**Proceedings of IDETC/CIE 2006**
**ASME 2006 International Design Engineering Technical Conferences**
**& Computers and Information in Engineering Conference**
**September 10-13, 2006, Philadelphia, Pennsylvania, USA**

**DETC2006-99592**

# OPTIMAL TOLERANCE ALLOCATION OF AUTOMOTIVE PNEUMATIC CONTROL VALVES BASED ON PRODUCT AND PROCESS SIMULATIONS

**Naesung Lyu**
Dept. of Mechanical Engineering
University of Michigan
Ann Arbor, MI, USA
nlyu@umich.edu

**Amane Shimura**
Production Engineering Development Division
Toyota Motor Corporation
Toyota, Aichi, Japan
amane_shimura@mail.toyota.co.jp

**Kazuhiro Saitou***
Dept. of Mechanical Engineering
University of Michigan
Ann Arbor, MI, USA
kazu@umich.edu

## ABSTRACT

This paper discusses a computational method for optimally allocating dimensional tolerances for an automotive pneumatic control valve. Due to the large production volume, costly tight tolerances should be allocated only to the dimensions that have high influence to the quality. Given a parametric geometry of a valve, the problem is posed as a multi-objective optimization with respect to product quality and production cost. The product quality is defined as 1) the deviation from the nominal valve design in the linearity of valve stroke and fluidic force, and 2) the difference in fluidic force with and without cavitation. These quality measures are estimated by using Monte Carlo simulation on a Radial-Basis Function Network (RBFN) trained with computational fluid dynamics (CFD) simulation of the valve operation. The production cost is estimated by the tolerance-cost relationship obtained from the discrete event simulations of valve production process. A multi-objective genetic algorithm is utilized to generate Pareto optimal tolerance allocations with respect to these objectives, and alternative tolerance allocations are proposed considering the trade-offs among multiple objectives.

## 1. INTRODUCTION

The allocation of the dimensional tolerances to a product highly affects their quality and manufacturing cost. In most cases, tighter tolerances realize smaller variations in the product performances and hence higher quality. On the other hand, tighter tolerances require precision machine tools and often longer process time, hence causing higher production cost. Since tolerances of some dimensions affect the quality and cost more than the other, it is desirable to allocate tight tolerances only to the dimensions that have high influences to the quality, to attain an optimal balance between the quality and cost. This is especially the case of mass-produced products, whose unit cost saving can sum up to a significant amount over production periods. In order to shave off maximum cost without compromising quality, accurate estimations of product quality and production cost are essential.

This paper presents a method for an optimal allocation of dimensional tolerances based on the computer simulations of the product function and production process, and its application to an automotive pneumatic control valve. The function of the valve is to regulate the fluid flow by changing the valve stroke, the distance between the boll-shaped tip of a plunger and the seat at the flow exit of a pipe (Figure 1). Fast and accurate control of the stroke is essential to the performance of the valve, which requires the prediction and compensation of fluidic force on the plunger at various strokes and under various operating conditions such as pressure and temperature of inlet fluid. Since the fluidic force is affected by the valve geometry, it is desired to allocate the nominal values and tolerances of its dimensions such that the variations of fluidic force from the one predicted for the nominal dimension is minimized. Due to the large production volume of the

* corresponding author

 

valve, on the other hand, costly tight tolerances should be allocated only to the dimensions that have high influence to the fluidic force on the plunger.

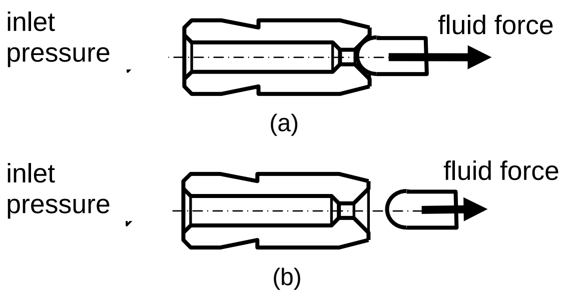


**Figure 1. Pneumatic control valve: (a) closed, and (b) opened.**

Figure 2 shows the overview of the method. Given a parametric geometry of a valve, the problem is posed as a multi-objective optimization with respect to product quality and production cost. The product quality is defined as 1) the deviation from the nominal valve design in the linearity of valve stroke and fluidic force, and 2) the difference in fluidic force with and without cavitation. These quality measures are estimated by using Monte Carlo simulation on a Radial-Basis Function Network (RBFN) [1] trained with computational fluid dynamics (CFD) simulation of the valve operation. The production cost is estimated by the tolerance-cost relationship obtained from the discrete event simulations of the valve production process. A multi-objective genetic algorithm [2] is utilized to generate Pareto optimal tolerance allocations with respect to these objectives.

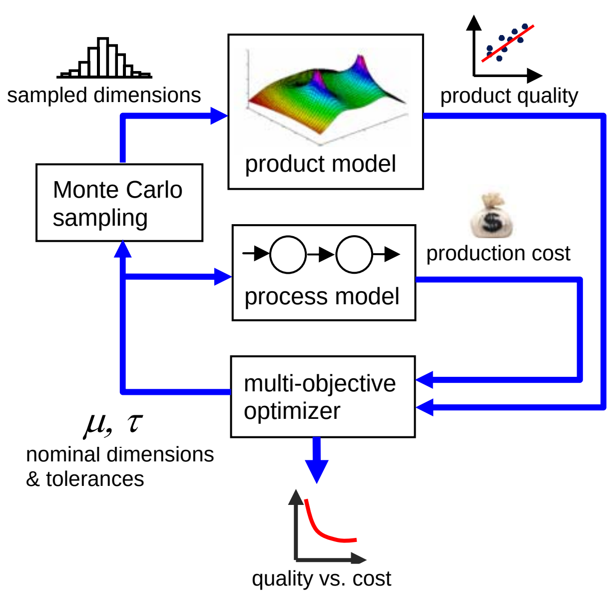


**Figure 2. Overview of the method.**

## 2. RELATED WORK

Tolerance allocation is a process for finding a best compromise between product quality and production cost. Early work on tolerance allocations employed some variants of reciprocal or exponential tolerance-cost models, and simple linear or nonlinear "design functions," which indirectly represent the product quality in terms of part dimensions [3,4]. These classic works are later extended to incorporate more detailed tolerance-cost models [5,6,7] and quality models such as reliability [8-10], quality loss [11-17], and both [18]. Some researchers adopted the direct measure of product functions as a quality model [19-22], and production simulation as a cost model [23, 24]

This paper applies a variant of the method proposed in our previous work [23,24] to automotive pneumatic control valves, where product quality is obtained by the Monte Carlo simulation of product functions and production cost is obtained by the discrete-event simulation of production processes. Dissimilar to [23,24] which considers the type and number of production machines with different precision as decision variables, the present work considers tolerance values as conventionally done in tolerance allocation, by assuming the flexible production system with CNC machining centers.

## 3. METHOD

The method, as illustrated in Figure 2, solves the following optimization problem:

- **Given:** parametric geometry of a product, models of product function and production process
- **Find:** nominal product dimensions and their tolerances
- **Subject to:** upper and lower bounds of dimensions and tolerances
- **Maximizing:** measures of product quality
- **Minimizing:** production cost

The product function model is implemented as a surrogate model (Radial-Basis Function Network: RBFN) of the computational fluid dynamics (CFD) simulations of the valve with various dimensions. The production process model is a discrete-event simulation of the valve production process. The product quality is defined as 1) the deviation from the nominal valve design in the linearity of valve stroke and fluidic force, and 2) the difference in fluidic force with and without cavitation. They are calculated by Monte Carlo simulation on the surrogate response model of the valve. The production cost is calculated by the tolerance-cost relationship obtained from the running the discrete event simulations with various tolerance values. Due to the existence of multiple objectives, a multi-objective genetic algorithm is utilized to generate Pareto optimal nominal dimensions and the tolerances. The rest of the section describes each item in detail.

## 3.1. Parametric product geometry

Figure 3 shows the parametric geometry of the pneumatic control valve considered in this paper, consists of four dimensions with high influence to the fluidic force on the plunger:

- Diameter of ball: $d_B$
- Diameter of pipe: $d_P$
- Angle of seat: $\theta$
- Depth of seat: $h$

These are the parameters that can be adjusted within given tolerances by the valve production process, and hence considered controllable.

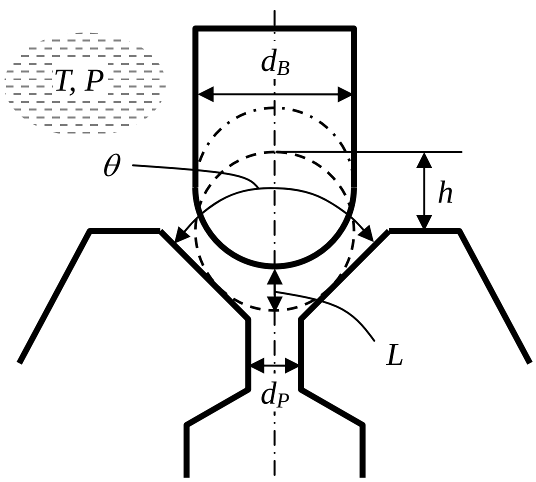


**Figure 3. Close-up view of the outlet cross section of pneumatic control valve, with controllable parameters ($d_B$, $d_P$, $\theta$, $h$) and uncontrollable parameters ($L$, $T$, $P$).**

In addition, the fluidic force is affected by the following parameters:

- Valve stroke: $L$
- Fluid temperature: $T$
- Outlet pressure: $P$

These are the parameters that cannot be adjusted by the valve production process, and hence considered uncontrollable and treated as noise factors during the evaluation of the product quality as described in the following section.

## 3.2. Product model

Due to the high computational cost of computational fluid dynamics (CFD) simulation, two surrogate response models are utilized, which can be represented as:

$$f_z = \text{fluidic-force}(d_B, d_P, \theta, h, L, T, P) \quad (1)$$

$$f_z^C = \text{fluidic-force-cav}(d_B, d_P, \theta, h, L, T, P) \quad (2)$$

where $f_z$ and $f_z^C$ are the fluidic forces on the plunger, with and without considering the effects of cavitation, respectively. Radial-Basis Function Network (RBFN) is chosen for its fast convergence and accuracy of interpolation among training samples.

Since the feasible ranges of the input parameters are fairly small but accurate estimates is necessary within the ranges, the 79 training samples are obtained from the 5 levels of the 7 input parameters $d_B$, $d_P$, $\theta$, $h$, $L$, $T$, and $P$, by using Central Composite Inscribed (CCI) design [25] combined with Fractional-Factorial designs [26]. CCI design was chosen since it allocates a relatively small number of samples with a large (5) factor level densely near the center points. Since there are 7 parameters (k=7), the number of samples is determined by using the following equation:

$$\text{N(fractional points)} + \text{N(axial points)} + \text{N(center point)} = 2^{k-1} + 2*k + 1 = 79 \quad (3)$$

Figure 4 shows the CFD model one of the 79 sample valve designs. Due to the axisymmetric geometry, only a right half of the outlet cross section is modeled. The CFD simulations are conducted by StarCD software on a 264 CPU PC cluster at the Center of Advanced Computing at the University of Michigan. The average, longest, and shortest CPU time of the 79 samples are 21.1 CPU-days, 38.0 CPU-days, and 11.6 CPU-days, respectively.

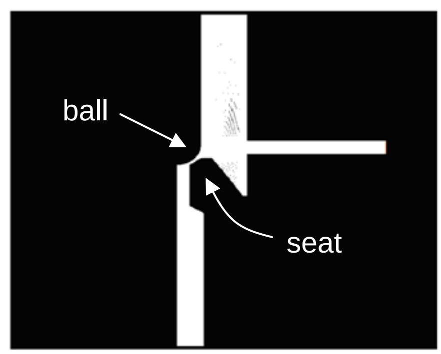


**Figure 4. Example CFD model of the pneumatic control valve. A right half of the outlet cross section is modeled.**

The large differences in the running time of samples are mainly due to the existence and magnitude of cavitation during the simulated time. When certain physical conditions are satisfied during the iteration, a simulation automatically switches to "cavitation mode," which causes far longer time for the results to converge. To further examine the effect of cavitation, the 79 samples are classified to 1) cavitation near edge of the outlet seat of the pipe (large pressure drop), and 2) no cavitation (small pressure drop). Figure 4 shows examples CFD results with cavitation.

Since the occurrence of cavitation largely reduces the fluidic force and its prediction by CFD simulation is not very accurate, it is desired to design valves with the minimum influence of cavitation. As such, the surrogate response model without cavitation (Equation 1) is built with the values of the fluidic force right before switching to the cavitation mode. The surrogate response model with cavitation (Equation 2), on the other hand, is built with the values of the fluidic force at the simulation convergence.

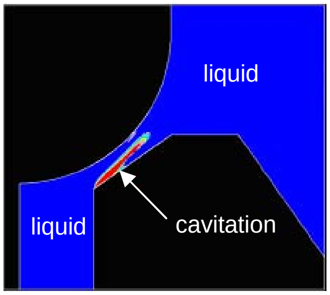


**Figure 4. Example CFD results with cavitation near edge of seat.**

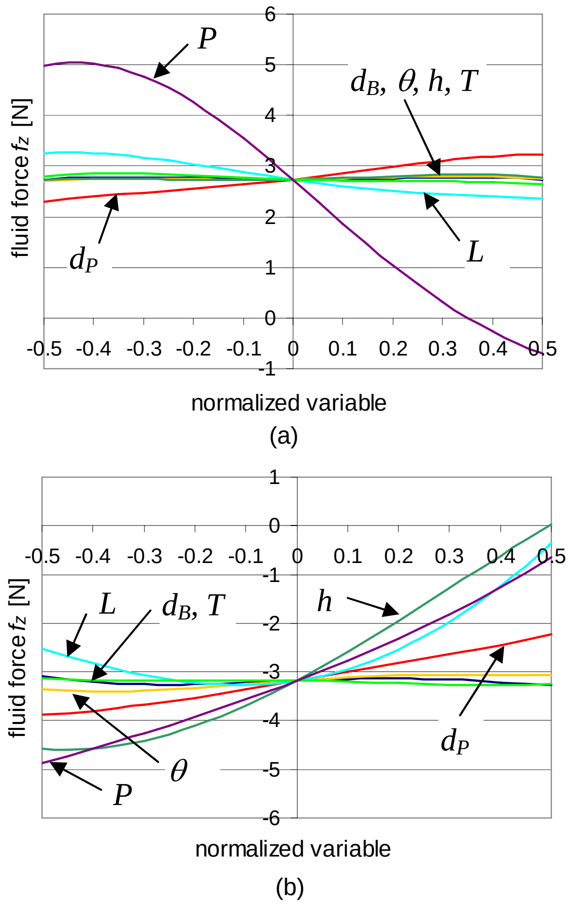


**Figure 5. Sensitivity to input parameters: (a) $f_z^C$ and (b) $f_z$**

Figures 5 (a) and (b) show the sensitivities of fluidic force with cavitation $f_z^C$ and without cavitaion $f_z$, respectively, to input parameters $d_B$, $d_P$, $\theta$, $h$, $L$, $T$, and $P$. Compared to the other inputs, $f_z^C$ very highly sensitive to outlet pressure $P$, whereas $f_z$ is highly sensitive to $P$, stroke $L$, and depth of seat $h$.

## 3.2. Production system model

In order to accurately estimate unit production cost, the production process of pneumatic control valves is modeled as a discrete event simulation, which can be represented as:

$$c = \text{production-cost}(\tau_B, \tau_P, \tau_\theta, \tau_h) \quad (4)$$

where $\tau_B$, $\tau_P$, $\tau_\theta$, and $\tau_h$ are the tolerances of $d_B$, $d_P$, $\theta$, and $h$, respectively, and $c$ is a part of the unit production cost of the valve that depends on the tolerances of $d_B$, $d_P$, $\theta$, and $h$. Typically $c$ is higher with tighter (smaller) tolerances due to the higher cost of precision tools, longer processing time, reduced tool life, and the need of additional process (*eg.*, grinding) for precision finish.

Figure 6 shows the production process of the pipe, where CNC machine 1 cuts the outlet geometry (hence determines $d_P$, $\theta$ and $h$), and CNC machine 2 drills the inlet hole. The production process of the ball, which determines $d_B$, was not modeled due to the unavailability of detailed processing data. Instead, an empirical formula provided by the supplier is used to estimate the contribution of $\tau_B$ to the production cost of the plunger.

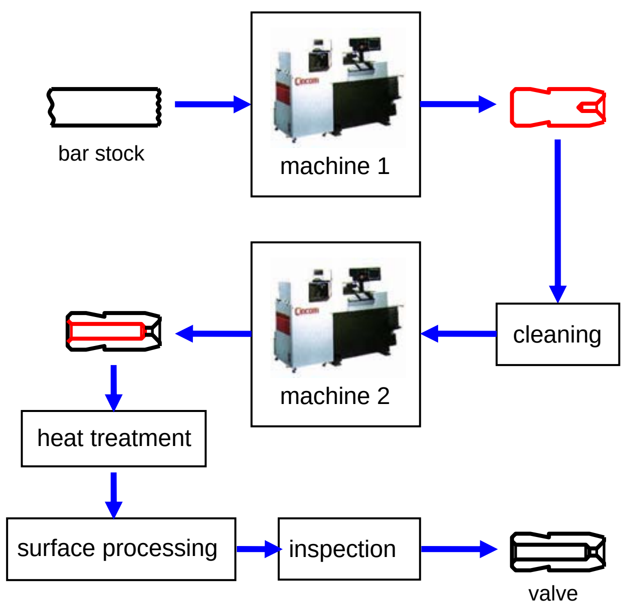


**Figure 6. Control valve production model**

A bar stock fed to CNC machine 1 goes through the following processes, as illustrated in Figure 7:

- Seat face milling (determines $h$)
- Seat angle milling (determines $\theta$)
- Seat angle grinding (determines $\theta$): required for high tolerance only
- Orifice drilling (determines $d_P$)
- Turning and cutting

Since the study shows CNC machine 1 has virtually no variations in processing time and unexpected failure, it was modeled as a deterministic single-server system, with input queue (raw material) is always full. Prior to each process, the need of tool replacement is checked, and if needed, the corresponding downtime is added to the clock. During the simulation, production cost is calculated as a sum of raw material cost, tool cost, labor cost, and machine operating cost.

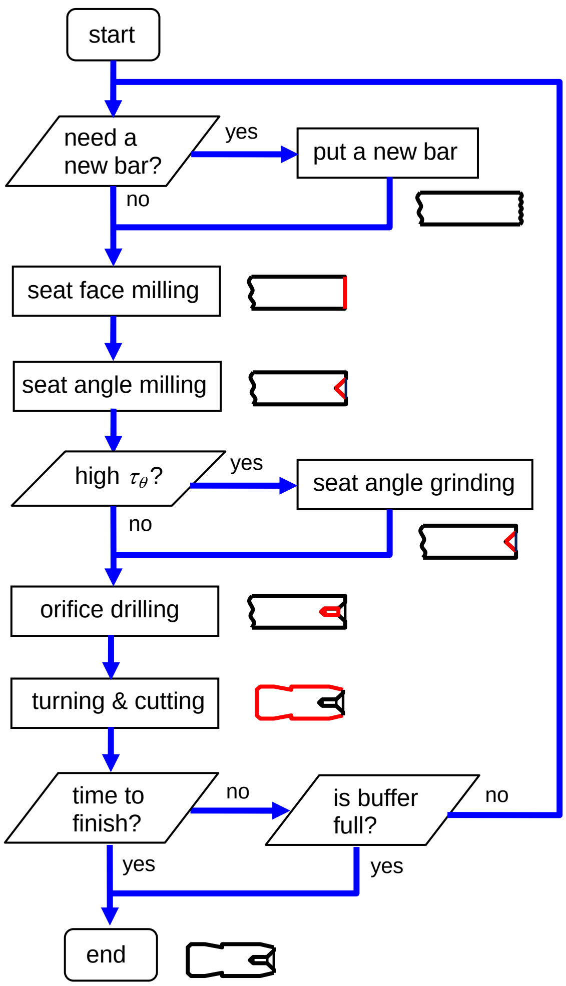


**Figure 7. Process flow chart of machine 1**

Figure 8 shows the non-dimensionalized unit cost of the pipe for small, medium, and large tolerances, calculated by the discrete event simulation of machine 1 in Figure 7. All three lines show initial transient range where the unit cost increases. This is because the production begins with new tools that do not need to be replaced for the time being. After a certain amount of valves are produced, the unit costs reach steady values. As expected, smaller tolerance design resulted in higher unit cost, mainly due to the decreased tool life from high tolerance machining processes. In the following results, the unit cost after 2,000,000 is used.

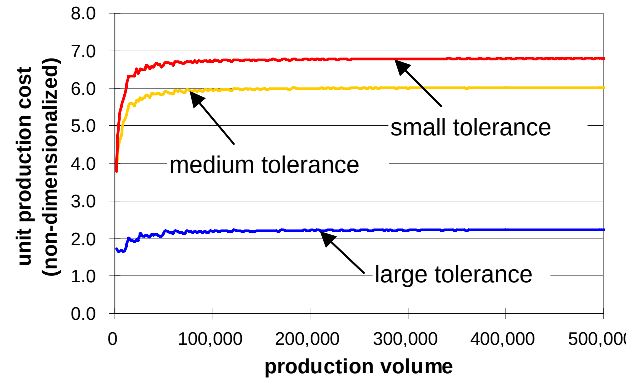


**Figure 8. Unit valve cost for machine 1**

## 3.3. Design variables and constraints

The design variables are the nominal and tolerance values of 4 controllable parameters in Figure 2: $\mu_B$, $\mu_P$, $\mu_\theta$, and $\mu_h$, and $\tau_B$, $\tau_P$, $\tau_\theta$, and $\tau_h$. There are only side constraints (upper and lower bounds) to these design variables. Due to the proprietary nature of the information, the values of the design variable are shown as normalized using these bounds to [-1, 1] for nominal values (baseline = 0) and to [0, 1] for tolerances (baseline = 0.67).

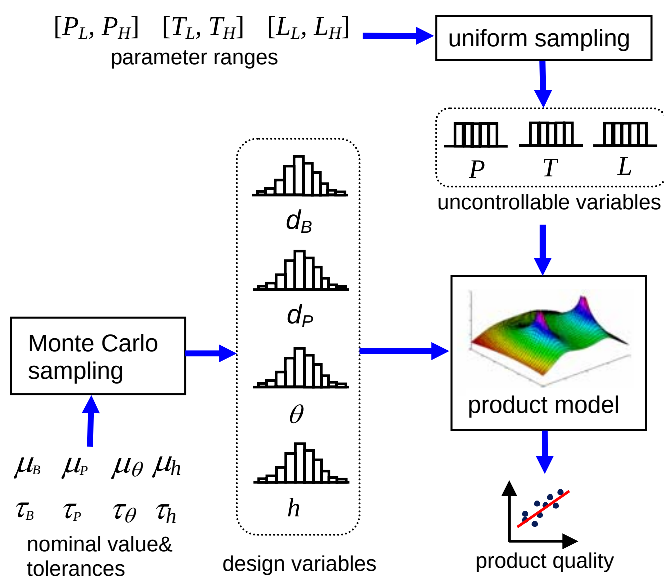


**Figure 9. Monte-Carlo Simulation**

## 3.4. Objective functions

The following two quality measures are used as the objective functions (to be minimized) representing the product quality:

- $f_1$: deviation from the nominal valve design in the linearity of valve stroke $L$ and fluidic force with cavitation $f_z^c$.

 

- $f_2$: difference in fluidic force with cavitation $f_z^c$ and fluidic force without cavitation $f_z$.

Given values of design variables ($d_B$, $d_P$, $\theta$, $h$, $\tau_B$, $\tau_P$, $\tau_\theta$, and $\tau_h$), these objective functions are obtained by the Monte-Carlo simulation on the surrogate response model in Equations 1 and 2, as shown in Figure 9. All design variables are assumed to be normally distributed with means being the nominal values, and standard deviation being 1/3 of the tolerances. Uncontrollable variables are assumed to be uniformly distributed within the given ranges, and sampled accordingly during the Monte Calro simulation.

The first objective function $f_1$ (to be minimized) is calculated as the error between the $f_z^c$ of a sampled design at various stroke $L$ and the linear fit of the $L$- $f_z^c$ plot of the nominal design, averaged over $n$ samples of the Monte Carlo simulation:

$$f_1 = \frac{\sum_{i=1}^{n} e_{1i}}{n} \tag{5}$$

$$e_{1i} = \sqrt{\frac{\sum_{j=1}^{m} \left\{ f_{zij}^c - (aL_j + b) \right\}^2}{m}} \tag{6}$$

where $f_{zij}^c$ is the fluidic force with caviation of sample $i$ at stroke $L_j$, $m$ is the number of discrete stoke values ranging from lower to upper bounds, and $a$ and $b$ are the slope and $L$-intercept of the linear regression of the $L$- $f_z^c$ plot of the nominal design with nominal values of $P$ and $T$:

$$a = \frac{m\sum_{j=1}^{m} L_j \hat{f}_{zj}^C - \sum_{j=1}^{m} L_j \sum_{j=1}^{m} \hat{f}_{zj}^C}{m\sum_{j=1}^{m} \left(L_j\right)^2 - \left(\sum_{j=1}^{m} L_j\right)^2} \tag{7}$$

$$b = \frac{\sum_{j=1}^{m} \hat{f}_{zj}^C - m\sum_{j=1}^{m} L_j}{m} \tag{8}$$

The second objective function $f_2$ (to be minimized) is calculated as the error between $f_z^c$ and $f_z$ of a sampled design at various stroke $L$ and outlet pressure $P$, averaged over $n$ samples of the Monte Carlo simulation:

$$f_2 = \frac{\sum_{i=1}^{n} e_{2i}}{n} \tag{9}$$

$$e_{2i} = \sqrt{\frac{\sum_{k=1}^{l} \sum_{j=1}^{m} \left\{ f_{zijk}^c - f_{zijk} \right\}^2}{lm}} \tag{10}$$

where $f_{zijk}^c$ and $f_{zijk}$ are the fluidic force with and without caviation, respectively, of sample $i$ at stroke $L_j$ and outlet pressure $P_k$, $m$ is the number of discrete stoke values ranging lower to upper bounds, and $l$ is the number of discrete values of outlet pressure, also ranging from lower to upper bounds.

The third objective function $f_3$ (to be minimized) representing the unit production cost of the valve is calculated by using the production process models in Equation 4:

$$f_3 = c_B(\tau_B) + c_P(\tau_P) + c_\theta(\tau_\theta) + c_h(\tau_h) \tag{11}$$

where $c_B$, $c_P$, $c_\theta$, and $c_h$ are the processing costs of ball surface, orifice drilling, seat angle milling, and seat face milling, respectively, shown in Figure 10. The tolerance-cost curves for $c_P(\tau_P)$, $c_\theta(\tau_\theta)$, and $c_h(\tau_h)$ in Figure 10 are obtained by running the discrete event simulation of machine 1 with various values of tolerances, and the curve for $c_B(\tau_B)$ is obtained by an empirical data provided by the supplier of the plunger. A step-like discontinuity in $c_\theta(\tau_\theta)$ is due to the additional grinding process necessary for small values of $\tau_\theta$. Since the discrete-event simulation in Figure 7 is deterministic, the tolerance-cost curves in Figure 10 generated off-line are simply looked up to calculate $f_3$ during the optimization.

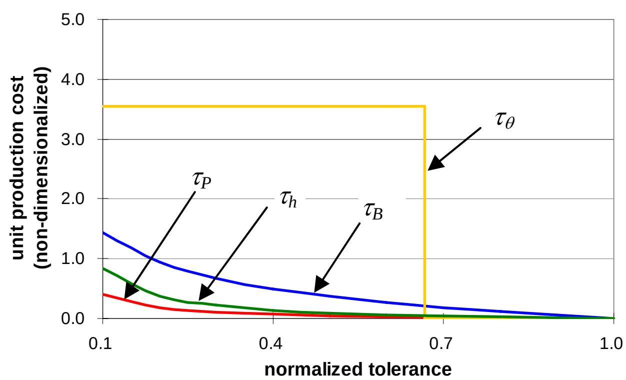


**Figure 10. Tolerance-cost curve of valve production.**

## 4. RESULTS

Figure 11 shows the Pareto optimal solutions in the 2-D projections of the 3-D objective function spaces, obtained by a multi-objective genetic algorithm (NSGA-II) with the following parameters:

- Population number: 400
- Generation number: 100
- Replacement Rate: 0.5
- Crossover Rate: 0.9
- Mutation Rate: 0.1

Pareto solutions in the $f_1$-$f_2$ space (Figure 11 (a)) show an inversely proportional distribution. With tighter tolerances, the design becomes closer to the nominal design, thereby decreases $f_1$. This strangely has an effect of increasing $f_2$. Close examination of individual design reveals that the value of $f_2$ is dominated by outlet presume $P$ as seen in Figure 5, and tends to decrease with larger variations in $f_z^c$ and $f_z$ since they "cover up" the effect of $P$. With similar tolerances, smaller $\mu_B$ and $\mu_h$ decreases $f_2$ but increases $f_1$, Pareto solutions in the $f_1$-$f_3$ space (Figure 11 (b)) also show inversely proportional distribution. This is natural since tighter tolerances increases production cost as evident in Figure 10, while they decrease $f_1$ as discussed above. Pareto solutions in the $f_2$-$f_3$ space (Figure 11 (c)) scatters over the space.

Figure 11 also shows four representative designs: representative designs: best for $f_1$ (triangle), best for $f_2$ (square), best for $f_3$ (diamond), and balanced in all objectives (star). Table 1 shows the normalized values of objective functions and design variables of these designs. The comparison of these designs suggests the tight $\tau_\theta$ is essential for product quality despite its large penalty on production cost. On the other hand, loosening $\tau_B$ and $\tau_P$ by a factor of 10 in the normalized scale can significantly improve the production cost with small penalty on product quality. Since $c_\theta$ ($\tau_\theta$) = 0 for $\tau_\theta > 0.67$ in the normalized scale, the minimum cost design ($f_3$ best) in Table 1 has this value $\tau_\theta = 0.67$ thereby dominating other minimum cost designs with respect to other objectives that generally favor smaller tolerances. However, designs with the best $f_1$ and $f_2$ values in Table 1 do not necessarily have the smallest tolerances. This is likely due to the high sensitivity of uncontrollable variables $P$ and $T$ to $f_1$ and $f_2$ (especially to $f_2$), which masks the relatively small effect of tolerances on these objectives.

Since production cost does not depend on the nominal dimensions, quality improvement by changing nominal values comes with no cost penalty. The results of the design best for $f_1$, however, suggest the current design ($\mu$ = 0 in the normalized scale) is fairly well designed for robustness.

## 5. CONCLUSION

This paper presents a method for an optimal allocation of dimensional tolerances based on the computer simulations of the product function and production process, and its application to an automotive pneumatic control valve. Given a parametric geometry of a valve, the problem is posed as a multi-objective optimization with respect to product quality and production cost. The product quality is defined as 1) the deviation from the nominal valve design in the linearity of valve stroke and fluidic force, and 2) the difference in fluidic force with and without cavitation. Pareto optimal solution obtained by a multi-objective genetic algorithm suggest that some tolerances essential for product quality have large penalty on production cost, while others can improve product quality with small effect on production cost.


## ACKNOWLEDGMENTS

The authors acknowledge Toyota Motor Corporation for proving funding for this research, and CD-Adapco for providing the licenses of StarCD through the educational program.


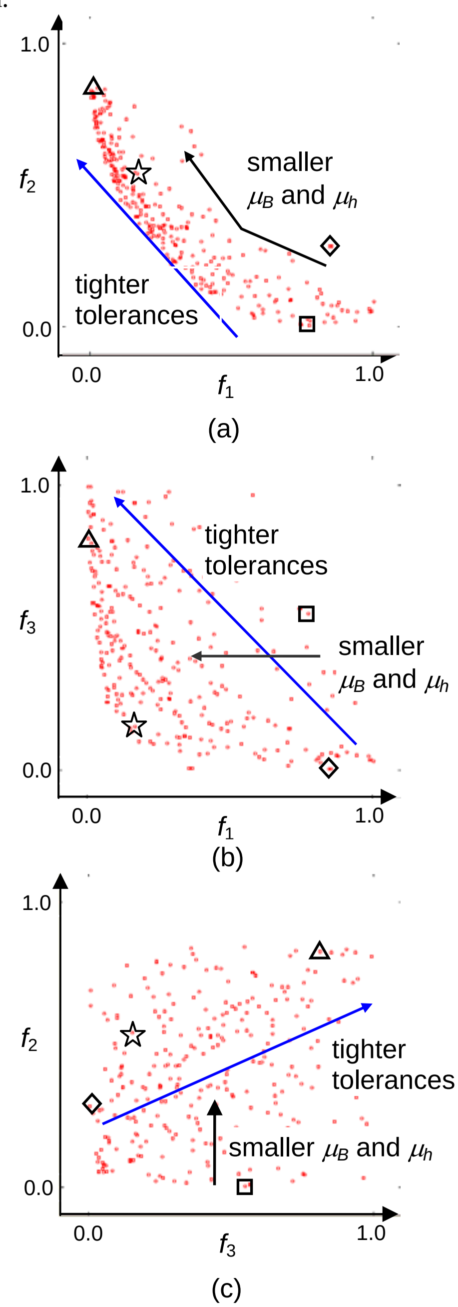


**Figure 11. Pareto optimal solutions with representative designs: best for $f_1$ (triangle), best for $f_2$ (square), best for $f_3$ (diamond), and balanced in all objectives (star).**

**Table 1. Representative optimal designs in Figure 11.**

| | $f_1$ | $f_2$ | $f_3$ |
|---|---|---|---|
| $f_1$ best | 0.00 | 0.82 | 0.81 |
| $f_2$ best | 0.77 | 0.00 | 0.55 |
| $f_3$ best | 0.85 | 0.28 | 0.00 |
| Compromised | 0.16 | 0.54 | 0.15 |

| | $\tau_B$ | $\tau_P$ | $\tau_\theta$ | $\tau_h$ |
|---|---|---|---|---|
| $f_1$ best | 0.08 | 0.01 | 0.04 | 0.09 |
| $f_2$ best | 0.47 | 0.17 | 0.46 | 0.07 |
| $f_3$ best | 0.99 | 0.99 | 0.67 | 1.00 |
| Compromised | 0.86 | 0.17 | 0.02 | 0.55 |

| | $\mu_B$ | $\mu_P$ | $\mu_\theta$ | $\mu_h$ |
|---|---|---|---|---|
| $f_1$ best | 0.06 | 0.04 | 0.00 | -0.03 |
| $f_2$ best | 0.97 | 1.00 | 0.97 | 1.00 |
| $f_3$ best | 0.88 | 0.24 | -0.90 | 0.69 |
| Compromised | 0.24 | -0.11 | 0.08 | 0.41 |

## REFERENCES


[1] Powell, M. J. D., 1987, "Radial basis functions for multivariable interpolation: a review,'' in *Algorithms for Approximation*, J. C. Mason and M. G. Cox, Eds. Oxford, UK: Clarendon, pp. 143-167.

[2] Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T., 2002, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182-197.

[3] Speckhart, F. H., 1972, "Calculation of tolerance based on a minimum cost approach," *Journal of Engineering in Industry*, vol. 94, pp. 447-453.

[4] Spotts, J. F., 1973, "Allocation of tolerancing to minimize cost of assembly," *Journal of Engineering in Industry*, vol. 95, pp. 762-764.

[5] Dong, Z., Hu, W., and Xue, D., 1994, "New production cost-tolerance models for tolerance synthesis," *Journal of Engineering in Industry*, vol. 116, pp. 199-206.

[6] Shiu, W., Apley, D. W., Geglarek, D., and Shi, J., 2003, "Tolerance allocation for compliant beam structure assemblies," *IIE Transactions*, vol. 35, pp. 329–342.

[7] Xue, J. and Ji, P., 2004, "Process tolerance allocation in angular tolerance charting," *International Journal on Production Research*, vol. 42, pp. 3929–3945.

[8] Lee, W. J. and Woo, T. C., 1989, "Optimum selection of discrete tolerance," *Journal of Mechanical Design*, vol. 111, pp. 243–251.

[9] Lee, J., and Johnson, G. E., 1993, "Optimal tolerance allotment using a genetic algorithm and truncated Monte Carlo simulation," *Computer-Aided Design*, vol. 25, pp. 601–611.

[10] Skowronski, V. J. and Turner, J. U., 1997, "Using Monte-Carlo variance reduction in statistical tolerance synthesis," *Computer-Aided Design*, vol. 29, pp. 63–69.

[11] Krishnaswami, M. and Mayne, R. W., 1994, "Optimizing tolerance allocation based on manufacturing cost and quality loss," *Advances in Design Automation*, DE-Vol. 69-1.

[12] Söderberg, R., 1994, "Robust design by tolerance allocation considering quality and manufacturing cost," *Advances in Design Automation*, DE-Vol. 69-1.

[13] Cheng, B., and Maghsoodloo, S., 1995, "Optimization of mechanical assembly tolerances by incorporating Taguchi's quality loss function," *Journal of Manufacturing Systems*, vol. 14, No. 4, pp. 264–276.

[14] Vasseur, H., Kurfess, T. R., and Cagan, J., 1997, "Use of a quality loss function to select statistical tolerances," *Journal of Manufacturing Science and Engineering*, vol. 119, pp. 410–416.

[15] Choi, H.-G. Park, M.-H. and Salisbury, E., 2000, "Optimal tolerance allocation with loss functions," *Journal of Manufacturing Science and Engineering*, vol. 122, no. 3, pp. 529-535.

[16] Ye, B. and Salustri, F. A., 2003, "Simultaneous tolerance synthesis for manufacturing and quality," Research in Engineering Design, vol. 14, pp. 98–106.

[17] Li, M. H. C., 2004, "Optimal target selection for unbalanced tolerance design," *International Journal of Advanced Manufacturing Technology*, vol. 23, pp. 743–749.

[18] Huang, Y. M. and Shiau, C.-S., 2006, "Optimal tolerance allocation for a sliding vane compressor," *Journal of Mechanical Design*, vol. 128, no. 1, pp. 98-107.

[19] Parkinson, D. B., 2000, "The application of a robust design method to tolerancing," *Journal of Mechanical Design*, vol. 122, pp. 149–154.

[20] Zhou, Z., Huang, W., and Zhang, L., 2001, "Sequential algorithm based on number theoretic method for statistical tolerance analysis and synthesis," *Journal of Manufacturing Science and Engineering*, vol. 123, pp. 490–493.

[21] Jordaan, J. P., and Ungerer, C. P., 2002, "Optimization of design tolerances through response surface approximations," *Journal of Manufacturing Science and Engineering*, vol. 124, pp. 762–767.

[22] Kazancioglu, E., Wu, G., Ko, J., Bohac, S., Filipi, Z., Hu, S. J., Assanis, D., and Saitou, K., 2003, "Robust optimization of an automotive valvetrain using multiobjective genetic algorithm," *Proceedings of the 2003 ASME Design Engineering Technical Conferences*, Chicago, Illinois, September 2-6, DETC2003/DAC-48714.

[23] Kazancioglu, E., and Saitou, K., 2004, "Multi-period capacity planning for integrated product-process design," *Proceedings of the Fifth International Symposium on Tools and Methods of Competitive Engineering*, Lausanne, Switzerland, April 13-17, pp. 415-423.

[24] Kazancioglu, E., and Saitou, K., 2004, "Multi-period robust capacity planning based on product and process simulations," *Proceedings of the WSC04: Winter Simulation Conference*, pp. 1781-1789, Washington, D.C., December 5-8.

[25] Box, G. E. P., Hunter, W. G., and Hunter, J. S., 1978, *Statistics for Experimenters: An Introduction to Design, Data Analysis, and Model Building*, John Wiley & Sons, New York.

[26] Montgomery, D. C., 1991, *Design and Analysis of Experiments*, John Wiley & Sons, New York.