Nontraditional Methods of Statistical Process Control

Netradiční postupy statistické regulace procesu

Ing. Tereza Smajdorová; **prof. Ing. Noskievičová Darja, CSc.**

VŠB – Technical University of Ostrava, Faculty of Metallurgy and Materials Engineering, Department of Quality Management, 17. listopadu 15/2172, 708 33 Ostrava-Poruba, Czech Republic

This paper presents the limitations of classical Shewhart control charts and some possibilities of statistical process control that can be used when the basic assumptions about data have not been fulfilled. These basic assumptions that must be met include mainly a requirement for the normality of the data, the requirement for constant mean and variance, and last but not least the requirement for mutual independence of data. In practice, those assumptions about the data are not necessarily always met. During preparation of this article accessible pieces of knowledge on the issue were compared. This article aims to describe some nonparametric and robust methods of the statistical process control including a practical example. And it opens the way for further exploration of these methods.

Key words*: Statistical process control; nonparametric control charts; robust control charts*

Tento článek se zaměřuje na inovativní řešení statistického řízení procesů, které lze využít v případech, kdy nejsou splněny základní předpoklady o datech. Mezi tyto základní předpoklady patří především předpoklad normálního rozdělení pravděpodobnosti, udržení konstantní střední hodnoty a rozptylu a v neposlední řade také předpoklad nezávislosti dat. V praxi nejsou vždy splněny všechny předpoklady pro uplatnění klasických Shewhartových regulačních diagramů a proto je důležité hledat nové metody, které jsou na těchto předpokladech nezávislé. Tento článek si klade za cíl popsat některé neparametrické a robustní metody statistického řízení procesů, včetně praktických příkladů. Konkrétně se jedná o neparametrický regulační diagram založená na Moodově statistice, dále pak neparametrický regulační diagram progresivního průměru a jeden robustní regulační diagram MAD (Median Absolute Deviation), tedy absolutní odchylky od mediánu. A zároveň otevírá cestu pro další zkoumání těchto metod, včetně rozšíření softwarové podpory, která je u těchto regulačních diagramů nedostatečná. Statistické řízení procesu (SPC) je okamžitá a průběžná kontrola procesu založená na matematicko-statistické vyhodnocování kvality výrobků. Jeho aplikace v praxi je důležitá pro udržení vysoké kvality produktů. Ta je důležitá pokud firma chce v maximální míře uspokojovat požadavky zákazníků a i všech ostatních zainteresovaných stran. Statistická regulace procesu umožňuje zásahy do procesu díky včasné detekci odchylek od předem stanovené úrovně. Cílem SPC je udržet proces na požadované a stabilní úrovni. Dosažení požadované úrovně procesu vyžaduje důkladnou analýzu variability. Pokud firma chce dosáhnout vysoké kvality, konzistentně musí systematicky shromažďovat, zpracovávat a vyhodnocovat dostupná data z výroby a využívat získané poznatky k neustálému zlepšování.

Klíčová slova: *statistická regulace procesu; neparametrické regulační diagramy; robustní regulační diagramy*

Statistical process control (SPC) is an immediate and continuous process control. To use the classical Shewhart control charts, the certain basic assumptions must be met (normal distribution of the quality characteristics, constant mean and variance, mutual independence of quality characteristic values. etc.). In the manufacturing practice, however it is not always possible to meet these basic assumptions. In the case of non-compliance with some assumptions, it is possible to apply nonparametric or robust methods.

1. Classical Shewhart Control Charts

Statistical process control allows interventions in the process based on the early detection of deviations from a predetermined level. The aim of the SPC is to keep the process at the required and stable level. It is implemented by regular monitoring of the controlled process variable or output variable. It finds out whether the process corresponds to the level required by the customer. Achieving the desired level of the process requires a thorough analysis of the process variability [10].

Before selection and application of the classical Shewhart control the charts assumptions about the distribution of the controlled variable must be checked. These assumptions include among others the independence of the data a normal probability distribution and constant mean and variance. This verification is performed using a variety of statistical tests or graphical tools. [5]

- Normality tests:
  - Shapiro - Wilk test [5]
  - Shapiro - Francia test [3]

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- Royston modification [7]
- Anderson - Darling test [6, 11]

- Tests of Independence:
  - Autocorrelation test [7]
  - Test of iterations up and down [5]
  - Runs Above and Below the Median [7]
- Tests of Homogeneity of means and variances:
  - Analysis of variance ANOVA [5, 7]

2. Not Meeting the Basic Assumptions

In the case of non-compliance with the data assumptions for application of the classical Shewhart control charts, it is also possible to apply other methods. The procedure for selecting the method can be seen in Fig. 1.

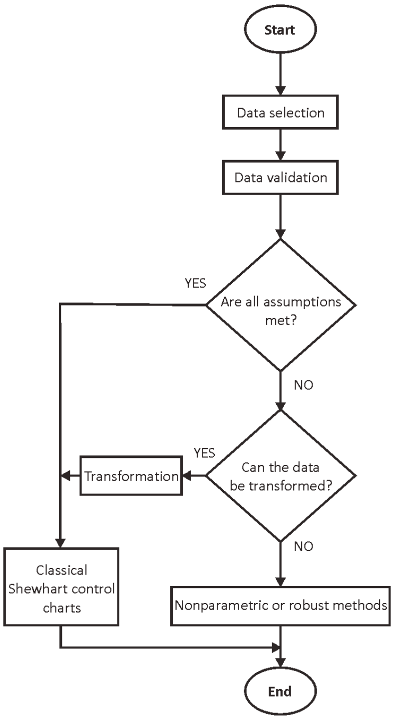

Fig. 1 Flowchart for selection of SPC methods. (Source: our own diagram)
Obr. 1 Vývojový diagram pro výběr metody SPC. (Zdroj: vlastní schéma)

In some cases an abnormal distribution may be transformed. It is necessary to find a suitable transformation function, thanks to which we obtain data about the normal distribution. Subsequently from the transformed data the required characteristics and control limits must be calculated. Then it is necessary to perform a retransformation to the original distribution. So we get a diagram with retransformation control limits. Not always, however, we manage to find a suitable transformation function. The most common types of transformations are a power, logarithmic, exponential and Box-Cox transformation Johnson [8].

3. Nonparametric Control Charts (NPCC)

Nonparametric statistical process control (NSPC) is based on methods that are not dependent on a specific type of the probability distribution. The use of these control charts is not only suitable for processes that do not meet normality and independence of the data but especially in the beginning of the SPC implementation when not enough data are available [4]. Below mention some nonparametric methods that can be used if the basic assumptions, such as data normality, mutual independence or constant mean and variance, are not met.

3.1 Nonparametric Progressive Mean Control Chart for monitoring process target

We use the progressive mean (PM) as the process monitoring statistic. PM is defined as the cumulative average of the sample values observed over time. Suppose we are interested in monitoring a quality characteristic X, following a distribution $f(x)$. Let X_i, $i = 1, 2, 3, \ldots$, is the sequence of independent and identically distributed observations from the process under investigation, then the PM statistic is defined as

$$PM_t = \frac{\sum_{i=1}^{t} X_i}{t} \tag{1}$$

The difference between PM and moving average is that in moving average we have a fixed moving interval such that we excluded the most previous observation before adding the next, but in PM we do not exclude previous but keep on including the next observation. Suppose $X_1 \ldots X_n$ represents a sample of the size n from a process with a target (or location) at m. Define p to be the probability of X greater than m. For an in-control process $p = p_0$, the process is said to be out-of-control for $p \neq p_0$.

Using the mean and the variance of PM_t given in the Eq. (1) the widely used 3-sigma limits are [1]

$$UCL_t = \mu_0 + 3 * \frac{\sigma_0}{\sqrt{t}} \tag{2}$$

$$CL_t = \mu_0 \tag{3}$$

$$LCL_t = \mu_0 - 3 * \frac{\sigma_0}{\sqrt{t}} \tag{4}$$

3.2 NPCC based on the Mood Statistic for dispersion

Statistics Mood is one of the strongest non-parametric statistics. Suppose that a reference sample of the size m, denoted by $X = (X_1, X_2. \ldots . X_m)$ is from an in-control process and that $Y = (Y_1, \ldots . Y_n)$ denotes an arbitrary test sample of size n. Let $R_1 < R_2 < \ldots < R_n$ be the combined-samples ranks of the X-value in an increasing order of magnitude. Then we have the following control chart based on Mood:

$$M_{m,n} = \sum_{i=1}^{m} \left(R_i - \frac{N+1}{2} \right)^2, where \ \ N = m+n \tag{5}$$

In addition. we know the mean and variance of the statistic $M_{m,n}$ as

$$E(M_{m,n}) = \frac{m\,(N^2-1)}{12} \tag{6}$$

$$\mathrm{var}\,(M_{m,n}) = \frac{mn\,(N+1)\,(N^2-4)}{180} \tag{7}$$

The chart signal of the proposed Mood chart as the charting statistic is

$$M_{m,n} < L_{mn} \ \ or \ \ M_{m,n} > U_{mn}$$

where $L_{m,n}$ and $U_{m,n}$ denote the lower (*LCL*) and upper (*UCL*) control limits. respectively.

For large sample sizes, we may use the control limits by

$$UCL = U_{mn} = E\,(M_{m,n}) + c * \sqrt{\mathrm{var}(M_{m,n})} \tag{8}$$

$$LCL = L_{mn} = E(M_{m,n}) - c * \sqrt{\mathrm{var}\,(M_{m,n})} \tag{9}$$

where c is selected to satisfy the ARL (ARL is Average Run Length). It is an average number of the points plotted within the limits of a control chart when evaluating the process behaviour of the $M_{m,n}$ control chart. [9]

4. Robust methods

The robust methods are one group of the most commonly used statistical methods when the underlying normality assumption is violated. These methods offer useful and viable alternative to the traditional statistical methods and they can provide more accurate results. By a robust estimator we mean an estimator which is insensitive to changes in the underlying distribution and is also resistant to the presence of outliers.

4.1 Mad Robust Control Chart

The median absolute deviation from the sample median (MAD) is considered to be one of the good robust estimators. Due to the good properties of this estimator it will be used as an alternative to the sample standard deviation. The MAD for a random sample of the size n observations x_1, x_2, ... x_n. is defined as follows:

$$MAD = \frac{1}{n} * \sum_{i=1}^{n} median \left| X_i - MD_j \right|; \ \ i = 1,2,\ldots,n \tag{10}$$

where MD is the sample median.

Thus we may set the control limits and central line for the Shewhart S-control chart based on

$$\overline{MAD} = \frac{\sum_{i=1}^{m} MAD_i}{m} \tag{11}$$

$$LCL = c_4\sigma - 3\sigma\sqrt{1-c_4^2} = c_4 b_n \overline{MAD} - 3b_n \overline{MAD}\sqrt{1-c_4^2} = = B_5 b_n \overline{MAD} = B_5^* \overline{MAD} \tag{12}$$

$$CL = c_4\sigma = c_4 b_n \overline{MAD} = c_4^* \overline{MAD} \tag{13}$$

$$UCL = c_4\sigma + 3\sigma\sqrt{1-c_4^2} = c_4 b_n \overline{MAD} + 3b_n \overline{MAD}\sqrt{1-c_4^2} = = B_6 b_n \overline{MAD} = B_6^* \overline{MAD} \tag{14}$$

$$c_4 = \frac{E(\overline{S})}{\sigma} \cong \frac{4*(n-1)}{4n-3} * c_4^* = b_n c_4 \tag{15}$$

$$B_5^* = B_5 b_n = b_n \left(c_4 - 3\sqrt{1-c_4^2} \right) \tag{16}$$

$$B_6^* = B_6 b_n = b_n \left(c_4 + 3\sqrt{1-c_4^2} \right) \tag{17}$$

The values of the control limit factors c_4^*, B_5^* and B_6^* and the correction factor b_n for different values of n are calculated and given in Tab. 1 [2].

Now, when the LCL and UCL and the central line CL are calculated, the values of MAD are plotted on the chart. If any of the plotted MAD's is falling outside the control limits the process is considered to be out of control [2].

5. Example

Control charts described in the previous chapters were applied to the data that did not meet the assumption of normal probability distribution. One hundred values were generated from the binomial distribution in twenty-five subgroups of the range five. The generated data can be seen in Tab. 1.

Tab. 1 Calculated data
Tab. 1 Vypočítaná data

Subgroup	x_1	x_2	x_3	x_4	x_5
1	33.05	32.50	29.69	31.78	31.07
2	32.65	31.30	29.11	30.34	33.71
3	36.42	29.83	30.46	32.88	29.18
4	34.43	34.63	23.27	32.49	32.43
5	32.76	34.25	36.09	34.52	36.93
6	35.26	25.67	30.76	32.55	32.28
7	26.15	28.99	29.67	29.63	31.18
8	30.44	31.51	28.42	29.54	31.78
9	29.30	31.68	33.48	28.31	30.93
10	32.94	32.72	32.37	28.70	30.68
11	29.49	31.08	28.62	35.93	31.05
12	26.98	33.43	28.44	31.73	40.45
13	29.35	30.02	30.39	29.58	35.90
14	29.50	33.05	34.12	26.86	36.79
15	31.30	31.10	29.10	28.78	32.16
16	29.51	30.54	31.96	41.52	26.38
17	29.71	26.87	25.29	32.70	36.00
18	36.68	28.81	31.18	42.84	30.92
19	28.80	29.89	23.16	30.93	32.71
20	30.87	31.09	29.60	28.87	31.43

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5.1 Nonparametric Progressive Mean Control Chart

First of all, it is necessary to calculate the progressive mean (PM) according to the Eq. (1). The resulting values are presented in Tab. 2.

Tab. 2 Progressive mean
Tab. 2 Progresivní průměr

Subgroup	x_1	x_2	x_3	x_4	x_5	PM_t
1	33.05	32.50	29.69	31.78	31.07	31.62
2	32.65	31.30	29.11	30.34	33.71	31.52
3	36.42	29.83	30.46	32.88	29.18	31.60
4	34.43	34.63	23.27	32.49	32.43	31.56
5	32.76	34.25	36.09	34.52	36.93	32.23
6	35.26	25.67	30.76	32.55	32.28	32.08
7	26.15	28.99	29.67	29.63	31.18	31.65
8	30.44	31.51	28.42	29.54	31.78	31.49
9	29.30	31.68	33.48	28.31	30.93	31.41
10	32.94	32.72	32.37	28.70	30.68	31.41
11	29.49	31.08	28.62	35.93	31.05	31.40
12	26.98	33.43	28.44	31.73	40.45	31.47
13	29.35	30.02	30.39	29.58	35.90	31.43
14	29.50	33.05	34.12	26.86	36.79	31.48
15	31.30	31.10	29.10	28.78	32.16	31.41
16	29.51	30.54	31.96	41.52	26.38	31.45
17	29.71	26.87	25.29	32.70	36.00	31.37
18	36.68	28.81	31.18	42.84	30.92	31.52
19	28.80	29.89	23.16	30.93	32.71	31.39
20	30.87	31.09	29.60	28.87	31.43	31.34

And subsequently it is possible to calculate the central line and control limits according to the Eqs. (2) – (4).

$$UCL_t = \mu_0 + 3 * \frac{\sigma_0}{\sqrt{t}} = 30.5 + 3 * \frac{5}{\sqrt{100}} = 3$$

$$CL_t = \mu_0 = 30.5$$

$$LCL_t = \mu_0 - 3 * \frac{\sigma_0}{\sqrt{t}} = 30.5 - 3 * \frac{5}{\sqrt{100}} = 29$$

Now. it is possible to construct a control chart that is shown in Fig. 2.

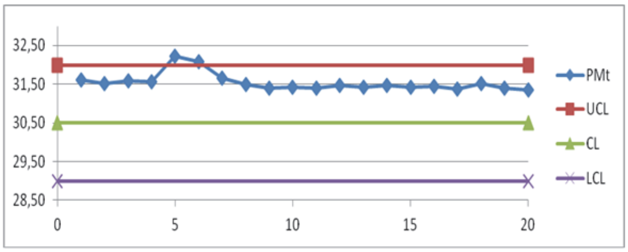

Fig. 2 NPCC of the progressive mean
Obr. 2 Neparametrický regulační diagram progresivního průměru

5.2 Nonparametric Control Chart Based on the Mood Statistics

As the first step, it is necessary to calculate the Mood statistic. The resulting values are presented in Tab. 3.

Tab. 3 Calculated values of the Mood statistics
Tab. 3 Vypočítané hodnoty Moodovy statistiky

Subgroup	x_1	x_2	x_3	x_4	x_5	M5.20
1	33.05	32.50	29.69	31.78	31.07	1740.17
2	32.65	31.30	29.11	30.34	33.71	1709.74
3	36.42	29.83	30.46	32.88	29.18	1793.29
4	34.43	34.63	23.27	32.49	32.43	1789.87
5	32.76	34.25	36.09	34.52	36.93	2411.42
6	35.26	25.67	30.76	32.55	32.28	1725.83
7	26.15	28.99	29.67	29.63	31.18	1313.41
8	30.44	31.51	28.42	29.54	31.78	1510.25
9	29.30	31.68	33.48	28.31	30.93	1590.01
10	32.94	32.72	32.37	28.70	30.68	1720.78
11	29.49	31.08	28.62	35.93	31.05	1694.66
12	26.98	33.43	28.44	31.73	40.45	1956.10
13	29.35	30.02	30.39	29.58	35.90	1659.08
14	29.50	33.05	34.12	26.86	36.79	1878.40
15	31.30	31.10	29.10	28.78	32.16	1537.64
16	29.51	30.54	31.96	41.52	26.38	1932.27
17	29.71	26.87	25.29	32.70	36.00	1539.61
18	36.68	28.81	31.18	42.84	30.92	2352.67
19	28.80	29.89	23.16	30.93	32.71	1347.83
20	30.87	31.09	29.60	28.87	31.43	1513.81

And subsequently it is possible to calculate the central line and control limits according to the Eqs. (8) and (9).

$$UCL = U_{mn} = E(M_{m,n}) + c * \sqrt{var(M_{m,n})} = 1736 + 2.78 * \sqrt{74369} = 2494.5$$

$$LCL = L_{mn} = E(M_{m,n}) + c * \sqrt{var(M_{m,n})} = 1736 - 2.78 * \sqrt{74369} = 977$$

Now. it is possible to construct a control chart that is shown in Fig. 3.

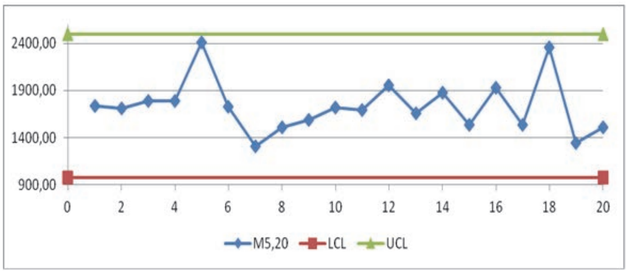

Fig. 3 NPCC based on Mood statistics
Obr. 3 Neparametrický regulační diagram založený na Moodově statistice

5.3 Mad Robust Control Chart

First of all, it is necessary to calculate the MAD according to the Eq. (10). The resulting values are presented in Tab. 4.

Tab. 4 Calculated MAD values
Tab. 4 Vypočítané hodnoty MAD

Subgroup	x_1	x_2	x_3	x_4	x_5	MD	MAD
1	33.05	32.50	29.69	31.78	31.07	31.78	29.76343
2	32.65	31.30	29.11	30.34	33.71	31.30	42.90212
3	36.42	29.83	30.46	32.88	29.18	30.46	63.89889
4	34.43	34.63	23.27	32.49	32.43	32.49	83.03903
5	32.76	34.25	36.09	34.52	36.93	34.52	37.35204
6	35.26	25.67	30.76	32.55	32.28	32.28	70.73537
7	26.15	28.99	29.67	29.63	31.18	29.63	35.43301
8	30.44	31.51	28.42	29.54	31.78	30.44	33.11425
9	29.30	31.68	33.48	28.31	30.93	30.93	46.97075
10	32.94	32.72	32.37	28.70	30.68	32.37	39.05715
11	29.49	31.08	28.62	35.93	31.05	31.05	55.25724
12	26.98	33.43	28.44	31.73	40.45	31.73	114.7288
13	29.35	30.02	30.39	29.58	35.90	30.02	45.74974
14	29.50	33.05	34.12	26.86	36.79	33.05	90.44829
15	31.30	31.10	29.10	28.78	32.16	31.10	34.68239
16	29.51	30.54	31.96	41.52	26.38	30.54	109.3237
17	29.71	26.87	25.29	32.70	36.00	29.71	102.7724
18	36.68	28.81	31.18	42.84	30.92	31.18	123.0551
19	28.80	29.89	23.16	30.93	32.71	29.89	72.55145
20	30.87	31.09	29.60	28.87	31.43	30.87	25.15334

And subsequently it is possible to calculate the central line and control limits according to the Eqs. (12) – (14).

$$UCL = B_6^* \overline{MAD} = 2.369 * 62.8 = 148.8$$

$$CL = c_4^* \overline{MAD} = 1.134 * 62.8 = 71.2$$

$$LCL = B_5^* \overline{MAD} = 0 * 62.8 = 0$$

Now. it is possible to construct a control chart that is shown in Fig. 4.

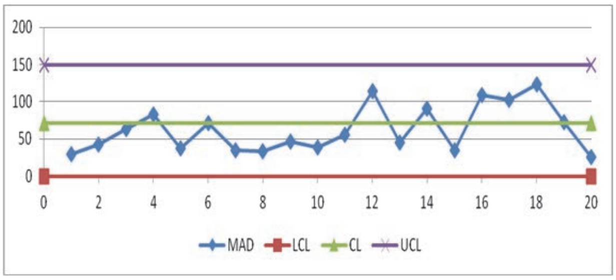

Fig. 4 MAD robust control chart
Obr. 4 Robustní regulační diagram MAD

Conclusions

We can see the resulting progressive mean control chart that the process looks like to be out of control (the point in the fifth subgroup is outside the limit), in spite of the fact that no real non-random cause has influenced the process. In the NPCC based on the Mood statistics. the point in the fifth subgroup is approaching the upper control limit. Only the robust control chart MAD shows no indication that the process was out of control.

Statistical non-stability signal in the progressive mean control chart is due to non-normal data, not by effect of non-random causes of variation. It follows that NPCC progressive mean has a greater risk of false signal in our example and it is the least effective. For the NPCC based on the Mood statistics, the false risk is smaller as compared to the previous chart. The robust control chart MAD seems to be the best, as it shows no signs of non-stability and is the only one that respects non normality of the data. We can say that the robust control charts are less sensitive to deviations from normality. These conclusions must be verified in other cases.

The aim of this article is to answer the question - how it is possible to control the production process when the basic assumptions for application of the classic SPC methods are not met. The aim of the next work is a detailed look at how to control the production process, which violates of the basic assumptions about the data and creating a methodology for production process control that do not meet these assumptions. The results of the work will contribute to the development of, for example, statistical process control and capability evaluation. The proposed methodology could help in the decision-making processes in practice.

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Další investice do výroby pružinové oceli pro automobilový průmysl v ArcelorMittal Ostrava

ArcelorMittal Ostrava investuje do přestavby chladicího lože pro řízené chlazení pružinové oceli na středojemné válcovně. Zakázku v hodnotě 80 mil. korun získala dceřiná společnost ArcelorMittal Engineering Products Ostrava. Svým rozsahem i hodnotou patří projekt mezi největší dosud realizované zakázky v historii kunčické strojírny. Přestavba zajistí lepší vlastnosti pružinové oceli, která nachází uplatnění zejména v automobilovém průmyslu a nákladní přepravě. Výrobek s vysokou přidanou hodnotou vyvinula ostravská huť v loňském roce a vyrábí jej jako jediný podnik ArcelorMittal v Evropě.

„*Investice nám umožní dodávat na trh větší objem pružinové oceli, a je tak dalším krokem ve zvyšování podílu výrobků s vysokou přidanou hodnotou v naší produkci. Chceme si tak zajistil lepší konkurenceschopnost,*“ říká Vijay Mahadevan, generální ředitel a předseda představenstva ArcelorMittal Ostrava.

Řízené chlazení umožní huti garantovat u plochých tyčí pro výrobu pružin maximální tvrdost, jakou požadují zákazníci, a dodávat tak na trh vyšší objemy tohoto výrobku. Výrobu pružinové oceli, která nachází uplatnění jako součást závěsného systému vozidel, zahájila ArcelorMittal Ostrava v loňském roce. Zavedení produkce tohoto nového výrobku s vysokou přidanou hodnotou si vyžádalo investici do středojemné válcovny ve výši více než 210 mil. korun.

„*Komponenty jsme začali vyrábět na počátku letošního roku a na konci roku bude nové chladicí lože připraveno k odzkoušení. Projekt je časově náročný, protože se jedná o výrobu složitých strojírenských celků. Ty musíme s vysokou přesností instalovat v průběhu dvou 12hodinových odstávek chladicího lože měsíčně, určených pro běžnou údržbu, aby nebyl ovlivněn provoz a výroba válcovny,*“ popisuje Radim Holoubek, obchodně-technický zástupce strojírny ArcelorMittal Engineering Products Ostrava, který zásadním způsobem přispěl k získání zakázky.

-z tiskové zprávy-

Indonéské rozhodnutí by mohlo odlehčit výrobce ušlechtilých ocelí

Stahl Aktuell *17.01.2017*

Spolkové ministerstvo vzdělávání a výzkum podpoří projekt na vývoj nové oceli v Max-Planck institutu pro výzkum železa v Düsseldorfu částkou 1,5 milionu €. Těžko hledat něco společného v pojmech jako jsou větrné turbíny a železnice. Přesto mají něco společného: tzv. bíle naleptávané praskliny (White Etching Cracks), do značné míry zatím nevysvětlený škodlivý mechanismus, který se v nepředpověditelné době vyskytuje na mechanických kontaktních bodech a ročně způsobuje enormní škody. Proto jsou na celém světě železniční koleje v pravidelných intervalech obrušovány, aby se těmto škodám zabránilo. Ještě dramatičtější je situace u větrných elektráren, kde se podobné jevy vyskytují také a jejichž převodové mechanismy mohou být vyměňovány jen s velkými náklady. Tvorba těchto prasklin probíhá na tak malých délkových škálách, že nemohla být doposud zkoumána ani nejmodernějšími mikroskopy.