SOFT COMPUTING OPTIMIZER FOR INTELLIGENT CONTROL SYSTEMS DESIGN: THE STRUCTURE AND APPLICATIONS

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Abstract. Soft Computing Optimizer (SCO) as a new software tool for design of robust intelligent control systems is described. It is based on the hybrid methodology of soft computing and stochastic simulation. It uses as an input the measured or simulated data about the modeled system. SCO is used to design an optimal fuzzy inference system, which approximates a random behavior of control object with the certain accuracy. The task of the fuzzy inference system construction is reduced to the subtasks such as forming of the linguistic variables for each input and output variable, creation of rule data base, optimization of rule data base and refinement of the parameters of the membership functions. Each task by the corresponding genetic algorithm (with an appropriate fitness function) is solved. The result of SCO application is the design of Knowledge Base of a Fuzzy Controller, which contains the value information about developed fuzzy inference system. Such value information can be downloaded into the actual fuzzy controller to perform online fuzzy control. Simulations results of robust fuzzy control of nonlinear dynamic systems and experimental results of application on automotive semi-active suspension control are demonstrated.
Keywords: Soft computing optimizer, knowledge base, intelligent control, robust fuzzy controller, fitness function

1. INTRODUCTION

Fuzzy control has emerged as one of the most active and fruitful fields in practical application of fuzzy systems theory based on a fuzzy logic and fuzzy sets theory introduced by L. Zadeh (1973). From control design point of view, fuzzy systems became so attractive because they can be considered as universal approximator of systems with unknown dynamics and structure. Fuzzy controllers (FC) allow for a simpler, more human approach to control design and provide reasonable, effective alternative to classical controllers (for example, see [1]). Fuzzy systems are based on a logic approach, which enables us to translate qualitative knowledge about the problem into a reasoning system capable of performing approximate pattern matching and interpolation. But, in fuzzy logic based technology the generation of membership functions (MF) and fuzzy rules (FR) is a task mainly done by a human expert. Human expert also solves the task of refining (or tuning) of knowledge base. It means that fuzzy logic approach itself does not have adaptation and learning capabilities for self-constructing and tuning of MF's, and FR's. Fuzzy control system can be designed by using *soft computing technology* including *Genetic Algorithms* (GA) and *Fuzzy Neural Networks* (FNN) learning algorithms [1]. 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 some times it is difficult to define optimal FNN structure manually. To avoid this disadvantage, we developed SCO as the new flexible tool for design of optimal structure and optimal knowledge base of a fuzzy system (for example, a FC) based on some measured or simulated data ("teaching patterns") about the modeled system. Random trajectories of the chaotic behavior of control object are generated by the stochastic simulation with appropriate probability density function according to the solution of Fokker-Planck-Kolmogorov equations. And with fuzzy simulation we study the individual peculiarities in the random dynamic behavior of control object through the definition of fitness function. Design of KB for robust fuzzy controller is based on the extraction of the value information about random dynamic behavior of control object using fitness function in stochastic and fuzzy simulation technologies. We demonstrate SCO tool's 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.

2. INFORMATION-THERMODYNAMIC BOUNDS IN DESIGN PROCESS OF INTELLIGENT CONTROL SYSTEMS

Figure 1 shows the structure of self-organizing intelligent control system based on SCO which approximates measured or simulated data about the modeled system with desired accuracy (call it as a teaching signal -TS). SCO uses chain of GAs to solve optimization problems connected with the optimal choice of number of MFs, their shapes and parameters and with optimal choice of fuzzy rules. Information-thermodynamic approach to design of fitness functions in GAs is based on the analysis of dynamic behavior of control object and FC [2]. Principle of minimum of entropy production in control object and fuzzy PID-controllers is the background for design of intelligent robust control. Robustness of control means that the minimum of initial information about uncertainty of external environments or structure's disturbances of control object is required.

Robustness criterion backgrounds. The problem of maximum of released work, i.e. $\max_{q_i,u}(W)$, where q_i, u are generalized coordinate and control correspondingly, is equivalent to the associated problem of the minimum of entropy production, i.e. $\min_{q_i, u}(S)$ [2,3]. For the general class of dynamic control systems, described by Hamilton-Jacobi-Bellman equations, the optimal solution of the variational fixed-end problem for the maximum work W is equivalent to the solution of variational fixed-end problem for the minimum entropy production [3]. Thus, the analytical formalism, which is strongly analogous to those in analytical mechanics and control theory, is effective in thermodynamic optimization too. Let us consider the dynamic control process described as follows: $\dot{q}_i = \varphi(q,t,u)$. According to generalized thermodynamic approach [2,4], we can choose Lyapunov function V for this process as $V = \frac{1}{2}\sum_{i=1}^{n} q_i^2 + \frac{1}{2}S^2$, where S is entropy production of an open system described by $\dot{q}_i$. $S = S_p - S_c$, where S_p is the entropy production of a plant (control object) and S_c is the entropy production of controller (fuzzy PID-controller).

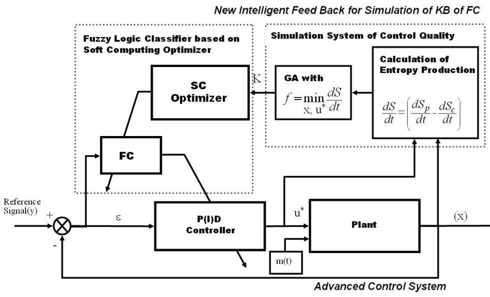

Figure 1: Structure of self-organizing robust intelligent control system based on SCO

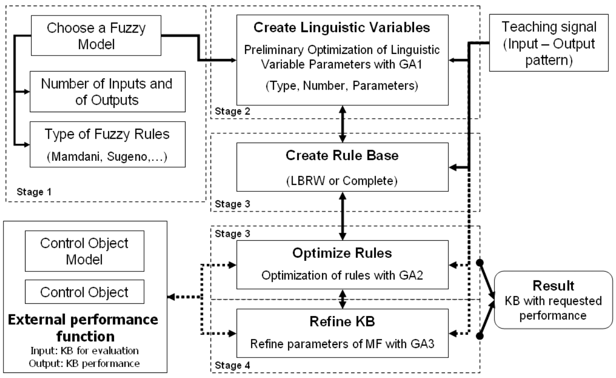

Figure 2: Flow chart of SC Optimizer

After simple transformations (as in [2]) we have

$$\frac{dV}{dt} = \sum_{i=1}^{n} \dot{q}_i \varphi(q,t,u) + (S_p - S_c)\left(\frac{dS_p}{dt} - \frac{dS_c}{dt}\right). \quad (1)$$

The interrelation between Lyapunov stability (V) and robustness ($\min(S \cdot \dot{S})$) described by Eq.(1) is the general physical law for design of intelligent control systems [2,4,5]. We apply this law for design of smart KB of robust intelligent control systems based on SCO tools. Thus, SCO is the universal approximator, which extracts information from simulated (or measured) data about the modeled system. SCO guarantees the robustness of FC, i.e. successful control performance in wide range of plant's parameters, reference signals, and external disturbances. Information bounds considered in [2] are described in Table 1.

3. THE STRUCTURE OF SOFT COMPUTING OPTIMIZER

Figure 2 shows the flow chart of SCO operations on macro level and combines several stages.

Table 1: Types and the role of GA fitness function in SCO

Type of GA	Criteria	Fitness Function	The Role of FF
GA_1: **Linguistic Variables Optimization**	**MAX** of mutual information entropy **AND** **MIN** of information amount in each signal	$H^j_{X_i} = -p^j{}_{X_i}\log(p^j{}_{X_i}) = -p\left(x_i \middle| x_i = \mu^j{}_{X_i}\right)\log\left[p\left(x_i \middle| x_i = \mu^j{}_{X_i}\right)\right] = -\frac{1}{N}\sum_{t=1}^{N}\mu^j{}_{X_i}(x_i(t))\log\left[\mu^j{}_{X_i}(x_i(t))\right] \to \max$ $H^{(j,l)}{}_{X_i \mid X_k} = H\left(x_i \middle|_{x_i=\mu^j{}_{X_i}, x_k=\mu^l_{X_k}}\right) = -\frac{1}{N}\sum_{t=1}^{N}\left[\mu^j{}_{X_i}(x_i(t)) * \mu^l{}_{X_k}(x_k(t))\right] \log\left[\mu^j{}_{X_i}(x_i(t)) * \mu^l{}_{X_k}(x_k(t))\right] \to \min$ where * denotes selected T-norm (Fuzzy AND) operation.	Data compressing; Choice of optimal number of MF approximating TS
GA_2: **Rule Base Optimization**	**MIN** of total error (a difference between the FIS and TS outputs)	$E = \sum_p E^p \to \min$, where $E^p = 1/2(d^p - F(x_1^p, x_2^p, \ldots, x_n^p))^2$	Choice of optimal number of rules and MF parameters
GA_3: **Refine KB**	**MIN** of total error (a difference between FIS and TS outputs) **OR** **MAX** of mutual information entropy	$E = \sum_p E^p \to \min$ $H^j_{X_i} \to \max$	Fine Tuning of MF parameters

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 MFs. **Stage 2**: *Create linguistic values*. GA optimizes linguistic variable parameters, using the information obtained on Stage 1, and TS, obtained from the in-out tables, or from dynamic response of control object (real or simulated in Matlab). **Stage 3**: *Rule base optimization*. GA optimizes a rule base, using the fuzzy model obtained on Stage 1, optimal linguistic variable parameters, obtained on Stage 2, and the same teaching signal as it was used on Stage 1. **Stage 4**: *Refine KB*. On this stage, the structure of FNN is already specified and close to global optimum. In order to reach the optimal structure, two methods can be used. First method is based on the minimum error criteria and similar to classical derivative based optimization procedures (like error back propagation algorithm for FNN tuning), with combination of initial conditions for back propagation, obtained on previous optimization stages. Second method is based on the maximum of mutual information entropy criteria. The result of the Stage 4 is a specification of fuzzy inference structure, optimal for solution of a current problem. In order to have robust solution, Stage 4 can be bypassed, and the robust structure obtained with GAs of stages 2-3 can be used.

4. MAIN SCO-OPERATIONS

SCO uses GA approach to solve optimization problems connected with the optimal choice of number of MFs, their shapes and parameters and with optimal choice of fuzzy rules. GA's are known as a very computational expensive approach in optimization, since each chromosome created during genetic operations must be evaluated. For example, GA with population size of 100 chromosomes evolved 100 generations requires as a maximum 10000 calculations of the fitness function. Usually this number is smaller, since it is possible to add some routine which will trace the same chromosomes, and will not evolve them two times, but still the total number of calculations is much greater than number of evaluations required by some sophisticated classical optimization algorithm. This computational expense is a payback for the robustness of FC obtained when GA is used. The great number of the evaluations gives the constraints on the practical applications of the GA. For example, if the evaluation function requires 10 minutes for calculation on the single processor, its evaluation with abovementioned GA will take 10*10000 minutes, which is about 1600 hours, and this time grows exponentially with increasing of the complexity of the fitness function. This practical constraint on GA application, leads to developing of the simpler fitness functions, dividing the total goal of the algorithm (KB extraction of the chosen FIS) into several simpler problems. Therefore SCO uses chain of GAs to solve optimization problems connected with the following sub-problems: (1) Define number and shape of MFs; (2) Select optimal rules; (3) Fix optimal rules structure; and (4) Refine the KB structure. Information-thermodynamic criteria from [2] as fitness functions of GAs in SCO are used and guarantee the robustness of intelligent control. In Table 1 types and the role of SCO-GA's fitness functions (FF) are shown.

5. SCO-APPLICATIONS EXAMPLES

We compare the results of robust fuzzy control obtained with presented approach and with other soft computing based approaches. Consider unstable control object as a swing dynamic system. The nonlinear equations of motion of the swing dynamic system are:

$$\begin{cases} \ddot{\theta} + 2\dfrac{\dot{l}}{l}\dot{\theta} + \dfrac{g}{l}\sin\theta = 0 \\ \ddot{l} + 2k\dot{l} - l\dot{\theta}^2 - g\cos\theta = \dfrac{1}{m}\left(k_p \cdot e_l + k_d \cdot \dot{e}_l + k_i \cdot \int e_l dt + \xi(t)\right) \end{cases} \tag{2}$$

Here $\xi(t)$ is the given stochastic excitation with an appropriate probability density function. Equations of entropy production are the following: $\frac{dS_\theta}{dt} = 2\frac{\dot{l}}{l}\dot{\theta}\cdot\dot{\theta};\ \frac{dS_l}{dt} = 2k\dot{l}\cdot\dot{l}$. The system, described by Eq.(2), represents a globally unstable (along a generalized coordinate l) dynamic system .

Example: Fuzzy Control of swing system with one PID-controller. We study a control problem only for the second state variable of the swing system (the length l). As a fitness function indicating the better control, we choose the *minimum* of the entropy production rate in the control object (plant) and *minimum* of the entropy production rate in the control system [2,4]. The final form of the fitness function of control in this case is as follows:

$$f = \left(S_p - S_C\right)\cdot\left(\frac{dS_P}{dt} - \frac{dS_C}{dt}\right); \qquad \frac{dS_p}{dt} = \frac{dS_\theta}{dt} + \frac{dS_l}{dt};\ \frac{dS_c}{dt} = k_d\,\dot{e}^2 \tag{3}$$

TS for the given control problem was obtained in [6]. The *SCO* application result of intelligent fuzzy control of the swing system is presented in Figure 3 in comparison with classical PID control and with fuzzy control, where KB was obtained by using FNN error back-propagation method [6]. Fitness functions in GAs of *SCO* are chosen from Table 1. Coefficient gains of fuzzy PID-controller obtained with presented approach have more stable behavior comparing with coefficient gains obtained with FNN based approach (see Figure 4).

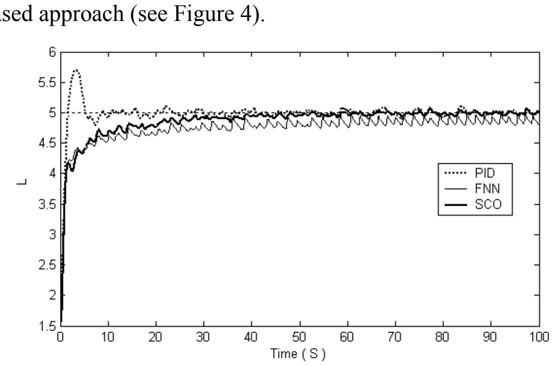

Figure 3: Result of intelligent control of swing system (controlled state variable)

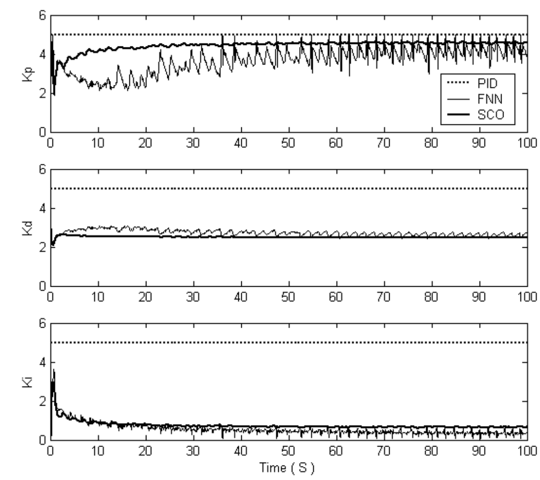

Figure 4: Behavior of the coefficient gains of fuzzy PID-controller

Example: Fuzzy Control of swing system with two PID-controllers. Consider excited motion of the swing system under fuzzy control of two PID-controllers along θ and l-axes using the following conditions. Let the system be disturbed by two different noises acting along θ and l-axes. Excitation along θ-axis is described by a *Gaussian*-like noise and excitation along l-

axis is described by a *Rayleigh*-like noise. Stochastic simulation of random excitations with appropriate probability density functions based on non-linear forming filters methodology in [7] is developed. The following swing parameters and initial conditions are considered: m = 1, k = 1 and [$\theta_0 = 0.25,\ l_0 = 1.5$] [$\dot{\theta}_0 = 0,\ \dot{l}_0 = 0.01$]. The reference signals are as follows**:** θ = 0.4; l = 3.5.

Traditional FNN based approximation of TS. At this step we extract KB of FC by using supervised learning of FNN with error back propagation algorithm. For realization of this step we use AFM tools developed by STM [17].

FNN based KB design process is described as follows:

• Numbers of MFs for each input variables have to be chosen manually: 3;

• Number of rules in KB: 3x3x3x3= 81 rules.

Remark: For the given case, if we choose more than 3 MFs for each input variables, AFM error back propagation algorithm is failed.

SC Optimizer based approximation of TS. FC KB design process by SC Optimizer is characterized as follows:

• Optimal numbers (and their shapes) of MFs for each input variables is defined by GA_2 : 9;

• Complete number of fuzzy rules: 9x9x9x9 = 2331 rules;

• Optimal KB is defined by GA_2: 143 rules.

Control quality and robustness comparison. Compare control quality and robustness property of FC_{SCO} obtained by SCO, FC_{FNN} obtained by traditional SC approach based on FNN-tuning and classical PID Controller. Results of comparison are shown in Figure 5. Let us take FC_{SCO} and FC_{FNN} developed for the case above (see Figure 5) and use them in a new control situation. Let us consider the following *new initial conditions* [-0.52 (-30°), 2.5] [0.01, 0] (reference signals and noises are the same as in Figure 5) and compare control performance of FC_{SCO} (obtained by SCO), FC_{FNN} obtained by traditional SC-approach based on FNN-tuning, and traditional PID Controllers with K = (8 6 8) for control along theta-axis and K = (7 6 7) for control along length-axis (see Figure 6).

Remark. We take these K-gains as mean values of variable K-gains obtained by SCO.

Simulation results show that FC_{SCO} control is robust, and FC_{FNN} control is not robust when initial conditions are changed. Figure 7 shows the comparison of fitness function values which are estimated by Eq.(3) (generalized entropy characteristics of control) in the new control situation (see Figure 6). From the simulation results in Figures 6 and 7 we can see that fuzzy PID-controller designed by SCO realizes effective control in comparison to FNN and traditional PID-controller where K-gains have been chosen by help of SCO. But SCO Controller is more effective than traditional PID Controller because it produces much smaller entropy than PID Controller (see Figure 8).

Consider another control conditions (control situation 2): (1) *initial conditions* [-0.52 (-30°), 2.5] [0.01, 0]; (2) *new reference signals***:** θ = 0.78 (45^0); l = 5; (3) *new noises amplitudes*: noise along θ is a *Gaussian*-like noise with max amplitude A = 1.5; and noise along length l is a *Rayleigh*-like noise with max amplitude A = 1.5.

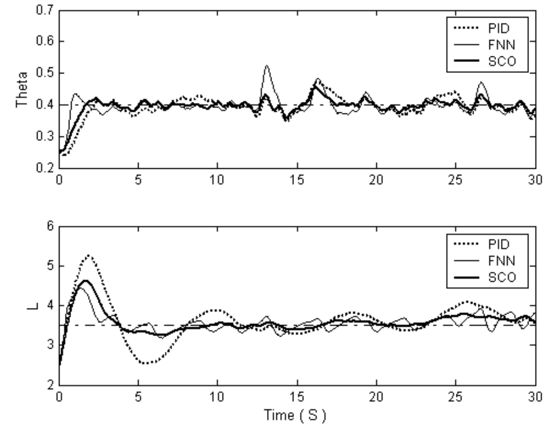

Figure 5: Comparison of control quality obtained by SCO, FNN and traditional l PID controller

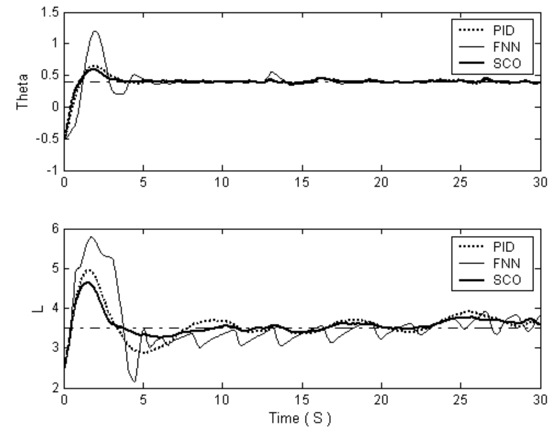

Figure 6: Control quality comparison of FC_{SCO} , FC_{FNN} and traditional PID controller in the new control situation.

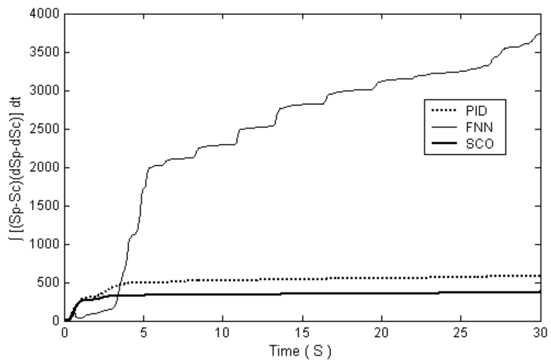

Figure 7: Fitness Function amount comparison of FC_{SCO} , FC_{FNN} and traditional PID controller in a new control situation

In this case max amplitudes of noises are 2 and 6 times smaller than in the case of KB design with the TS in Figure 5. Compare control performance of FC_{SCO} (obtained by SCO) and FC_{FNN} (obtained by traditional SC-approach based on FNN-tuning) (see Figure 9).

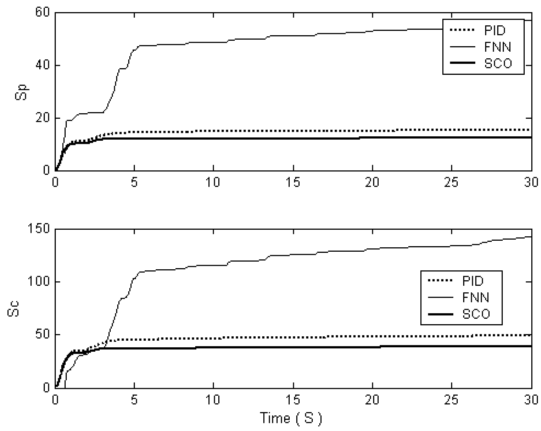

Figure 8: Plant and controller entropy production under FC_{SCO}, FC_{FNN} and traditional PID controller in new control situation

Simulation results show that FC_{SCO} control is robust, and FC_{FNN} control is failed (unstable), i.e. it is not robust when initial conditions and reference signals are changed and disturbance amplitudes are much smaller. Figure 10 shows the comparison of fitness function values which are estimated by Eq.(3) (generalized entropy characteristics of control) in the control situation 2. The simulation results in Figures 9 and 10 show that fuzzy PID-controller designed by SCO realizes effective control in comparison to FNN and traditional PID-controller.

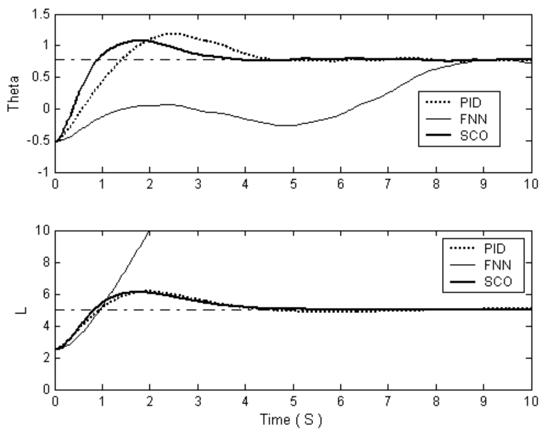

Figure 9: Control quality comparison of FC_{SCO}, FC_{FNN} and a traditional PID controller in control situation 2

Example: Intelligent control of semi-active automotive suspension system. We have applied this tool also to design intelligent control systems in practical areas such as intelligent control of semi-active vehicle suspension system. Perspective interrelations between SCO and quantum computing technologies of robust controller design are considered in [8]. Design methodology of a fuzzy controller for a semi-active suspension system using genetic algorithms that optimizes only the membership functions [9] was begun originally by Karr. Hashiyama et al. expanded the function of genetic algorithms to find control rules [10][11], and the algorithms they developed were based on skyhook control of Karnopp [12] with some original additions.

Hagiwara et al. [13] presented an idea for a method to create a knowledge base that is completely self-organized according to only fitness functions without any other predefined rule base [13], and an idea for an effective knowledge base creation method [6]. In this report we expand an idea by applying SC optimizer for KB design and refinement.

In order to make it possible to represent non-linear movement, four local coordinates for each suspension and three for the vehicle body, totaling 19 local coordinates are considered to form a mathematical vehicle model (see Figure 11). Equations of motion are derived by Lagrange's approach [13][14].

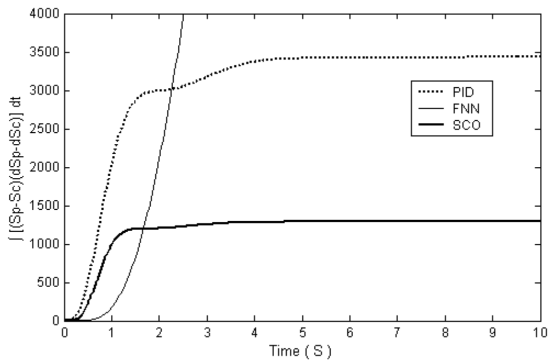

Figure 10: Fitness Function comparison of FC_{SCO} and a traditional PID controller in control situation 2

Optimization of intelligent control of shock absorber based on soft computing technology (FNN approach) is developed in [14], [15] and [16].

Principal parameters of the test vehicle are presented in [13]. As a fitness function for SCO in this example we choose the minimum of the low frequency (less than 2Hz) components of heave, pitch and of roll movements of the car body. Experimental results presented in the Figure 12 demonstrate better reduction of the selected low frequency components of the vehicle movements under actual control conditions when suspension system is controlled by fuzzy controller prepared by SCO

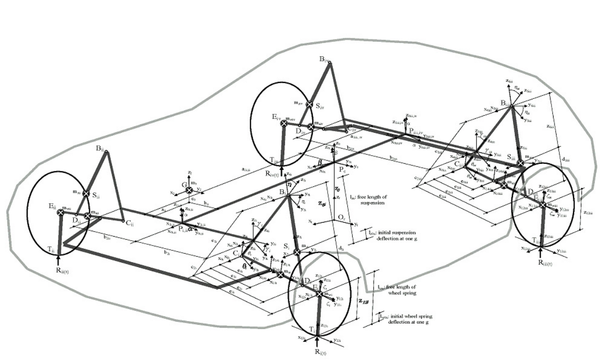

Figure 11: Mathematical vehicle model

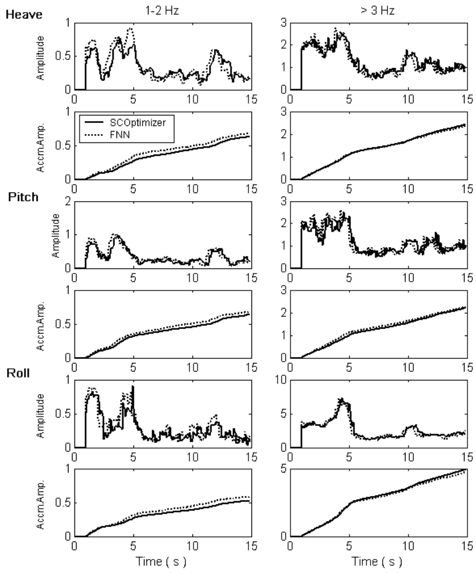

Figure 12: Experimental results of fuzzy control of semi-active suspension system

6. CONCLUSIONS

With SCO tool, using a GA-based randomized search of optimal robust control, we have modeled different versions of robust KB's of FC, which allow us to control essentially non-linear stable and, especially, unstable dynamic systems in the presence of uncertainty information about external excitations and in the presence of changing reference signals. The robustness of control laws is achieved by the introduction of vector GA-fitness functions, one of which contains physical principle of minimum entropy production rate as in a control object and in a control system. Such approach allows us: (1) to design optimal intelligent control system with maximal level of reliability and controllability for complex dynamic systems in the presence of uncertainty in initial information [4]; (2) to decrease the number of sensors as in a control circuit channel and in a measuring system without loss of accuracy and quality of control [5]. The robust intelligent control system designed on the basis of such approach needs the minimum of initial information as about the behavior of controlled object and about external random excitations. Experimental results of effective fuzzy intelligent control of automotive semi-active suspension system based on SCO application are demonstrated. SCO tools are the background of a new high informational design technology of smart robust control systems.

7. REFERENCES

[1] L.V. Litvintseva and S.V. Ulyanov**, Artificial Intelligence applied to design of intelligent systems (a Soft Computing Approach), *Lectures Notes*,** Vol.38, Note del Polo (Ricerca), Universita degli Studi di Milano, 2000, 134p.

[2] S.V.Ulyanov, K.Yamafuji, V.S.Ulyanov, S.A. Panfilov, *et al.*, Computational intelligence for robust control algorithms of complex dynamic systems with minimum entropy production. Part1: Simulation of entropy-like dynamic behavior and Lyapunov stability, **J. of Advanced Computational Intelligence**, 1999, Vol.3, No.2, pp. 82-98; B.N. Petrov, G.M. Ulanov and S.V. Ulyanov, **Models of control processes: Information-thermodynamics approach**, Moscow, Sci. Publ, 1978; **Information-semantic problems in control and organization systems**, *ibid,* 1977.

[3] S. Sieniutycz, Hamilton-Jacobi-Bellman theory of dissipative thermal availability, **Phys. Rev**., 1997, Vol. 56E, No 5, pp. 5051-5064.

[4] **US** *Patent* N 6,411,944 B1, 1997, **Self-organizing control system** (*Inventor*: S.V.Ulyanov)

[5] **US***Patent* N 6,415,272 B1, 1998, **System for intelligent control based on soft computing** (*Inventor*: S.V. Ulyanov)

[6] S.A.Panfilov, L.V. Litvintseva, S.V. Ulyanov, K.Takahashi and A.V.Yazenin, The stochastic simulation system of robust fuzzy control of essentially non-linear dynamic systems based on soft computing, **Proc. ICAFS'2002**, Milan, Italy, September 17-18, 2002, pp. 69-80.

[7] 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.

[8] S.V. Ulyanov, K. Takahashi, S.A. Panfilov, L.V. Litvintseva, I.S. Ulyanov, I. Kurawaki, T. Hagiwara and A.V. Yazenin, Design of robust intelligent control systems based on soft and quantum computing: From 1965 with our teacher B.N. Petrov, In: **Proc. Conference on Control System Design** (**Dedicated to the memory of B.N. Petrov**), Moscow, 11 March, 2003, Sci. Publ., 2003, pp. 34-35.

[9] C.L.Karr, Design of an Adaptive Fuzzy Logic Controller Using a Genetic Algorithm, **Proc. of the 4th. Int'l Conf. on Genetic Algorithms**, 1992, pp. 450/457.

[10] T. Hashiyama, T. Furuhashi, Y. Uchikawa, Fuzzy Controllers for Semi-Active Suspension System Generated through Genetic Algorithms, **Proc. of IEEE Int'l Conf. Syst Man Cybern**, , Vol.95, No. 5, 1995, pp. 4361/4366.

[11] T. Hashiyama, T. Furuhashi, and Y. Uchikawa, On Finding Fuzzy Rules and Selecting Input Variables for Semi-Active Suspension Control Using Genetic Algorithm, **Proc. of 11th Fuzzy System Symposium**, 1995, pp. 225-228.

[12] D. Karnopp, et al., Vibration Control Using Semi-Active Force Generators, **ASME J. of Engineering for Industry**, Vol.96, No.2, 1974, pp. 619-626.

[13] T. Hagiwara, S.A. Panfilov, S.V. Ulyanov, K. Takahashi and O. Diamante, Application of smart control suspension system based on soft computing to a passenger car, **Yamaha Motor Technical Review** 2003-3, No.35.

[14] **US** *Patent* N 6,212,466, 2000, **Optimization control method for shock absorber** (*Inventors*: S.V. Ulyanov, T. Hagiwara)

[15] **US** *Patent* N 6,496,761, 2000, **Optimization control method for shock absorber** (*Inventors*: S.V. Ulyanov, T. Hagiwara)

[16] **US** *Patent* N 6,463,371, 1998, **System for intelligent control of the vehicle suspension based on soft computing** (*Inventors*: S.V. Ulyanov, T. Hagiwara)

[17] Adaptive Fuzzy Modeler (AFM), http://eu.st.com