6] T. Hagiwara, I. Kurawaki, O. Diamante, "Smart Suspension Control System Based on Soft Computing", *Proc. ICSCCW-2003, 2nd International Conference on Soft Computing with Words in System Analysis, Decision and Control*, September 9-11, Antalya, Turkey, 2003, pp.104-112.