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Hardware Implementation of an AIS-Based Optimal Excitation Controller for an Electric Ship

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Abstract - **The operation of high energy loads on Navy's future electric ships, such as directed energy weapons, will cause disturbances in the main bus voltage and impact the operation of the rest of the power system when the pulsed loads are directly powered from the main dc bus. This paper describes an online design and laboratory hardware implementation of an optimal excitation controller using an artificial immune system (AIS) based algorithm. The AIS algorithm, a clonal selection algorithm (CSA), is used to minimize the effects of pulsed loads by improved excitation control and thus, reduce the requirement on energy storage device capacity. The CSA is implemented on the MSK2812 DSP hardware platform. A comparison of CSA and the particle swarm optimization (PSO) algorithm is presented. Hardware measurement results show that the CSA optimized excitation controller provides effective control of a generator's terminal voltage during pulsed loads, restoring and stabilizing it quickly.**

Index Terms - **Clonal selection algorithm (CSA), Electric ship, optimal excitation controller, particle swarm optimization (PSO), pulsed loads.**

I. Introduction

The Navy's future electric ship power system is based on the integrated power system (IPS) architecture consisting of power generation, propulsion systems, hydrodynamics, and DC zonal electric distribution system (DC-ZEDS) [1]. In order to maintain power quality in IPS, immediate energy storage devices with their corresponding charging systems are proposed to make the pulsed power required compatible with the supply system [16]. However, this will increase the system weight and volume. To some extent, the generator field excitation control can be used along with energy storage to maintain the system voltage. The excitation control is one of the most effective and economical techniques for stabilizing the terminal voltage of the synchronous generators [17]. Excitation control elements mainly include an automatic voltage regulator (AVR) which senses and maintains the terminal voltage of the generator and a power system stabilizer (PSS) which provides the required auxiliary control signal to improve the dynamic performance. The key element in the design of the optimal excitation controller is finding the controller parameters (gain and time constants) to provide optimal performance during normal and pulsed loads. In order to optimize these parameters, many intelligent algorithms are extended to the design of the optimal excitation controller for the synchronous generator including fuzzy set theory [2, 3], finite-time approach [4], adaptive control theory [5, 6] and PSO [7], all of which have good performance at maintaining the terminal voltage. However, none have been implemented online for electrical machine excitation system. Therefore, the online hardware implementation is needed to show the stability and adaptability of the proposed algorithms.

Artificial immune system (AIS) can be defined as computational systems that are inspired by theoretical immunology. Clonal selection algorithm (CSA) is a member of the family of AIS techniques. In the past few years, CSA has been gradually used to solve the optimal control problems [16]-[18]. In this paper, an online CSA-based optimal excitation controller for the electric ship is implemented on the MSK2812 DSP hardware platform to minimize the voltage deviations when high power pulsed loads are directly powered from the dc side; exploring the possibility of reduced energy storage. The hardware results show that the on-line CSA-based controller improves the dynamic performance of the synchronous generator with stability and adaptability.

This paper is organized as follows: Section II provides a power system model for the electric ship and a description of its hardware implementation. Section III provides a detailed description of the DSP based hardware implementation of a CSA-based optimal excitation controller. Section IV presents the experimental results and finally, the conclusion is given in section V.

II. Power System Model For The Electric Ship And Its Hardware Implementation

A. IPS for the Electric Ship

The power system of the all-electric ship system mainly consists of four parts: prime movers, advanced propulsion induction motors, dc zonal distribution loads, and other auxiliary loads which are shown in Fig. 1 (a). All prime mover power is first converted into electric power, and then it is distributed and allocated between propulsion, pulsed power

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weapons, ship service power and other electrical loads as required. In the laboratory setup, these four parts are separately implemented.

B. Laboratory Setup: Power Generation

The DDG-1000 proposed electric ship power system architecture consists of four gas turbine-generator sets. Two main 36MW and two auxiliary 4MW generator sets, generate a total of 80MW of electric power [11]. In the laboratory setup (Fig. 1 (b)), a small-scale power generation system is used to emulate the gas turbine-generator sets of the electric ship. This small-scale system consists a three-phase 60Hz 5kVA synchronous generator and a 15kW dc motor to supply mechanical torque for the synchronous generator. The command line-to-line voltage of the generator is set to 180V. The parameters for the synchronous generator are shown in the Table I. Since the propulsion load and pulsed loads are proportionally reduced, the proposed system is a scaled down laboratory implementation of the IPS in an electric ship.

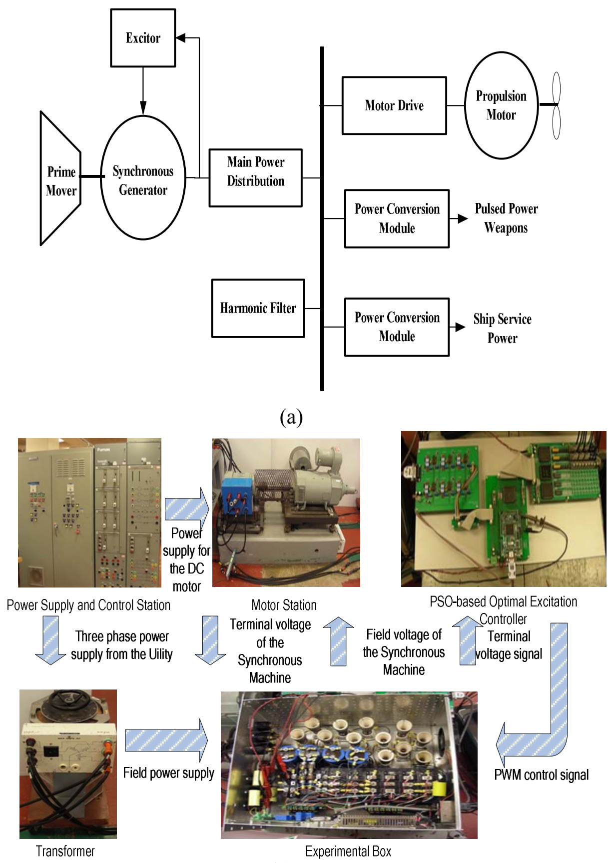


Fig. 1. Laboratory implementation with (a) simplified IPS of an electric ship and (b) laboratory hardware implementation.

C. Laboratory Setup: Propulsion System

In the notional electric ship, a propulsion system consists of a transformer, a rectifier, an inverter, and a propulsion motor [11]. In the laboratory setup, a 1.62kW resistive load in the dc side is used to simulate the load impact of the propulsion motors on the IPS.

TABLE I
PARAMETERS OF SYNCHRONOUS MACHINE

Horsepower	3.00	L_{ls}	1.12e-3H
GEN	2.5KVA	L_{mq}	24.9e-3H
Armature Voltage	230V	L_{md}	39.3e-3H
Field Voltage	150VMAX	R_{kq1}	5.07 Ω
Full Load Amps of Armature	6.28A	L_{kq1}	4.21e-3H
Full Load Amps Field	1.05A	r_{kq2}	1.06 Ω
RPM	1800	L_{kq2}	3.5e-3H
POLES	4	r_{kq3}	0.447 Ω
r_{kd1}	128.25 Ω	L_{kq3}	26.2e-3H
L_{kd1}	7.902e-3H	r_{kd2}	1.77e3 Ω
r_{fd}	0.11 Ω	L_{kd2}	4.828e-3H
L_{fd}	1.497e-3H	r_s	0.382 Ω

D. Laboratory Setup: DC Zone Distribution Load

In the electric ship, there are many different pulsed loads of various energy levels and variable durations [12]. In the laboratory setup, a diode rectifier is used along with a passive filter to realize the power conversion model and three IGBT-controlled resistive loads are used to represent three different energy-level loads on the dc side (1.62kW, 3.24kW, 3.24kW). By switching on different IGBTs over time the effects of a time varying power profile which represent the pulse power consuming load can be studied [1]. Compared with the pulsed loads, the impact of other auxiliary load to the IPS can be neglected.

E. Laboratory Setup: Excitation System

In the laboratory setup, the excitation controller consists of a sensor board, an A/D conversion board, a MSK2812 DSP board consisting of the TMS320F2812 processor, and a D/A conversion board. The A/D conversion board receives terminal voltage signal form the sensor board and output digital signal to the central controller. The D/A conversion board receives the PWM signals from the central controller and outputs them to the IGBTs. The field of the synchronous generator is connected with a four-quadrant PWM dc drive supplied by 200-V dc.

III. IMPLEMENTATION OF AN ONLINE CSA BASED OPTIMAL EXCITATION CONTROLLER

A. Excitation System

The synchronous generator excitation system includes a terminal voltage transducer and load compensator, excitation control elements and an exciter [11]. Since the proposed excitation system is simplified, some parts such as power system stabilizer and under-excitation limiter are not considered. A simple functional block diagram for excitation controller is shown in Fig. 2.

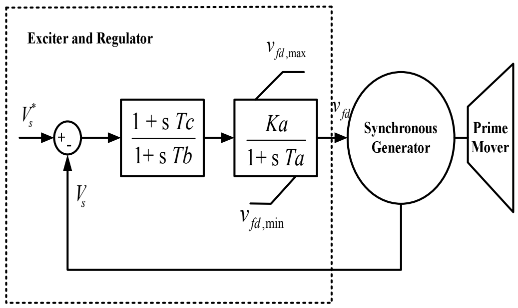


Fig. 2. Simple functional block diagram for synchronous machine excitation control system.

In this case, the key element in the design of the optimal excitation controller is finding the optimal controller parameters (K_a, T_a, T_b and T_c) to provide optimal performance during the pulsed loads. As is shown in Fig. 2, V_s^* is the rms terminal voltage reference of the synchronous generator which is set to be 180V and V_s is the measured value. The rms line-to-neutral terminal voltage is calculated in terms of instantaneous quantities using

$$V_s = \frac{\sqrt{v_{as}^{\ 2} + v_{bs}^{\ 2} + v_{cs}^{\ 2}}}{\sqrt{3}} \tag{1}$$

B. Clonal Selection Algorithm and its Application to Optimal Excitation Controller

The clonal selection algorithm is a biologically motivated computational intelligent algorithm developed by Castro and Zuben in 2001 [19]. The clonal selection principal based immune response generated when a non-self antigenic pattern is recognized by the B cells (antibodies) is explained in [19]. Just like the GA, the CSA is shown to be an evolutionary strategy capable of solving complex machine learning and pattern recognition tasks by adopting the clonal operator and also the problem of global optimization with high convergence speed, emphasizing multimodal and combinatorial optimization [17]. The detailed operation of CSA in optimization is shown in Fig. 3 and explained briefly below..

Initialization: Randomly choose a population N of antibodies (Ab). Since there is no explicit antigen population (Ag) to be recognized, the objective function is to be optimized as the Ag. In the laboratory setup, N is set to be 20.

Evaluation: In the excitation control loop of Fig. 2, the proportional gain K_a and time constants T_a, T_b and T_c have to be carefully selected to provide satisfactory performance under normal and pulsed load conditions. The objective of the CSA algorithm is to find these parameters in order to restore and stabilize the terminal voltage quickly especially after pulsed loads of different magnitudes and durations. In the laboratory setup, a sampling period of 2ms is used and total sampling points are 500. The performance of the optimal excitation controller in the design stage is evaluated by the objective function given in (2).

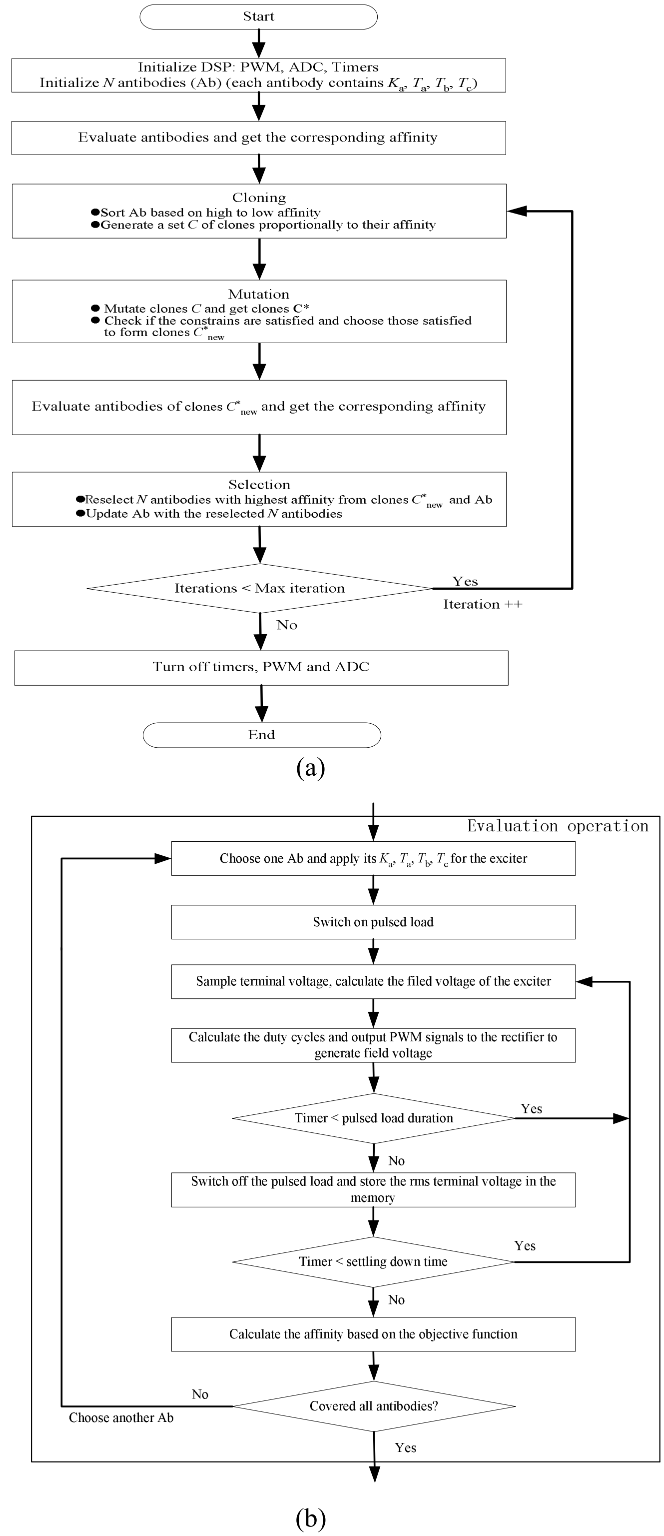


Fig. 3. Flowchart of the CSA-based optimal excitation controller design with (a) Main Flowchart and (b) Flowchart of Evaluation Operation

$$Fitness = \frac{1}{2}\sum_{i=1}^{500}\left\{\left[V_s^* - V_s(i)\right]^2 + \left[V_s^* - V_s(i+1)\right]^2\right\}(i\Delta t)\Delta t \tag{2}$$

Where i = the number of sampling points

t_s = the settling time of the terminal voltage

Δt = the sample time

$i\Delta t$ = the weighting factor which aims to punish disturbance while time varying.

The affinity could be evaluated by using the following equation:

$$Affinity_i = \frac{1}{1 + Fitness_i} \quad (3)$$

Where i = the number of antibodies with the range of 1~20

$Fitness_i$ = the fitness of the i antibody

Cloning: Sort all antibodies based on high to low affinity. Generate a set C of clones proportionally to the affinity. The number of clones generated is described by the equation

$$N_c = \sum_{i=1}^{n} \text{round}\left(\frac{\beta * N}{i}\right) \quad (4)$$

Where β = multiplying factor and is taken to be 0.5

i = 1 for highest affinity and 2 for second highest affinity.

n = the number of selected highest antibodies and is taken to be 5

Mutation: The mutation rate is proportional to the individuals' affinities described in (5)

$$\alpha = \exp\left(-\rho * f\right) \quad (5)$$

Where α = mutation rate

ρ = decay factor of the mutation rate

f = antigenic affinity

The antigenic affinity and mutation rate are both normalized over the interval [0, 1].

The process of mutation uses (6) developed in [18]

$$C^* = C * \alpha * randn * C + \alpha * randn * \left(C - Ab_{best}\right) \quad (6)$$

Where C^* = the matured clones

Ab_{best} = the antibody with highest affinity

In the laboratory setup, the stability constraints for K_a, T_a, T_b, T_c were determined by testing the synchronous generator manually. Choose the antibodies that satisfy the constraints in set C^* to generate a set C^*_{new} .

Selection: reselect N antibodies with highest affinity from clones C^* and C^*_{new} and update Ab.

The detailed training process for each Ab in one iteration is shown in Fig. 4.

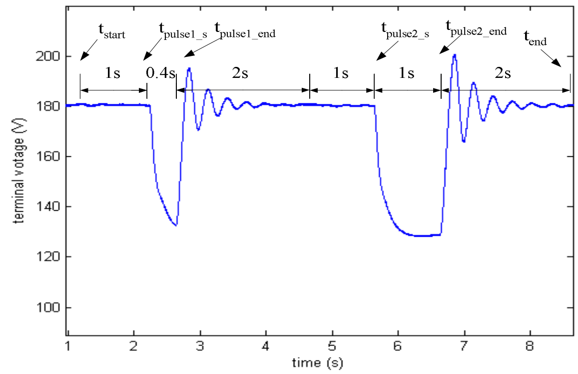


Fig. 4. Evaluation process using two different pulsed loads

As is shown in Fig. 4, t_{start} and t_{end} are the starting and end times of the evaluation process respectively; t_{pulse1_s} and t_{pulse1_s} are the starting and end times of the first pulsed load respectively, which is of duration 0.4s; t_{pulse2_s} and t_{pulse2_s} are the starting and end times of the second pulsed load respectively, which is of duration 1s. A settling time of 1s and a 2 s is allowed before and after each pulsed load respectively. Thus, the total time for evaluating each Ab evaluating per iteration is 7.4s. The pulsed load magnitudes and duration used in controller development and testing are shown in Table II.

TABLE II

PULSED LOAD TRAINING AND TESTING SETS

Pulsed load \ Duration	100 ms	200 ms	400 ms	1000 ms
1.62 kW	Test	Test	Test	Test
3.24 kW	Test	Test	Test	Train
4.86 kW	Test	Test	Train	
8.10 kW	Test	Test		

IV. HARDWARE RESULTS

The CSA has been implemented on a MSK2812 DSP hardware platform. A comparison of CSA and particle swarm optimization (PSO) is carried out for the online excitation controller design. The comparison is made under the following conditions: same value and dimension of initialized particles or antibodies, same training iterations and constrain conditions. Thus, the influence introduced by the randomly initialization is minimized.

A. Time Consuming

Both CSA and PSO are implemented on the hardware platform. The computational time taken by CSA and PSO is presented in Table III.

TABLE III
PARAMETERS OF SYNCHRONOUS MACHINE

	PSO	CSA
Code time for each particle/Ab (one iteration/genertion)	0.022s	0.064s
Evaluation time for each particle/ Ab (one iteration/generation)	7.4s	7.4s
Search time for each particle/Ab (one iteration/generation)	7.422s	7.464s
Total development time (10 iterations/generations, 20 particles/antibodies)	24minutes & 44s	24minutes & 53s

As shown in Table III, the code time of CSA for each antibody per generation is nearly three times of the code time of PSO for each particle per iteration. However, for this application, comparing the total development time between CSA and PSO, the difference is negligible.

B. *Convergence Characteristics*

The convergence of the PSO algorithm during the search is shown in Fig. 5. The comparative performance of a manually designed and CSA designed excitation controllers are shown in Figs. 6 to 9 respectively. The parameters of excitation controller designed using PSO and CSA optimal strategies are given in Table IV. The initially designed controller is tuned manually. The comparative performance of the excitation controllers under pulsed loads (including search and test sets) is shown in Table V.

TABLE IV
PARAMETERS OF THE EXCITATION CONTROLLERS

	K_a	T_a	T_b	T_c
Initial	4000.000	0.300	0.001	0.001
PSO	4051.000	0.279	0.174	0.928
CSA	4329.000	0.395	0.621	0.108

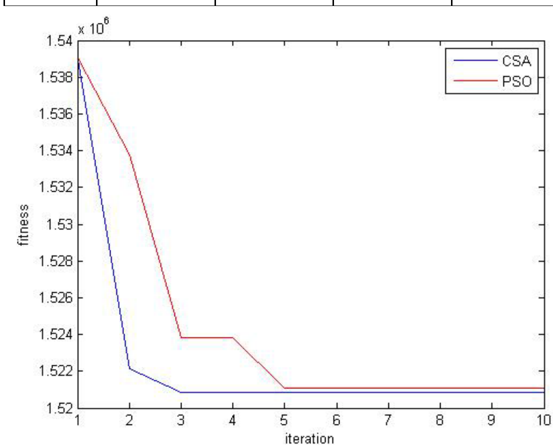
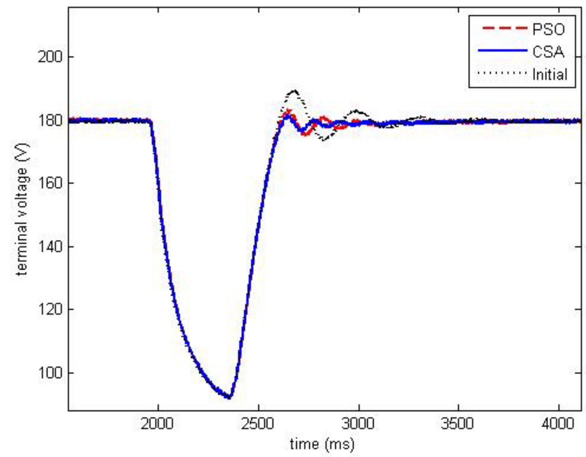


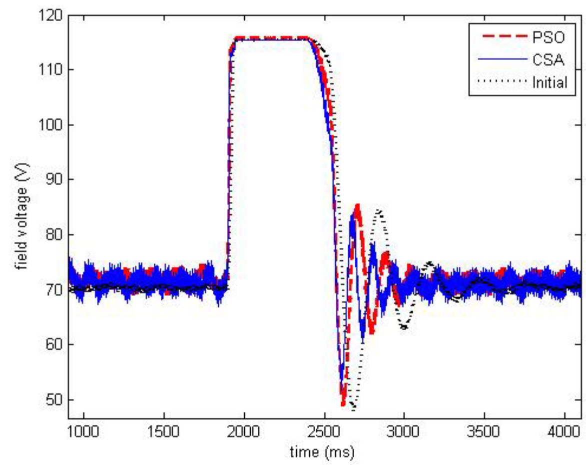
Fig. 5. Fitness variations with PSO and CSA algorithms in the first 50 iterations of the controller developments.

TABLE V
COMPARATIVE PERFORMANCE OF THE EXCITATION CONTROLLERS

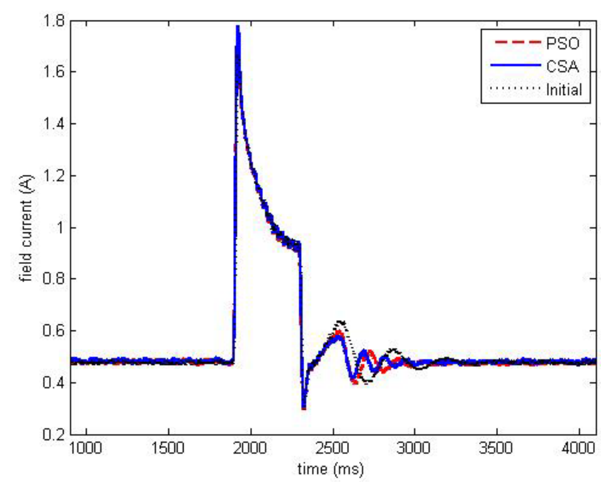
		Setting Time ts (s)	Maximum Overshoot (%)
Pulsed load 1.62kW for 1s	CSA	0.36	1.33
	PSO	0.44	2.69
	Initial	0.98	5.58
Pulsed load 1.62kW for 0.4s	CSA	0.36	1.27
	PSO	0.60	2.83
	Initial	1.00	5.56
Pulsed load 1.62kW for 0.2s	CSA	0.39	1.75
	PSO	0.59	2.86
	Initial	0.99	5.72
Pulsed load 1.62kW for 0.1s	CSA	0.41	1.52
	PSO	0.54	2.32
	Initial	0.89	5.21
Pulsed load 3.24kW for 1s	CSA	0.49	0.67
	PSO	0.56	1.69
	Initial	0.82	5.28
Pulsed load 3.24kW for 0.4s	CSA	0.47	1.25
	PSO	0.50	2.25
	Initial	1.07	5.39
Pulsed load 3.24kW for 0.2s	CSA	0.35	1.50
	PSO	0.51	2.56
	Initial	0.89	5.28
Pulsed load 3.24kW for 0.1s	CSA	0.50	1.72
	PSO	0.54	2.75
	Initial	1.04	5.50
Pulsed load 4.86kW for 0.4s	CSA	0.49	1.00
	PSO	0.59	1.94
	Initial	0.94	5.44
Pulsed load 4.86kW for 0.1s	CSA	0.49	1.61
	PSO	0.56	2.67
	Initial	1.06	5.50
Pulsed load 4.86kW for 0.2s	CSA	0.45	1.67
	PSO	0.59	2.83
	Initial	0.96	5.56
Pulsed load 8.10kW for 0.2s	CSA	0.34	1.68
	PSO	0.50	3.13
	Initial	0.98	5.75
Pulsed load 8.10kW for 0.1s	CSA	0.50	1.39
	PSO	0.62	2.59
	Initial	1.12	5.42



(a)

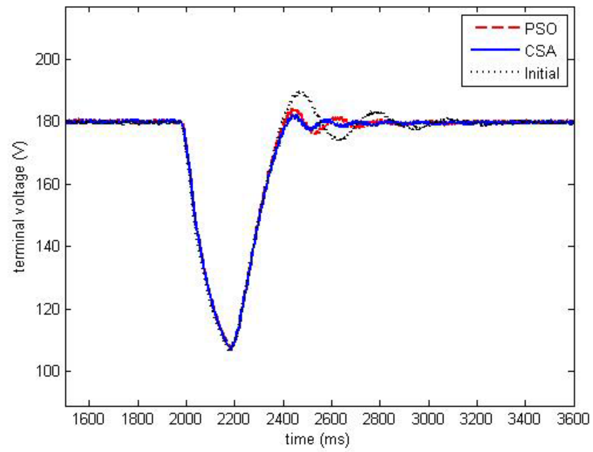


(b)

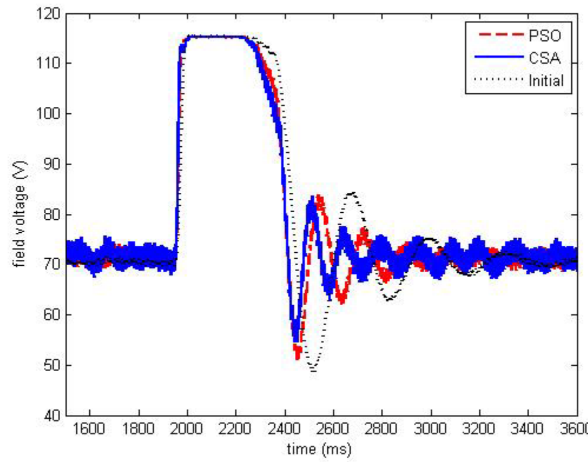


(c)

Fig. 6. Pulsed load at 4.86kW with 0.4s duration
(a) terminal voltage, (b) field voltage, (c) field current.



(a)



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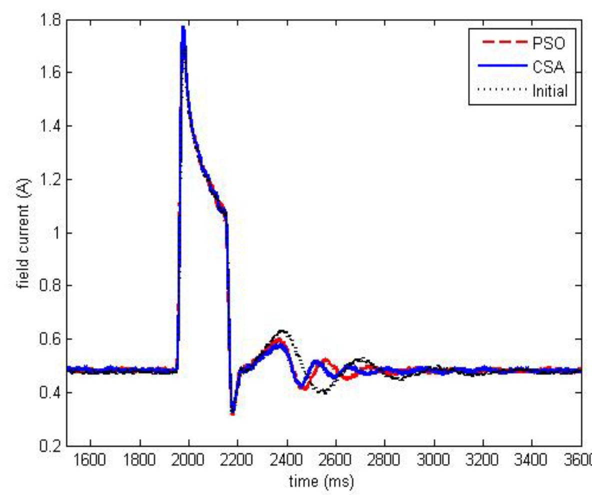
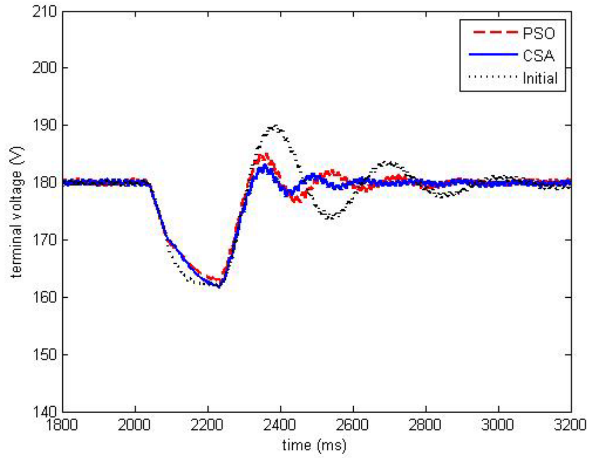
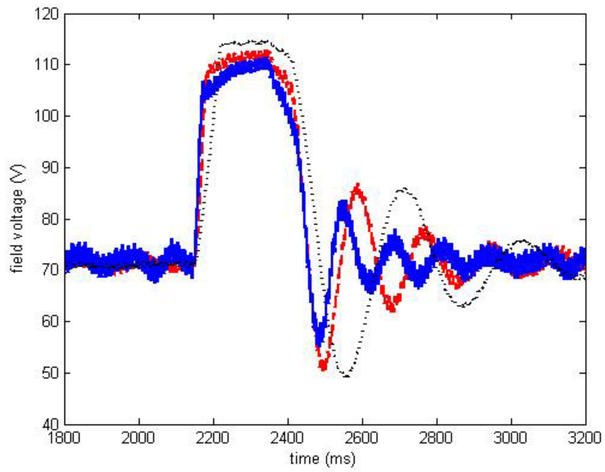


(c)

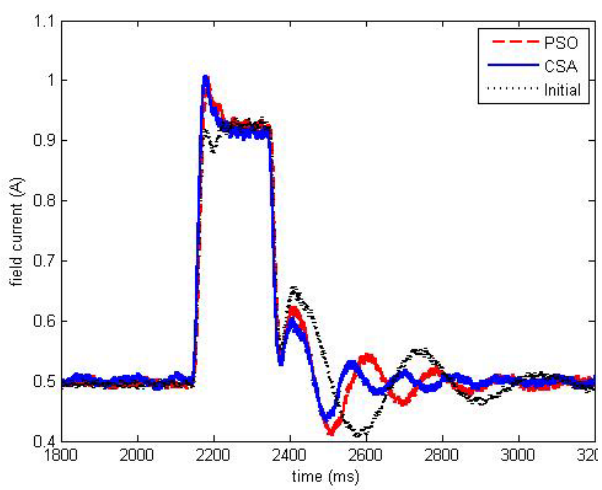
Fig. 7. Pulsed load at 4.86kW with 0.2s duration
(a) terminal voltage, (b) field voltage, (c) field current.



(a)

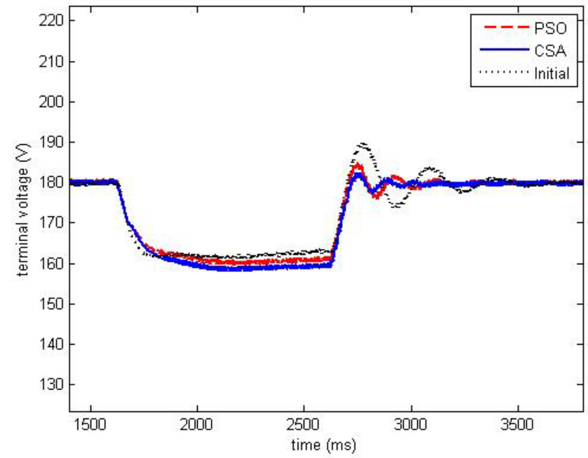


(b)

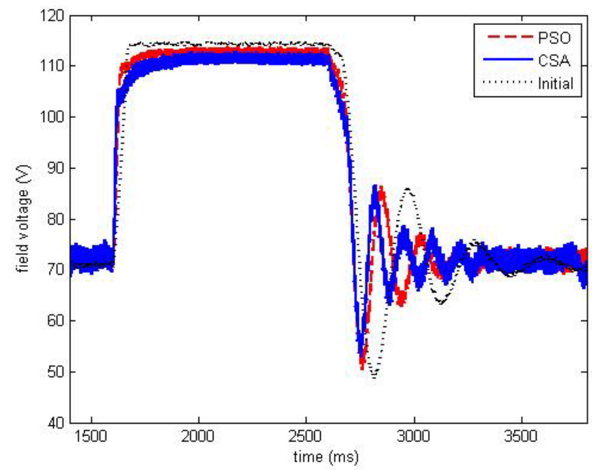


(c)

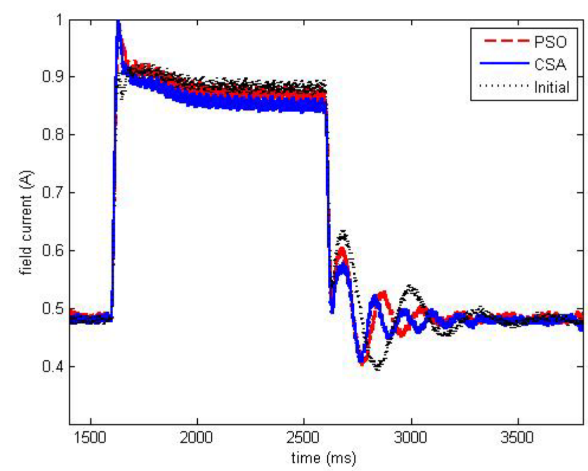
Fig. 8. Pulsed load at 1.62kW with 0.2s duration
(a) terminal voltage, (b) field voltage, (c) field current.



(a)



(b)



(c)

Fig. 9. Pulsed load at 3.24kW with 1s duration
(a) terminal voltage, (b) field voltage, (c) field current.

C. System Disturbance

Since all antibodies or particles are randomly initialized in the searching space, CSA and PSO have different strategies to converge them. CSA discards antibodies with lower affinity and only clone those with highest one. PSO involves global best and local best to guide the convergence of all particles. A comparison of the worst antibody/particle after 2 iterations of search is shown in Fig. 10.

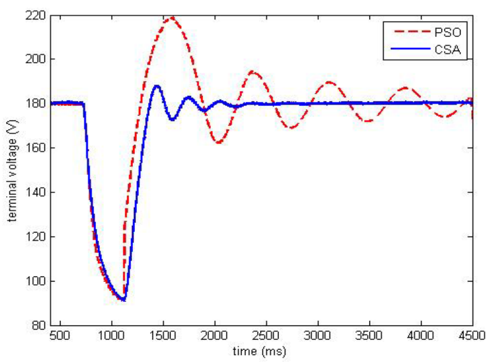


Fig 10. Performance comparison of the worst antibody in CSA and the worst particle in PSO after the second iteration of the search process.

As is shown in Fig. 10, after the second iteration, the worst antibody in CSA has a better performance than the worst particle in PSO which means lesser disturbance to the system during the search process. A general comparison of CSA and PSO algorithms is given in Table VI.

TABLE VI
A GENERAL COMPARISON OF CSA AND PSO ALGORITHMS

	PSO	CSA
Computational complexity	Small, mainly "+, -, × operation"	Large, contains "sorting, round, exponential, and division operation"
Storage space	Small, mainly "particles position and velocity"	Medium, "antibody, affinity, new group of antibody and affinity"
System disturbance	Large, the bad particles survive and converge in the whole searching process gradually	Small, bad antibody will be replaced with the clones of good antibody
Computational time	Medium	Medium

V. CONCLUSION

An online designed optimal excitation controller using a clonal selection algorithm, from artificial immune systems, has been presented in this paper. The controller and the CSA has been implemented on a MSK2812 DSP hardware platform to control a laboratory scaled down version of the Navy's future electric ship power system. The objective for the CSA algorithm is to minimize the voltage deviations when pulsed loads are directly energized by shipboard power system, thus reducing energy storage devices capacity. Comparing CSA with PSO, the hardware results show that CSA-based controller can restore and stabilize the terminal voltage effectively and quickly with little disturbance introduced after high power pulsed loads are experienced.

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