İstanbul Üniversitesi İşletme Fakültesi Dergisi
Istanbul University Journal of the School of Business Administration
Cilt/Vol:39, Sayı/No:2, 2010, 241-257
ISSN: 1303-1732 – www.ifdergisi.org © 2010

Process modelling for quality improvement in annealing process

Özlem Akçay Kasapoğlu[1]
Department of Production
Faculty of Business Administration
Istanbul University, Istanbul, Turkey.

Abstract

The best and the most direct route to world class competitiveness for the products and services is through variability reduction on the processes. This variability reduction decreases defect rates, improves yields, lowers scrap rates, expands market potential, reduces rework, warranty costs and the difference between customer needs and process performance. A critical tool in accomplishing variability reduction is the statistical design of experiments. The purpose of this paper is to explain the theory of design of experiment method and to make an improvement on a process. In the theoretical part of the paper, the basic principles related to quality improvement, design of experiment, and annealing process is explained. In the applicaton part, a quality problem in solid chain industry is discussed and a model proposed by experimental design method is obtained, and the response surface method is used to find optimum solution to the problem. In this article the process improvement on the solid chain production is aimed and design of experiment techniques is implemented to find out the affecting factors and their influence on the process.

Keywords: *Process improvement, design of experiment, annealing, solid chain industry.*

Tavlama prosesinin kalite iyileştirilmesi için modellenmesi

Özet

Ürün ve servislerin dünya çapında rekabetinde başarıya giden, en iyi ve en direk yol proseslerdeki değişkenliğin azaltılmasından geçer. Bu değişkenlik azaltılması; hata oranlarını azaltır, verimi arttırır, pazar potansiyelini genişletir, yeniden işlemeyi, garanti masraflarını ve müşteri ihtiyaçları ile proses performansı arasındaki farkı azaltır. Değişkenliğin azaltılmasının sağlanmasında kullanılan kritik bir araç, istatistiksel deney tasarımıdır. Bu çalışmanın amacı, deney tasarımı teorisinin açıklanarak, bir proseste iyileştirme yapılmasının sağlanmasıdır. Bu makalenin teorik kısmında, kalite iyileştirmenin, deney tasarımının ve tavlama prosesinin temel prensipleri açıklanmıştır.

Uygulama kısmında, katı zincir endüstrisindeki bir problem tartışılmış, deney tasarımı yoluyla bir model elde edilmiş ve yanıt yüzeyi metodu ile de probleme optimum sonuç bulunması için çalışılmıştır. Bu makalede, katı zincir üretiminde proses iyileştirilmesi amaçlanmış olup deney tasarımı teknikleri de prosese etki eden faktörlerin bulunmasında kullanılmıştır.

Anahtar Kelimeler: *Proses iyileştirilmesi, deney tasarımı, tavlama işlemi, katı zincir endüstrisi.*

[1] *ozlemak@istanbul.edu.tr (Ö. Akçay Kasapoğlu)*

1. Introduction and Literature Search

Quality and process improvement has becoame an essential of overall strategic plan for most organizations. Statistical process design is a powerfull approach to product and proces development and for improving the yield and stability of an ongoing manufacturing process.[1]

Experimental Design (or DOE) economically maximizes information. DOE begins with determining the objectives of an experiment and selecting the process factors for the study. An Experimental Design is the laying out of a detailed experimental plan in advance of doing the experiment. Well chosen experimental designs maximize the amount of "information" that can be obtained for a given amount of experimental effort. [2]

To survive and thrive in today`s globally competitive environment, your products, services and processes must be on target the first time, everytime. The only way to accomplish this is through a comprehensive quality and reliability management strategy that optimizes your products and services during the design and development stages and continuously improves them throughout their life cycle. This variability reduction decreases defect rates, improves yields, lowers scrap rates, reduces rework, expands market potential, and reduces warranty costs. A critical tool in accomplishing variability reduction is the statistical design of experiments. [3]

Experimental design is a growing era of interest in an increasing number of applications. Initially, experimental design found application in agriculture, biology, and other areas of hard science. It has since spread through the engineering arenas to the social sciences of economics and behavioural analysis. This trend was further encouraged by the Total Quality Management (TQM) movement originating in the mid-1980s and continuing today [4]. In the history of design of experiment, works on physicology and medicine can be seen in the initial studies [5].

There have been four eras in the modern development of statistical experiment design. The agricultural era was led by the pioneering work of Sir Ronald A. Fisher in the 1920`s and early 1930s. Fisher systematically introduced statistical thinking and principles into designing experimental investigations, including the factorial design concept and the analysis of variance. Although applications of statistical design in industrial settings certainly began in the 1930`s, the second, or industrial era was catalyzed by the development of response surface methodology (RSM) by Box and Wilson in 1951. The increasing interest of Western industry in quality improvement that began in the late 1970s ushered in the third era of statistical design. Taguchi advocated using design of experiments for what he termed robust parameter design. The work of Genichi Taguchi had a significant impact on expanding the interest in and use of design of experiments. By the late 1980s the results of peer review indicated that although Taguchi`s engineering concepts and objectives were well founded, there were substantial problems with his experimental strategy methods of data analysis. The fourth era of statistical design included a renewed general interest in statistical design both by researchers and practitioners and the development of many new and useful approaches to experimental problems in the industrial world including alternatives to Taguchi`s technical methods that allow his engineering concepts to be carried into practice efficeiently and effectively. [6]

Hung, Joseph, and Meltoke [7] designed and analyzed computer experiments with branching and nested factors.

Computer experiments are often performed to allow modeling of a response surface of a physical experiment that can be too costly or difficult to run except by using a simulator.

Gramacy and Lee [8] made an adaptive design and analysis of supercomputer experiments.

Liao and Cha [9] worked on a two-level factorial experiments with partial replication. A set of sufficient conditions is presented for the designs to be D-optimal for the specified effects, assuming that the other effects are negligible, over the class of competing parallel-flats designs. The proposed partially replicated designs are highly efficient in estimating the possibly active effects and provide a replication-based estimate of the error variance, they provide a practical compromise between the power in identifying truly active effects and the number of runs in experiments.

Borkowski and Piepel [10] worked on uniform designs for highly constrained mixture experiments. This article introduces two number-theoretic methods for generating space-filling (specifically uniform) designs for constrained mixture experiments defined by single- and multiple-component constraints. The two methods are illustrated for a simple 3-component mixture problem and a more complicated 16-component waste-glass mixture problem.

Johnson, et al. [11] worked on comparing computer experiments for fitting high-order polynomial metamodel. Often the underlying function for a computer experiment result has too much curvature to be adequately modeled by a low-order polynomial. In such cases, finding an appropriate experimental design is not easy. They evaluated several computer experiments assuming the modeler is interested in fitting a high-order polynomial to the response data considering both optimal and space-filling designs. They also introduced a new class of hybrid designs that can be used for deterministic or stochastic simulation models.

Meulen, Koning, and Mast [12] worked on nonrepeatable gauge R&R (repeatability and reproducibility) studies assuming temporal or patterned object variation. For nonrepeatable measurements, it is not feasible to obtain replications because objects are destroyed when they are measured or because the object changes over time. They show that the experimental design used in this type of nonrepeatable gauge R&R studies is best constructed in a way that is similar to a Latin square design.

Guo, Simpson and Pignatiello debated on the construction of efficient mixed-level fractional factorial designs. interest has focused on developing orthogonal or near-orthogonal mixed-level fractional factorial designs. Currently existing mixed-level designs are all balanced. However, relaxing the requirement of balance may result in a reduced number of experimental runs in practice. [13].

Chung, Goldfarb, and Montgomery [14] worked on optimal designs for mixture-process experiments with control and noise variables. Choosing an appropriate experimental design for this type of problem is addressed in the paper. They show how designs that have small prediction variance for the mean and the slope variance can be obtained. They also show how designs that are robust to the level of interaction between control and noise variables can be constructed.

Works have been done on quality improvement and experimental design. Luciano [15] worked on the design, experimental tests, and performance after annealing on single phase 1-kVA amorphous core transformer. Kolomejtsev and Kolomejtseva [16] used design and experimental method of estimating limit stressed state of cast-melted refractory castings under crystallization and annealing. Paul, Chinoy, and Singh [17] made evolving design to perfection of high frequency inverter for induction heating applications with a design of experiment approach. Dumond [18] used experience from U.S. manufacturing firms in learning from the quality improvement process. Adam and Everett [19] studied alternative quality improvement practices and organization performance. Cessna and Chidester [20] worked on productivity and quality improvement in a vertical team approach. Huang, Lung, and Chih [21] examined the economic design of quality improvement strategy for manufacturing process. Walker and Hon [22] examined the key to long-term quality relationships, the supplier quality improvement. Hong and Hayya [23] looked for the ways of joint investment in quality improvement and setup reduction. Gupta [24] brought a systematic approach to process quality improvement. Chen and Tsou [25] calculated an optimal design for process quality improvement. Pang and Sink [26] developed a quality improvement taxonomy. Antony and Kaye [27] developed methodology for Taguchi Design of experiments for continuous quality improvement. Belaire and Deacon [28] made a strategic approach to quality improvement using design of experiments concepts and methods. Nembhard and Valverde [29] integrated experimental design and statistical control for quality improvement. Antony, Kaye, and Frangou [30] developed a strategic methodology to the use of advanced statistical quality improvement techniques. Chan, Gan, and Mak [31] developed management procedure for design of experiments. Mazu [32] tried to improve the products through design of experiments. Ahire and Dreyfus [33] made an empirical investigation on the impact of design management and process management on quality. Nasser and Jawad [34] used design of experiments as effective design tools. Tong, Tsung and Yen [35] worked on a DMAIC (Design, Measure, Analyze, Improve, Control) approach to printed circuit board quality improvement. Goh, Tang, and Xie [36] applied statistical design of experiments as a change agent in industry.

2. Quality Improvement

Quality is a predictable degree of uniformity and dependebility, at low cost and suited to the market. Improvement and innovation are both required if a form is to be healty in the future. The purpose of process improvement is to modify current methods to continuously reduce the difference between customer needs and process performance.

Continuous quality improvement and cost reduction are necessarry for an organizaton’s health and competitive ecomomy. Quality improvement requires never ending reduction of variation in product and or process performance around nominal values. Society`s loss due to performance variation is frequently proportional to the square of the deviation of the performance characteristic from its nominal value. Product and prosess design can have a significant impact on product`s quality and cost. Performance variation can be reduced by expoiliting nonlineer effects between a product`s and \or process`s parameters and product`s desire performance characteristics. Product and\or process parameter settings that reduce performance variation can be identified with statistically design experiments. [37]

2.1. Design of Experiment

Factorial designs are most frequently employed in engineering and manufacturing experiments. In a factorial experiment, several factors are controlled at two or more levels, and their effects upon some response are investigated. The experimental plan consists of taking an observation at each of all possible combinations of levels that can be formed from the different factors. Each different combination of factor levels is called a “treatment combination”. Suppose that an experimenter is interested in investigating the effect of two factors, amperage (current) level and force, upon the response y, the measured resistivity of silicon wafers. [38]

It is common to begin with a process model of the `black box’ type, with several discrete or continuous input factors that can be controlled that is, varied by the experimenter, and one or more measured output responses. The output responses are assumed continuous. Experimental data are used to derive an empirical approximation model linking the outputs and inputs. These empirical models generally contain first and second-order terms. [2]

In the past, one common experimental approach has been the so-called one-factor-at-a-time approach. This experimental strategy studies the effect of first varying amperage levels at some constant force and then applying different force levels at some constant level of amperage. The two factors would thus be varied one at a time with all other conceivable factors held as constant as possible. The results of such an experiment are fragmentary in the sense that we learn about the effect of different amperage levels only at one force level and the effect of different force levels at only one amperage level. The effects of one factor are conditional on the chosen level of the second factor. The measured resistivity of the wafer at different current levels may, of course, be different when a different force level has been chosen. Similarly, any observed relation of resistivity to force level might be quite different at other amperage levels. In statistical language, there may be an "interaction effect" between the two factors over the range of interest, and the one-at-a-time procedure does not enable the experimenter to detect the interaction. [38]

Obtaining good results from a DOE involves these seven steps [2]:

1. Set objectives
2. Select process variables
3. Select an experimental design
4. Execute the design
5. Check that the data are consistent with the experimental assumptions
6. Analyze and interpret the results
7. Use/present the results (may lead to further runs or DOE's).

In a factorial experiment, the levels of each factor are chosen, and a measurement is made at each of all possible combinations of levels of the factors. Suppose that five levels of amperage and four levels of force are chosen. There would thus be 20 possible combinations of amperage and force, and the factorial experiment would consist of 20 trials. In this example, the term "level" is used in connection with quantitative factors, but the same term is also used when the factors are qualitative. In the analysis of factorial experiments, one speaks of "main effects" and "interaction effects" (or simply "interactions"). Estimated main effects of a given factor are always functions of the average yield response at the various levels of the factor. When a factor has two levels, the estimated main effect is the difference between the average responses at the two levels, i.e., the averages computed over all levels of the other factors. In the case in which the factor has more than two levels, there are several main effect components (linear, quadratic, cubic, etc.), the number of estimable main effect components being one less than the number of levels. Other comparisons, called treatment "contrasts," are possible. If the difference in the expected response between two levels of factor A remains constant over the levels of factor B (except for experimental error), there is no interaction between [38].

2.2. Annealing Process

Annealing, in metallurgy and materials science, is a heat treatment where in a material is altered, causing changes in its properties such as strength and hardness. It is a process that produces conditions by heating to above the re-crystallization temperature and maintaining a suitable temperature, and then cooling. Annealing is used to induce ductility, soften material, relieve internal stresses, refine the structure by making it homogeneous, and improve cold working properties.

In the cases of copper, steel, silver, and brass this process is performed by substantially heating the material (generally until glowing) for a while and allowing it to cool slowly. In this fashion the metal is softened and prepared for further work such as shaping, stamping, or forming [39].

3. The Process and The Experimental Design

The experimental design is done on solid golden chain production process. The golden chains are manufactured as bracelet and necklace. The raw materials of the chains are pure gold, copper, silver and zinc.

3.1. The Process

The metals are brought together and melted between the 900°C–1100°C and solidified as sticks in 8 mm diameters. In this paper the percentage of the mixture metals and melting heat is not discussed, the experiments are done in the next process.

The semi finished product (work in process material) sized as 8 mm diameter is used in golden chain production. The sticks in 8 mm diameters are thinnered to the sizes changing between 0,1-1,0 mm. The thinnering process is step by step process. In order to have 1 mm stick, the sticks are first thinnered to the diameter 7 mm and then to the 5 mm by the rolling press and so on. After being reached to the diameter 7 mm, to soften the indurated metal, it is being heated in the annealing furnaces in the 600°C–800°C. If the metal is not heated the thin metal can be broken. After the wire comes to the expected values, the annealing process is repeated in another special furnace. After the second annealing the wire goes to the knitting machines. To be able to have a high quality wire, the wire has to be in the proper condition. In the knitting process, the scrap rate is so high. The design of experiment is done at the latest annealing process which is the most important step in the quality of the wire. In the latest annealing process there are three factors, affecting the success. These are annealing heat, the speed of the wire passing through the furnace, and the ratio of the H2 and N2 gases which is given to the annealing atmosphere. The wire in the proper size could be annealed between the 600°C–800°C. If the wire annealed in a low speed, it can not be shaped. If the wire passes through the furnace in a short time, it can not absorb the heat, and in the opposite it can have shape disorders. The speed changes from 100 m/min to 300 m/min. During the annealing process with the H2 and N2 gases NH3 is formed, which helps the wire surface hardness to soften and gives brightness to the surface. The H2\N2 ratio changes from 1-5.

3.2. The Experimental Design

Box Behken design is used in the experiments. There are 3 factors, which have 3 levels each. Five replicates are done for the experiment

Table 1 Factor Levels of the Experiment

	HEAT	SPEED	GAS RATIO
LEVEL 1:	780	230	4
LEVEL 2:	740	180	3
LEVEL 3:	700	130	2

The Box-Behnken design is an independent quadratic design that does not contain an embedded factorial or fractional factorial design. In this design the treatment combinations are at the midpoints of edges of the process space and at the center. These designs are rotatable (or near rotatable) and require 3 levels of each factor. The designs have limited capability for orthogonal blocking compared to the central composite designs [2].

Box Behnken Design is one of the response surface methods and this design requires less runs. Box Behnken Design is also used for the optimization.

3.2.1. Outputs

After the threatments those wires are measured in the metalurgy lab. Every measurement consisted of 4 outputs; they are:

Rp (yield strenght) (N/mm^2)

Rm (tensile strenght) (N/mm^2)

Rm-Rp (yield point) (N/mm^2)

Ag (breaking elongation ratio)

The main purpose of this experimental design is to find the effect of heat, speed and gas rate to the outputs Rm, Rp, Rm-Rp and Ag.

3.2.2. Box-Behnken Design

In the Box-Behnken design 3 factors, with 3 levels, 15 runs with 5 replicates are done making 75 total runs. The experiments are done in 1 block.

3.2.2.1. Response Surface Regression: rp; rm; rm-rp versus heat; speed; gas rate

The analysis was done using coded units.

Estimated Regression Coefficients for rp

Term	Coef	SE Coef	T	P
Constant	317,000	1,0464	302,933	0,000
heat	-22,000	0,6408	-34,332	0,000
Speed	7,275	0,6408	11,353	0,000
gas rate	-5,375	0,6408	-8,388	0,000
heat*heat	-10,275	0,9432	-10,893	0,000
Speed*Speed	-3,125	0,9432	-3,313	0,002
gas rate*gas rate	-4,625	0,9432	-4,903	0,000
heat*Speed	-3,800	0,9062	-4,193	0,000
heat*gas rate	3,400	0,9062	3,752	0,000
Speed*gas rate	-2,950	0,9062	-3,255	0,002

S = 4,053   R-Sq = 96,0%   R-Sq(adj) = 95,4%

Analysis of Variance for rp

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	25628,1	25628,1	2847,57	173,36	0,000
Linear	3	22632,6	22632,6	7544,22	459,30	0,000
Square	3	2301,4	2301,4	767,15	46,70	0,000

Interaction	3	694,0	694,0	231,35	14,08	0,000
Residual Error	65	1067,7	1067,7	16,43		
Lack-of-Fit	3	1047,6	1047,6	349,22	1082,57	0,000
Pure Error	62	20,0	20,0	0,32		
Total	74	26695,8				

Estimated Regression Coefficients for rp using data in uncoded units

Term	Coef
Constant	-2981,05
heat	9,04137
Speed	2,17850
gas rate	-29,9050
heat*heat	-0,00642187
Speed*Speed	-0,00125000
gas rate*gas rate	-4,62500
heat*Speed	-0,00190000
heat*gas rate	0,0850000
Speed*gas rate	-0,0590000

It can be seen that while heat and speed's main effects have positive strong impacts (9,04137 and 2,17850), the gas rate (-29,9050) has a negative strong effect on rp. Most of the factor interactions have slightly negative effect on Rp. Gas rate's second degree effect has stronger negative effect as compared to the other interactions

3.2.2.2. Response Surface Regression: rm versus heat; speed; gas rate

The analysis was done using coded units.

Estimated Regression Coefficients for rm

Term	Coef	SE Coef	T	P
Constant	507,000	0,5875	862,950	0,000
heat	-27,950	0,3598	-77,686	0,000
Speed	8,875	0,3598	24,668	0,000
gas rate	-4,725	0,3598	-13,133	0,000
heat*heat	-10,375	0,5296	-19,591	0,000
Speed*Speed	-2,525	0,5296	-4,768	0,000
gas rate*gas rate	-2,725	0,5296	-5,146	0,000
heat*Speed	-1,700	0,5088	-3,341	0,001
heat*gas rate	1,800	0,5088	3,538	0,001
Speed*gas rate	-1,850	0,5088	-3,636	0,001

S = 2,275   R-Sq = 99,1%   R-Sq(adj) = 99,0%

Analysis of Variance for rm

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	37586,1	37586,1	4176,2	806,58	0,000
Linear	3	35291,8	35291,8	11763,9	2272,04	0,000
Square	3	2103,3	2103,3	701,1	135,41	0,000
Interaction	3	191,0	191,0	63,7	12,30	0,000
Residual Error	65	336,5	336,5	5,2		
Lack-of-Fit	3	315,3	315,3	105,1	307,42	0,000
Pure Error	62	21,2	21,2	0,3		
Total	74	37922,7				

Estimated Regression Coefficients for rm using data in uncoded units

Term	Coef
Constant	-2635,09
heat	8,91612
Speed	1,28110
gas rate	-15,0150
heat*heat	-0,00648437
Speed*Speed	-0,00101000
gas rate*gas rate	-2,72500
heat*Speed	-8,50000E-04
heat*gas rate	0,0450000
Speed*gas rate	-0,0370000

It can be seen that while heat and speed’s main effects have positive impacts (8,91612 and 1,28110), the gas rate (-15,0150) has a negative strong effect on rm. Most of the factor interactions have slightly negative effect on Rm.

3.2.2.3. Response Surface Regression: rm-rp versus heat; speed; gas rate

The analysis was done using coded units.

Estimated Regression Coefficients for rm-rp

Term	Coef	SE Coef	T	P
Constant	190,400	0,4994	381,270	0,000
heat	-6,075	0,3058	-19,865	0,000
Speed	1,500	0,3058	4,905	0,000
gas rate	0,625	0,3058	2,044	0,045
heat*heat	-0,550	0,4501	-1,222	0,226
Speed*Speed	0,400	0,4501	0,889	0,377
gas rate*gas rate	1,850	0,4501	4,110	0,000
heat*Speed	1,950	0,4325	4,509	0,000
heat*gas rate	-1,700	0,4325	-3,931	0,000
Speed*gas rate	1,250	0,4325	2,890	0,005

```
S = 1,934   R-Sq = 88,2%   R-Sq(adj) = 86,6%
```

Analysis of Variance for rm-rp

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	1820,80	1820,80	202,311	54,08	0,000
Linear	3	1581,85	1581,85	527,283	140,96	0,000
Square	3	73,85	73,85	24,616	6,58	0,001
Interaction	3	165,10	165,10	55,033	14,71	0,000
Residual Error	65	243,15	243,15	3,741		
Lack-of-Fit	3	207,95	207,95	69,317	122,09	0,000
Pure Error	62	35,20	35,20	0,568		
Total	74	2063,95				

Estimated Regression Coefficients for rm-rp using data in uncoded units

Term	Coef
Constant	178,129
heat	0,308875
Speed	-0,824100
gas rate	16,4750
heat*heat	-3,43750E-04
Speed*Speed	0,000160000
gas rate*gas rate	1,85000
heat*Speed	0,000975000
heat*gas rate	-0,0425000
Speed*gas rate	0,0250000

It can be seen that while heat and gas rate’s main effects have positive impacts, gas rate has a strong positive effect (0,308875 and 16,4750), and the speed (-0,824100) has a negative effect on rm-rp. Most of the factor interactions has slightly positive effect on rm-rp, except heat`s second degree and heat and gas rate interactions. The surface plot for rp can be seen in Figure 1.

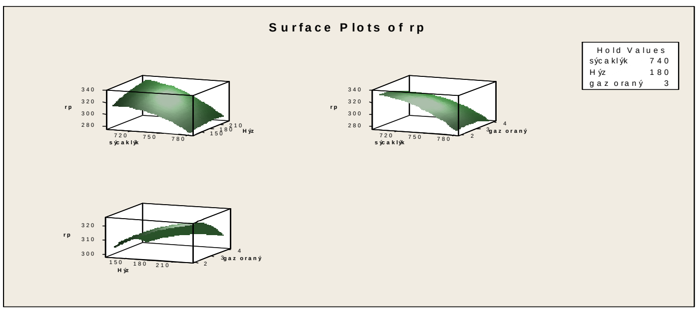

Figure 1 Surface Plots of Rp

Analysis of variance for Ag, using adjusted SS for tests can be found below:

Source	DF	Seq SS	Adj SS	Adj MS	F	P
heat	2	0,0290117	0,0290117	0,0145059	37,92	0,000
speed	2	0,0038086	0,0038086	0,0019043	4,98	0,008
gaz	2	0,0061227	0,0061227	0,0030614	8,00	0,001
heat*speed	4	0,0051412	0,0051412	0,0012853	3,36	0,012
heat*gaz	4	0,0077230	0,0077230	0,0019308	5,05	0,001
speed*gaz	4	0,0010702	0,0010702	0,0002675	0,70	0,594
Error	116	0,0443802	0,0443802	0,0003826		
Total	134	0,0972576				

S = 0,0195599   R-Sq = 54,37%   R-Sq(adj) = 47,29%

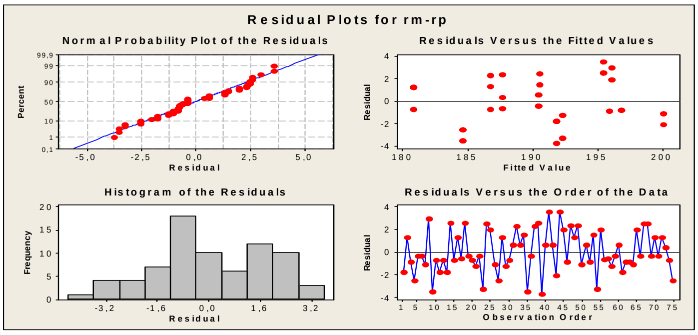

Figure 2 The Normality Plots for Rm-Rp

From the variance analysis it can be seen that with R-Sq = 96 % and R-Sq(adj) = 95,4 % all the factors and their interactions are significant for Rp. It is the same for Rm (R-Sq = 99,1% R-Sq(adj) = 99 %) and Rm-Rp (R-Sq = 88.2,67% R-Sq(adj) = 86.6 %). In Figure 2, one can find the normality plots for Rm-Rp. The measurements are not following a pattern. They are randomly distributed which certifies the normality, but in the variance analysis for Ag, R-Sq = 54,37% and R-Sq(adj) = 47,29% values are not acceptable, so Ag is not included in the model.

4. Conclusion

The optimum values of the factors can be seen in Figure 3. All the experimental designs and optimization are done on Minitab. The optimum value for heat is 762.5115, the speed is 230, and gas rate is 4.0. If the process can be set to these values, the rp takes the value 292,3392, rm takes the value 485,0903 and the rm-rp v takes the value 192,5726.

Box Behnken Design is one of the response surface methods and this design requires less runs. Box Behnken Design is also used for the optimization purpose.

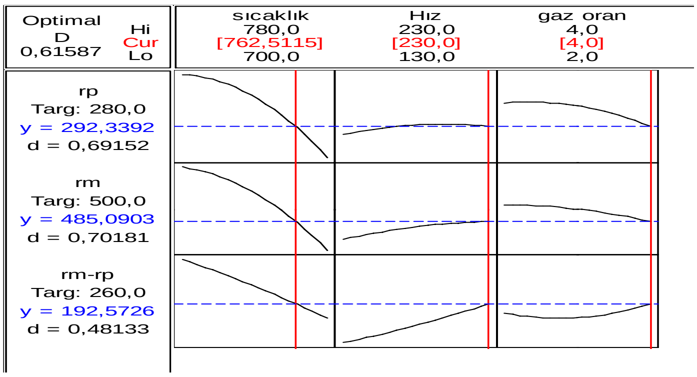

Figure 3 Optimal Results of the Factors

From the Box Behnken Design, it can be seen that while heat and speed's main effects have positive strong impacts (9,04137 and 2,17850), the gas rate (-29,9050) has a negative strong effect on rp. Most of the factor interactions have slightly negative effect on Rp. Gas rate's second degree effect has stronger negative effect as compared to the other interactions.

From the Box Behnken Design, it can be seen that while heat and speed's main effects have positive impacts (8,91612 and 1,28110), the gas rate (-15,0150) has a negative strong effect on rm. Most of the factor interactions have slightly negative effect on Rm. Again from the Box Behnken Design, it can be seen that while heat and gas rate's main effects have positive impacts, gas rate has a strong positive effect, (0,308875 and 16,4750), and the speed (-0,824100) has a negative effect on rm-rp. Most of the factor interactions has slightly positive effect on rm-rp, except heat`s second degree and heat and gas rate interactions. In Figure 4 to 9 one can find the main effects and interaction plots. The optimum results in Figure 3 are tested and 10 more experiment is done and it is found that the obtained mathematical model works very close to the real values. The results of the Rp, Rm and Rm-Rp values can be seen in Table 1.

Table 1 Confirmation Experiment

Heat (C)	Speed(meter/minute)	Gas Ratio (H2/N2)	Result No	Rp	Rm	Rm-Rp
762	230	4	1	272	477	205
			2	270	476	206
			3	269	477	208
			4	270	476	206
			5	273	475	202
			6	273	481	208
			7	269	473	204
			8	271	475	204
			9	270	475	205
			10	270	474	204

In this article the process improvement of the gold chain production is aimed and design of experiment technique is implemented to find out the affecting factors and their influence on the process and finally the optimum values of the factors are found. Working with the optimum values will increse the efficiency of the process and decrease the scrap rate.

Acknowledgement

The financial support for this study from the Research Fund of Istanbul University (YADOP-5161) is gratefully acknowledged.

References

[1] D.C. Montgomery, The Use of Statistical Process Control and Design of Experiments in Product and process improvement. IIE Transactions. 24, 5, 4, ABI/INFORM Global (1992).

[2] http://www.itl.nist.gov/div898/handbook/ (01/2/2010).

[3] N. Frigon, D. Mathews, Practical Guide to Experimental Design. John Wiley&Sons Inc., 1997, p.1.

[4] P.D. Berger, R.E. Maurer, Experimental Design with Applications in Management, Engineering and the Sciences. Duxbury, 2002.

[5] Ş.A. Baray, T. Sarı, Kalite Geliştirmede deney Tasarımı Yöntemi ve Otomativ Sektöründe Bir Uygulama. İşletme Fakültesi Dergisi. 35, 2, 37-62 (2006).

[6] D.C. Montgomery, Design and Analysis of Experiments. John Wiley & Sons Inc., 6th Edition, 2005, p.20.

[7] Y. Hung, V.R. Joseph, S.N. Melkote, Design and Analysis of Computer Experiments with Branching and Nested Factors. Technometrics. 51, 4, 354-365 (2009).

[8] R.B Gramacy, H.K.H Lee, Adaptive Design and Analysis of Supercomputer Experiments. Technometrics. 51, 2, 130-145 (2009).

[9] C.T. Liao, F.S. Cha, Design and Analysis of Two-Level Factorial Experiments with Partial Replication. Technometrics. 51, 1, 66-74 (2009).

[10] J.J. Borkowski, G.F. Piepel, Uniform Designs for Highly Constrained Mixture Experiments. Journal of Quality Technology. 41, 1, 35-47 (2009).

[11] R.T. Johnson, et al., Comparing Computer Experiments for Fitting High-Order Polynomial Metamodels. Journal of Quality Technology. 42, 1, 86-102 (2010).

[12] F.V. Meulen, H. Koning, J. Mast, Nonrepeatable Gauge R&R Studies Assuming Temporal or Patterned Object Variation. Journal of Quality Technology. 41, 4, 426-439 (2009).

[13] Y. Guo, J.R. Simpson, J.J Pignatiello, Construction of Efficient Mixed-Level Fractional Factorial Designs. Journal of Quality Technology. 39, 3, 241-257 (2007).

[14] P.J Chung, H.B. Goldfarb, D.C Montgomery, Optimal Designs for Mixture-Process Experiments with Control and Noise Variables. Journal of Quality Technology, 39, 3, 179-190 (2007).

[15] B.A. Luciano, Single phase 1-kVA amorphous core transformer: Design, experimental tests, and performance after annealing. IEEE Transactions on Magnetics, 35, 4, 2152-2154 (1999).

[16] V. Kolomejtsev, V. Kolomejtseva, Design and experimental method of estimating limit stressed state of cast- melted refractory castings under crystallization and annealing. E.F.Steklo i Keramika (0131-9582), 12, 6-8 (1991).

[17] A.K. Paul, N. Chinoy, S. Singh, Making evolving design to perfection of high frequency inverter for induction heating applications: Design of experiment approach. IEEE 35th Annual Power Electronics Specialists Conference. 4, 2632-2638 (2004).

[18] E.J. Dumond, Learning from the quality improvement process: experience from U.S. manufacturing firms. Production and Inventory Management Journal. 36, 4, 7-13, Fourth Quart (1995).

[19] Jr. Adam, E. Everett, Alternative quality improvement practices and organization performance. Journal of Operation Management. 12, 1, 27-44 (1994).

[20] L.C. Cessna, G.F. Chidester, Productivity/quality improvement (a vertical team approach). Annual Quality Congress Transactions. 545-551 (1985).

[21] Y.C. Huang, et al., The economic design of quality improvement strategy for manufacturing process: Journal of Quality. 16, 5, 347-367 (2009).

[22] J.Walker, S.E.Hon, Supplier quality improvement - the key to long-term quality relationships.: IEEE Journal on Selected Areas in Communications, v 6, n 8, p 1322-1325,1988.

[23] J.D. Hong, J.C. Hayya, Joint investment in quality mprovement and setup reduction. Computers and Operations Research. 22, 6, 567-574 (1995).

[24] P. Gupta, Process quality improvement: A systematic approach. Surface Mount Technology. 6, 8, 51-56 (1992).

[25] J.M.Chen, J.C.Tsou, An optimal design for process quality improvement: Modelling and application Production Planning and Control, v 14, n 7, p 603-12, 2003.

[26] E. Pang, D.S. Sink, Developing a quality improvement taxonomy. Annual Quality Congress Transactions. 45, 439-445 (1991).

[27] J. Antony, M. Kaye, Methodology for Taguchi Design of experiments for continuous quality improvement. Quality World. Suppl, 98-102 (1995).

[28] P.M. Belaire, R.J. Deacon, Strategic approach to quality improvement using design of experiments concepts and methods. American Society of Mechanical Engineers. Production Engineering Division (Publication) PED, 27, 157-167 (1987).

[29] H.B. Nembhard, V.R. Valverde, Integrating experimental design and statistical control for quality improvement. Journal of Quality Technology. 35, 4, 406-423 (2003).

[30] J. Antony, M. Kaye, A. Frangou, A strategic methodology to the use of advanced statistical quality improvement techniques. TQM Magazine. 10, 3, 169-176 (1998).

[31] L.K. Chan, E.H. Gan, T.K. Mak, Management procedure for design of experiments. Annual Quality Congress Transactions. 46, 317-324 (1992).

[32] M.J. Mazu, Product improvement through design of experiments. Annual Quality Congress Transactions. 635-641 (1996).

[33] S.L. Ahire, P. Dreyfus, Impact of design management and process management on quality: An empirical investigation. Journal of Operations Management. 18, 5, 549-575 (2000).

[34] M. Nasser, B. Jawad, Design of experiments as effective design tools. ASME International Mechanical Engineering Congress and Exposition Proceedings. 4, 441-448 (2008).

[35] J.P.C. Tong, F. Tsung, B.P.C. Yen, A DMAIC approach to printed circuit board quality improvement. International Journal of Advanced Manufacturing Technology. 23, 7-8, 523-531 (2004).

[36] T.N. Goh, L.C. Tang, M. Xie, Applying statistical design of experiments as a change agent in industry. IIE Annual Conference and Expo 2008. 1802-1806 (2008).

[37] H. Gtlow, A. Oppenheim, R. Oppernheim, Quality Management. Irwin Inc. Ilinois, 1995.

[38] J.M., Juran, Juran’s quality handbook. Fifth Edition, McGraw-HillNew York, 1998.

[39] http://en.wikipedia.org/wiki/Annealing_(metallurgy) (25.12.2009).

Appendix 1: Figures

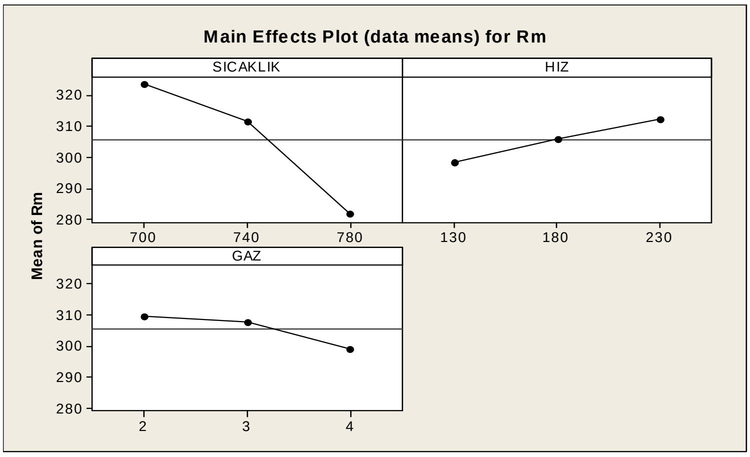

Figure 4 Main Effects plot for Rm

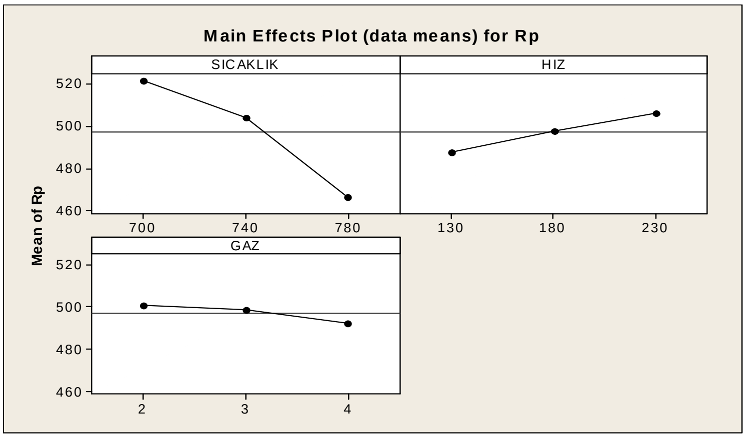

Figure 5 Main Effects plot for Rp

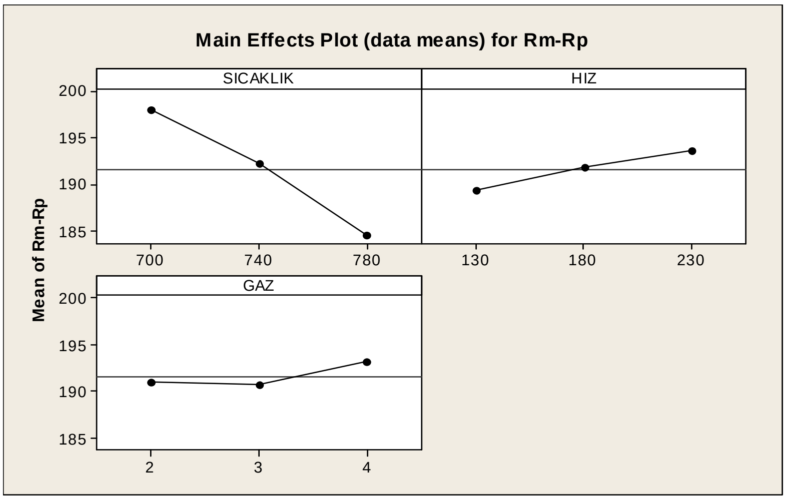

Figure 6 Main Effects Plot for Rm-Rp

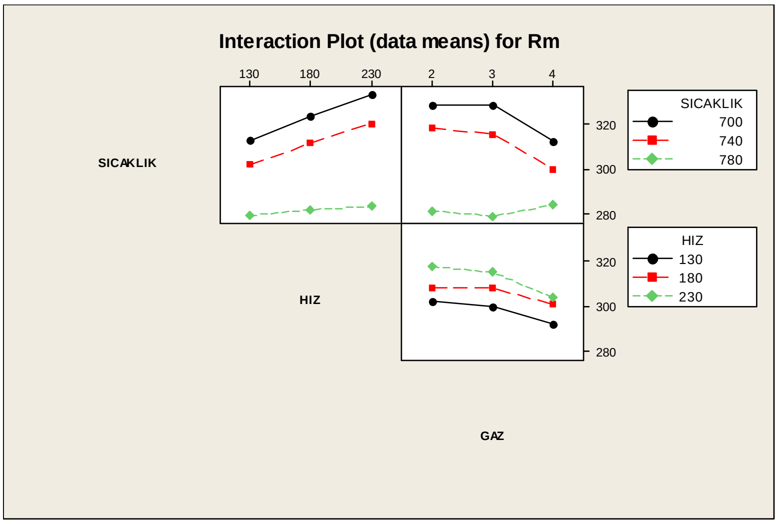

Figure 7 Interaction Plot for Rm

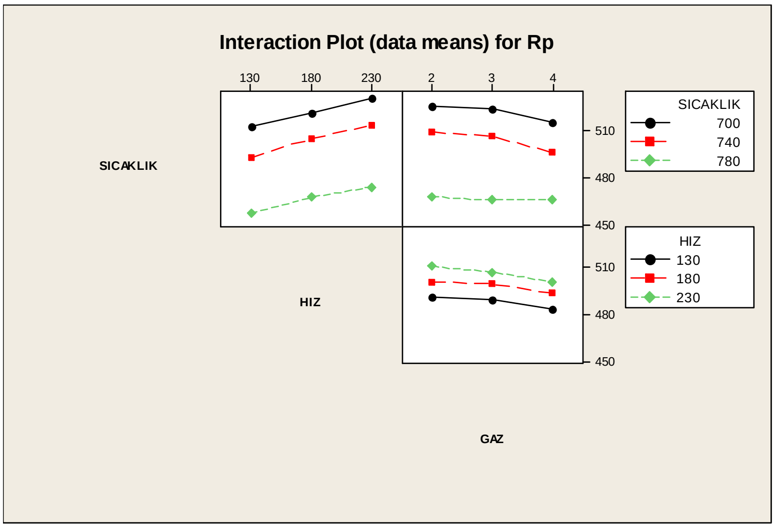

Figure 8 Interaction Plot for Rp

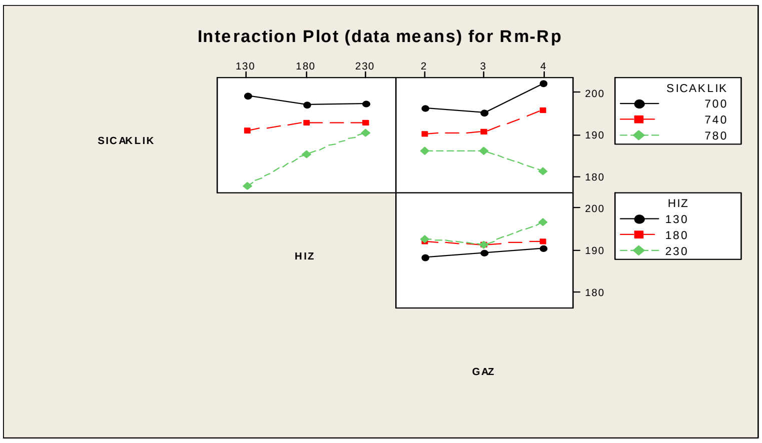

Figure 9 Interaction Plot for Rm-Rp