Intelligent Control of Induction Motor Using Hybrid System GA-PSO

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Abstract: This paper focuses on intelligent control of induction motor by hybrid system consisting of GA-PSO. Induction motor has been using in industrial area. However, it is challengeable on how we control effectively. From this point, an optimal solution using GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) is introduced to intelligent control. In this case, it is possible to obtain local solution because chromosomes or individuals which have only a close affinity can convergent. To improve an optimal learning solution of control, This paper deal with applying PSO and Euclidian data distance to mutation procedure on GA's differentiation. Through this approaches, we can have global and local optimal solution together, and the faster and the exact optimal solution without any local solution. Four test functions are used for proof of this suggested algorithm.

Keywords: GA (Genetic Algorithm), PSO (Particle Swarm Optimization), Hybrid system, Optimal algorithm

1. INTRODUCTION

In the last decade, evolutionary based approaches have received the increasing attention of engineers dealing with problems not amenable to existing design theories. A typical task of a GA in one of artificial intelligence in this context is to find the best values of a predefined set of free parameters associated to either a process model or a control vector. One of an active area of research in GA is system identification.

The general problem of evolutionary based engineering system design has been tackled in various ways. GA has also been used to optimize nonlinear system strategies. Among them, a large amount of research focused on the design of fuzzy controllers using evolutionary approaches for knowledge about the controlled process in the form of linguistic rules and the fine tuning of fuzzy membership function is often necessary to reach satisfactory results.

Many efforts on the enhancement of traditional GAs have been proposed. Among them, one category focuses on modifying the structure of the population or the role an individual plays in it, such as distributed GA, cellular GA, and symbiotic GA. Another category aims to modify the basic operations, such as crossover or mutation, of traditional GAs.

In this paper, to improve an optimal learning solution of GA, we apply PSO and Euclidian data distance to mutation procedure on GA's differentiation. This research can have global and local optimal solution together and faster solution without any local solution through this approaches. We use four test functions for proof of this suggested algorithm.

2. EUCLIDIAN DISTANCE FOR GA-PSO

2.1 Overview of PSO

The PSO conducts searches using a population of particles which correspond to individuals in GA. A population of particles is randomly generated initially. Each particle represents a potential solution and has a position represented by a position vector. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a velocity vector. At each time step, a function representing a quality measure is calculated by using as input. Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector. Furthermore, the best position among all the particles obtained so far in the population is kept track as output. In addition to this global version, another local version of PSO keeps track of the best position among all the topological neighbors of a particle. At each time step, by using the individual best position, and global best position, a new velocity for particle is updated by (4) where and are positive constants and are uniformly distributed random numbers in [0, 1]. Changing velocity this way enables the particle to search around its individual best position, and global best position.

The computation of PSO is easy and adds only a slight computation load when it is incorporated into GA. Furthermore, the flexibility of PSO to control the balance between local and global exploration of the problem space helps to overcome premature convergence of elite strategy in GA, and also enhances searching ability.

This paper introduces the advantage of PSO to mutation procedure of GA, for improving of GA learning efficiency. Euclidian distance is used on crossover to avoids local optimal and obtain fast running time of solution. To do this, four test functions are used.

2.2 Euclidian Data distance

In GA or PSO, on procedure of individual differentiation, when we obtain optimal solution using GA, initial differentiated data is used to search optimal solution, since near data is only used, convergence time is fast but local optimization can be done. In this paper, data which has longest Euclidian distance on data set can dominantly affect crossover procedure to avoid this local optimization. That is, global optimization can be obtained by means of crossover on total data set.

$$F_1(x) = \sum_{i=1}^{3} x_i^2 \qquad (1)$$

Table 1 Initial condition for performance

Function	Definition		ID	IT
	$x_i^{(L)}$	$x_i^{(U)}$		
$F_1(x) = \sum_{i=1}^{2} x_i^2$	-5.12	5.11	60	100

Equation (1) is used to perform the Euclidian distance and initial condition for performance is on table 1. In table 1, ID and IT means the number of individuals, iteration, respectively. Figs. 1 and 2 illustrate relationship between objective function and generation by a GA. Figs. 1, 2 explain variation of objection function depending on generation.

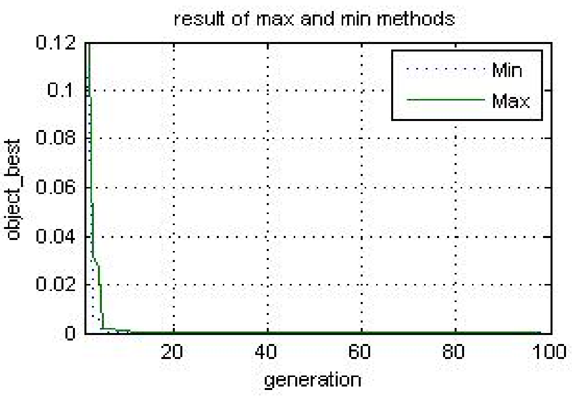

Fig. 1 Optimal value of objective function.

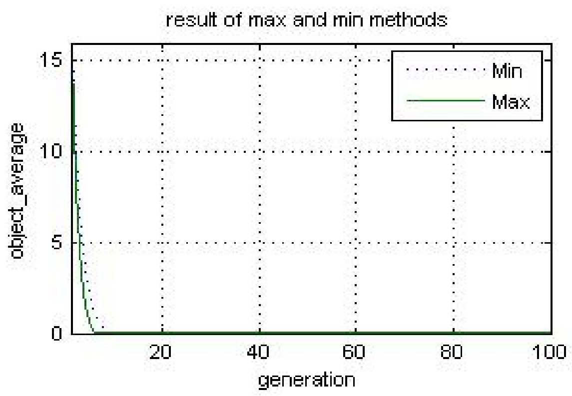

Fig. 2 Average value of objective function.

The bigger Euclidian distance the faster divergence time in optimal value of objective function but the smaller Euclidian distance the faster in the average value of objective function.

3. IMPROVEMENT OF OPTIMAL LEARNING OF GA USING EUCLIDIAN DISTANCE

3.1 Comparison of the conventional GA and the EUGA

In this paper, GA with Euclidian distance (EUGA) is introduced into process of crossover of GA and Euclidian distance is used as decision method for selection of parent individual of GA. Namely, parent's individuals with the longest Euclidian distance are selected in processing of crossover of GA.

In this method, because tall data can have an effect on searching optimal solution, we can avoid a local solution and it is possible to obtain the exact solution.

To see characteristics of optimal solution, this paper compared relationship between results by the conventional GA and results by the proposed approach (EUGA). Selection methods of dada set is used equation as

$$A(x_1, y_1) \oplus B(x_1, y_1) \Rightarrow A', B'\left(x_1'\Big|_{\min(x_1,y_1)}^{\max(x_1,y_1)}, y_1'\Big|_{\min(x_1,y_1)}^{\max(x_1,y_1)}\right) \quad (2)$$

For this performance comparison, the Himmelblau function is used as test equation:

$$F(x) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 \quad (3)$$

Contour phase of Fig. 3 is displaying that there is optimal solution in only one place and optimal solution is obtained at 200 generators. Contour graph of Fig. 4 obtained by the proposed GA based on Euclidian distance shows there is optimal solution in both place (local place and total place) and its solution is obtained at 50 generators completely.

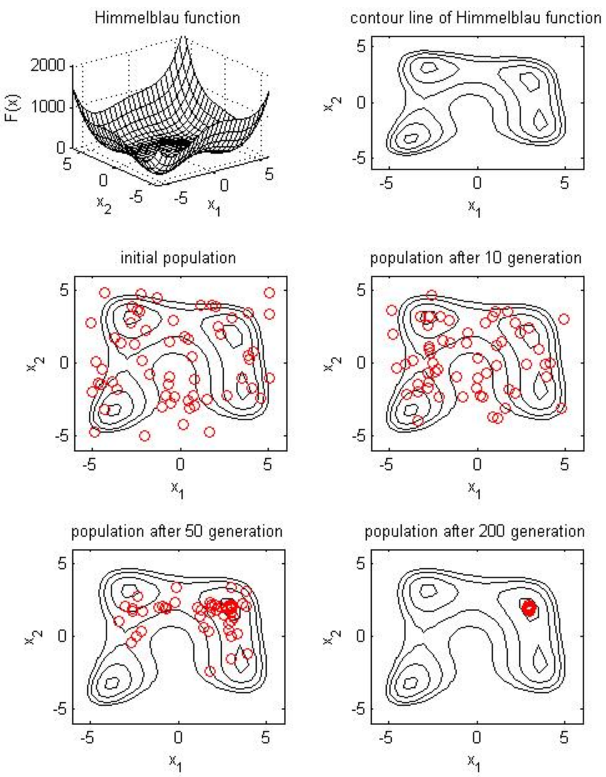

Fig. 3 Contour of optimal procedure by GA.

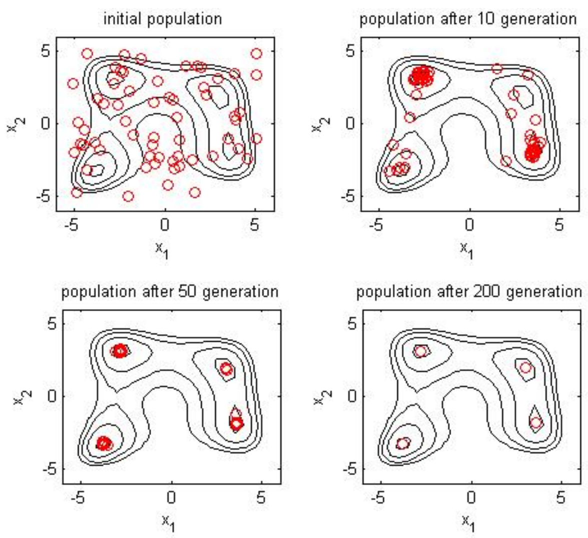

Fig. 4 Contour of GA obtained by Euclidian distance.

3.2 Improvement of GA by PSO and Euclidian distance

The characteristic by mutation of GA in PSO or hybrid system of PSO and GA have been studied for speed up of running time to optimal solution. [3-5] In this paper, position and speed vector of PSO is given by

$$
\begin{aligned}
v_{j,g}^{(t+1)} &= w \cdot v_j^{(t)} + c_1^* rand()^* \left(pbest_{j,g} - k_{j,g}^{(t)}\right) \\
&\quad + c_2^* Rand()^* \left(gbest_g - k_{j,g}^{(t)}\right) \\
& j = 1,2,\ldots,n. \\
& g = 1,2,\ldots,m. \\
k_{j,g}^{(t+1)} &= k_{j,g}^{(t)} + v_{j,g}^{(t+1)}, \quad k_g^{\min} \le k_{j,g}^{(t+1)} \le k_g^{\max}
\end{aligned} \tag{4}
$$

n : The number of agent in each group

m : The number of member in each group

t : Number of reproduction step

$v_{j,g}^{(t)}$: The speed vector of agent j in reproduction step of t^{th}. $V_g^{\min} \le v_{j,g}^{(t)} \le V_g^{\max}$

$k_{j,g}^{(t)}$: The position vector of agent j in reproduction step of t^{th}.

w : Weighting factor

$c1, c2$: Acceleration constant

$rand(), Rand()$: Random value between 0 and 1

$pbest_j$: Optimal position vector of agent j

$gbest$: Optimal position vector of group

The value of position vector and speed vector is determined by acceleration constant $c1, c2$. If these values are large, each agent moves to target position with high speed and abrupt variation. If vice versa, agents wander about target place. As weighting factor w is for the searching balance of agent, the value for optimal searching is given by

$$
w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter, \tag{5}
$$

where $w_{\max}$: max mum value of w (0.9),

$w_{\min}$: minimum value of w (0.4),

$iter_{\max}$: the number of iterative number

$iter$: the number of iterative at present.

The speed vector is limited by $V_g^{\min} \le v_{j,g}^{(t)} \le V_g^{\max}$. In this paper, the value of speed vector for each agent is limited with 1/2 to avoid abrupt variation of position vector. Calculation procedure for each step is as the following step

[Step1] Initialize each variables of GA.

[Step 2] Initialize each variables of PSO.

[Step 3] Calculate affinity of each agent for condition of optimal solution of GA. At this point, optimal position condition of PSO is introduced into GA.

[Step 4] Arrange the group of PSO.

[Step 5] Update position vector $pbest$ and speed vector $gbest$.

[Step 6] Operate crossover in GA using Euclidian distance and position vector PSO.

[Step 7] Operate mutation in GA.

[Step 8] If condition of GA is satisfied with target condition (iterative No. or target value), reproduction procedure stop. Otherwise, it go to step 3.

4. SIMULATION AND RESULTS

4.1 The characteristics of Differentiation Rate of PSO

To prove the learning structure suggested in this paper, function $F(x) = \sum_{i=1}^{2} x_i^2$ is used as performance function.

4.2 Variation to Differentiation Rate of Agent

In this paper, differentiation procedure of only PSO is simulated to study the characteristics of differentiation of PSO on GA as shown in Fig. 5. Fig. 5 is showing when the number of individuals 60, reproduction times is 30, differentiation rate is 5, 10, 20, and 30 on PSO, respectively.

The differentiation rate is smaller, the convergent speed is faster but at final step, the differentiation rate is larger, the convergent speed is faster. Namely, since the larger in one group the more variety information is collected and the faster optimal solution is obtained.

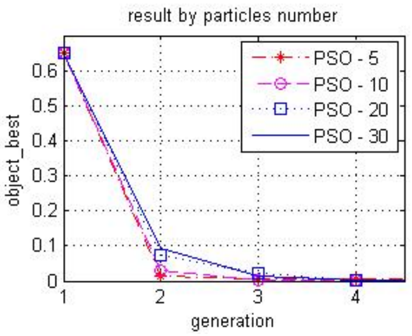

Fig. 5 Relationship between objective function and generation in PSO.

4.3 Comparison of characteristic of the combined GA and PSO

This section represents the characteristic of the combined system which introduced Euclidian distance and PSO to GA. Differentiation rate for comparing the characteristic in this section is 10. At first step, the conventional GA is higher convergent speed but at final step, GA-PSO is more stable speed because GA-PSO search for optimal solution with having position and direction for search. In table 2, No. of IDs; the number of individuals, No. of Re; the number of reproduction; Rate of DF; the rate of differentiation.

Table 2 The comparison of combined system (GA+PSO)

	x_1 (1.0e-006)	x_2 (1.0e-006)	The value of optimal objective function	The value of average objective function
GA - PSO	0.0325	0.0197	1.4408e-015	0.0700
GA	-0.2249	0.2585	1.1741e-013	0.1962

4.4 The characteristic of parameter selection of GA

In GA, in order to transfer gene information of parents or grandfather to offsprings effectively, differentiation is carried out through crossover, reproduction, and mutation.

That is, RemSel (Remainder stochastic Sample with replacement Selection), UnivSel (stochastic Universal sampling Selection), and RwSel(Roulette wheel Selection) have been performed. This paper compare and discuss the characteristics of the conventional GA and the proposed combined system (GA-PSO) to variation of operator mentioned in the above. The results are shown in Fig. 6-9 and initial condition of test function is Table 3.

1) The characteristic by Test function $F_1 = \sum_{1}^{2} x_i^2$:

This section applies function F_1 to the conventional GA and the combined system (GA-PSO) and discusses minimization procedure. Fig. 6 is showing the conventional

Table 3 Search space of test functions and initial conditions.

Function	Definition $x_i^{(L)}$	Definition $x_i^{(U)}$	No. of IDs	No. of Re	Rate of DF
$F_1(x) = \sum_{i=1}^{2} x_i^2$	-5.12	5.11	60	100	10
$F_2(x) = 100(x_2^1 - x_2)^2 + (1-x_1)^2$	-2.048	2.047			
$F_3(x) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$	-6	6			
$F_4(x) = (0.002 + \sum_{j=1}^{25} (j + \sum_{i=1}^{2} (x_i - a_{ij})^6)^{-1})^{-1}$	-65.536	65.535			

method still spreads at 5 generators but the proposed method has optimal solution well.

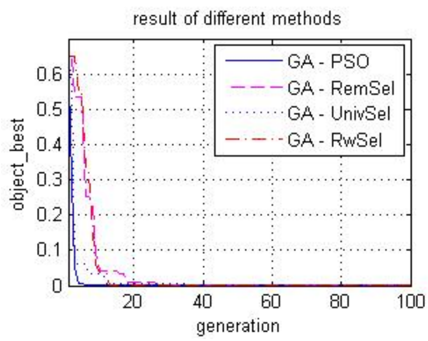

Fig. 6 Test function $F_1 = \sum_{1}^{2} x_i^2$

Table 4 Comparison of $F_1(x)$.

	x_1 (1.0e-005)	x_2 (1.0e-005)	Optimal value of objective function	Average value of objective function (1.0e-009)

4

GA - PSO	-0.0001	-0.0001	2.0656e-018	3.7940e-014
GA - RemSel	-0.8788	-0.0064	7.7228e-011	3.3378e-008
GA - UnivSel	-0.3056	0.1973	1.0706e-010	2.2349e-008
GA - RwSel	0.3535	-0.9724	1.3233e-011	5.3544e-008

2) Minimum Value to Rosenbrock function $F_2(x) = 100(x_1^2 - x_2)^2 + (1 - x_1)^2$: Fig. 7 is showing optimal procedure to Rosenbrock function. GA-PSO is the faster speed in searching optimal solution.

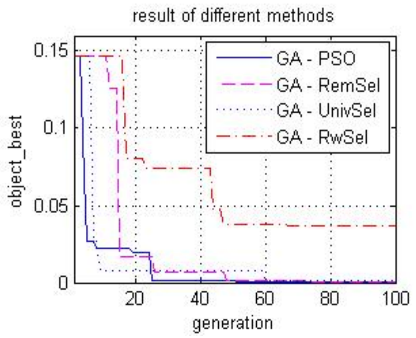

Fig. 7 Optimal procedure to generation of function Roenbrock.

Table 5 Comparison of $F_2(x)$.

	x_1	x_2	Optimal value of objective function	Average value of objective function
GA - PSO	1.0026	1.0052	6.7405e-006	2.0807
GA - RemSel	0.9720	0.9447	7.8523e-004	3.0355
GA - UnivSel	0.9612	0.9243	0.0015	5.4145
GA - RwSel	0.8084	0.6540	0.0367	1.2021

3) Function Himmelblau F_3: Fig. 8 shows how the proposed method has the characteristics based on Himmelblau function $F_3(x) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$. The GA-PSO is showing better optimal procedure at 5 generations. On the other hand, at 50 generations, GA-PSO represents both optimal solutions (local optimal and global optimal) but it is showing that it is possible to have a local optimal solution because the conventional method has optimal solution on only site. The speed of convergence is well showing in Fig. 8.

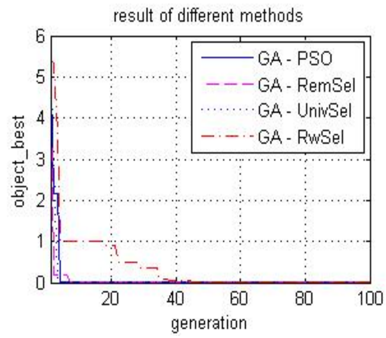

Fig. 8 Himmlbla function.

Table 6 Comparison to function $F_3(x)$.

	x_1	x_2	Optimal value of objective function (1.0e-005)	Average value of objective function
GA - PSO	3.5844	-1.8481	0.0002	0.0285
GA - RemSel	3.0000	2.0000	0.0003	1.1161e-005
GA - UnivSel	2.9998	2.0002	0.1121	2.1361e-005
GA - RwSel	3.0000	2.0000	0.0003	1.0902e-005

4) The results of Test Function F_4 :

In this section, test function, Fox hole $F_4 = \left(0.002 + \sum_{j=1}^{25}\left(j + \sum_{i=1}^{2}(x_i - a_{ij})^6\right)^{-1}\right)^{-1}$ is applied to the proposed system.

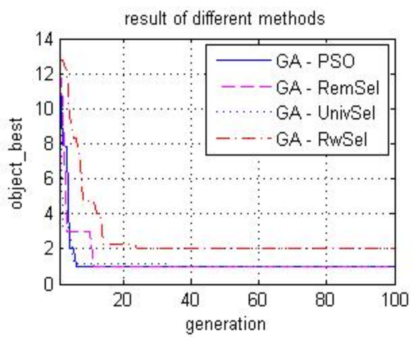

Fig. 9 Foxhole.

Table7 The results to function $F_4(x)$.

5

	x_1	x_2	Optimal value of objective function (1.0e-005)	Average value of objective function
GA - PSO	-31.9783	-31.9783	0.9980	0.9980
GA - RemSel	-31.9764	-31.9833	0.9980	0.9980
GA - UnivSel	-31.9788	-31.9790	0.9980	0.9980
GA - RwSel	-15.9861	-31.9702	1.9920	1.9920

5. CONCLUSION

Generally, the GA uses three basic operators (reproduction, crossover, and mutation) to manipulate the genetic composition of a population. Reproduction is a process by which the most highly rated individuals in the current generation are reproduced in the new generation. The crossover operator produces two offsprings (new candidate solutions) by recombining the information from two parents.

In this paper, GA Euclidian based distance conception and PSO are introduced into enhancement of optimal learning of the conventional. By Euclidian distance, total data set can have an effect on mutation or crossover of GA. Therefore, GA can provide for the exact optimal solution, while it can avoid local optimal.

On the other hand, this paper deals with applying PSO (Particle Swarm Optimization) to have a faster convergence. A candidate solution for a specific problem in GA is called an individual or a chromosome and consists of a linear list of genes. Each individual represents a point in the search space, and hence a possible solution to the problem. A population consists of a finite number of individuals. Each individual is decided by an evaluating mechanism to obtain its fitness value. Based on this fitness value and undergoing GA-PSO operators with Euclidian distance, a new population is generated iteratively with each successive population referred to as a generation. In case of PSO, it can have the faster convergence and function to limit data. The GA-PSO system proposed in this paper can have a superiously optimal solution function to local optimal and total optimal method.

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