



**OFFLINE TECHNIQUE FOR MODELLING OF INJECTION
MOULDING PROCESS PARAMETERS IN SME's BASED ON SIX
SIGMA APPROACH METHOD**

Mr. Raj Kumar

Scholar, Department of Mechanical Engineering
Geeta Engineering Collage, Panipat, Hariyana

ABSTRACT

A modified six sigma cycle called DAURR (Diagnose, Analyze, Upgrade, Regulate and Review) based on Taguchi method, Regression analysis and Artificial Neural Network has been proposed in this work that can be used to find the best compromises between performance measures in IM, and potentially other polymer processes. Its feasibility was studied with the help of a study. Selecting the proper settings for an Injection Moulding process is crucial because the behaviour of the polymeric material during shaping is highly influenced by the process variables. Consequently, the process variables govern the quality of the parts produced. This thesis demonstrates a method of achieving six sigma standards in small and medium plastic injection moulding enterprises. The method has been employed for the improvement in two quality characteristics (hardness and over shrinkage) of injection-moulded nylon-6 kamani bush produced in a small enterprise. After the implementation of the proposed method, targets for improvement are clearly defined with the problems and causes being identified. The process parameters are then optimized for quality characteristics improvements so that the Six Sigma standard is reached. This research work provides methodology so that six sigma approaches can be applied and adjusted according to the requirements of small and medium enterprises (SMEs). This work also presents a novel, general and intelligent approach to multi response process optimization, with a purpose to obtain a single optimum setting of process parameters that meets specifications of all considered, possibly correlated, responses.

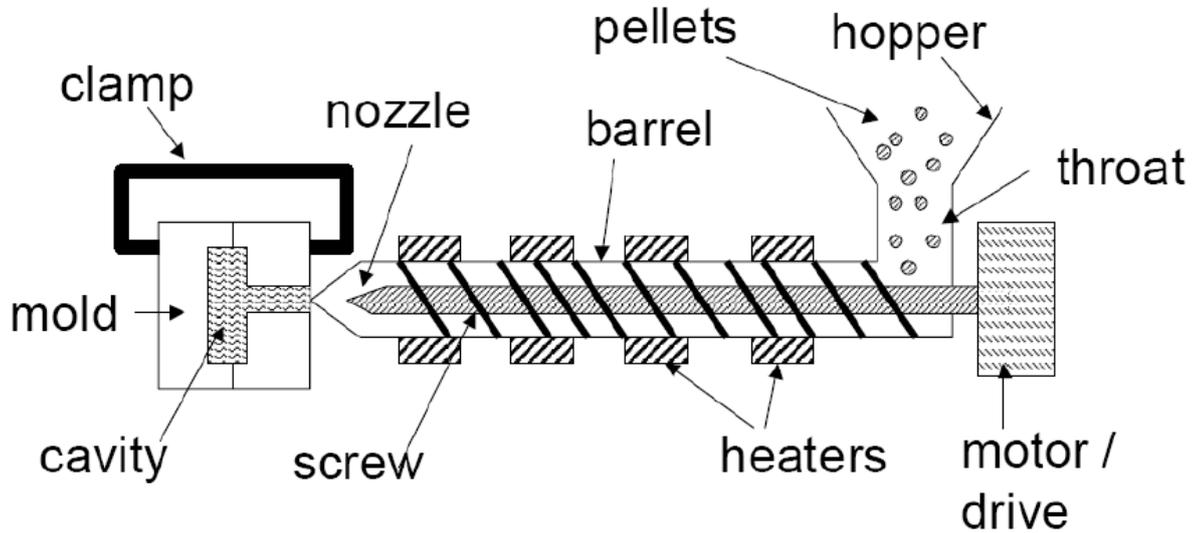
Keywords:- Six Sigma and theory, DMAIC, Injection moulding process and cycle,

Introduction

The “sigma approach”, named for the standard unit of variation around the mean, caught the attention of Bob Galvin, CEO of Motorola, and soon became the way of doing business at Motorola. With an emphasis on continuous improvement as well as a continuous aspiration towards perfection, “Motorola adopted a Six Sigma goal in everything they did, roughly equivalent to a process producing only 3.4 defects per million opportunities; near perfection”. Decade by the birth of the Six Sigma concept, Motorola saw a “five-fold growth in sales, with profits climbing nearly 20 percent per year; cumulative savings based on Six Sigma efforts pegged at \$14 billion, stock price gains compounded to an annual rate of 21.3 percent”. Since Six Sigma program focus on data-driven analysis and rigorous methodology to improve quality, it seems to be gaining significant popularity in industrial settings. Most of the plastic injections moulding firms in India are in unorganized sector, where negligible attention is paid on quality, due to financial constraints and lack of skilled personals. Keeping in mind the importance of injection moulding process in the current scenario this thesis tries to find out a modified Six Sigma approach which suits the requirements of small and medium scale plastic injection moulding industry. Injection Moulding (IM) is considered the most prominent process for mass production of plastic parts. More than one third of all plastic products are made by injection moulding, and over half of the world’s polymer processing equipments are used for the injection moulding process.

Injection Moulding Process

Injection moulding is the most widely used polymeric fabrication process. It evolved from metal die casting, however, unlike molten metal’s polymer melts have a high viscosity and cannot simply be poured into a mould. More melt must also be packed into the mould during solidification to avoid shrinkage in the mould. An injection moulding machine produces components by injection moulding process. Most commonly used machines are hydraulically powered in-line screw machines, although electric machines are appearing and will be more dominant in the market in near future. The main units of a typical injection moulding machine are the clamping unit, the plasticizing unit, and the drive unit; they are shown in Fig. 1. The clamping unit holds the mould. It is capable of closing, clamping, and opening the mould. Its main components are the fixed and moving plates, the tie bars and the mechanism for opening, closing and clamping.



The Injection Moulding Cycle

There are three main stages in the injection moulding cycle; stage 1, injection, followed by stage 2, holding pressure and plasticating, and finally, stage 3, ejection of the moulded part. When stage 3 is completed, the mould closes again and the cycle starts over again.

- 1) Stage 1- Injection of the Plastic Melts into the Mould
- 2) Stage 2- Holding Pressure and Plasticating
- 3) Stage 3- Ejection

Six Sigma and Problem Solving Theory

The Six Sigma Quality-

Six-Sigma has been used by some of the world's most successful companies leading to savings of billions of dollars, striking increases in speed and capacity in their processes and achieving new, stronger customer relationships. Six-Sigma is a flexible system used to achieve, sustain and maximize business success.

- 1) First key- Critical to Quality
- 2) Second key- Defect
- 3) Third key- Process Capability
- 4) Fourth key- Variation
- 5) Fifth key- Stable Operations
- 6) Sixth key- Design for Six-Sigma

DMAIC in Six-Sigma

Define- Define (D) is the first step of the Six Sigma methodology where leaders are expected to select projects, set initial goals or targets, and develop a project charter or statement of work (SOW). Costs of poor quality associated with the new or existing process being analyzed are estimated. Improvement targets are set often in terms of sigma and cost. Leadership selects the appropriate team members.

Measure- Measure is the second step of the Six Sigma methodology and is denoted by the capital letter M. The goals of Measure appear to activate only in the mode of data management, which includes both collection and organization of the data for the purpose of observation.

Analyze- The third step, A, is analyze. Here teams identify several possible causes (X's) of variation or defects that are affecting the outputs (Y's) of the process. One of the most frequently used tools in the analyze step is the cause and effect diagram.

Improve- The team then enters the improve (I) step. Here a team would brainstorm to come up with counter measures and lasting process improvements that address validated root causes. The tool most preferred for this process is the affinity diagram, which is a brainstorming technique where a topic or issue is presented to a small team who then quickly list ideas or solutions.

Control- The final step for at least the black belt and many of the team members is control, which is signified by the capital letter C. At this point devices should be put in place to give early signals when a process is heading out of control. Teams may develop poka-yokes or mistake proof devices that utilize light, sound, logic programming, or no-go design to help control a process. The ultimate goal for this step is to reduce variation by controlling X's (i.e., the inputs) and monitoring the Y or Y's (i.e., the outputs).

Literature Review

Duncan, 1988, Montgomery, 2001, opined that, a control chart is the primary tool of SPC and is basically used to monitor the process characteristics, e.g., the process mean and process variability.

Rawin et al.1997, presented a neural network-based design support tool to help designers to assess the impact of mould design on mould manufacturability (or mould complexity) before releasing the drawings to actual production.

As per Klir & Yuan 1998, fuzzy logic involves a fuzzy interference engine and a fuzzification-defuzzification module.

Mikel Harry et al.2000, began to study and apply the concepts of process variation developed by W. Edwards Deming in order to find ways to reduce variation and improve performance.

Sharma and Pandla, 2001, reported that the performance enhancement enabled the client to have an improved product with the overriding Benefit that the end customer perception of the quality of the client's product is improved.

Forouraghi et al. 2002, state that the classical experimental design methods are time consuming.

Shi et al. 2003 Focused on process operating parameters, such as mould temperature, melt temperature, injection time and injection pressure. There are other physical factors such as gating scheme design (style, size, location of the gate) and geometry of the parts that are not taken into consideration.

Klefsjo and Bergman, 2004, reported that the knowledge from the organisation must be used and it is impossible to “copy and paste” an implemented Six Sigma from another company, no matter how similar the processes or organization seems to be.

Jeyapaul et al. 2005, state that, during production, quality characteristics may deviate due to drifting or shifting of processing conditions caused by machine wear, environmental change or operator’s fatigue.

Jeyapaul et al. 2005, states, adjusting the mean to the target by any method renders the problem to a constrained optimization problem.

Joseph C. et al. 2006, described the development of a fuzzy neural network-based in-process mixed material-caused flash prediction (FNN-IPMFP) system for injection moulding processes.

Datta et al.2008, opined that the standard S/N ratios generally used are as follows: Nominal is best (NB), lower the better (LB) and higher the better (HB). The optimal setting is the parameter combination, which has the highest S/N ratio.

Mathivanan & Parthasarathy 2009, developed a nonlinear mathematical model, in terms of injection moulding variables, the model was developed using response surface methodology.

Data Analysis

Before implementation of six sigma projects hundred random samples were taken from production line at ten different occasions in a week and over shrinkage in samples was measured, using dial gauge attached with a V shaped anvil, placed over a surface plate. SPC software was used to analyze the process.

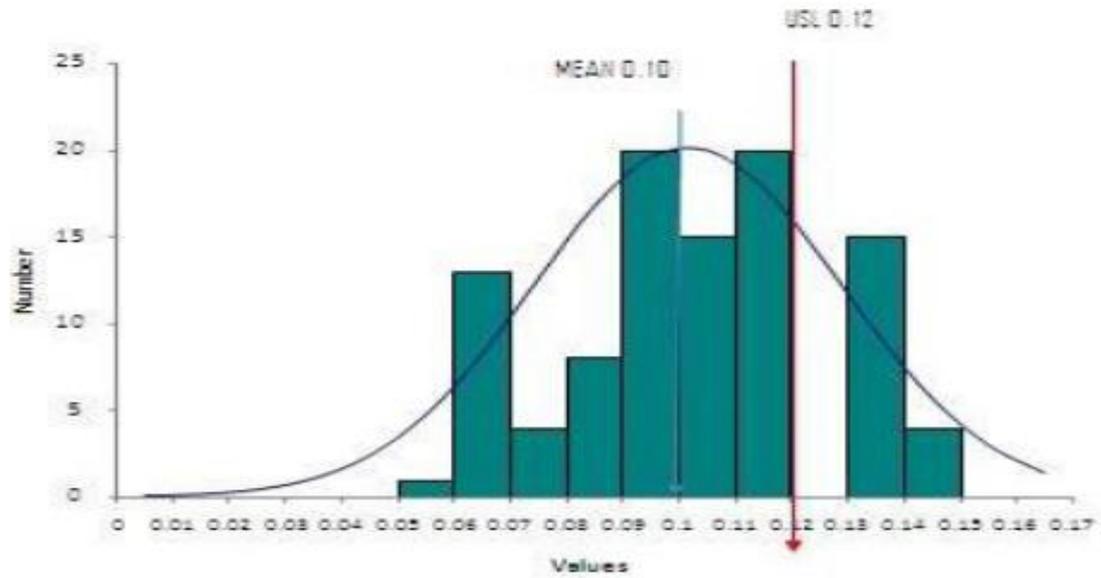


Fig.2 histogram for hundred random samples taken from production line at ten different occasions in a week (over shrinkage measurements shown on x-axis).

Value of CPL calculated from hundred random samples for over shrinkage was 0.24 and production was of 2.38 sigma standard and the process mean was 0.1015. Analysis indicates that 19% defects are expected. This is obvious from the Fig.2. Similarly SPC analysis for hardness was carried out with the help of hundred samples taken from production line at ten different occasions in a week. The histogram for these measurements is shown in Fig.3. Value of CPU calculated from hundred random samples for hardness was 0.56 and production is of 3.19 sigma standard and the process mean was 69.79. This is obvious from the Fig.3. SPC analysis for hardness was carried out with the help of hundred samples taken from production line at ten different occasions in a week. The histogram for these measurements is shown in Fig.3.

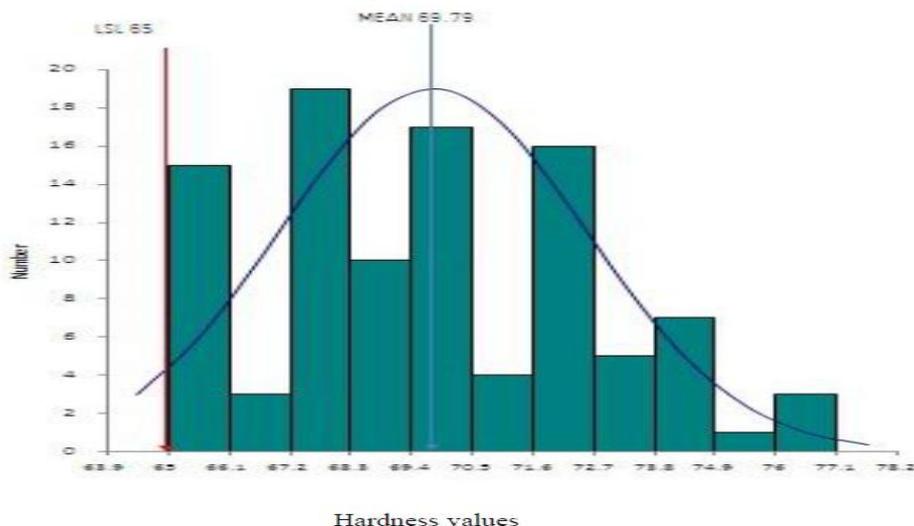


Fig.3. Histogram for hardness of hundred samples (horizontal axis shows hardness, vertical axis shows number of samples)

Analyze

Using Taguchi method L27 orthogonal experiment was performed setting above eight parameters at three different levels.

Table-1 Different parameters and their levels

Parameter	Symbol	Values at different levels		
		Level 1	Level 2	Level 3
Melting temperature	A	260 ⁰ C	275 ⁰ C	290 ⁰ C
Injection pressure	B	60 MPa	75 MPa	90 MPa
Injection speed	C	40 cm ³ /sec	50 cm ³ /sec	60 cm ³ /sec
Mould temperature	D	40 ⁰ C	60 ⁰ C	80 ⁰ C
Packing pressure	E	70 MPa	75 MPa	80 MPa
Packing time	F	3 sec	4 sec	5 sec
Cooling time	G	20 sec	30 sec	40 sec
Screw speed	H	50 rpm	65 rpm	80 rpm

S/N (signal to noise) ratio in Taguchi method is helpful in the selection of process parameters at better levels. A large number of different S/N ratios have been defined for a variety of problems, though in this work we have used larger the better characteristic for hardness and smaller the better characteristic for over shrinkage (bulging defect). The method used to calculate S/N ratio for both the types is as follows:

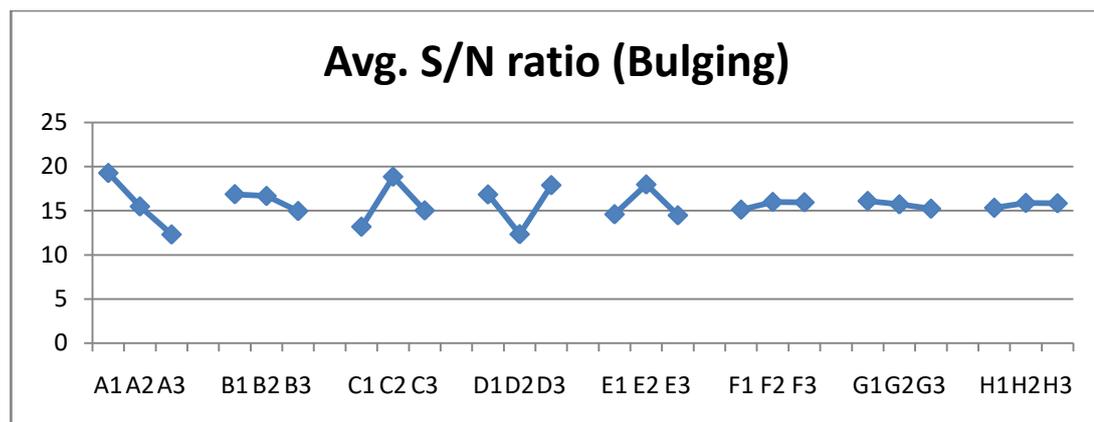


Fig. 4. Variation in S/N ratio (vertical axis) because of change in parameter levels (for bulging)

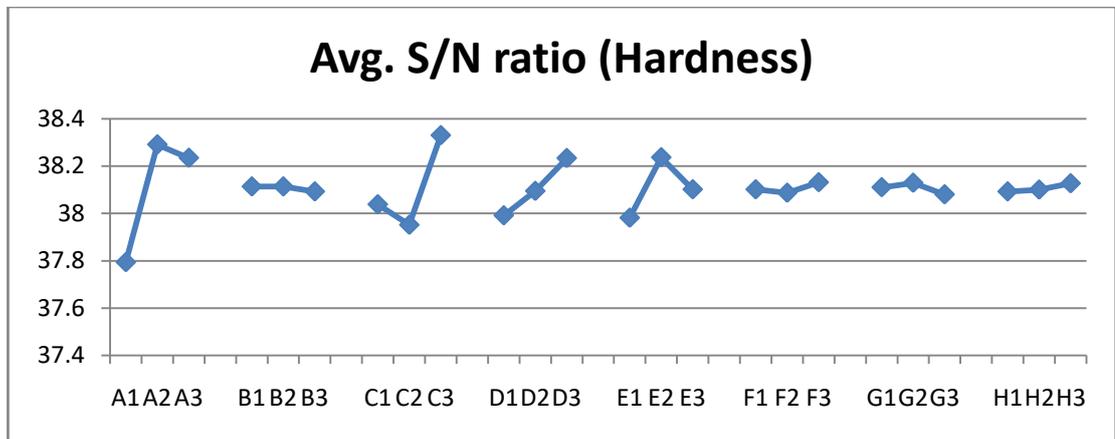


Fig.5. Variation in S/N ratio (vertical axis) because of change in parameter levels (for hardness)

From Fig.4 it is obvious that parameters affecting bulging in order of preference are A, C, D E, B, F, G, and H. The parameter A, C, D and E has larger impact on the bulging defect therefore these parameters were selected to make regression and neural network models. While Fig.5 depicts that parameters affecting hardness in order of preference are A, C, E, D, G, F, H, B. The parameters A, C, E and D have larger impact on the hardness therefore these parameters were selected to make regression and neural network models. Both the properties hardness and bulging are affected the most by the parameters A, C, D and E therefore these will be considered for further analysis. The first order regression equation with the above variables did not give better results; therefore we opted for second order regression analysis. With the help of the above data we formed a second order regression equation for hardness as below-

$$\text{HARD} = 6.3732839507248 A + 0.012305555556039 D - 2.0035555555469 C + 10.93255555366 E - 0.011343209876806 A^2 + 0.00034861111110563 D^2 + 0.021377777777698 C^2 - 0.072155555545211 E^2 - 1182.3028394404 + e \dots \dots \dots (1)$$

Where 'e' is an error term

The regression statics for this model is depicted in Table- 2

Table-2 Regression Statistics (Student Distribution Probability) for equation (1)

Student Distribution Probability (mathematical equation plotter)	
T- Test	10.5206
Degree of Freedom	18

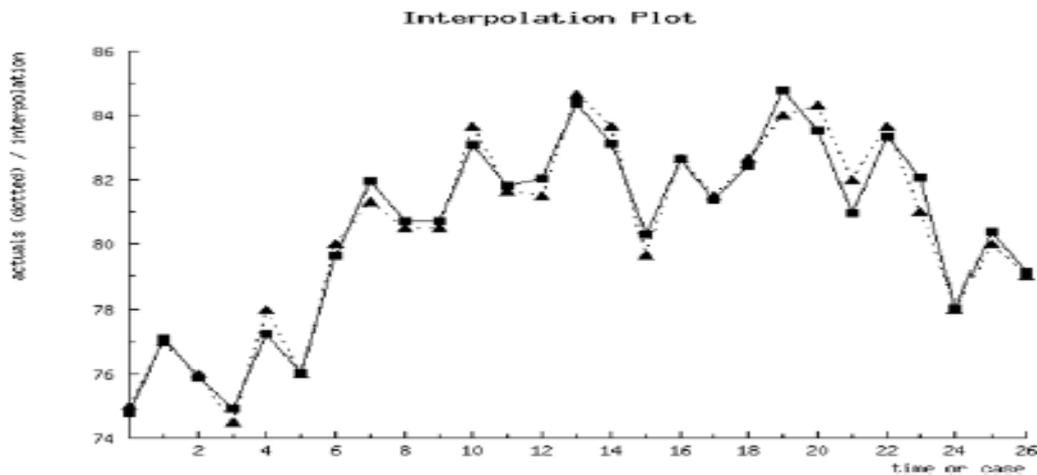


Fig.6 Comparison between actual hardness values (dotted) and predicted hardness values (from equation one) for twenty seven experimental samples.

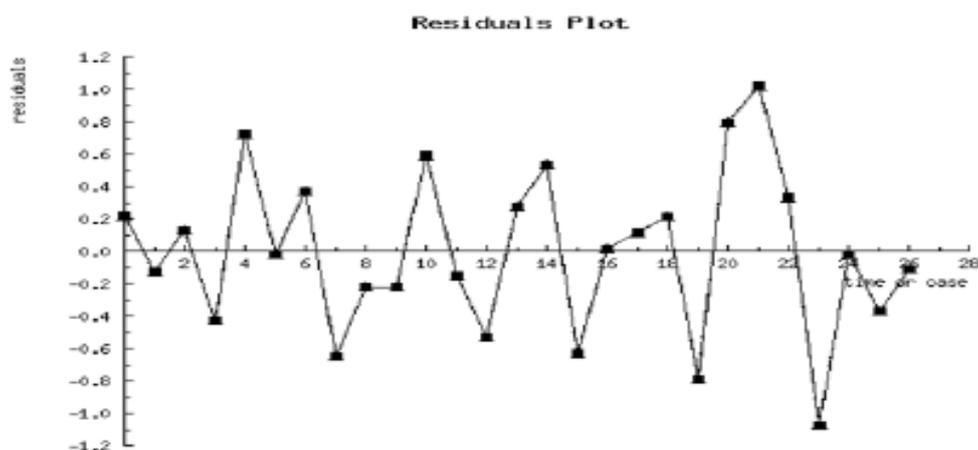


Fig.7 Residuals plot for twenty seven experimental samples.

Similarly the second order regression equation for bulging was formed as below-

$$\text{BULGING} = 0.061682428194518 A + 0.0364504629528 D - 0.10546870372806 C - 0.33662925904979 E - 0.0001034650209666 A^2 - 0.00030389351847241 D^2 + 0.001034425926114 C^2 + 0.0022465925911414 E^2 + 5.2475707471113 + e \dots \dots \dots (2)$$

Table-3 Student Distribution Probability for bulging model shown by equation (2)

Student Distribution Probability (mathematical equation plotter)	
T- Test	2.7817
Degree of Freedom	18

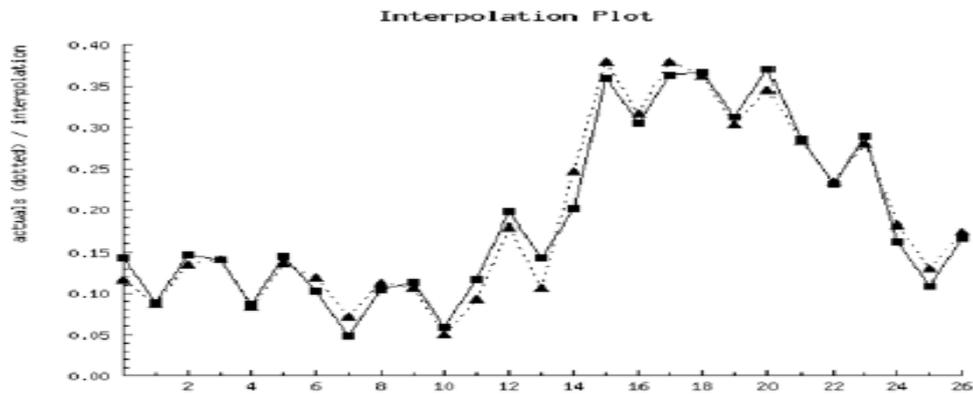


Fig. 8 Comparison between actual shrinkage values (dotted) and predicted shrinkage values for twenty seven experimental samples.

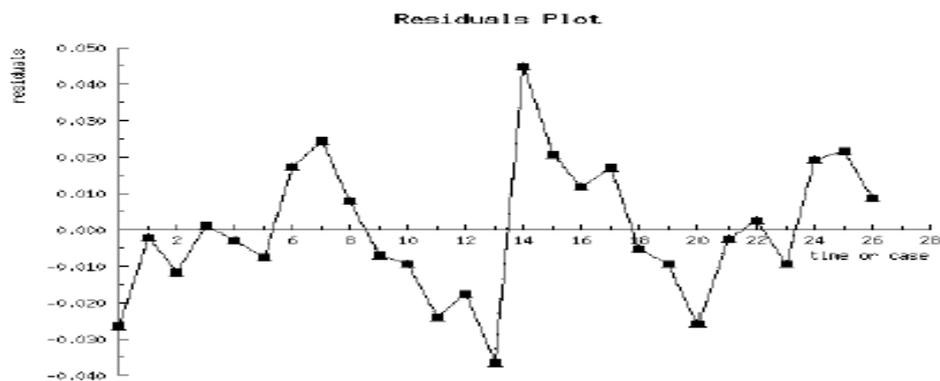


Fig. 9 Residual plot for twenty seven experimental samples

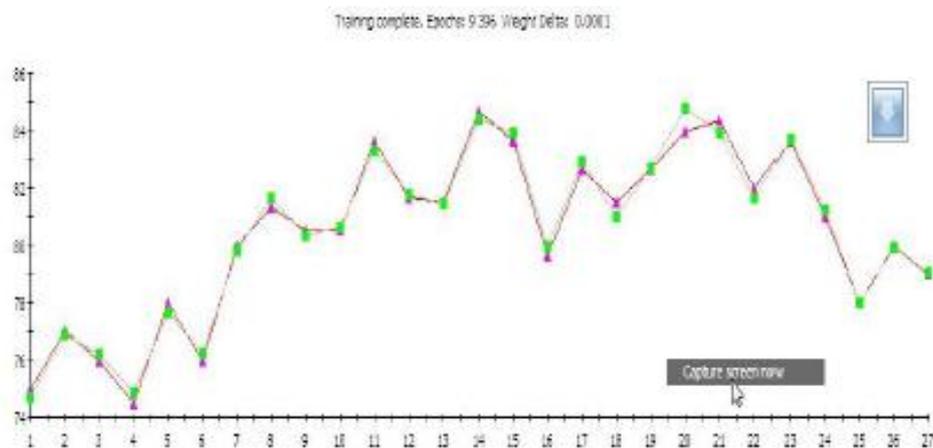


Fig.10 Comparison between actual hardness values (red) and predicted hardness values (green) for twenty seven experimental samples.

Similarly the twenty seven results were used for training neural network model for prediction of bulging. The model had following specifications.

Minimum weight- 0.0001	Limit of epochs- 10,000
Initial weight- 0.3	Learning rate- 0.3
Momentum- 0.6	

Activation function – log sigmoid function with no neurons in hidden layer

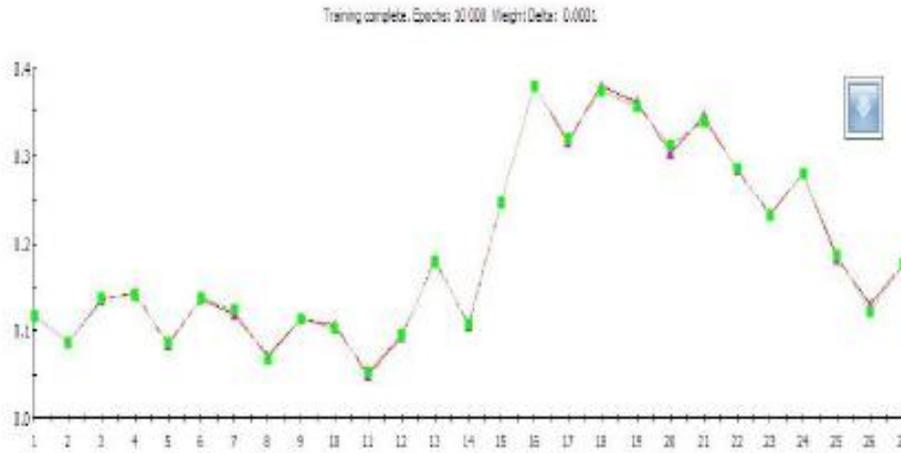


Fig.11 Comparison between actual shrinkage values (red) and predicted shrinkage values (green) for twenty seven experimental samples.

Taguchi design of experiment indicates that hardness is maximum when parameters are at A2, C3, D1 and E2 levels while over shrinkage is minimum when parameters are at A2, C2, D3 and E2 levels. Since the parameters A and E give optimum value of both the quality characteristics at the same level a compromise was made between parameters C and D with the help of regression and neural net work models prepared with the help of experiment. After analyzing the predicted values of hardness and over shrinkage, obtained from both the models, we selected parameter A-275, D-80, C-54 and E-75, which shows best compromise between hardness and over shrinkage.

T test

Table-4 T test for hardness with alternative hypothesis that true mean is greater than 83 at confidence level of 99.5 percent

One sample t-test	
H0	83
Alternative	Greater
CI	0.99
Sample mean	83.95555555555555
T- test	3.61804719244034
Degree of freedom	8
P- value	0.00340091193327827

Since the p value is smaller than significance level and tabulated value of t (3.355) is less than calculated value (3.61804) null hypothesis that actual mean is 83 is rejected and alternate hypothesis that actual sample mean is more than 83 is accepted.

Confidence interval for hardness in the above case can be given as

$$83.95555 \pm 3.355 \times 0.792324288/3$$

i.e. the hardness value lies between 83.06 and 84.8416 can be predicted at 99.5 percent confidence limit.

Table- 5 T test for over shrinkage with alternative hypothesis that true mean is less than 0.075 and at confidence level of 99.5 percent

One sample t-test	
H0	0.075
Alternative	Less
CI	0.99
Sample mean	0.062
T- test	-4.65308989292077
Degree of freedom	8
P- value	0.000819043782834587

Since the p value is smaller than significance level and tabulated value of t (3.355) is less than calculated value (4.65308) null hypothesis that actual mean is .075 is rejected and alternate hypothesis that actual sample mean is less than .075 is accepted.

Confidence interval for over shrinkage in the above case can be given as

$$0.062 \pm 3.355 \times 0.0083815/3$$

i.e. the over shrinkage value lies between 0.053 and 0.071 can be predicted at 99.5 percent confidence limit

Upgrade phase

First the optimal parameter setting decided in analyze phase such as-

Melting temperature (A)- 275⁰C, Mould temperature (D)- 80⁰C, Injection speed (C) 54 cm³/sec., Packing pressure (E)- 75 MPa, Injection pressure (B)- 75 M Pa, Packing time (F)- 4 second, Cooling time (G)- 30 second, Screw speed (H)- 65 rpm. The adequate number (nearly 100 to 150) of nylon-6 bushes were produced under the above setting of parameters and all the quality characteristics of bush were measured thoroughly. To measure the improvement in shrinkage values after process improvement, we selected hundred samples from the production line at different times in a week. The process capability index for these samples was calculated.

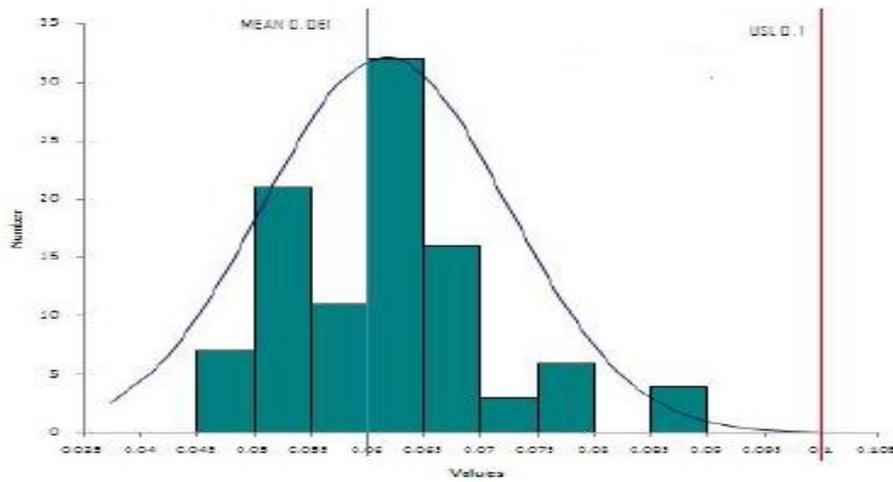


Fig.12 Histogram for hundred samples (over shrinkage measurement)

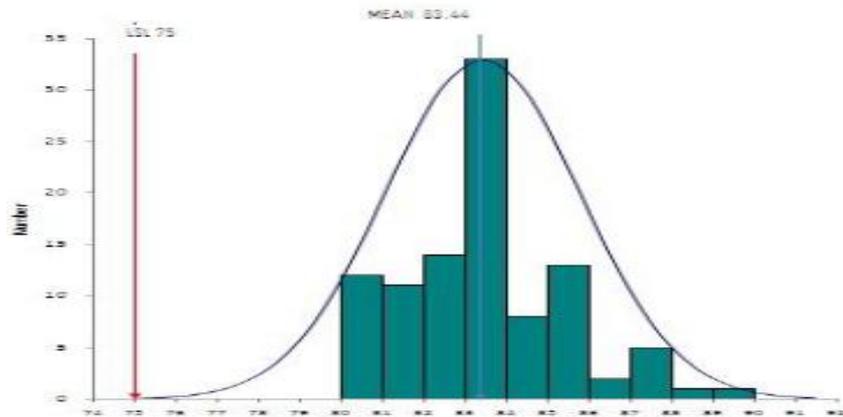


Figure-4.15 Histogram for hardness (horizontal axis)

If we compare the histograms for hardness in diagnose phase and upgrade phase as well as process capability analysis in both the phases we can easily draw the following conclusions.

- 1) Process capability index CPL has increased from 0.56 to 1.16.
- 2) Process mean has increased from 69.79 to 83.44, which is very much desired.
- 3) Process has improved from 3.19 σ standard to 4.99 σ standard.

Conclusion

Since the early 1980s, when the Six Sigma approach was first introduced and adopted by Motorola and later successfully tested by GE Corp. in 1990, the method has become the most prominent administrating technique for quality improvement. Having arisen in large corporations, Six Sigma is surely one of the most comprehensive approaches for company development and performance improvement of products and processes. Nevertheless, it appears that the majority of small and medium sized enterprises (SMEs) either do not know the six sigma approach, or find its organization not suitable to meet their specific requirements. In the SME environment, there is little spare resource; every employee has a key role and usually several.

A general Six Sigma concept for SMEs needs to be adjusted to their core requirements. Which represents a major difference to Six Sigma programmes in large corporations. Keeping in mind above points a modified Six Sigma cycle has been demonstrated in this work which suits the small industries especially plastic injection moulding enterprises. The modified cycle called DAURR (Diagnose, Analyze, Upgrade, Regulate and Review) has been designed according to need of small and medium injection moulding enterprises. The above proposed cycle can be used in small and medium plastic injection moulding firms having limited talent pool and funding. The management tools and statistical methods used in each phase of the cycle have been demonstrated with the help of the study. The feasibility of modified cycle was also proved with the help of a case study. The method has been employed for the improvement in two major quality characteristics (hardness and over shrinkage) of injection-moulded nylon-6 kamani bush produced in a small enterprise.

Prior to application of the Six Sigma approach, compromise among various interacting process parameters were difficult for obtaining the desired quality characteristics. After the implementation of the proposed method, targets for improvement were clearly defined with the problems and causes being identified. The process parameters were then optimized for quality characteristics improvement so that the Six Sigma standard was reached. This approach not only significantly improved quality characteristics of the bush but also achieved the targets of further improvement in review phase. Furthermore, the Taguchi method adopted in the analysis step successfully identified the optimal combinations of process parameters within the experimental window, as well as the most significant factors affecting the quality characteristics. In the meantime, the factors are evaluated via ANOVA of S/N ratio for various combinations of process parameters throughout the experiments. Further the second order regression model was prepared separately for both the characteristics. These second order regression models were further validated with the help of neural network models which had been prepared separately for both hardness and bulging prediction.

The most important part of this work was that the prediction of both quality characteristics (over shrinkage and hardness) were made with the help of regression model as well as neural network model, by varying the process parameters already optimized by Taguchi method. This helped in enhancing prediction capability as well as selection of more optimized process parameter levels. A comparison of prediction capability of both the models was also shown in work, which proved that neural network model has slightly better prediction capability. Simultaneous use of both the models (ANN and Regression model) for prediction, of the quality characteristics at different values of process parameters, is very much convenient in selection of optimum parameter levels. In present work, the upper process capability index CPU for hardness of nylon-6 bush has improved from 0.56 to 1.16, process

mean increased from 69.79 to 83.44 ,while the lower process capability index CPL, for over shrinkage of nylon-6 bush has improved from 0.24 to 1.225, process mean decreased from 0.1015 to 0.0615. The process has improved from 3.19 σ standard to 4.99 σ standard for hardness while it improved from 2.38 σ standard to 5.18 σ standard for over shrinkage.

This work shows that process was improved closer to Six Sigma standard by changing the processing conditions only without any change in the part design, mould design, and machine performance. To further take the process up to Six Sigma standard, in future, we can apply the proposed approach for, mould design as mentioned in review phase of the work. The present work offers advantage in choosing the best tools that fit the SMEs as well as it can be used for achieving six sigma standards in plastic injection moulding companies having limited resources and expertise. This work also demonstrates a process for finding the best compromises between several performance measures for one case of IM. Through finding the efficient compromises between performance measures, one can trace back the corresponding levels of the controllable variables.

Reference

- Duncan, A. J. ,Richard D. (1986), Quality Control and Industrial Statistics, Richard D. Irwin publication, pp. 476-511, pp. 513-534.
- Griffith G. K. (1996), Statistical Process Control Methods for Long and Short Runs, ASQC Quality Press, pp. 39-57, pp. 101-117, pp. 167-195.
- Ghobadian, A. and Gallear, D. (1997), TQM and Organization Size, International Journal of Operations & Production Management, 17(2): 121-132.
- Kwong C. K., Smith G. F. (1998), A Computational System for Process Design of Injection Moulding: Combining a Blackboard-Based Expert System and a Case-Based Reasoning Approach, International Journal of Advanced Manufacturing Technology, 1(4):350-357.
- Bincheno J. (2000), The Lean Toolbox, UK Picsie Books, pp.234-238.
- Pande, P.S., Neuman, R.P., Cavanagh, R.R. (2000), The Six Sigma Way- How GE, Motorola and other Top Companies are Honing their Performance, McGraw-Hill, pp.232-245.
- Tarng Y. S., Yang W. H. ,Juang S. C. (2000), The Use of Fuzzy Logic in the Taguchi Method for the Optimization of the Submerged Arc Welding Process, International Journal of Advanced Manufacturing Technology, 6:688–694.
- Yusof, S.M. and Aspinwall, E. (2000), TQM Implementation Issues: Review and Case Study, International Journal of Operations & Production Management, 20(6): 634-655.
- Cesarone John (2001), the power of Taguchi, Pro Quest Science Journal, IIE Solutions, 33(11): 36-43.
- Pande Peter, Holpp Larry (2001), what is Six Sigma? McGraw- Hill, pp.146-176.
- Sharma Manisha, Pandla Kapil (2001), Case study on Six Sigma at Wipro Technologies: Thrust on Quality, pp.1-15.
- Wu F.C. (2002), Optimisation of Multiple Quality Characteristics based on Percentage Reduction of Taguchi's Quality Loss, International Journal of Advanced Manufacturing Technology ,20:749–753.

- Studt T. (2002), Data Management and Analysis Implementing Six Sigma in R&D, R&D Magazine, pp. 21-23.
- Osswald, T., Sheng, L., Gramann P.J. (2002), Injection Moulding Handbook, Hanser Verlag, pp.432-467.
- Forouraghi, B. (2002), Worst-Case Tolerance Design and Quality Assurance via Genetic Algorithms, Journal of Optimization Theory and Applications, 113(2): 251–268.
- Pyzdek, T. (2003), the Six Sigma Handbook, McGraw Hill.
- Shi,F; Lou,Z. L.; Lu ,J. G. and Zhang Y. Q. (2003), Optimization of Plastic Injection Moulding Process with Soft Computing operations , International Journal of Advanced Manufacturing Technology, 21:656–661.
- Das Subodh K., Hughes Margaret (2004), Improving Aluminum Can Recycling Rates: A Six Sigma Study in Kentucky, Journal of Materials, 21:233-242.
- Koch P.N., Yang R. J., Gu L. (2004), Design For Six Sigma through Robust Optimization, Journal of Structural Multidiscipline Optimization, 26: 235–248.
- Jie Zhu , Joseph C. ,Chen (2006), Fuzzy Neural Network-Based In-Process Mixed Material-Caused Flash Prediction in Injection Moulding Operations, International Journal of Advanced Manufacturing Technology, 29: 308–316
- Yadav B. (2007), Retrospective Analysis of a Designed Experiment, Pro Quest Science Journal Quality Progress, 40(8): 23-32.
- Singh R., Khamba J. S. (2007), Macro Model for Ultrasonic Machining of Titanium and its Alloys: Design of Experiment, Pro Quest Science Journal Proceedings of the Institution of Mechanical Engineers, 221(8): 221-233.
- Dong Sung Kim, Jong Sun Kim, Young Bae Ko (2008), Experimental Characterization of Transcription Properties of Microchannel Geometry Fabricated by Injection Moulding based on Taguchi Method, Microsystem Technology, 14:1581–1588.
- Jeong L. W., Yang Y.K., Jeng M.C. (2009),Optimization of Die Casting Conditions for Wear Properties of Alloy AZ91D Components using the Taguchi Method and Design of Experiments Analysis , International Journal of Advanced Manufacturing Technology , 41:430–439.
- <http://www.isixsigma.com>
- <http://www.wipro.com>
- http://www.ptslc.com/nylon_intro.htm, A Guide to Nylon
- <http://www.sixsigmaqualtec.com/Transactional/dmaic.html>
- http://www.bluemay.co.uk/plastic_fasteners/flanged_bushes.html, Plastic Bushes, Bluemay Limited.
- <http://www.me.gatech.edu/jonathan.colton/me4793/injection.pdf>.
- http://www2.imm.dtu.dk/pubdb/views/publication_details.php