# A Neural Multi-agent-based Approach for Preventing Blackouts in Power Systems

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Abstract: A neural multi-agent-based approach for system monitoring and preventing large-scale emergencies in power systems is presented in this paper. The automatic emergency control process is represented as a neural multi-agent system with hierarchical architecture. The proposed system consist of two main parts: the alarm trigger, a Kohonen neural network-based system for early detection of possible alarm states in a power system, and the competitive–collaborative multi-agent control system. For demonstration purposes, we investigated conventional and neural multi-agent automatic control schemes. Results are presented and discussed.

## 1 INTRODUCTION

The ongoing deregulation and restructuring in power system worldwide require more complex control and decision making. In many cases, the current generation of automatic emergency control systems is ineffective and unreliable. Moreover, in emergency condition, a power system operator has to deal with a large amount of data and apply most appropriate remedial actions. At such times it becomes difficult to reach a correct diagnosis of the problem or to formulate the correct decision when actions must be taken. As a result, large scale blackouts still happen (PSDP 2007, Wang 2005)

Computational intelligence techniques in power systems provides a way forward to give new possibilities for energy management systems, especially in the field of preventing large scale emergencies. There are many benefits to using a multi-agent system as automatic control system, such as the ability to perform multiple computationally intensive tasks in parallel such that effective optimized real-time control can be achieved. These parallel tasks include neural network training, parameter optimization, and system monitoring. The multi-agent system approach also allows for intelligent control that is robust and flexible in that it can autonomously make decisions and adjust to partial control system failure to maintain control with minimal performance degradation, to name a few of the potential benefits. What's more decentralized emergency control is showing important advantages over centralized control, especcialy with large data, calculation and communication.

Several intelligent approaches have been proposed for preventing large-scale emergencies. On the one hand, there have been some previous attempts to take advantage of agents and multiagent systems as control systems (Lehnhoff 2011, Häger 2012, Panasetsky 2012, Negnevitsky 2008). On the other hand, some different machine learning models – including artificial neural networks (ANNs) – have been successfully applied for power system security assesment, as for example (Kalyani 2012, Voropai 2012, Niebur 1994).

The use of ANN models as a trigger system of the multi-agent control systems let take advantage of some of the properties of ANNs (such as pattern recognition) and agents (reactivity, proactivity and sociability) making preventing large-scale

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emergencies is more effective and reliable (Tomin 2013, Negmevitsky 2013) . The paper proposes a neural multi-agent-based system for preventing blackouts in power systems. This system includes some experience and developments obtained at the University of Tasmania (Australia), the Melentiev Energy Systems Institute (Russia) and the TU Dortmund (Germany) in developing intelligent systems for a disaster management in modern power systems.

# 2 PROBLEM DESCRIPTION

Several studies identified voltage instability as one of the major reasons of blackouts (PSDP 2007, Tomin 2013, CAMS 2008). A typical blackout scenario develops as follows: high system loading (due to heavy transfers across the grid) is followed by events that initiate protection system actions. As a result, some lines are disconnected, the grid becomes even more overloaded, and consumption of reactive power is increased, causing a cascading effect in which voltages drop even further. Practical experience demonstrates that most blackouts begin with a large disturbance (a disturbance, which may or may not cause cascading failures), which leads to a slow deterioration of the system conditions (PSDP 2007, Tomin 2013).

Failures of protection and emergency control devices as well as human errors are the two biggest causes of large-scale blackouts. Most blackouts begin with a large disturbance, which leads to a slow deterioration of the system conditions. The system parameters may still remain within specified limits, but many of these parameters are on the boundary of stability. If such conditions are identified as pre-emergency, preventive actions can be taken, and major events avoided.

Unfortunately, in current competitive environment, such conditions may not be easily detected because different problems may simultaneously occur in different parts of a large network within different jurisdictions. The liberalisation process in power systems has created an additional interface which can adversely impact communication and coordination activities between operators on both sides.

Multi-agent models are oriented towards interactions and collaborative phenomena. It is perfect suitable for resolve so called the irony of interconnected power grids that are owned by separate and often competing companies. In this case a technical cooperation between interconnected grids to a certain extent militates against the pure profit motive.

# 3 PROPOSED SYSTEM

The proposed system consists of two main parts: the alarm trigger, which is an intelligent neural network-based system for detecting possible alarm states in a power system, and the competitive–collaborative multi-agent control system (MACS).

## 3.1 The Hierarchy Multi-agent Control System

The innovation here in using a decentralized structure in which distributed "agents" operate in either competitive or collaborative modes, depending on the system security state, so that fast and robust responses can be provided in both normal and emergency conditions – responses directly tailored to the very different needs of each of these two conditions. Agents are hardware or software entities operating in virtual or real environments, and will be distributed among all serial devices in a power system – generators, transmission lines, transformers, and power flow controllers (PFCs).

The MACS is a hierarchy of agents located at different levels (Fig. 1):

1) The top-level agent (Advisor) – the objective is to initiate a collaborative protocol of agents located on the middle level, setting up their priorities, and coordinating their actions. In practice this might be a joint security center of several TSOs.
2) Middle-level agents (the transmission system operator-level) – the objective is to initiate control actions according to the goals set by the Advisor. These actions include PFCs between different systems.
3) Low-level agents (i.e. device-level agents – generators, transmission lines, transformers and loads) – the objective is to achieve the goals set by the respective middle-level agents within their jurisdictions. The low-level agents are specialized devices responsible for specific areas of power generation, transmission and distribution.

The Advisor receives messages from middle-level agents about the current state of the interconnected system, and if required proposes appropriate actions to control power flows between different systems. If the Advisor receives an alarm message from the

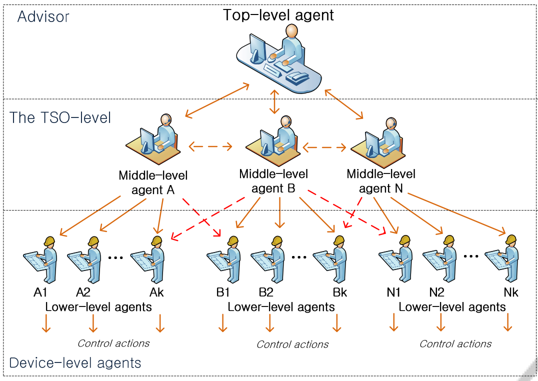


Figure 1: Block diagram of the MACS.

security alarm system, it assesses the severity of the situation, and if required takes control over the middle-level agents.

For normal conditions, we organise competitive control by the middle-level agents as follows: optimal power flow (OPF) is used to determine the optimal settings of power-flow controlling devices in the area of responsibility of each agent. Using PFC devices as an example, representing them by phase-shifting transformers and flexible alternating current transmission system (FACTS) devices (Häger 2012). The PFCs were installed to increase transmission capacity and controllability of the grid. In normal operation conditions, each transmission system operator (TSO) used OPF methods to optimise settings of their PFC devices, to reduce internal congestions as required by market rules. The objective function is to minimise the generation costs by optimising power flows according to the market situation.

However, in emergency conditions, all TSOs will need to coordinate their PFC devices to stabilise the system. We achieve this coordination through the use of MACS. In the collaborative mode, the objectives of the agent operation changes: a middle-level agent seeks and receives help from the low-level agents that belong to the neighbouring middle-level agents. For example, under an emergency in System A due to voltage instability, a middle-level agent A will redefine the objective function of low-level agent B1 of System B (Systems A and B are be connected via a tie transmission line) to increase reactive power input from the neighbouring system.

## 3.2 a Neural Multi-agent-based Approach

In order to distinguish between competitive and collaborative mode, we need to overcome an issue of identifying pre-emergency conditions. This paper is concerned with the real time identification of alarm states that are dangerous for the system security. We examined a clustering approach based on the self-organized Kohonen neural network. The Kohonen alarm trigger identifies pre-emergency conditions using enormous amounts of data with incomplete and distorted alarm patterns and activates the MACS (Fig. 2).

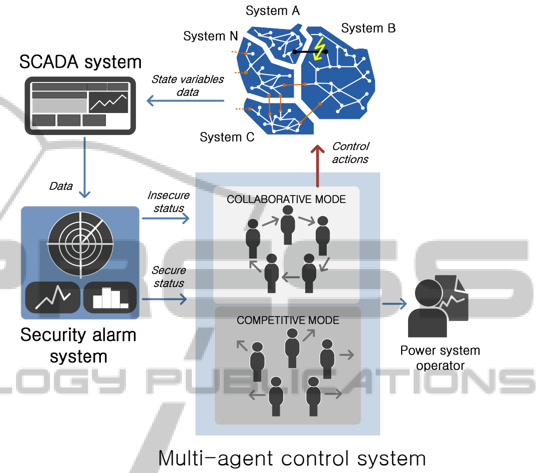


Figure 2: Diagram of a neural multi-agent-based system.

The security alarm system is trained using a set of training examples based on randomly generated events in a power system. The clusters is identified using test cases representing a set of normal and emergency conditions in the power system. As a result, a Kohonen ANN-based clustering system is able to classify power system states in real time and, if required, to produce an alarm. The main objective is to rank power system states with respect to their potential for causing voltage instability.

The Kohonen network is trained off-line and used on-line to classify the system operating state based on the patterns created in the off-line mode. The Kohonen network is divided into power system states as follows: normal, alarm, emergency (correctable) and emergency (non-correctable). Here, a normal state implies that all parameters of the power system are maintained within specified normal operation limits:

$$\sum_{i=1}^{N_G} P_{Gi} = P_D + P_{loss} \qquad (1)$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}.\ i = 1,2,\dots,N_G \qquad (2)$$

$$|U_k^{min}| \le |U_k| \le |U_k^{max}|, k = 1,2,\dots,N_B \qquad (3)$$

$$P_{km} \leq P_{km}^{max} \text{ for every branch } k - m \quad (4)$$

where $P_{Gi}$ is the real power generation at bus $i$, $P_D$ is the total system demand, $P_{loss}$ is the total real power loss in the transmission line, $|U_k|$ is the voltage magnitude at bus $k$, $P_{km}$ represents the real power flow at branch $k - m$, $N_G$ and $N_B$ being the number of generators and the number of buses in the power system, respectively.

Real-time measurements are used to assess the system state. Kohonen network-based monitoring provides a warning when the system security is under threat (Fig. 2).

# 4 CASE STUDY

The proposed neural multi-agent-based system was implemented in JADE (Java Agent Development Framework). The Kohonen security clustering model is realized in STATISTICA 6.0. MATLAB and Power System Analysis Toolbox are used as modeling tools. In this paper, we demonstrate the proposed approach on the modified IEEE One Area RTS-96 power system. Active power flow is directed from Subsystem B to Subsystem A. Subsystem A is a low-voltage distribution subsystem being in stressful conditions because of reactive power shortage, which potentially may cause voltage instability. Subsystem B is a high-voltage transmission subsystem with surplus of reactive power.

The modified system has 53 buses and dynamic elements to represent generators and loads. In Subsystem B, there is an excess of reactive power produced by reactors at busses 107, 111, 113. Subsystem A has a deficit of reactive power. In Subsystem A, the sources of reactive power are Non-controlled Reactive Power Sources (NRPS) – capacitor. Each load is modeled as exponential recovery load. The exponential recovery load model can adequately represent the load behavior during voltage instability.

To demonstrate the proposed approach, the test system is subjected to the following sequence of disturbance: t=10 s – the loss of transformer T101-208. We assumed that two types of automatic control can be used in the power system: Conventional Automatic Control System (CACS) (includes TGs, AVRs and OXLs on each generator, and OLTCs on transformers connected to buses 204–210), and MACS (Fig. 3) – in addition to the set of local controllers, it includes OLTCs on transformers connected to busses 101, 102 and 103.

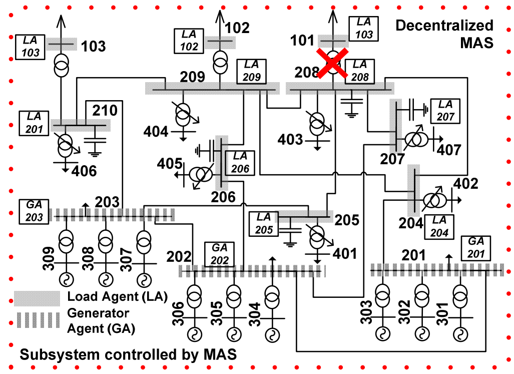


Figure 3: Subsystem A with installed Load Agents and Generator Agents (the device level agents).

## 4.1 Conventional Automatic Control Modeling

The loss of transformer T101-208 immediately leads to an overload of generators connected to bus 201. After about t=15s, the OLTC starts to change the transformation ratio for boosting the secondary voltage at the load. This leads to a gradual overload of all generators in the subsystem. At t=300 s, the rotor current limits are exceeded on all generators as the system does not have any reactive power reserves. At t=500 s, the primary voltage at the load reaches 0.8 p.u. due to the OLTC actions and insufficient reactive power, while the secondary voltage is maintained close to the nominal (Fig.4).

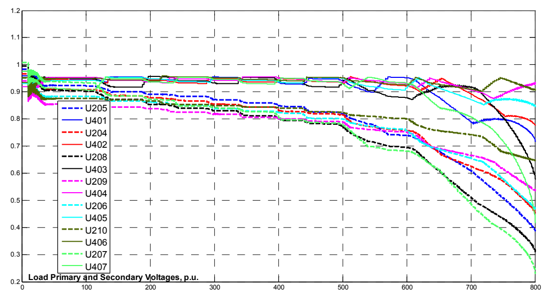


Figure 4: The system voltage profile under the CACS control.

In this case, the AVR fails to secure critical voltage levels in the primary network, and at about t=500 s, cascading voltage decrease takes place. As a result, after t=600 s, stator currents of the generators increase rapidly (Fig. 5), and the voltage at generator busses decrease even further. This leads to the disconnection of generators by their protection systems, and as a result, the system voltage collapses (Fig. 4).

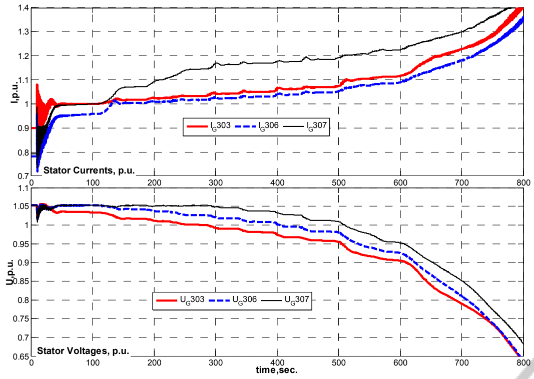


Figure 5: Stator current and voltage profiles under the CACS control.

## 4.2 Neural Multi-agent Automatic Control Modeling

The MACS coordinates main controllers of reactive power in the system in order to prevent voltage instability. The MACS detects dangerous levels of excitation currents of a number of generators and blocks the OLTCs on transformers.

The Kohonen network-based security alarm system uses the following inputs: voltages at busses 204 – 210 (primary voltages); voltages at busses 401 – 406 (secondary voltages); AVR excitation voltages for generators G301 – G309; OXL output signals for generators G301 – G309 and stator currents of generators G301 – G309. Fig. 6 represents a topological map of the Kohonen network. The network is trained off-line to identify clusters corresponding to the following operating states of the power system: normal (cluster A); alarm 1–5 (cluster B); emergency 1 and 2 (correctable) (cluster C); and emergency 3 (non-correctable) (cluster D).

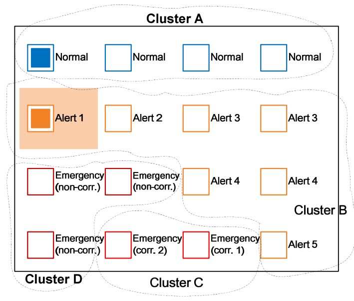


Figure 6: The Kohonen topological map.

After the loss of transformer T101-208, generators connected to bus 201 are overloaded (Figs7,8). When the multi-agent scheme is available, as soon as the Kohonen network detects the alarm state at time $t$=10 s, the MACS is activated in order to prevent the system from further deterioration.



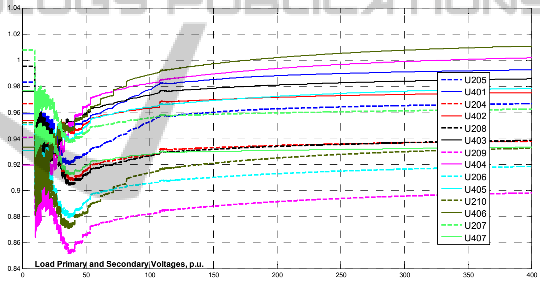


Figure 7: The system voltage profile under the MACS control.

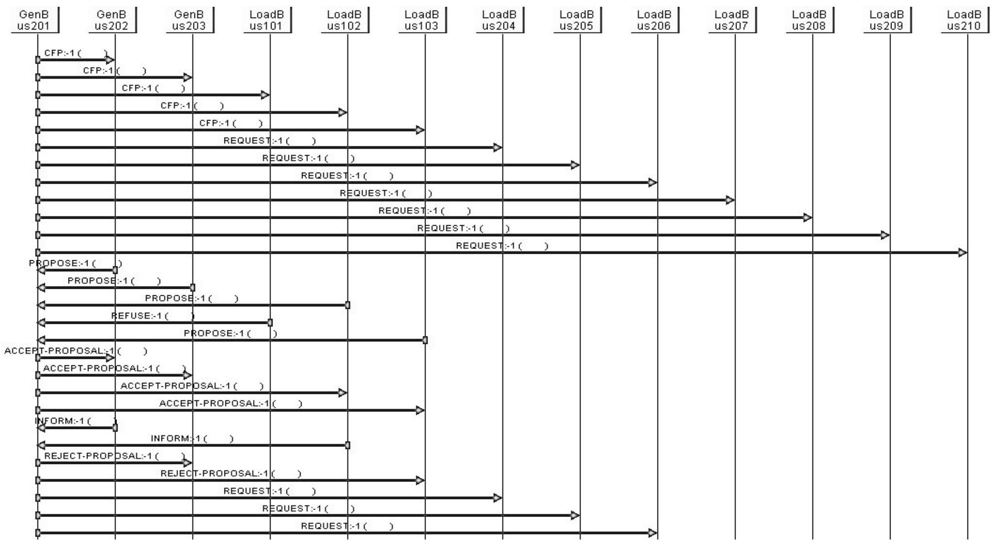


Figure 9: The sequence of messages between agents in the elimination of emergency.

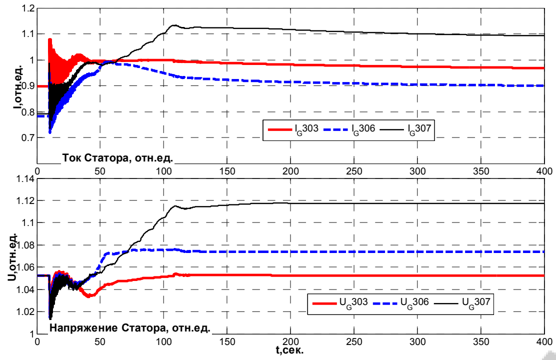


Figure 8: The system stator current and stator voltage profiles under the MACS control.

The local automation reduces the AVR setting. GAs at busses 202 and 203 begin to increase reactive power output until the generator excitation currents reach their near-critical values. Collaborative actions of GAs and LAs are allowed to unload G301-303 (Fig. 9).

As a result, the system voltage profile improves, as can be seen in Fig. 7, and the Kohonen network does not detect any deterioration at t=130.63 s. From t=206 s, the Kohonen network identifies the normal state, however, the alarm 3 state is also still activated because the system is still in the normalization of post-emergency state.

Thus, as a result of the MACS control actions, the subsystem can maintain its stability without load shedding via coordinating available sources of reactive power.

## 5 CONCLUSIONS

This paper proposes a neural multi-agent-based approach to the system monitoring and control with the goal of identifying potential voltage instability problems before they lead to major blackouts. The proposed MACS structure is hierarchical; it consists of the top-level agent, middle-level agents and low-level agents. Under normal operating conditions, the MACS operates in a competitive mode; low-level agents exchange information with other agents to maintain their local conditions within specified limits and to maximize profits of their respective companies. An alarm state triggers a collaborative mode in which the agents coordinate their actions to prevent a system blackout.

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