Proceedings of the 7th WSEAS International Conference on Neural Networks, Cavtat, Croatia, June 12-14, 2006 (pp47-52)

INTELLIGENT BEHAVIOUR INCORPORATION ON ELECTRIC TRANSPORTATION SYSTEMS

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KEYWORDS

Diagnostics, neural network, intelligent agent, electric transportation system

ABSTRACT

The purpose of the current work is to analyze algorithms for neural networks. The main idea of this work is to use multi-agent system and multi-agent negotiation algorithms to create decision support system for diagnostics of public electric transport workability.

The intelligent multi-agent system structure is developed. The base of multi-agent is neural network, which analyze input signals and offer suitable action in case of problem. For neural network learning well-known back-propagation algorithm is selected.

Intelligent agents are created using a database and the appropriate programming languages, that allows a simpler and effectively negotiation.

Intelligent multi-agent provides the possibility to detect problem and offer solution immediately. It is a chance to avoid superfluous charges connected with problem detection, fixation and consequences of the problem.

INTRODUCTION

This work is based on the development of intelligent multi-agent systems [1]. The purpose of this paper is to analyze algorithms for neural networks on this field. Neural network algorithms are among the most popular data mining and machine learning techniques used today. As computers become faster, the neural net methodology is replacing many traditional tools in the field of knowledge discovery and some related fields.

Thus the main idea of present paper is, by using intelligent agent system and intelligent agent negotiation algorithms, to create a decision support system to perform the diagnostic of an electric transportation system (ETS).

This work is centered into the task of immediate problem detection and decision making according to the problem in emergency situations. To solve such task, when neither people nor expert group can make a decision operatively, the usage of intelligent systems models is suggested. Such systems can perform an immediate decision mandatory in case of an emergency situation.

Since the ETS is a cooperative system, the emergency problem with one transport unit could not be solved autonomously, i.e. independently on other transportation process participants. That is why coordination mechanism is needed. It is suggested to use intelligent super agents to cooperate work of all agents in transportation system

The role of super agent is the following:

- to perform the negotiation between the intelligent agents when one of the agents reports the emergency situation;
- to evaluate the extent of the emergency situation influence to the system operation;
- to decide about the changes (if necessary) on the system operation accordingly with the evaluation.

The usage of the back-propagation algorithm is offered to train intelligent agents of the ETS to assess its operation and to detect operation problems immediately.

INTELLIGENT ELECTRIC TRANSPORT SYSTEM ELEMENTS

The general schema of informational system for the control of ETS's suggested is shown in figure 1.

In figure 1 it can be seen that the ETS are composed of several fundamental structures: the physical system; the telemetric system; and the intelligent agents (tab.1)

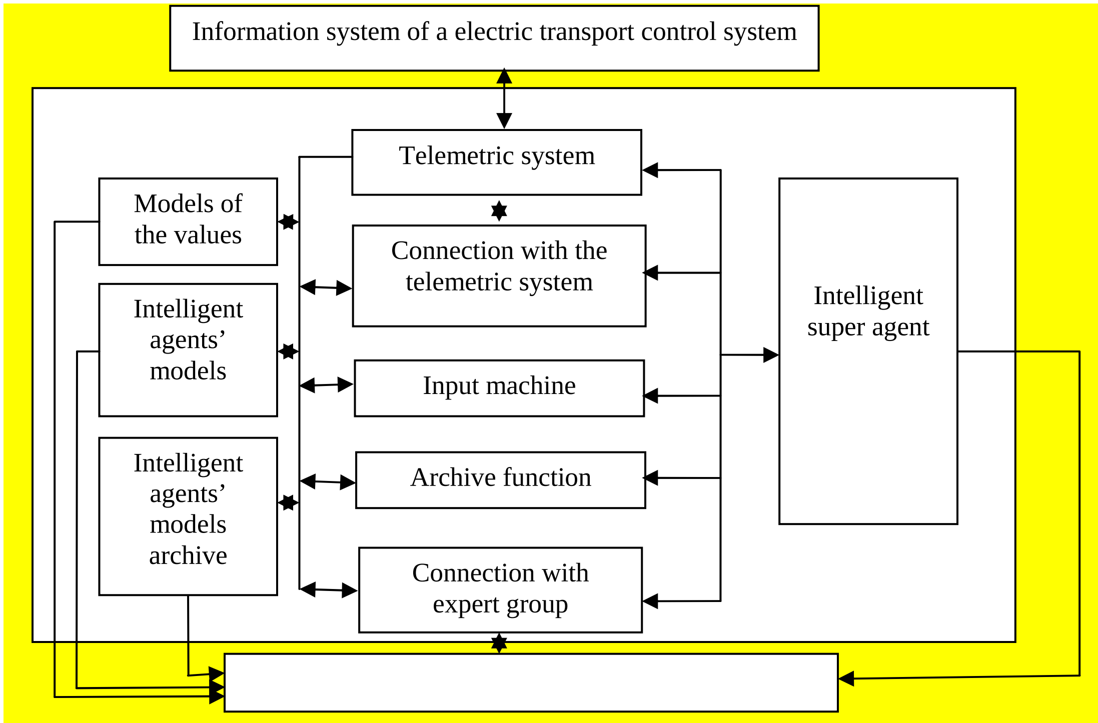

Figure 1. ETS considered

The intelligent agents – the elements of artificial intelligence - are incorporated into the electric transport control system. This system is managed and controlled by the super agent. The super agent is responsible for the intelligent agent negotiation and to also by the cooperation between the work of autonomous agents to achieve common goals of the system. A super agent is an intelligent agent, which is not responsible for any object, but for the processes where several object's intelligent agent participate.
Intelligent agents input and process the information on the physical transport unit as well as send it to intelligent super agent for the analysis of the condition of the transport system in general and to realize the decision making procedure.
The agents' classification is presented in table 1.

Table 1. Agents' classification

Features Nr.	Types of the agents and their features	Conventional agents	Intelligent agents
1	Autonomous performance	+	+
2	Co-operation with other agents and/or users	+	+
3	Environment monitoring	+	+
4	Ability to use abstractions		+
5	Ability to use knowledge about the subject		+
6	Ability to operate adaptively for goal achieving		+
7	Learning ability from the environment		+
8	Error un sensitivity and/or wrong signals		+
9	Operation in real time		+
10	Co-ordination and influence of another agents		+

The connection of the information system block with the expert group is done to control the necessary decision making in the working order, but in the case of an emergency the intelligent super agent just informs an expert group and if the answer is not obtained in time then the super agent acts accordingly with the predefined regulations.
Also an expert group performs and controls the training of intelligent agents to recognize new problems and to offer better solutions

INTELLIGENT ETS UNIT AGENT STRUCTURE

Each electrical transport unit has own intelligent agent. An intelligent agent is a software package that is responsible for an object or a process. The schematic of an agent is given in figure 2.

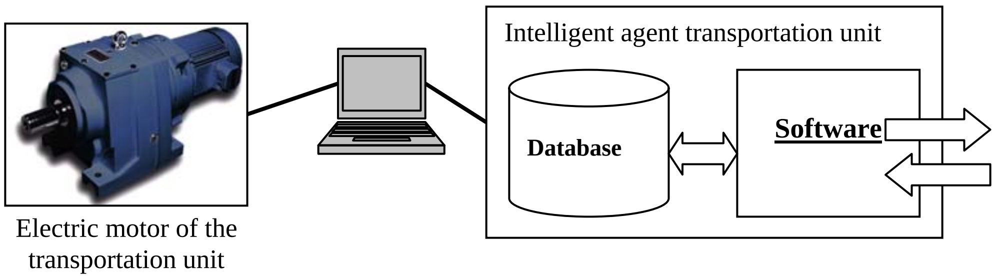

Figure 2. Intelligent agent of a transportation unit

A intelligent agent consists of 2 necessary components: the database; and the multi-function software.
All information about an object such as technical characteristics and parameters, strategies, schedules, calculated data, among others, are incorporated into the intelligent agent's database. The software is used to process this data.
Each intelligent agent considered has the parts presented in figure 3.

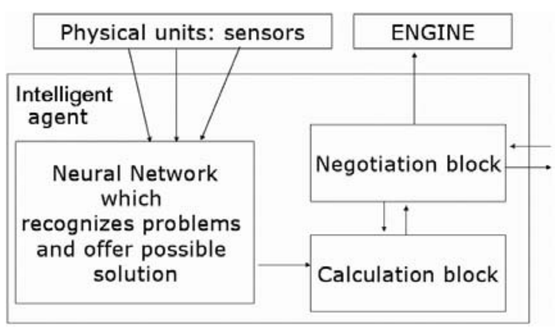

Figure 3. Structure of an intelligent transportation unit agent

From figure 3 the parts of the intelligent agent are: the neural network structure; the negotiation block; and the calculation block.
The neural network structure helps to identify the problems and offers the strategy for solution accordingly with the problem. The negotiation block is responsible for the data exchange with the other intelligent agents. The calculation block contains the mathematical functions that verify the expediency, i.e. the benefits and charges of using the offered strategy
Each public electric transport unit has its own intelligent agent, which is responsible only for the current unit. Physically each transport unit is equipped with the telemetric system (sensors) that collects data to perform the diagnostic of operation. Collected data is then processed by intelligent agent's neural network, which makes a decision of serviceability and if a problem is detected the strategy of solution will be offered accordingly with the class of the problem found [2].
The main functions of an intelligent transportation unit agent are the following:

- to analyze input parameters from the transportation unit telemetric system in real time;
- to offer the solution immediately upon the problem detection;
- to evaluate the extent of risk accordingly with the problem found;
- to take an immediate decision accordingly with the risk (e.g. to stop the electric motor);
- to inform other participants about the situation and initialize negotiation with the super agent.

NEURAL NETWORK MATHEMATICAL MODEL

Intelligent agent neural network mathematical model is based on the perceptron structure:

- Input data set:
  $X = \{x_1, x_2, \ldots, x_n\}$
- Weights:
  $W = \{w_1, w_2, \ldots, w_n, w_{n+1}\}$
- Fitness function:
  $F = x_1{*}w_1 + x_2{*}w_2 + \ldots + x_n{*}w_n + w_{n+1}$
- Result classes (clusters):
  $C = \{c_1, c_2, \ldots, c_m\}$

FLOWCHART OF NEURAL NETWORK TRAINING BY BACK-PROPAGATION ALGORITHM

Back-propagation is the basis for training a supervised neural network. Static back-propagation is used to produce an instantaneous mapping of a time independent input to a static output. These networks are used to solve classification problems.

At the core of all back-propagation methods is an application of the chain rule for ordered partial derivatives to calculate the sensitivity of a cost function with respect to the internal states and weights of a network. In other words, the term back-propagation is used to imply a backward pass of error to each internal node within the network, which is then used to calculate weight gradients for that node. Learning progresses by alternately propagating forward the activations and propagating backward the instantaneous errors.

The algorithm used is the one presented in figure 4.

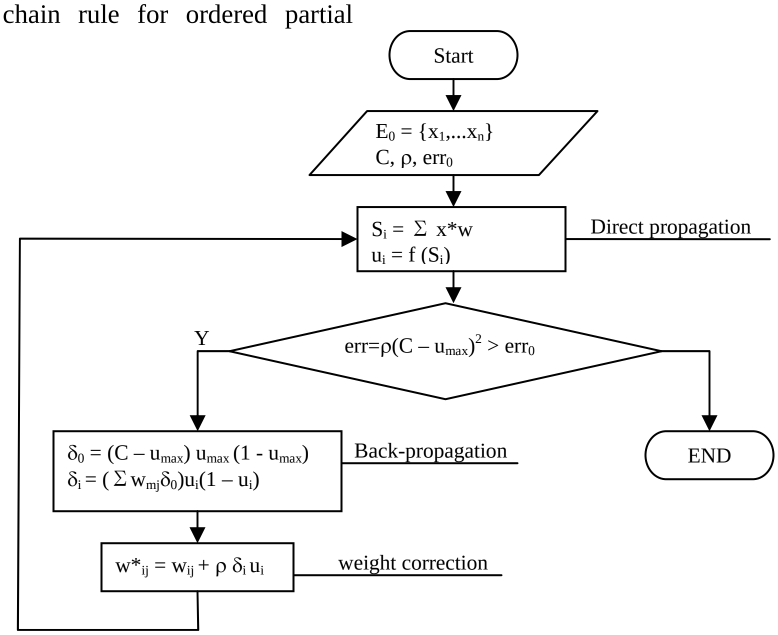

Figure 4. Flowchart of back-propagation algorithm

NUMERICAL EXAMPLE

The neural network presented in figure 5 was considered for a numerical test.

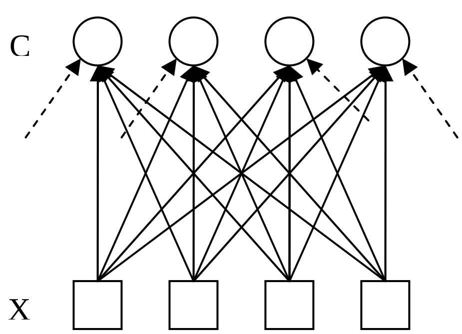

Figure 5. Test neural network.

The neural network system, presented in figure 5, has 4 sensors, which give measurements to intelligent agent neural network input neuron layer:

X = {inp1, inp2, inp3, inp4};

For this neural network there are 4 possible actions (strategies) to do according to measurements:

C = {out1, out2, out3, out4};

By applying the proposed scheme the obtained result is the following:

Iteration 0

Step 1. Start by setting up the weights' value before training. Usually random numbers are taken, but in this example zero values are taken to simplify calculations.

W (inp1,out1) = 0
W (inp2,out1) = 0
W (inp3,out1) = 0
W (inp4,out1) = 0
Corr (out1) = 0
W (inp1,out2) = 0
W (inp2,out2) = 0
W (inp3,out2) = 0
W (inp4,out2) = 0
Corr (out2) = 0
W (inp1,out3) = 0

W (inp2,out3) = 0
W (inp3,out3) = 0
W (inp4,out3) = 0
Corr (out3) = 0
W (inp1,out4) = 0
W (inp2,out4) = 0
W (inp3,out4) = 0
W (inp4,out4) = 0
Corr (out4) = 0

Iteration 1
Cycle 1
Step 1. The first sample for training is taken:

Sample 1
Input: inp1 = 2
Input: inp2 = 0
Input: inp3 = 0
Input: inp4 = 0
Output: out1 = 0
Output: out2 = 1
Output: out3 = 0
Output: out4 = 0

Step 2. Direct propagation.
Fitness function (sigmoid function) calculation for each non-input layer neuron moving from the inputs to the outputs: In this network the next level the is output level, so:
*U(out1) = f (0*2 + 0*0 + 0*0 + 0*0 + 0*1) = 0.5*
*U(out2) = f (0*2 + 0*0 + 0*0 + 0*0 + 0*1) = 0.5*
*U(out3) = f (0*2 + 0*0 + 0*0 + 0*0 + 0*1) = 0.5*
*U(out4) = f (0*2 + 0*0 + 0*0 + 0*0 + 0*1) = 0.5*

Step 3. Total error for layer calculation
Error = Σ learning rate(value needed – real value)^2*

Error = 0.2(0 - 0.5)^2 + 0.2*(1 - 0.5)^2 + 0.2*(0 - 0.5)^2 + 0.2*(0 - 0.5)^2 = 0.2*

Step 4. Back-propagation
Perform the error calculation for each non-input neuron starting from the output layer moving backwards to the input layer.

δ (out1) = (0 - 0.5) 0.5*(1 - 0.5) = -0.125*
δ (out2) = (1 - 0.5) 0.5*(1 - 0.5) = 0.125*
δr (out3) = (0 - 0.5) 0.5*(1 - 0.5) = -0.125*
δ (out4) = (0 - 0.5) 0.5*(1 - 0.5) = -0.125*

For next non-input levels, if existing, the following formula is used:

$$\delta_i = (\Sigma\, w_{mj}\, \delta_0)\, u_i\, (1 - u_i)$$

This approach uses the back-propagated error from level above to correct weights.

Step 5. Weight correction
Using calculated error, weight correction is realizes as following:

$$w^*_{ij} = w_{ij} + \rho\, \delta_i\, u_i$$

where ρ - learning rate.

W (inp1,out1) = 0 + 0.2-0.125*2 = -0.05*
W (inp2,out1) = 0 + 0.2-0.125*0 = 0*
W (inp3,out1) = 0 + 0.2-0.125*0 = 0*
W (inp4,out1) = 0 + 0.2-0.125*0 = 0*
Corr (out1) = 0 + 0.2-0.125 = -0.025*
*W (inp1,out2) = 0 + 0.2*0.125*2 = 0.05*
*W (inp2,out2) = 0 + 0.2*0.125*0 = 0*
*W (inp3,out2) = 0 + 0.2*0.125*0 = 0*
*W (inp4,out2) = 0 + 0.2*0.125*0 = 0*
*Corr (out2) = 0 + 0.2*0.125 = 0.025*
W (inp1,out3) = 0 + 0.2-0.125*2 = -0.05*
W (inp2,out3) = 0 + 0.2-0.125*0 = 0*
W (inp3,out3) = 0 + 0.2-0.125*0 = 0*
W (inp4,out3) = 0 + 0.2-0.125*0 = 0*
Corr (out3) = 0 + 0.2-0.125 = -0.025*
W (inp1,out4) = 0 + 0.2-0.125*2 = -0.05*
W (inp2,out4) = 0 + 0.2-0.125*0 = 0*
W (inp3,out4) = 0 + 0.2-0.125*0 = 0*
W (inp4,out4) = 0 + 0.2-0.125*0 = 0*
Corr (out4) = 0 + 0.2-0.125 = -0.025*

Cycle 2
Step 1. Next sample is taken to train.

Sample 2
Input: inp1 = 2
Input: inp2 = 0
Input: inp3 = 0
Input: inp4 = 1
Output: out1 = 0
Output: out2 = 1
Output: out3 = 0
Output: out4 = 0

Step 2. Direct propagation.
U(out1) = f (-0.05*2 + 0*0 + 0*0 + 0*1 + -0.025*1) = 0.47
U(out2) = f (0.05*2 + 0*0 + 0*0 + 0*1 + 0.025*1) = 0.53
U(out3) = f (-0.05*2 + 0*0 + 0*0 + 0*1 + -0.025*1) = 0.47
U(out4) = f (-0.05*2 + 0*0 + 0*0 + 0*1 + -0.025*1) = 0.47

Step 3. …
Iteration ends when all samples were used. Then training continues repeating all samples from the very beginning but with new weights calculated in the previous iteration.

COMPUTER REALIZATION OF NEURAL NETWORK TRAINING FOR INTELLIGENT AGENT

For the realization of intelligent agent neural network Apache Server is used in connection with PHP programming language and MySQL database management system.

The database created for the intelligent agent contains 4 tables:

- Neural network structure – neurons and layers
- Samples for learning
- Test samples to check learning quality
- Weights – results of learning

For realization very simple neural network is taken. The structure is shown in figure 5. It has only two layers – input neuron layer and output neuron layer (without hidden layer).

The example tested to train neural network is abstract and was not used to any real transport unit.

During the training process 100000 iterations were completed. When the neural network is trained, next step is expert evaluation of training quality.

For that reason the personal test is offered. Expert enters parameters and check results of training. For the numerical example considered these values are X = {5, 0, 0, 1}.

The test network has 2 levels,4 inputs and 4 outputs. It is trained on 18 samples, which are considered true and are not mutually contradictory.

Training happens by continuously repeating these samples 100000 times, each time correcting weights according to error of previous iteration.

It is not always possible to obtain the correct training, but the developed approach, when in the presence of wrong results, allows the entering of correct actions and therefore to train the intelligent agent again.

Another quality test is possible in the develop strategy, to be used by experts, having knowledge of problem details. This test gives two possibilities, to perform the correction to the samples or to add new samples. In some cases could be necessary to enter a new action strategy, i.e. change network structure by adding new output neuron The network will be trained to use this action too after the relearning process.

CONCLUSIONS

The aim of the present work is to develop the methods for electric transportation systems logistics processes, taking into account the following features: existing of global networks with a large number of objects, including servers, computers, existence of difficult dynamic topology; priority of the users and its changing with time; not enough statistical data for the modelling.

The necessity and advantages of using such system are several, since it offers the possibility to detect the problem immediately, to fix it in some cases without human intervention or to inform all other participants about the problem. The negotiation between intelligent agents can give a chance to avoid superfluous charges connected with problem detection, fixation and consequences of the problem.

Further research steps are to analyze specifics of electrical public transport, realize calculation block, realize negotiation algorithm, realize coordination super agent for intelligent agent system. Analysis of logistic multi-criterial decisions for electric transport systems will significantly develop the application of decision making theory for the logistics problems solving with the help of nowadays IT means. The result of the work proposed will be the modelling of a part of multi-criterial decisions system. The area of the system application will be formed, output data will be summarized for the decision making, types of criteria will be analyzed for the decision making in the electrical transport systems, the functions realized in the system will be described, the requirements for the devices will be defined for realizing the modelling of the logistics decisions systems, types of the data obtaining will be defined, the process of the decision making will be modelled in the correspondence with power system expert groups, the limiting method will be applied, the main system window, area and operational windows for the analysis of the logistics processes will elaborated, the reporting forms will be tested.

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