ISSN 0018-8069

Utilization of Neural Networks for Evaluation of Material Properties of Structural Steels based on SPT Results

Využití neuronových sítí pro identifikaci materiálových vlastností konstrukčních ocelí z výsledků SPT

Ing. Ladislav Kander, Ph.D.[1]; **Ing. Jan Špička**[2]

[1] MATERIAL & METALLURGICAL RESEARCH Ltd., Pohraniční 693/31, 703 00 Ostrava-Vítkovice, Czech Republic

[2] Výzkumný a zkušební ústav Plzeň, s.r.o., Tylova 1581/46, 301 001 Plzeň, Czech Republic

Tato práce shrnuje výsledky experimentálních prací a numerického modelování, které byly provedeny v rámci řešení projektu TAČR č. TE01020068 Centrum výzkumu a experimentálního vývoje spolehlivé energetiky, pracovního balíčku WP 8 Výzkum a vývoj nových zkušebních metod pro hodnocení materiálových vlastností. Tento projekt se zabývá využitím penetračních testů pro hodnocení degradace materiálů kritických komponent klasických elektráren ve společnosti ČEZ, a.s. Hlavním záměrem řešení uvedeného pracovního balíčku WP8 je zpřesnění empirických korelací vybraných materiálů používaných v energetice pro výrobu kritických komponent jako jsou parovody, rotory turbin atd. Mimoto se činnosti realizované v rámci pracovního balíčku rovněž zaměřují na využití metody konečných prvků (MKP) a neuronových sítí (NN) pro stanovení mechanických vlastností (meze kluzu, meze pevnosti a lomové houževnatosti) při laboratorní teplotě z výsledků penetračních testů. Konečným cílem experimentálních prací prováděných v rámci tohoto projektu je vytvoření softwaru, který by na základě již provedených experimentů SPT (small punch test), tahovou zkoušku a zkoušku lomové houževnatosti dokázal pro nově provedený SPT predikovat materiálové parametry bez nutnosti provádět tahovou zkoušku a zkoušky lomové houževnatosti a tyto parametry z výsledku SPT identifikovat.

***Klíčová slova**: penetrační testy; neuronové sítě; lomové chování; oceli pro energetiku*

This paper summarizes results of experimental work and numerical simulations carried out within the project TE01020068 "Centre of research and experimental development of reliable energy production, work package 8: Research and development of new testing methods for evaluation of material properties". This project deals with the utilization of the small punch test for evaluation of material degradation of critical components of a power station in the company ČEZ. The main goal of the WP8 activities is an improvement of empirical correlation of selected materials used in power industry for manufacturing of the critical components (rotors, steam-pipes, etc.). Moreover, WP8 activities are also focused on utilization of FE method and neural networks (NN) for evaluation of mechanical properties (yield stress, tensile strength, and fracture toughness) at a room temperature, based on SPT results. Neural networks are computing systems inspired by the biological neural networks that constitute animal brains. Such systems learn to perform tasks by considering examples, generally without task-specific programming. They have found most use in applications difficult to express in a traditional computer algorithm using rule-based programming. Neural networks have been used on a variety of tasks, including computer vision, speech recognition, machine translation, social network filtering, playing board and video games, medical diagnosis and in many other domains. The aim of the experimental work in this project presented in this paper is to develop a software for prediction of mechanical properties (yield stress, tensile strength and fracture behaviour in the term of $J_{0,2}$) of the new materials used in the power industry. Such investigation is based only on built database and SPT results. Additional experimental tests, such as tensile and fracture toughness, requiring quite large volume of experimental material taken from operating components, are not desirable here.

***Key words**: small punch test; neural networks; fracture behaviour; steel for power engineering*

In connection with the effort to maximize the service life of almost worn out operating components while maintaining the conditions for reliable and safe operation, the use of new test methods for evaluation of residual service life, or for determination of the actual strength values and brittle fracture properties of the exploited components is becoming more and more accentuated.

One of the methods that was used on a long-term basis to evaluate the current state of mechanical properties is the small punch test (SPT). This method is used both for assessing the current condition of the material used by operating power plants, as well as for evaluating the so-called zero states of newly manufactured components for power plants with ultra super critical parameters (USC), in order to map their initial state during commissioning. The aim of this work is to create a program, which, on the basis of already performed experiments for penetration test (SPT) and tensile test, will be able in the future for the newly performed SPT experiments to estimate material parameters without necessity to perform the tensile test and to identify from it these parameters. This procedure could facilitate identification of the actual material parameters of steel used in turbines in a timely and economical manner. These materials degrade during the process of their exploitation and they lose their original properties. For ensuring the safe operation, it is necessary to test the actual values of the material parameters. Use of the results of this work would avoid the necessity to perform a costly tensile test, since it would be sufficient to perform just a penetration test and, using a suitable mathematical apparatus, to estimate/identify the mechanical parameters that would otherwise be obtained from the tensile test.

A neural network (NN) was chosen as a suitable mathematical apparatus. The neural network is a computational system originally inspired by nature and the human brain. Dr. Robert Hecht-Nielsen defined the neural network as follows:

"...a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.

In "Neural Network Primer: Part I" by Maureen Caudill, AI Expert, Feb. 1989 [1]

The original intention of NN was to solve the problems in a way that human brain solves them, but over time many other applications were also found. The basic idea, however, is that this network can be trained/taught using input and output data to give reasonable outputs for new inputs. The structure of the neural network is in the so-called layers (Figure 1), where the first layer is the input; the last layer is the output and between them is (any) number of suitable hidden layers. Each layer contains mutually connected nodes, and these are further connected to other nodes in the next layer. In this way, we get to the last layer, i.e. to the output data. However, it is necessary to properly train the network in order to create suitable connections between the layers and the nodes. Ideally, several hundred to several thousand input/output pairs would be needed to properly train the network [2, 3].

In this case, the network would have the data from the penetration test as input and one of the following material parameters as output: Young's modulus of elasticity E, yield strength R_{p02}, the strength limit R_m and possibly the Poisson number *Nu* (Fig. 2).

The network thus created could be used just after the training namely for identification of the given material constant. For better functionality of the network, one network was always created for one output (parameter). We have therefore a total of 3 NN (The Poisson constant has not yet been solved in this case), where each network has the data from the penetration test as input (curve of Force versus Strain) and the output is always one material constant.

The procedure is described in the next paragraph.

The input data for this work were the curves measured from tensile and penetration test, altogether with three types of steel (materials P91, P92 and 14MoV6-3). In the first instance, it was necessary to identify the material characteristics of the steel from the tensile test.

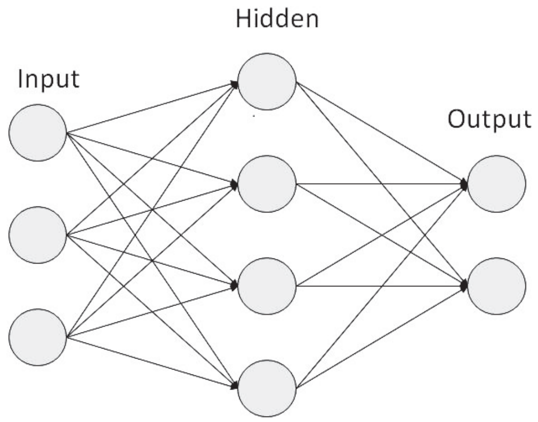

Fig. 1 Structure of the Neural Network
Obr. 1 Struktura neuronové sítě.

Fig. 2 Diagram of the program
Obr. 2 Schéma programu

For this purpose, a model based on finite element method (FEM) was created with the use of the ANSYS software, which simulated the tensile test. The Gurson-Tvergaard's material model was used in order to take into account also material failures. This model is characterized by 11 constants (including yield strength and strength limit), Young's modulus of elasticity, and the Poisson constant. Numerical optimization in the MATLAB software was used for identification of these constants. This program gradually varies these constants using the gradient method and it simulates the tensile test with the use of the ANSYS software. The aim was to achieve that response of the numerical simulation (MATLAB + ANSYS) matched most closely possible the curve of the tensile test experiment. The *Mean Square Error* was used as a target optimization function between the experiment curve and the simulation.

Hutnické listy č. 4/2017, roč. LXX
ISSN 0018-8069

In this way, the material characteristics were identified for all the supplied test specimens.

The next step consisted of creation and training of the NN. The input, in this case, was directly the penetration test curve (Force vs. Strain) and material parameters (*E*, R_{p02} a R_m) obtained by optimization were the output. Due to the fact that strain was a controlled variable, it was the same everywhere and we did not consider it; so only the values of the force vector served as our input. For better consistency of calculations, it was advisable to have the input vectors always of the same length and range. The curve was here taken from zero to its maximum, it was cut here and sampled for a given number of points. In the future, it would be advisable to consider the curve also beyond the value of its maximum.

The neural network must not only be trained, it is always necessary to test it with the use of some known pair of the input-output, which was not used in training. The largest number of samples - 18 was available for the material P91. We always took from these samples 17 pairs for network training and left one pair for testing. This was done gradually with all 18 values (each of which thus will become a test value).

Experimental methods

In order to obtain experimental data, the following structural steels were used that are exploited in power engineering: steel 15 128 (14MoV6-3), which is used on a long term basis and successfully particularly in the design parts for the power engineering, and also steels of type P91 (X10CrMoVNb9-1) containing 9% Cr, and 1% Mo, and steel P92, in which it was attempted to replace the expensive molybdenum by tungsten.

All of the above steels were subjected to simulation heat treatment procedures in order to achieve various levels of mechanical properties and to provide thus enough experimental data for the neural networks. In this way for each material six different levels of mechanical properties were thus achieved.

For every heat-treated state we then performed tensile tests with subsequent determination of the curve of actual stress-actual strain, SPT and fracture toughness tests that resulted in the R curves, since the characteristic feature of the fracture behaviour at the laboratory temperature for all of the above materials and their states after heat treatment was a stable crack growth.

Due to the fact that both tensile and fracture toughness tests are standardized and adequately described in the literature [4, 5], the next paragraph will deal only with the method of the SPT penetration tests.

The SPT method belongs to advanced testing methods that are developed on the long term basis in the company MATERIAL & METALLURGICAL RESEARCH LtD. This method makes it possible to obtain a number of mechanical properties with the use of the relatively small size of the test specimen. The method is used mainly for evaluation of the actual level of mechanical properties of the components exploited in classical power engineering. In the recent past, this method was newly used also for determination of the effect of the sigma phase on the fracture properties of steels used for the USC parameters [6 – 8].

The main advantage of the SPT method lies in the low volume of the experimental material and also in the fact that it is possible to obtain from the conducted SPT tests a number of properties. The SPT principle is illustrated in Fig. 3. The test specimen is a disc with a diameter of 8 mm and a thickness of 0.5 mm, which is penetrated by a hemispherical puncher with a diameter of 2 mm till the failure. Record of the test result is shown in Fig. 4, from which it is then possible, on the basis of correlation relationships, to obtain the required values of mechanical properties [9].

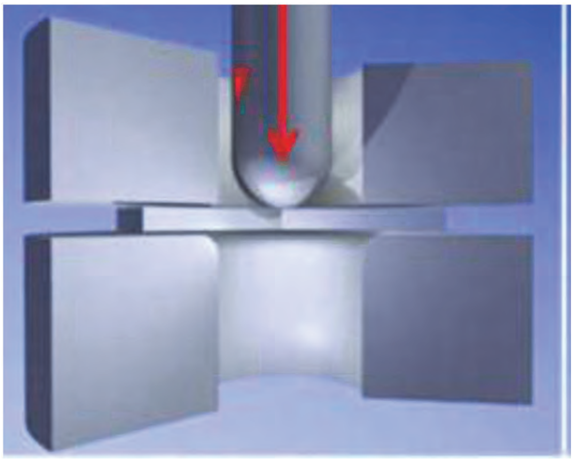

Fig. 3 Principle of small punch test
Obr. 3 Princip penetračního testu

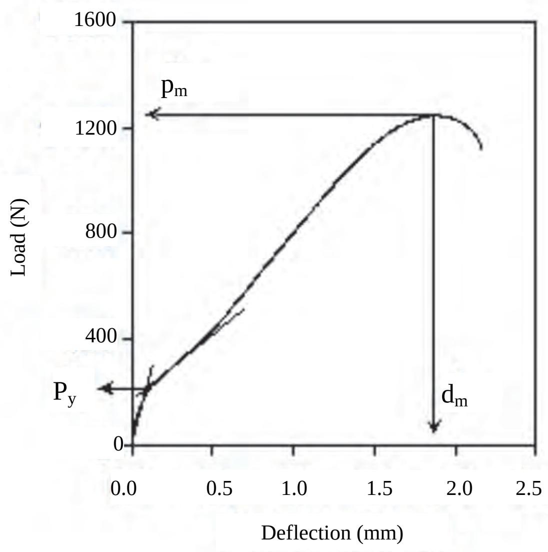

Fig. 4 Record of small punch test
Obr. 4 Záznam penetračního testu

Obtained results and their discussion

Due to the fact that presentation of all the data and outputs obtained during the solution of this project would significantly exceed the possibilities of this article, we will limit ourselves to the presentation of only the most important facts.

Figures 5 to 7 show the consistency between the experimental records of the tensile test and the model. As it can be seen from Figs. 5 and 6, in the case of materials exhibiting an indistinctive yield point ($Rp_{0,2}$) the conformity is very good, unlike Fig. 7, valid for material 15 128, which shows a significant yield strength. Here, the model does not copy the record accurately, it can not handle the discontinuity and it interleaves it, similarly as in the two above cases, with a monotonous curve.

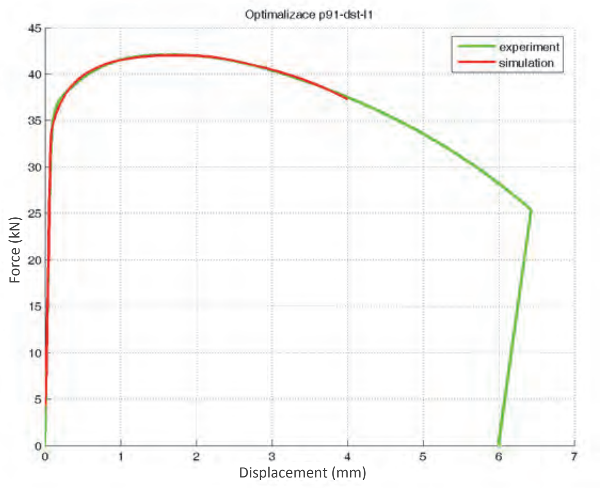

Fig. 5 Record of tensile test, experiment, and model, P91
Obr. 5 Tahová zkouška, experiment a model, P91

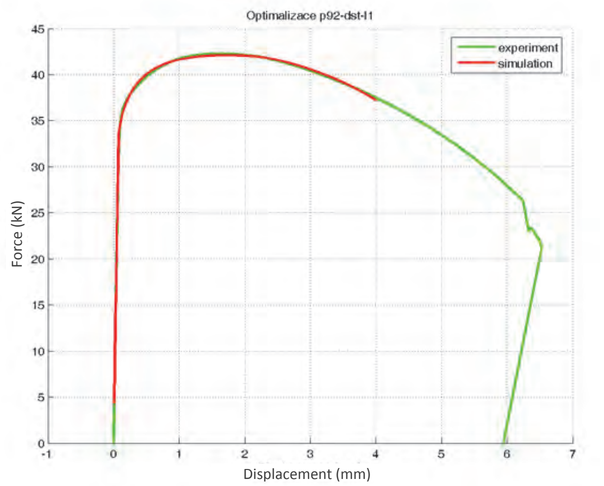

Fig. 6 Record of tensile test, experiment, and model, P92
Obr. 6 Tahová zkouška, experiment a model, P92

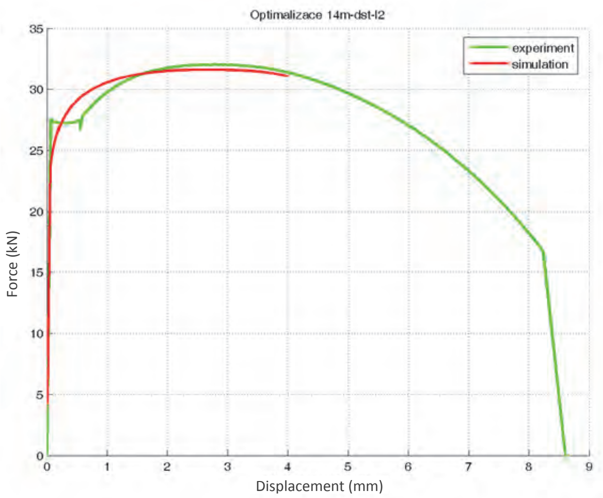

Fig. 7 Record of tensile test, experiment, and model 15 128 discontinuous yield strength
Obr. 7 Tahová zkouška, experiment a model, 15 128, nespojitá mez kluzu

Figure 8 illustrates a similar comparison of the experiment and the model for SPT, specifically for material P92, where relatively good agreement between the model and the experiment is evident. This agreement was recorded for all three investigated materials.

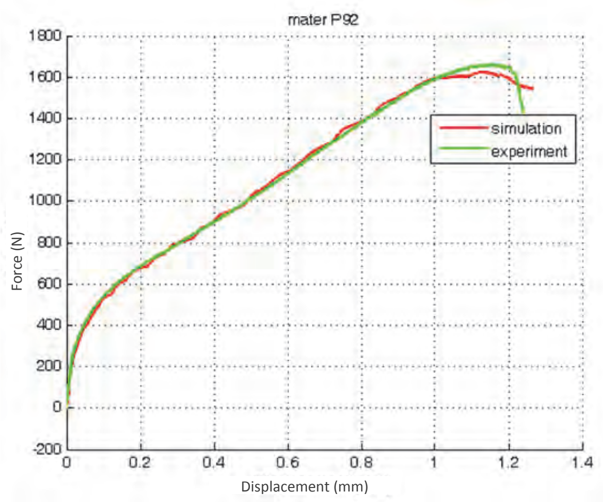

Fig. 8 SPT record, experiment, and model, P92
Obr. 8 Záznam SPT, experiment a model, P92

Table 1 presents the results of the simulation with the use of the neural network for the modulus of elasticity, yield strength and ultimate strength for all three investigated materials. The results obtained show a fairly good agreement for the modulus of elasticity, with variations of approx, units of per cent. However, the difference between the simulated and actual results and the overall error of the estimate for the yield strength and ultimate strength is high. For Young's modulus of elasticity the error (direct error and error of absolute values) is around -0.739, or 1.645%. For the values of R_{p02} we have an error of -0.354, or 16.52%, and for R_m -0.265 and 8.712%.

Hutnické listy č. 4/2017, roč. LXX
ISSN 0018-8069

Tab. 1 Results of NN simulation of mechanical properties
Tab. 1 Výsledky simulace mechanických vlastností neuronovými sítěmi

		delta rel round	delta rel round ABS	Max. error
		(%)		
P91	E	-0.07	1.65	3.18
	Rp02	-3.39	14.89	30.5
	Rm	-1.60	9.08	18.8
P92	E	-0.14	1.00	2.2
	Rp02	-1.50	11.01	38.6
	Rm	0.15	6.51	14
15 128	E	-0.34	4.65	8.41
	Rp02	0.34	8.65	15.8
	Rm	0.09	1.75	4.25

It was also tested variouc set-up, configuration and structure of NN, however no significat improvment was found. In the next step we try to use whole (extended) file of imput force vector (without cutting of at the maximum). However neither this change in input conditions caused any improvement in the results. Only small improvement has been found in yield stress test results if extended input force vector is used.

In absolute numbers we are within 10% of actual values.

Tab. 2 Results of NN simulation of fracture toughness
Tab. 2 Výsledky simulace lomové houževnatosti neuronovými sítěmi

J_{02}_sim	J_{02}_orig	delta rel	delta rel round	delta rel round ABS
		(%)		
341.5976	326.6	-4.592054283	-4.6	4.6
474.6676	342.6	-38.54862274	-38.55	38.55
338.3784	254.8	-32.80156127	-32.81	32.81
322.8736	341.1	5.343427442	5.35	5.35
		Average error	**-17.6525**	**20.3275**

For R_m, an increase of approx. 0.5% was achieved by means of an extended force vector (till the rupture). Tab. 2 summarizes the initial state of modelling of the initiating value J of the $J_{0.2}$ integral. This is the value considered to be the initial value, at which a stable growth of a ductile crack occurs. The value of $J_{0.2}$ is determined from the R curves at a given temperature and it describes the fracture behaviour of the material, or it is a material characteristic if the relevant conditions are met in the course of testing [4].

It follows from the results obtained, that are summarized in Tab. 2, that the simulation here so far does not have good agreement with the experimental results. The cause consists also in a very complicated process of construction of the R curve, as well as the determination of the initiation value, which in itself is affected by an error at interleaving the curve by the data points from individual experiments during the determination of the fracture toughness.

In the future, our aim is to focus on refinement of this model by increasing the number of experimental data, as well as by expanding the investigated materials also by such steel grades, the characteristic features of fracture behaviour of which is also a sudden unstable fracture in the area of validity of elastoplastic or elastic fracture mechanics.

Conclusions

The paper summarizes the essence and the results obtained so far within the framework of the TAČR project TE01020068, work package WP 8.

The project is focused on the use of the SPT tests for evaluation of material degradation of critical components of conventional power plants. The aim of the project consists, among other things, in the creation of a link between the SPT tests performed within the frame of evaluation of the actual material properties of the exploited and newly manufactured components and numerical simulation using neural networks. The first results indicate the possible application of the neural network method, especially for determining the values of mechanical properties. Application to the values of fracture toughness gives so far only relatively rough results.

Achievement of better results when estimating material characteristics using neural networks would probably require a much bigger number of training samples. This is consistent with the literature, which states the need for at least several hundred pairs, for the proper functioning of the neural network.

Acknowledgments

*This work was created during the solution of the **TAČR project ´TE01020068 Centre of Research and Experimental Development of Reliable Power Engineering´** funded by the Czech Technology Agency.*

Literature

[1] *"Neural Network Primer: Part I" by Maureen* Caudill, AI Expert, Feb. 1989.

[2] https://en.wikipedia.org/wiki/Artificial_neural_network

[3] https://www.tutorialspoint.com/artificial_intelligence/artificial_intelligence_neural_networks.htm

[4] ČSN EN ISO 9862-1

[5] ASTM E 1820

[6] KANDER, L., KORČÁKOVÁ, L. The Influence of Sigma Phase Precipitation on Mechanical Properties of Tp347H Austenitic Steels after 100.000 Hours Service in Coal-fired Power Plant. In *Metal 2015*, Brno, Czech Republic.

[7] STEJSKALOVÁ, Š., KANDER, L., HERMANOVÁ, Š. The Change of the Structure and Mechanical Properties of the Austenitic Steels after Exposure at the Critical Temperature. In *Metallography 2016*, p. 100, Stará Lesná, Slovak Republic.

[8] KANDER, L. Precipitation of Sigma Phase in Austenitic Steels Used in Supercritical Conditions. In *Metal 2016*, p. 103, Brno, Czech Republic.

[9] *Small Punch Test Method for Metallic Materials*. CEN WORKSHOP AGREEMENT CWA 15627, December 2007.

Ocelářský průmysl: Na pokraji obchodní války

Der Spiegel *08.04.2017*

USA a Evropská unie učinily další krok ve směru k obchodní válce. Jako odpověď na výhrůžku amerického ministerstva obchodu zavést trestná cla proti dvěma německým ocelářským firmám (Salzgitter a Dillinger Hütte), zkoumá nyní Evropská komise, zda by mohla zavést vlastní ochranná cla proti americkým výrobcům oceli. „Musí to být ovšem požadováno od některého postiženého evropského ocelářského podniku," říká jeden vysoce postavený člen vedení EU. Poté by takové protiopatření mohlo být rychle (během několika měsíců) schváleno Evropskou komisí. To by se mohlo stát nezávisle na event. žalobě, podané u WTO, která by se mohla táhnout po dobu několika let. Prezident WV Stahl Hans Jürgen Kerkhoff protestuje proti nařčení ministerstva obchodu USA, členské podniky napadají americké oceláře dumpingovými cenami. Říká: „Německé ocelářské podniky agitují na světových trzích o tržně hospodářských pravidlech, Američané nemohou částečně naši kvalitu vůbec vyrábět“. Viní Američany, že se nedrží pravidel WTO pro posuzování dumpingu a varuje před protekcionismem USA. Začíná to u pravidel, kterými je americkým podnikům nařizováno, například u projektů plynovodů používat jen polotovary, vyrobené v USA.

Suroviny tlačí kurzy dolů

Handelsblatt *19.04.2017*

Politika má finanční trhy i nadále pevně v rukou: poté, co britská premiérka Mayová překvapivě oznámila ve Velké Británii nové volby, spadl burzovní index FTSE 100 o 1,7 %. Sestupnému trendu se nevyhnuly ani německé akcie. Největším poraženým byl ocelářský koncern Thyssenkrupp, který ztratil 2,5 %. Tuto ztrátu pomohl vytvořit pád ceny železné rudy v Číně, který činil 6,5 %. Poptávku po železné rudě dusil přebytek nabídky oceli. Cena oceli klesla na burze v Šanghaji o 3,7 %. Vývoj, kterému neunikla ani konkurence Thyssenkrupp v Německu – Salzgitter, ztratil více jak 2,5 %, ArcelorMittal šel dokonce o 5 %. Od poloviny března ztratily tyto tři koncerny již 9 – 21 % na burzovní hodnotě. Podobně se nedařilo i důlním koncernům (Glencore, Rio Tinto). Optimisticky hledí ale investoři na Turecko. Po svém vítězství v referendu si Erdogan upevnil svoji pozici a burza reagovala proti evropskému kurzu směrem vzhůru. Podle názoru Commerzbank bude mít ale zotavení turecké měny a burzovních cen jen krátké trvání.