Neural network model of rupture conditions for elastic material sample based on measurements at static loading under different strain rates

I Bolgov, T Kaverzneva, S Kolesova, T Lazovskaya, O Stolyarov and D Tarkhov
Peter the Great St-Petersburg Polytechnic University, 29 Politechnicheskaya Str, 195251 Saint-Petersburg, Russia
E-mail: tatianala@list.ru

Abstract. The article deals with the problem of predicting the temporal elongation law of the sample under dynamic loading. The determination of tensile behavior of samples under uniaxial loading is performed by a standard tensile method. The neural network approach is applied to construct an approximate elongation-force dependence using measurement data and posterior model of the dependence of rupture conditions on the neural network parameters. The considered approach can be used in the building industry.

1. Introduction

The statistic of accidents indicated that despite the safety requirements, which are connected with the implementation of risky operations, which exists in the world community, more or less serious traumatizing of the workers still happens. A number of these requirements concern the technical objects, which must satisfy, for example, the requirements of solidity and stability. Also, there are requirements, which regulate the behavior of the people in the execution of the works in different situations: in the normal operating regime and in an emergency situation. It is a question of so-called human factor, which influence we are trying to decrease as far as we can. Erroneous human actions can lead to serious consequences, which are difficult to predict.

There is a set of security tools which is used in relation to a particular workplace with the aim to reduce the risk of personal injury. In the case of work at height, we can name the following security tools: harnesses, strapping for positioning and retaining a person falling, ropes. Rescue stretchers and scarves are widely used in the organization of rescue operations on the cable cars. All materials from which these security measures were made must withstand certain load regulations throughout all the time of use. They should have the declared characteristics of strength and elastic, keeping them all the time of operation. The material from which is made the security system with the passage of time under the influence of external conditions aging and loses its mechanical properties.

Elasticity of various materials depend on many factors to take which into account is not always possible. Especially if we consider the materials with a complex structure. Elastic properties modeling allows us, for example, to predict the loss of material strength (rupture of a sample), deformation conditions, which, in turn, can lead to breakdowns and emergencies. This gives us
the opportunity of promptly acting on changes in the elastic characteristics of considered objects and creating such constructs to which high requirements for safe operation are applicable. High extensible materials are continually gaining importance owing to their application in various fields including civil engineering, sport, marine, and safety. These materials include a variety of ropes, slings, cords [1-4]. The application of such material in as high-deformable elements in various structures provides new possibilities in various applications. The properties of these materials depend on their structures and constituent materials and may be significantly varied. They may possess high extensibility under low load or have resistance to high strength, high energy absorption depending on the application. A detailed study of their properties is required for optimal use of these materials in a certain application.

2. Problem statement
In this work, we approximate the initial part of the dependence of the elongation of a rubber thread on a tensile force by the neural network. The aim is to study the dependence of rupture conditions on the neural network parameters. The neural network is used in two stages. The first stage is to approximate the experimental dependence of the elongation on the load. In the second stage, we determine the dependence of the sample rupture conditions on neural network parameters (weights) obtained in the first stage.

From our point of view, building a model, reflecting the circumstances of disruption of sample, which is made from an elastic material, can help us to estimate the probability of loss of mechanical properties.

Especially difficult to predict conditions of destruction, which usually occurs suddenly and are determined by the rapid growth of small damages the integrity of the object - cracks, irregularities, cavities, etc. Permanent diagnosis of such injuries in the course of operation of the facility is often difficult. It is desirable to diagnose the state of the object.

However, theoretical models do not allow to establish a similar relationship, as general considerations leave aside the peculiarities of the individual elements and the actual state of the samples.

3. Measures
The tensile test was carried out on an Instron-5965 universal testing machine (Figure 1) with an automatic data acquisition system. The determination of tensile behavior of samples under uniaxial loading is performed by a standard tensile method. The thin elastomeric yarns were selected as samples. Considered in the work methods can be applied to other samples of an elastic material.

The sample is rigidly fixed at one end in a stationary clamp and at another end in a movable clamp. It should be noted that tensile strains were calculated from crosshead displacement. When testing we set different strain rates. Plots of deformation (mm) against force (N) were obtained with a 50 and 80-mm sample gauge length and strain rates of 50, 250, 500 (Figure 2) and 1000 mm/min.

Elongation of the sample is proportional to the initial length of the sample. These graphs were able to establish that the break point and the elongation-force curve are weakly dependent on the strain rates. In addition, the tensile load is not dependent on the length of the samples.

Figure 2 shows the three phases of the elongation process. The dependence between the elongation and the load does not match the Hooke’s law and is essentially nonlinear. In the first section, we observe the maximum rigidity of the sample at small deformations, gradually turning into the second stage, characterized by less deformation rigidity. In the third section, with increasing deformation, the dependency is almost linear with small perturbations before the destruction characterized by an obvious deformation rigidity increase. The rupture happens without the occurrence of a significant non-linear section. Such behavior of the sample
Figure 1. Instron-5965 universal testing machine. Position Measurement Accuracy: ±0.01 mm or 0.05 percent of displacement (whichever is greater), Load Measurement Accuracy: ±0.5 percent of reading down.

Figure 2. The dependencies of the elongation (mm) against force (N), sample length 50 and 80-mm, strain rate of 500 mm/min. corresponds to the results of [9]. The lack of non-linear section before rupture it significantly complicates predicting.

4. Neural network approach

4.1. Network 1

Elongation-force dependence is looking as a neural network approximation with two neurons in the form

\[ u(x, c, a, xc) = c_1 \text{th}(a_1(x - xc_1)) + c_2 \text{th}(a_2(x - xc_2)), \]  

(1)
where neural network weights, linearly incoming parameters $c_i$ and nonlinear input parameters $a_i, x_i$, are determined in the process of gradual learning network based on the minimization of the error functional given in a discrete form

$$J = \sum_{j=1}^{M} (u(x_j, c, a, x) - F_j)^2. \quad (2)$$

The error functional optimization is conducted by RProp algorithm or by combination of Particle Swarm and RProp algorithms [6].

Figure 3 shows an example of a plot of deviation of neural network approximation from the measurements. Figure 4 shows a typical situation: before the rupture, the neural network approximation error increases significantly, which may serve as another indicator of closeness to the point of rupture. For all experiments, neural network approximation relative error does not exceed 3 percent.

4.2. Network 2

For each of the eight approximations, we have the tensile force at rupture of the sample and the neural network parameters. Using these values, we build the neural network models of the dependence of the rupture tensile force on the neural network approximation parameter $c = \max(c_1, c_2)$ in the form $f(x, c, a, x) = dth(g(c - h))$. To determine the weights of the neural network used are the same as before functional errors and such as nonlinear optimization algorithms. Figure 4 shows one of the obtained dependencies.
Taking into account the complex nature of rupture processes and a strong influence on it of a particular sample defects, the result can be considered satisfactory. If we know the behavior of the sample in the initial part of the load, it is possible to predict the limit force and elongation at which rupture occurs. The obtained relationships can be used in predicting of the temporal elongation law of the sample under dynamic loading using the techniques discussed in the works [5-8].

5. Prediction

To predict the rupture conditions, we can use measurements taken not on the whole interval but on a small fraction of the points preceding the rupture. Further, we present the result corresponding the sample measuring points from 100 to 50 before the rupture.

In the first stage the dependence of the elongation on the tension force is approximated by a neural network, as previously. The simplicity of dependence allows to use the neural network with only one neuron $F(x) = c_0 \text{th}(a_0(x - x_{c0}))$. In the second step, the dependence of the tensile force on the neural network coefficients obtained in the first stage for each sample is approximated by new neural network. Figure 5 shows an example of such dependence for the parameter $x_{c0}$.

![Figure 5. The tensile force dependence on the parameter $x_{c0}$ of the neural network approximated the elongation-force dependence corresponding the sample measuring points from 100 to 50 before the rupture.](image)

These dependencies allow the dynamic prediction of the elastomeric yarn rupture, relearning the specific sample neural network used the newly entered data in the process of strain.

6. Conclusions

The considered approach can be applied in the construction industry in justifying the choice of lifeline, which is used during construction work including industrial alpinism, in the calculation of risk during the evacuation of people by "jumping on the tent" [10]. Work at height is a dangerous type of work, which is associated with a large number of accidents caused by the fall of man, despite the regulated security measures [11]. That is why it is important to provide the strength of safety and amortization elements (slings, ropes, cables), which will depend on the elastic properties of the materials making up the harnesses elements. It should also be borne in mind that the strength characteristics can change significantly during the process of wear [12].

Acknowledgments

The work is supported by the Russian Foundation for Basic Research (Grant no. 14-01-00660).

References

[1] Hearle JWS 2016 One-dimensional textiles. Handbook of Technical Textiles (Elsevier) 345-360
[2] McKenna HA, Hearle JWS, O'Hear N 2004 Handbook of Fibre Rope Technology. Handbook of Fibre Rope Technology (Elsevier) 1-34
[3] Weller SD, Johanning L, Davies P, Banfield SJ 2015. Synthetic mooring ropes for marine re-NEWable energy applications. Renew Energy. Nov; 83:126878
[4] McLaren AJ 2006 Design and performance of ropes for climbing and sailing. Proc. of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications 220 (1) 1-12

[5] Vasilyev A, Tarkhov D 2014 Mathematical Models of Complex Systems on the Basis of Artificial Neural Networks Nonlinear Phenomena in Complex Systems 17 327-335

[6] Riedmiller M and Braun H 1993 A direct adaptive method for faster backpropagation learning: The Rprop algorithm. Proceedings of the IEEE International Conference on Neural Networks (IEEE Press) 586-591

[7] Tarkhov D, Vasilyev A 2005 New neural network technique to the numerical solution of mathematical physics problems. I: Simple problems Optical Memory and Neural Networks (Information Optics) 14 59-72

[8] Tarkhov D, Vasilyev A 2005 New neural network technique to the numerical solution of mathematical physics problems. II: Complicated and nonstandard problems Optical Memory and Neural Networks (Information Optics) 14 97-122

[9] Kainov N, Tarkhov D, Shemyakina T 2014 Application of neural network modeling to identification and prediction problems in ecology data analysis for metallurgy and welding industry Nonlinear Phenomena in Complex Systems 17 (1) 57-63

[10] Kaverzneva T, Savchenkova L 2012 Selection of materials for reliable evacuation by the method "jumping on the tent" LI Science Week SPb GPU Materials of the international scientific-practical conference with international participation.: P.II (Publishing house Politehn. University)

[11] Kaverzneva T, Mazurenko K 2015 Security control when working on hight Science forum with international participation "Science Week SPbSPU": materials of scientific-practical conference. Institute of Military-Technical Education and Safety SPbSPU (Publishing house Politehn. University) 187-190

[12] Kaverzneva T, Smirnova O 2013 The Impact of wear of construction equipment and hand tools on the working conditions Safety in technosphere 3 (42) 14-18