An adaptive neuro-fuzzy control strategy for the bridge type superconducting fault current controller

Guo W.Y. [1,2], Zhao C.H. [1,2], Xiao L.Y. [1]

[1]Applied Superconductivity Lab, Inst. of Electrical Engineering, CAS, Beijing 100080, P.R.China
[2]Graduate School of CAS, Beijing 100039, P.R.China

This paper presents an adaptive neuro-fuzzy control strategy for the bridge type superconducting fault current controller (SFCC), which can automatically decide the phase-delay angle according to the fault current amplitude, limit the fault current amplitude to the degree that the system can endure, and recover to the normal situation immediately after the fault current ceases. Simulation results show that this design's performance is good.

INTRODUCTION

The bridge-type fault current controller (FCC), which was previously called fault current limiter (FCL), consists of a full-wave bridge, an inductance, and an optional bias power supply. The FCC can make the inductor switched automatically into the ac circuit and limit the amount of fault current, when values are higher than a preset current value; and present no impedance to the ac current flow, when load current values are smaller than the preset value [1]. By using a superconducting core, no loss will occur, here this is called SFCC. By changing the phase-delay angle, it can limit the fault current to any degree. It may be appropriate to preset the phase-delay angle if only short-circuit will occur, yet in some situation, for example, sudden overload may occur, in this situation the preset phase-delay angle is no longer appropriate.

This paper proposes an advanced adaptive neuro-fuzzy control strategy for SFCC, which can automatically determine the proper phase-delay angle. Simulations of single-phase mode will also be presented. Simulation results demonstrate that this design's performance is good.

THE BRIDGE-TYPE SUPERCONDUCTING FAULT CURRENT CONTROLLER AND THE PROPOSED ADAPTIVE NEURO- FUZZY CONTROL STRATEGY

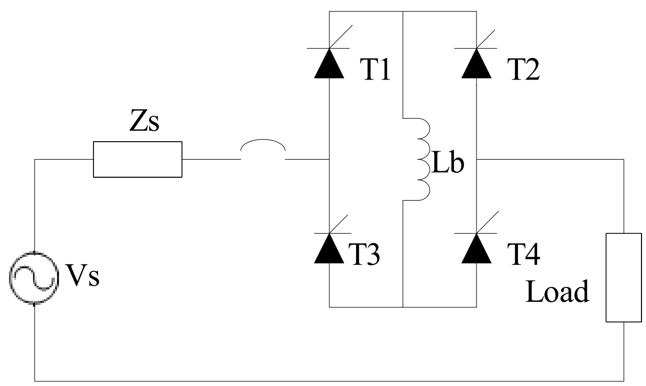

Figure 1 The circuit of SFCC

The bridge-type superconducting fault current controller without a bias power supply is shown in Figure 1. Consider the most common 10KV/400A subsystem in China, the parameters are set as follows: $V_S = 10KV/\sqrt{3}$, $L_S = 6.6mH$, $R_S = 264m\Omega$, $L_b = 20mH$, $Load = 25\Omega$. And the system frequency is 50Hz. By setting the phase-delay angle, the fault current amplitude can be adjusted. Changing the phase-delay angle α from 0 to 90 degrees results in a gradual decrease of the fault current. The ac current has a sinusoidal wave shape for phase angles up to 90°. The short-circuit current will decrease further for angles greater than 90°. At $\alpha = 90°$ the effect of the SFCC is the same as if it were replaced by a series connected inductor Lb. For angles $\alpha > 90°$ the SFCC produces ac currents that are discontinuous and adjustable in amplitude[1].

What is interested here is how to set the phase-delay angle automatically according to the overload or short-circuit level. As it's known, fuzzy reasoning is capable of handling imprecise and uncertain information whilst neuro networks are capable of being identified using plant data, and the neuro-fuzzy networks combine the advantages of both fuzzy reasoning and neuro networks[2], so the neuro-fuzzy networks can be used to model SFCC and obtain the proper phase-delay angle.

In simulation, in large scale (during the first two cycles of the fault current), the neuro-fuzzy inference structure is used. In the neuro-fuzzy inference structure, three input parameters are used. They are the current phase angle minus the voltage source phase angle θ, the fault current amplitude A, and the fault current amplitude minus nominal current amplitude ΔA. When the inductance is switched into the circuit, the parameter θ is changed according to overload level. For example, if the load resistance is changed to 2.5Ω in the above-mentioned systems, and the other parameters is not changed, θ will be -71.7°, and 5Ω will be -57.8°. So the parameter θ can indicate the overload level. To measure θ quickly and precisely, a very fast phase angle estimation algorithm for a single phase system having sudden angle jumps [3] is applied. In small scale (the fault current amplitude is near the nominal one), PI control strategy is better suited, so a PI regulator is used to modify the phase-delay angle. The input of the PI regulator is the parameter ΔA.

SIMULATION PROCESSES

To obtain the inference structure of the neuro-fuzzy networks, data for training must first be collected. And then these data are trained to generate the neuro-fuzzy inference structure.

<u>data obtaining and training</u>

To obtain the data described before, simulations are done on different overload level. In project, experiments should be done in similar condition to obtain these data. Here the overload resistance is set to: 20.83Ω， 10Ω ,5Ω， 3.33Ω， 2.5Ω， 0Ω， corresponding to the fault current of 1.2 times, 2.5 times, 5 times, 7.5 times, 10 times of the nominal one and the short-circuit current . Table1 is part of the data acquired when the overload resistance is set to 5Ω .

Table1 data when overload resistance is 5Ω

θ (rad)	-0.9825	-0.9825	-0.9825	-0.9825	-0.9825	-0.9825	-0.9825	-0.9825
A	1359.6	1258.7	1171.8	942.3	888.9	795.6	577.1	460.0
ΔA	971.2	870.3	783.4	553.9	500.5	407.2	188.7	71.6
α (deg)	50	60	70	90	100	110	130	140

By using the data obtained before, membership functions of the inputs and the output can be obtained. To obtain the neuro-fuzzy inference structure precisely, up to 60 epochs of training is applied. After training, the neuro-fuzzy inference structure is obtained.

control strategy

The strategy used here is that when the current detector detects that the load current is 20% larger than the nominal level, the fault current control program starts to work. The phase-delay angle is preset to 90^o, thus before the fault current falls to zero, the inductance is completely switched into the circuit. At the peek amplitude of the fault current, the parameters A, ΔA , θ are measured and these parameters and the preset phase-delay angle $\alpha=90^0$ are used as the checking data to modify the membership function parameters of the neuro-fuzzy inference structure, so as to make the neuro-fuzzy inference structure to adapt the real-time situation. Then the nominal value of the load current , here A=400, $\Delta A=0$,and the measured θ are used as the input of the adaptive neuro-fuzzy inference structure， so as to produce the phase-delay angle α and it is applied to the next half-cycle of fault current. During the following three half-cycles, the same method is used except that the previously obtained α is used as the checking data. After that, a PI regulator is used to produce the phase-delay angle instead.

SIMULATION RESULT

Using the strategy mentioned above, the simulation results are obtained. Here, two cases are shown. In the first case, at 0.06s , the overload resistance is set to 5Ω (five times overload)，at 0.16s, the fault current ceases(the load resistance is reset to 25Ω), at 0.24s, the overload resistance is set to 2.5Ω (ten times overload)，and at 0.34s, the fault current ceases again. In the second case, at 0.1s, the overload resistance is set to 12.5Ω (two times overload), at 0.2s, short circuit occurs (the overload resistance is 0Ω), and at 0.3s, fault current ceases. These two cases are shown in Figure 2 and Figure 3.

From the figures, it is can be found that whatever the fault current amplitude is, after the first half-cycle of the fault current (when the phase-delay angle is preset to 90^o,and the inductance is completely switched into the circuit), the fault current amplitude can be always limited to the amplitude near the nominal level, and after the fault current ceases, it will recover to the normal situation immediately (within 1~2 cycles).

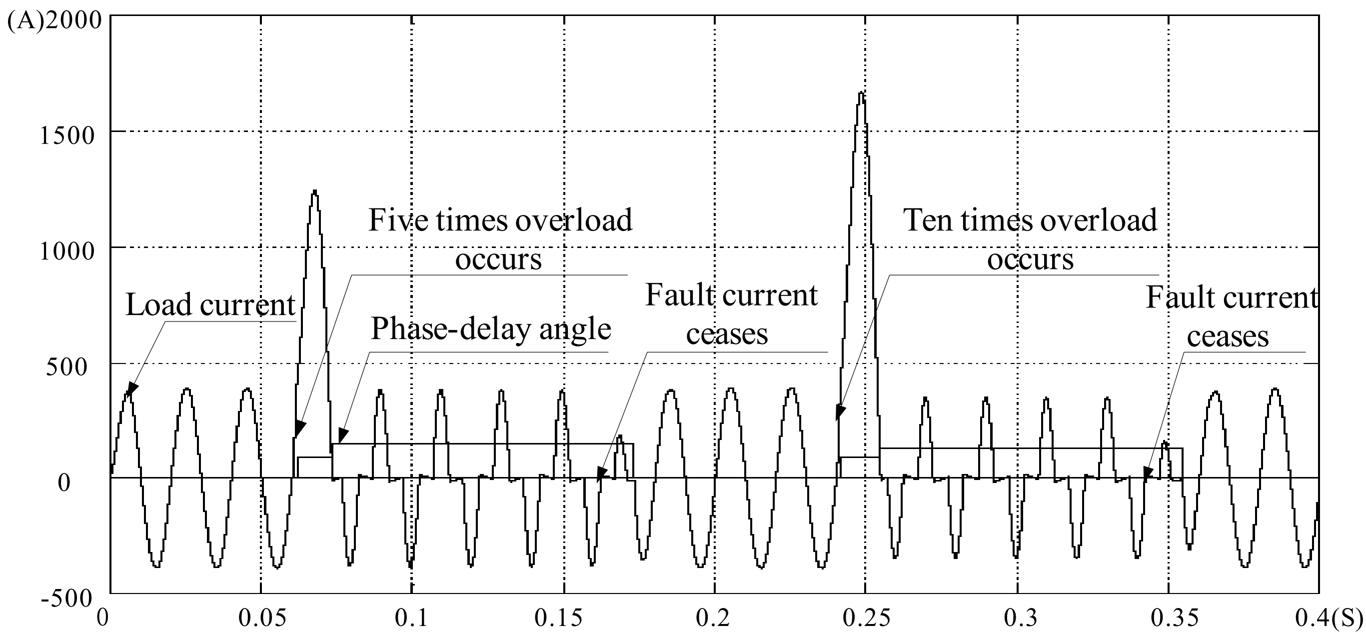

Figure 2 The first case

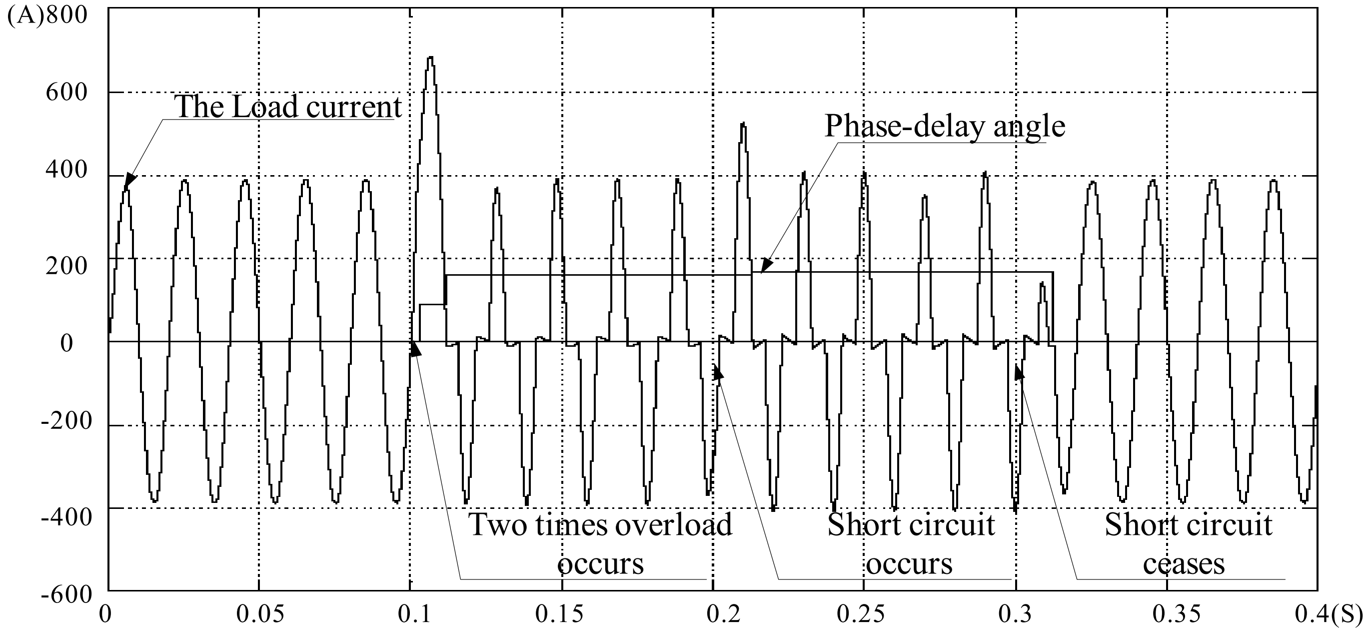

Figure 3 The second case

CONCLUSION

The simulations show that the adaptive neuro-fuzzy control strategy for SFCC can suit with any overload and short-circuit situation, and can limit the fault current amplitude near the nominal level. After fault current ceases, it can also recover to the normal situation immediately .The transient fault current limiting ability can be increased by selecting a larger inductance L_b, and the stable fault current limiting ability is always good by using this control strategy. This control strategy will then greatly enhance the bridge-type superconducting fault current controller's performance, and provide a potential application to the electrical system.

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