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Simulation of Complex Engineering Systems' Damages with Auxiliary of Neural Networks

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Abstract: This study is about the simulation of complex engineering systems' damages with auxiliary of neural networks. We start off with a brief definition of details. We will discuss the use of neural networks in determining the conclusions of the study. A detailed definition of semi-trailer, which is the machine in study, will also be given. The study then moves on towards the main body of the study which will discuss in full details of the damages done on a semi-trailer. The analysis is being done using neural networks to analyze this complex phenomenon and to study the operation analytically. The discussion is ended by a conclusion that clearly indicates advantages, limitations and possible applications.

Key words: Neural networks, semi-trailers, simulation and complex engineering systems, auxiliary

INTRODUCTION

A neural network is a collection of interconnected elements or units (Mozer *et al*., 1996). Beyond that characterization, neural network means a variety of things to a diversity of researchers. However, to put aside neuroscience and cognitive science, we regard a neural network as a purely formal object or as a rich family of formal objects. For narrowing our scope to mathematical perspectives, 'neural network' still has a striking diversity of construals.

Neural networks are dynamical systems that compute functions that best capture the statistical regularities in training data: their study inevitably brings together concepts from dynamical systems theory, computation theory and statistics. Correlated with, but logically independent of, the tripartite division of computational, dynamical and statistical perspectives, there is the following tripartite decomposition of a neural network:

The processing component:

- Of a neural net is an algorithm (or set of differential equations) by means of which activation patterns input to the network are converted into activation patterns that comprise the net's output. The computational and dynamical perspectives tend to address this component most, since the input/output function computed is of primary concern to the computational perspective and the dynamics by which it is computed is of central interest to the dynamical perspective.

But the computational and dynamical perspectives also address the learning component:

- Since the computational difficulty of the learning problem and the weight dynamics of learning algorithms are both of great interest. It is the statistical perspective, though, that has the most to say about the central problem in most neural network learning: what are justifiable procedures for drawing inferences from given training examples to unseen data--the problem of induction.

Lastly, the third component, representation:

- Is the least-studied aspect of neural networks: it concerns the link between the input/output activation patterns and the items that they encode from whatever domain the network's problem comes.

Now that we have an idea about neural networks, what about semi-trailers? What is it? Since it is our main object, we should at least define what it is.

A semi-trailer is a trailer without a front axle. A large proportion of its weight is supported either by a road tractor or by a detachable front axle assembly known as a dolly. A semi-trailer is normally equipped with legs, which can be lowered to support it when it is uncoupled. A road tractor couple to a semi-trailer is often called a semi-trailer truck or semi (http://en.wikipedia.org/wiki/Semitrailer).

The automobile semi-trailers life cycle simulation is based onto process of damage "assigning" to a given area from the list of previously selected possible hazard locations, that being grounded onto statistical data and operational dynamics from one side and stochastic conditions of operation from another (Balan, 1999).

As such assigning represents several variables threshold function (determined and stochastic ones) and with respect to: different factors' specific influence onto these variables, that influence varied degree by the measure of damages accumulation and repairs effected, to simulate the semi-trailers frame life cycle we used the neural networks logic mathematical apparatus.

The threshold logic allows structuring devices with n binary inputs $x_1,\dots,x_n$

$$y = 1 \text{ at} \sum_{i=1}^{n} \xi_i x_i \geq \eta \text{ , } y = 0 \text{ at} \sum_{i=1}^{n} \xi_i x_i < \eta \tag{1}$$

and one output y, which function follows to such relation: Where the i-th input weight ξ_i and the threshold η are given as finite real numbers. Such devices, conventionally shown at Fig. 1, are known as threshold elements.

The arbitrary set of weight ξ_i and the threshold η, as every threshold element always can be correlated with some logic function known as threshold function. Nevertheless not every logic function can be realised through one threshold element. That is why the first problem of threshold logic consists in assigning a class of threshold functions with determining the structure of threshold element implementing the threshold function (threshold element synthesis). Provided such implementation is impossible or inexpedient; we'll face the second problem of scheme synthesis with threshold elements.

Important constituent of threshold logic is the formal neuron (Fig. 1 and 2). Neuron's inputs, dendrites, influence its body through two types of fibres: these exciting with weight 1 and these inhibitory, with weight-1. The point of fibre-to neuron body contact is called a synapse (exciting fibres' synapses are marked with bold points). The output is located immediately at the neuron body. Apart that there occur the denying fibres with termination at denied fibre, through which signal arrival is blocked when denying input excited (Fig. 4; denied is input's x_3 fibre at x_1 =1). Just like threshold element the neuron has characteristic threshold η, at that it excites (y = 1) when the weight function, corresponding to the given input variables' values set is not less that η value. So, the neuron shown at Fig. 1 and 2 will be excited when sets (0,1,0), (1,0,0), (1,0,1), (1,1,0) and (1,1,1).

As a distinct from threshold elements, with one formal neuron we can implement any logic function. For neuron and neural schemes synthesis usual practice is to involve Venn's diagrams and their modifications . at that the goal consists in obtaining schemes, where total fibres number is minimum (here implementing the process with only one neural scheme would be preferable when compared to only one neuron). These last years running the formal neuron reached to become universal model both in cybernetics and some other engineering fields. The more complete model of abstract neuron introduces time-dependent relations: signals passage through synapses with one time-step delay and the threshold value represent discrete time function (Sigorsky, 1975).

The research (Balan, 1999) suggests a system of complex engineering objects' operation prognosis based onto processing the current data received from subsystems executing global study of object condition at different stages of its life cycle: From project design up to withdrawal from operation.

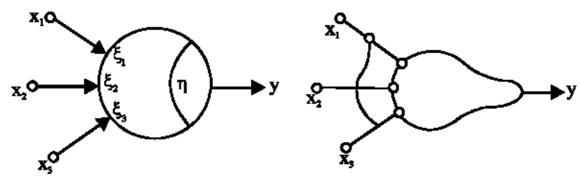

Fig. 1: Logic network elements 1- threshold element; 2- formal neuron

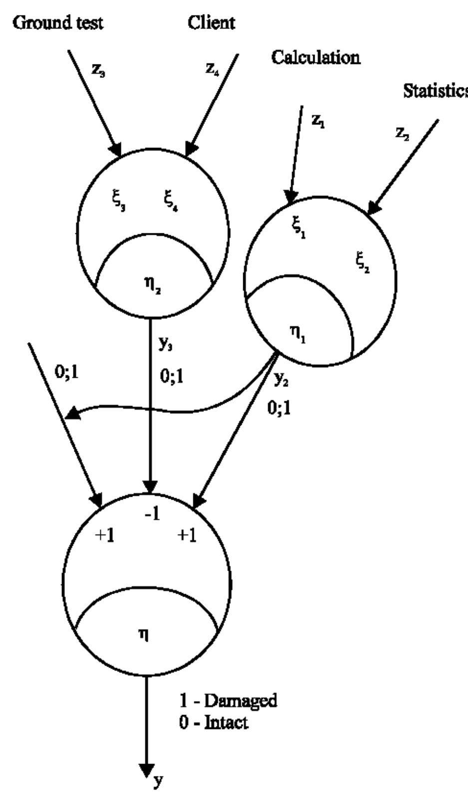

Fig. 2: Scheme of cell model

Let we shape such system model with neural logic auxiliary. Such model cell scheme is given at Fig. 2. it consists of three threshold elements implementing the following functions:

y_i-binary random-number generator (0 either 1)
{
$y_2 = f(z_1, z_2, \xi_1, \xi_2)$,
$y_3 = f(z_3, z_4, \xi_3, \xi_4)$,
$y = f(x_1, x_2, x_3)$
$x_2 = y_2$; $x_3 = y_3$

$x_1 = 0$, if $y_3 = 1$
1, if $y_2 = 0$, $y_1 = 1$.

Denominations of the given at Fig. 2:
x_1,- Binary signal from tension calculation unit;
x_2,- Binary signal from test bench unit;
x_3,- Binary signal from ground test unit;
x_4,- Binary signal from client's data processing unit;
ξ_1,- Weight of signal from tension calculation unit;
ξ_2,- Weight of signal from test bench unit;
ξ_3,- Weight of signal from ground test unit;
ξ_4,- Weight of signal from client's data processing unit;
η- Excitation threshold,
y- Binary excitation signal.

The input cells are

$$z_1=\sigma_{calculated},\ z_2=\sigma_{measured},\ z_3=P_{ground\text{-}test},\ z_4=P_{client\text{-}data},$$

Where
$\sigma_{calculated}$ - Calculated tension at corresponding damaged point,
$\sigma_{measured}$- Measured tension at corresponding damaged point,
$P_{ground\text{-}test}$- Eeventuality of damage calculated by ground-test data,
$P_{client\text{-}data}$- Eventuality of damage calculated by data from client.

The cell threshold element No 1 implements the function:

$y_1 = 0$ at

$$x_1\xi_1 + z_2\xi_2 = \frac{2K_1}{\sigma_{calcul} + \sigma_{rated}} < \eta_1 \tag{3}$$

$y_1 = 1$ at

$$x_1\xi_1 + z_3\xi_3 = \frac{2K_1}{\sigma_{calcul} + \sigma_{rated}} \geq \eta_1 \tag{4}$$

Where
ξ_1 - Weight of parameter at z_1 input,
ξ_2 - Weight of parameter at z_2 input,

Table 1: Cell threshold element No 3 (neuron) states

State no.	X_1 +1	X_2 -1	X_3 +1	Weighted sum η*	Threshold η	Axon y
1	0	0	0	0	1	0
2	1	0	0	1	1	1
3	0	1	0	-1	1	0
4	0	0	1	1	1	1
5	0	1	1	0	1	0
6	1	0	1	2	1	1
7	1	1	0	-1	1	0
8	1	1	1	0	1	0

K_i- Resource coefficient by mechanical tension.

The cell threshold element No 2 implements the function:

$y_1 = 0$ at

$$z_3\xi_3 + z_4\xi_4 = P_{rated}C_{ground-test} + P_{client-data}C_{client-data} < \eta_2 \tag{5}$$

$y_1 = 1$ at

$$z_3\xi_3 + z_4\xi_4 = P_{rated}C_{ground-test} + P_{client-data}C_{client-data} \geq \eta_2 \tag{6}$$

Where
$C_{ground\text{-}test}$ - Weight coefficient of damage probability obtained at ground-test;
$C_{client\text{-}data}$ - Weight coefficient of damage probability obtained at statistical processing of data received from clients.

The neuron 3 function is given at Table 1.

Binary inputs x_1, x_2 and x_3 have the following content:
x_1- (Exciting input) receives binary signal from random number generator:
1- If random number coincides to the cell number,
0- If contrarily,
x_2- (Inhibiting input) receives binary signal from threshold element No 1:
1- If weighted average sum of calculated and measured mechanical tensions at eventual damage point is less that tolerated tension (with reference to resource coefficient K_i)
0- If contrarily,
x_3- (Exciting input) receives binary signal from threshold element No 2:
1- If weighted average sum of calculated and measured mechanical tensions at eventual damage point exceeds either equal to the given threshold value,
0- If contrarily.

As we see from Table 1, the neuron's excitation (y =1) occurs when 2, 4 and 6 states, id. e., when at the least one factor is eventual (x_1) either connected to the real events (x_i), assigns the damage to a given location if at that the mechanical tension level is sufficiently significant (x_2) for not hindering that process.

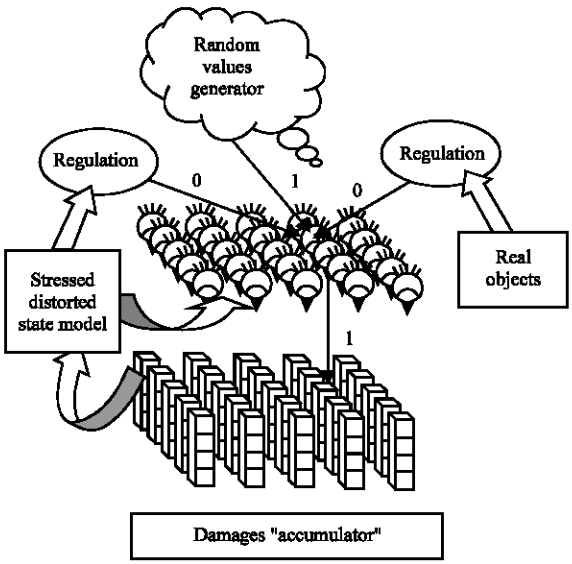

Fig. 3: Scheme of semitrailer frame damages accumulation model functioning on the basis of neural logic

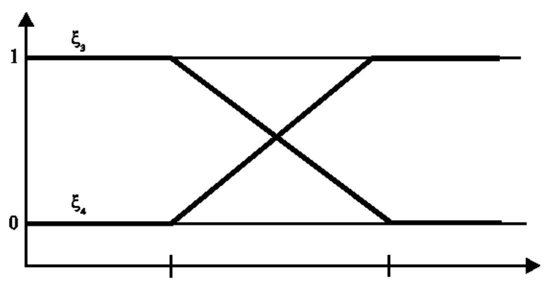

Fig. 4: Correlation of weight coefficients ξ_3 and ξ_4 by the measure of clients' data accumulation

The general model of semitrailer frame damages accumulation, on the basis of neural logic is shaped with the use of elements shown at Fig. 2. Such model functioning scheme is given at Fig. 3. It includes the following levels:

- "Net stochastic" level (random-values generator),
- Object's current state level,
- Calculated level (models of object's internal processes),
- Empirical level (real object's internal processes),
- Logic level (neural network).

The model functions in such a way:

The random-values generator produces a sequential real number W from the series 1…N, where N-quantity of considered points of damage at the object. Accordingly to that, the n-th neural cell input x_{0n} (Fig.3) receives a signal, logic "unit".

$y_n = 1$, if W =n;
$y_n = 0$, if W=/= n.

Calculation level is given with correlation:

$$\eta_i^* = x_1\xi_1 + z_2\xi_2 = \frac{2K_3}{\sigma_{calcul} + \sigma_{rated}} \quad (7)$$

Where η_1* - weighted sum compared to the threshold value η_i:

$$\eta_i = 1/[\sigma].$$

When researching it was adopted:$\xi_1 = \xi_2 = 0{,}5/K_3$

Id. e., the influence of calculated and bench test internal mechanical tensions inside of frame structure was considered in equilibrium. As a rule the client can select another correlation between weight coefficients ξ_1 and ξ_2 corresponding to his confidence level seeking the calculations' and bench tests' results. Provided the bench test has not been effected , ξ_2 is equalised to zero.

The object current state level corresponds to the real dynamics of operation being given with formula:

$$\eta_2^* = z_3\xi_3 + z_4\xi_4 = P_{rated}C_3 + P_{client-data}C_4 \quad (8)$$

where η_2* - weighted sum compared to the threshold value η_2 and to the coefficients.

C_3 and C_4 values. As $\xi_3 = C_3$; $\xi_4 = C_4$, these coefficients represent the weights specifying the values of probabilities for such or another from considered areas damage, resulting from ground-test data ($P_{ground-test}$) and the probabilities of the same points damaging resulting from clients' data processing ($P_{client-data}$) ; the issues being compared with probability threshold value η_2.

CONCLUSION

At the model practical application after concluding an agreement to a client referring to a new object there were effected accelerated preliminary ground tests of automotive vehicle. At this period the ξ_4 value when simulation has been equalised to zero. Initial stage completed, when the "centre" started receiving the clients' data, the ξ_4 value begin increasing at the same time that ξ_3 decreasing up to the point where the data source for second threshold element passes completely to the clients sector (Fig. 4.).

With reference to that the neuron excitation threshold η=1 and with respect to weight coefficients, the logic level is given by:

$$x_1 - x_2 + x_3 \geq 1$$

The neural network teaching consists in: Blocking several neural cells by the measure of corresponding damaged areas' complete disabling; accounting of load redistribution between completely enabled and partially disabled areas and also the corresponding elements' threshold values specification, that serving to adequate representation of increasing data massif onto simulated objects' real operational parameters with the sougn neural model.

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