한국기계가공학회지, 제8권, 제4호, pp.110～121 (2009. 12)
Journal of the Korean Society of Manufacturing Process Engineers, Vol. 8 No. 4, pp.110～121 (2009. 12)

Application of Operating Window to Robust Process Optimization of Sheet Metal Forming

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기능창을 이용한 박판성형의 공정 최적화

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(Received 16 November 2009; received in revised form 22 December 2009; accepted 29 December 2009)

ABSTRACT

It is essential to embed product quality in the design process to win the global competition. Many components found in many products including automobiles and electronic devices are fabricated using sheet metal forming processes. Wrinkle and fracture are two types of defects frequently found in the sheet metal forming process. Reducing such defects is a hard problem as they are affected by many uncontrollable factors. Attempts to solve the problem based on traditional deterministic optimization theories are often led to failures. Furthermore, the wrinkle and fracture are conflicting defects in such a way that reducing one defect leads to increasing the other. Hence, it is a difficult task to reduce both of them at the same time. In this research, a new design method for reducing the rates of conflicting defects under uncontrollable factors is presented by using operating window and a sequential search procedure. A new SN ratio is proposed to overcome the problems of a traditional SN ratio used in the operating window technique. The method is applied to optimizing the robust design of a sheet metal forming process. To show the effectiveness of the proposed method, a comparison is made between the traditional and the proposed methods using simulation software, applied to a design of particular sheet metal forming process problem. The results show that the proposed method always gives a more robust design that is less sensitive to noises than the traditional method.

Key Words : Sheet metal forming, Operating window, Conflicting defects, Robust design, Process optimization

1. Introduction

Sheet metal forming is a mass manufacturing process for components used in many products including automobiles, airplanes, and electronic devices due to its low cost per part and high reproducibility.

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Although it can produce complex shapes, products may suffer from defects such as fracture, wrinkle, and springback. Trial and error has been the industrial practice in dealing with the problem to reduce the defects. To avoid the time consuming and costly practice, many attempts have been made to obtain the optimal solution based on software simulations and design optimization methods. Most of the design optimization methods, however, handle the cases when the design parameters are deterministic, and they cannot solve the real industrial problems in which many operational conditions are uncontrollable and the material properties are inconsistent. Furthermore, the defects may conflict with each other in such a way that reducing a certain defect cause increasing another or vice versa. A design method is needed so that all defects can be reduced at the same time.

The robust design method developed by Taguchi is one of the most frequently used off-line quality control techniques in which product quality is improved by finding optimal settings of design factors that are insensitive to noise conditions.[1] On the other hand, a process design with two or more conflicting defects is a very difficult problem to solve. The operating window approach proposed by Don Clausing[2] has been considered as an effective method in solving such design problems with conflicting defects.

In this research, a new design method that improves the shortcomings of the traditional operating window method is proposed. The method is applied to a sheet metal forming process so that two conflicting defects (fracture and wrinkle) are reduced effectively

1.1 Sheet Metal Forming

Only recently, the concept of robust optimization has been introduced to the process design of sheet metal forming to reduce the rates of producing defects such as wrinkle, fracture, and springback. Such defects are caused by uncontrollable variations of process parameters and material properties.[3-10] Traditional deterministic optimization method is the typical approach found in the literature of the sheet metal forming process design. Among the fewer approaches considering the uncontrollable noises, many use probabilistic design techniques or Monte Carlo simulations based on meta-models such as response surface.[4-10]

Zhang and Shivpuri[4] propose a probabilistic model from the weighted linear sum of the occurrence probabilities of wrinkle and fracture in the sheet metal forming process, and apply it to the drawing process of aluminum sheet. They define a “quality index”, and show that the index can be improved by performing a probabilistic optimization process on the variations of material properties and process parameters, comparing with traditional deterministic optimization methods. Donglai *et al*[5] propose a two-step procedure for the optimization and tolerance prediction of sheet metal forming process. Their procedure consists of a deterministic optimization on controllable variables using an adaptive response surface method, and a tolerance prediction on the noise factors using a stochastic response surface method. They apply it to a drawing process of deck-lid outer panels to optimize the fracture and thinning. Buranathiti *et al*[6] propose a weighted three-point-based method that estimates response variance using an uncertainty propagation model. They apply it to a robust design problem of a wheelhouse drawing process to show that the method can obtain the results similar to those with a Monte-Carlo simulation only with fewer calculations. Chen *et al*[7] propose a method with which the uncertainties of process variables (material properties, blank holder force, and friction) are introduced by generating random numbers. They analyze springback variations of an open channel made of advanced high strength steel (AHSS).

1.2 Robust Design and Operating Window Approach

Increasing global competitions drive companies to produce quality products with lower costs to stay in business. Recently, robust design has been an important design-for-quality tool of innovating mechanical manufacturing processes, along with the Design for Six Sigma (DFSS) methodology. Conventional optimal design methods consider only the parameters that designers can control. There are many uncontrollable factors, however, that affect the quality characteristics of the product. These uncontrollable factors, called noises in robust design, cause the variations of quality characteristics, increasing the defect rates and degrading the performance of the products. In the robust design, the optimal values of design parameters are determined such that the quality characteristics of the products or processes are stable even under the influence of such noise factors.

Defect rate is used for a long time in evaluating product and process quality on a managerial purpose, but it is not appropriate for accurately assessing the system performance in a design process because all products falling within an acceptable range are treated equally in defect rates.[1] A product meeting the design target will certainly perform better than a product that barely meets the specification at the border of the acceptable range. For an accurate evaluation of the performance of a product, continuous functional characteristics that span within the acceptable range will be better than the traditional step function used in the defect rate that gives a constant value in the range.[1] In practice, however, choosing proper functional characteristics for a particular design system is not trivial, and the operating window can be used as a practical alternative method.[11]

The operating window (OW) is defined by the boundaries of a critical parameter, and certain defects are excited when the parameter value is at or beyond the boundaries. The concept of the operating window was first developed by Don Clausing in the late 1970's. He used an operating window response for the design of friction-retard paper feeder in copier machines.[12] Later the concept has been applied to various design problems including wave soldering, printed circuit board, imaging, and resistance welding.[13]

The concept of the operating window can be explained using a paper feeder of a copier machine as shown in Fig. 1.[2]

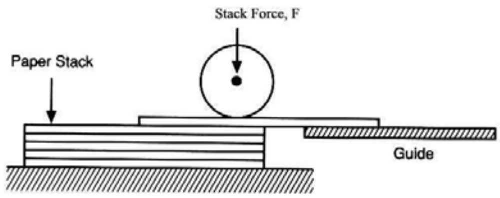


Fig. 1 Mechanism of a paper feeder[2]

If the stack force, **F**, is too small, the paper may not be fed. If the force is too large, on the other hand, multiple pieces of paper will be fed at the same time. Thus, it may be easy to avoid one defect, but difficult to avoid both of them simultaneously. For a range of forces that is not too small and not too large ($F \in (l,u)$) the paper is fed correctly. In this case, the stack force, **F**, is called *operating window factor*, and the range of values, (l,u), in which a system performs correctly is called operating window. (See Fig.2.)

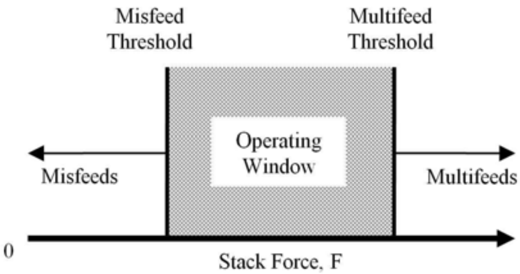


Fig. 2 Definition of operating window

To make the matters worse, the tendency for the defects to occur is aggravated by noises. Fig. 3 illustrates the effects of noises on the operating window. Because the noises are uncontrollable under various production or usage conditions, the combinations of the noise effects (N_1, N_2, N_3) will reduce the overall size of the operating window to (max(l_i), min(u_i)). Intuitively, the rates of the two defects can be minimized by keeping the operating window factor at the center of the operating window. A large operating window then corresponds to a robust system. Thus, the objective of achieving robust design is translated as maximizing the size of the operating window.[11]

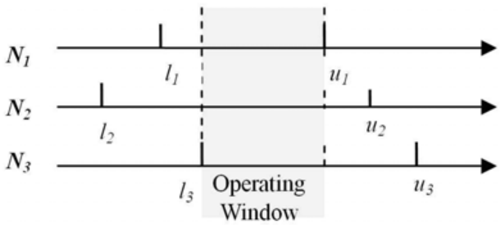


Fig. 3 Reduction of operating window due to noises

The method is considered to be effective particularly in reducing the defect rates caused by conflicting defects.[11] As most of mechanical manufacturing systems produce conflicting defects due to a certain process parameter, the operating window approach will be useful.

2. SN Ratios for Operating Window

Taguchi[13] defines quality as "the loss imparted by the product to the society from the time the product is shipped". To evaluate the quality loss of a product, Taguchi suggests loss functions. Estimating the loss is critical in the design process, as the evaluation of design alternatives largely relies on the average loss of a product throughout the product life cycle. Phadke[1] describes the basic concepts of the loss in detail. The robust design is achieved by maximizing the signal-to-noise (SN) ratio of the characteristic chosen for the evaluation of the product process, which essentially minimizes the average loss under various noise conditions.

In the operating window approach, the two types of defects can be eliminated if the lower limit of the operating window, l, is reduced to zero (smaller-the-better-characteristic) and the upper limit of the operating window, u, is increased to infinity (larger-the-better-characteristic). Hence, Clausing[2] intuitively defined the SN ratio for the operating window as a simple sum of the two types of SN ratios corresponding to l and u as in Eq. (1).

$$SN_{trad} = -10\log[\sum_{i=1}^{n} l_i^2 / n] - 10\log[\sum_{i=1}^{n} (1/u_i^2)/n] \quad (1)$$

where the summation is taken over all the noise conditions. In this paper, Clausing's traditional SN ratio for the operating window is denoted by SN_{trad}.

The traditional SN ratio has been used in the operating window problems for a long time. Recently, Joseph and Wu[11] have reported, however, that the maximization of SN_{trad} can minimize the average loss only when the functional form of the defect rate with respect to the operating window factor belongs to a particular subset of a family of one parameter quadratic functions. Joseph and Wu[11],[14] proposed a new design strategy for the operating window approach, but they used the same objective function as Clausing's[2], and they fail to overcome the problem of the traditional SN ratio. In this paper, a new SN ratio for the operating window, SN_{prop}, is proposed to overcome the problem. The proposed SN ratio is expected to be independent from the functional form of the defect rate, reflecting the loss more effectively.

In the case of defect rate, Taguchi[13] suggests $L=cp/(1-p)$ as the loss function, where p is the defect rate and c is a cost-related constant. Extra units must be produced to get one unit of non defective item to compensate for the fraction of defectives, which consists the loss. The loss is considered to be proportional to the expected number of extra units to get a non-defective product. In the case of two types of defects, we can similarly define the loss function as in Eq. (2).

$$L = c_1 \frac{p_1}{1-p_1} + c_2 \frac{p_2}{1-p_2} \tag{2}$$

Given a set of design variables, X, the thresholds of the operating window factors, l and u, can be assumed to be random variables as they vary by some random noise factors. Assuming that l and u under various noise conditions follow the normal distributions, the defect rates for a given value of **F**, operating window factor, can be calculated from Eq. (3) and Eq. (4) as shown in Fig. 4.

$$p_1(F:X) = \Pr\{F \le l : X\} = 1 - \Phi(\frac{F - m_l(X)}{s_l(X)}) \tag{3}$$

$$p_2(F:X) = \Pr\{u \le F : X\} = \Phi(\frac{F - m_u(X)}{s_u(X)}) \tag{4}$$

where

$m_l(X)$: average value of l's obtained under various noises

$m_u(X)$: average value of u's obtained under various noises

$s_l(X)$: standard deviation of l's obtained under various noises

$s_u(X)$: standard deviation of u's obtained under various noises

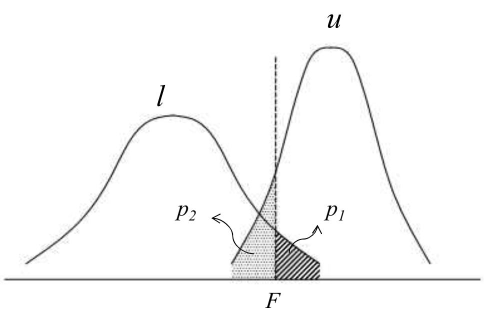


Fig. 4 Distribution of *l* and *u* at design X under various noise conditions

Therefore, the average loss, $L(F{:}X)$, under the design $\boldsymbol{X}$ and operating window factor F can be represented as in Eq. (5).

$$L(F:X) = c_1 \frac{p_1(F:X)}{1-p_1(F:X)} + c_2 \frac{p_2(F:X)}{1-p_2(F:X)} \tag{5}$$

Since F is an operating window factor whose nominal value must be determined by the designer, the optimal value of F (denoted by F^*) under the design $\boldsymbol{X}$ can be determined by minimizing the average loss as in Eq. (6).

$$L(F^*:X) = \min_F [L(F:X)] \tag{6}$$

Therefore, the proposed SN ratio for the operating window that reflects the average loss can be defined as in Eq. (7).

$$SN_{prop} = -10\log[L(F^*:X)] \tag{7}$$

Hence, the minimization of average loss can be achieved by maximizing the SN_{prop}.

3. Sequential Search Method

For optimizing a manufacturing process, software tools such as finite element analysis (FEA) are used in many cases to predict the output responses from given design conditions. As such numerical analysis and simulation packages often require heavy computational time, reducing the number of simulations is important to obtain the solutions within a reasonable time. Furthermore, as the optimal solution in a Design of Experiments (DoE) technique is determined from a set of predefined discrete values of the design factors, a solution that is not close enough to the true optimal solution may be obtained, if the search space is large. To obtain the true optimal solution using DoE, therefore, we need a design space reduction method that reduces the search space effectively.[15] In this research, a sequential search method that integrates the DoE with a search-space reduction method is proposed. The DoE is recursively performed based on a two-level orthogonal array, and at each step, the search space is reduced based on the results of the experiments.

It is possible that some interactions may exist among process parameters, because the process parameters and the output response of a manufacturing process often have non-linear relationships. To avoid the additional experiments to analyze the interaction effects, an experimental design without interaction is adopted in this study. The best result among all experiments is chosen as the optimal solution based on the pick-the-winner-rule. The orthogonal array is used only as a searching tool.

Using a two-level orthogonal array without interactions, a smaller sub-region of the design space is found such that the sub-region may contain the true optimal solution. The sub-region is set to be the next new design space (design space reduction), and the same process is applied recursively. The overall procedure of the proposed search process is described in Fig. 5, and the design space reduction process is described in Fig. 6

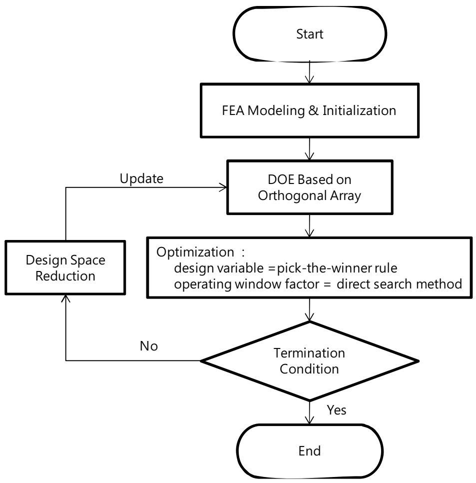


Fig. 5 Overall procedures of sequential search

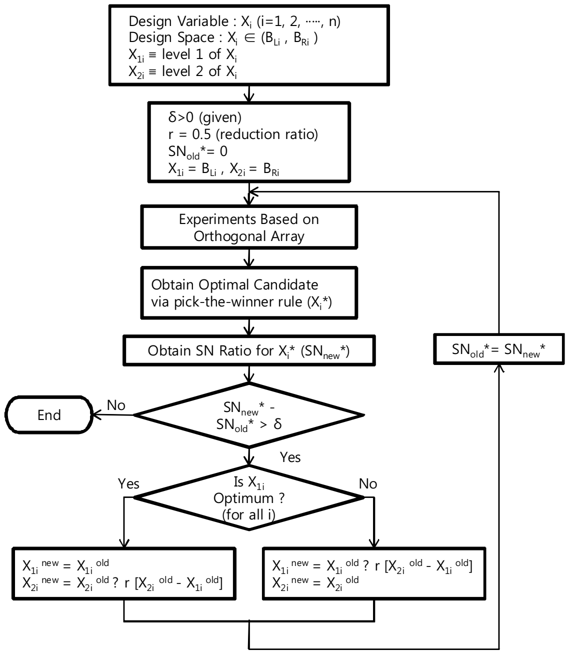


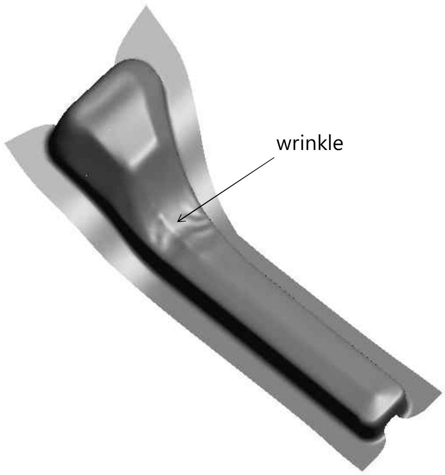
Fig. 6 Details for design space reduction

4. Sheet Metal Forming Problem

The method proposed in this paper is applied to a sheet metal forming process of a side member of an automobile chassis. Typical defects found in the drawing process of the component are wrinkle and fracture as illustrated in Fig. 7.

The wrinkles may occur when the thickness of the sheet metal changes as the width and height of a section of the sheet metal part changes radically under a drawing process. The fracture defects may occur when the combination of two principal strains at a point on the sheet metal part is over a certain threshold value. A more details will be discussed in the next section.

Both of the two defects depend upon the blank holding force (BHF). The wrinkles can occur as the blank holding force is decreased (Fig. 7 (a)) when the fracture occurrence is less probable. The fractures can occur as the BHF is increased while the chance of having wrinkles is decreased (Fig. 7 (b)). The defects also depend on various other factors such as blank size, die radius, and draw beads.



(a) Low blank holding force

(b) High blank holding force

Fig. 7 Typical defects of a side member

4.1 Experimental Design

In this study, we chose the blank holding force (BHF) as the operating window factor as it has a conflicting effect on the wrinkles and fractures most. Other factors such as blank size (*L, W*) and die radius (R) as shown in Fig. 8 are considered as design variables. The drawing die radius is the local radius of the die as shown in Fig. 8. This is the parameter that actually gets modified during the die modification process when a manual trial-and-error process is needed.

For the noise factors in the sheet metal forming process, strain hardening exponent (n) and strength coefficient (K) according to Swift's hardening law are selected as shown in Eq. (8)

$$\sigma = K(\varepsilon_0+\varepsilon^p)^n \tag{8}$$

where ε^p is effective plastic strain.

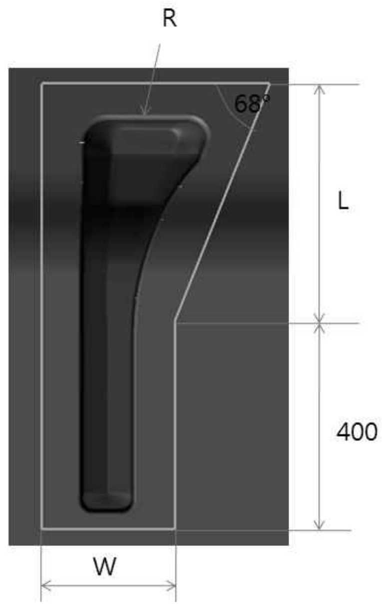


Fig. 8 Definitions of design variables

The particular sheet metal drawing process studied in this paper does not use any lubricant. Therefore, the variation of the lubricant property is not considered as a noise factor. However, a dry friction coefficient, *f*, may vary in different locations of the die. In addition to the variation of material properties, the variation of the friction coefficient, *f*, was selected as a noise factor.

Autoform[16], one of commercial sheet metal analysis software programs, is used for the computer simulations through FEA analyses based on elastic plastic shell elements. The sheet metal material is mild steel DC04 with the thickness of 1.8mm.

Fig. 9 shows a plot of the major and minor strains of various sample points on the sheet metal part after a drawing process. A forming limit curve (FLC) for a particular sheet thickness is shown in the figure and if a point is plotted on or above the curve, the part will have a fracture at the point. A ratio can be defined between the vertical heights of the plot point and the FLC curve as shown in Fig. 9 and Eq. (9). The maximum ratio of all the calculated ratios is called *maximum failure*. It is considered that a crack occurs if the maximum failure equals or exceeds 1 after a simulation ends.

$$Failure_{max} = a / b \quad (9)$$

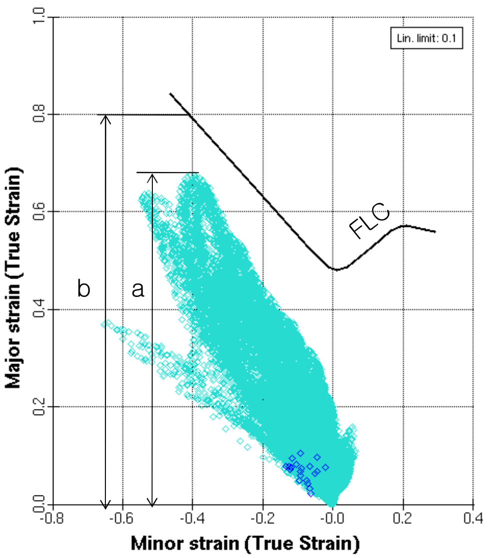


Fig. 9 Definition of max. failure on the forming limit diagram

There are different ways of identifying the wrinkle[17], but we consider the ratio of the thickness changes (thickening ratio) before and after the forming process. We assume that a wrinkle occurs at a particular point when the maximum thickening ratio at the point is greater than 2.5%. In this case study, we only focus on the area, A, as identified in Fig. 10, where the most wrinkles are known to occur around this particular geometry of the part.

Fig. 10 Zone for wrinkle evaluation

4.2 Experiments and Analysis

The design factors and their factor levels are chosen as shown in Table 1. Table 2 lists the noise factors and their factor levels.

Table 1 Design factors and levels

Control Factors	Level 1	Level 2
L	440 mm	470 mm
W	245 mm	265 mm
R	6 mm	14 mm

Table 2 Noise factors and levels

Noise factors	Level 1	Level 2	Variation (%)
K (N/mm^2)	530.59	563.41	6
n	0.2244	0.2556	13
f	0.135	0.165	20

Table 3 shows the layout of the factors in a cross-product experimental design that uses $L_4(2^3)$ in both the inner and outer arrays.

To reduce the number of experiments, the inner array is a 2-level orthogonal array but a larger orthogonal array can be used for a better result if the cost of experiments is not expensive. With a given set of control factors and noise factors, the operating window of the blank holding force (BHF), *l* and *u*, are obtained using the Autoform. Multiple simulations are performed by varying the BHF from 30 tons to 240 tons to find the *l* and *u* for each combination of control and noise factors. Table 3 shows the *l*'s and *u*'s obtained in the final iterations of the sequential search.

Table 3 Experimental design and *(l,u)* of final iteration

					N1	N2	N3	N4
				K	1	2	2	1
				n	1	2	1	2
no	L	W	R	f	1	1	2	2
1	1	1	1	*l* *u*	39.2 156.7	29.5 140.1	32.4 123.4	50.9 203.3
2	1	2	2	*l* *u*	47.4 189.3	32.3 146.5	34.0 144.4	55.6 210.8
3	2	1	2	*l* *u*	42.6 175.4	23.7 144.8	32.6 128.4	40.9 220.3
4	2	2	1	*l* *u*	48.6 175.2	23.8 148.5	32.8 132.0	43.1 216.3

Table 4 summarizes the results of the normality test of *l* and *u* using Minitab[18]. As the number of data (n=4) is small, the cumulative distribution function method using nonparametric estimation[19] is utilized for the goodness-of-fit test. The results show that *l* and *u* follow the normal distribution as all the value of R^2 (goodness-of-fit index) approaches to 1.

Table 4 Results of normality tests of *l* and *u*

no	l_1	l_2	l_3	l_4	R^2	u_1	u_2	u_3	u_4	R^2
1	39.2	29.5	32.4	50.9	.96	156.7	140.1	123.4	203.3	.97
2	47.4	32.3	34.0	55.6	.96	189.3	146.5	144.4	210.8	.94
3	42.6	23.7	32.6	40.9	.96	175.4	144.8	128.4	220.3	.98
4	48.6	27.8	32.8	43.1	.98	175.2	148.5	132.0	216.3	.98

Without loss of generality, the costs incurred due to the two defects are set to be $C_1=1$ and $C_2=2$ in Eq. (5) in this case study. Table 5 summarizes the defect rates (p_1, p_2), the optimal value of operating window factor (F^*), average loss ($L(F^*:X)$) for design X, and the SN ratio (SN_{prop}) calculated for each row of the inner array. The optimal values of the operating window factor, F^*, are obtained using Eq. (6) via the solver module in Microsoft Excel.

Table 5 Results of the final iteration

no	*L*	*W*	*R*	p_1	p_2	F^*	$L(F^*:X)$	SN_{prop}
1	1	1	1	.0022	.0042	65.18	.0107	19.71
2	1	2	2	.0011	.0016	76.53	.0044	23.61
3	2	1	2	.0016	.0041	60.47	.0098	20.08
4	2	2	1	.0014	.0029	66.42	.0072	21.46

Table 6 lists the changes of the optimal value calculated at each iteration step for the second row of Table 5. The sequential search is terminated at the 3rd iteration when the improvement of the SN ratio from the previous iteration is insignificant.

Table 6 Optimal solutions vs. iterations

	Iteration number	1	2	3
Proposed method	Average loss	0.0207	0.0062	0.0044
	SN_{prop}	16.83	22.09	23.61
	F^*	54.55	58.21	76.53
Traditional method	Average loss	0.0284	0.0272	0.0272
	SN_{trad}	12.52	12.60	12.60
	F^*	62.07	62.01	62.01

The values of average losses are plotted against the iterations graphically in Fig. 11, comparing the proposed approach with the traditional approach. It shows that the approach proposed in this research leads to a lower loss. The final parameter values of the optimal robust design are summarized in Table 7.

Table 7 Optimal solutions of the two methods

Factors	Optimal solutions	
	Proposed method	Traditional method
L^*	462.5 mm	470.0 mm
W^*	255.0 mm	245.0 mm
R^*	12.0 mm	14.0 mm
F^*	76.53 ton	62.01 ton

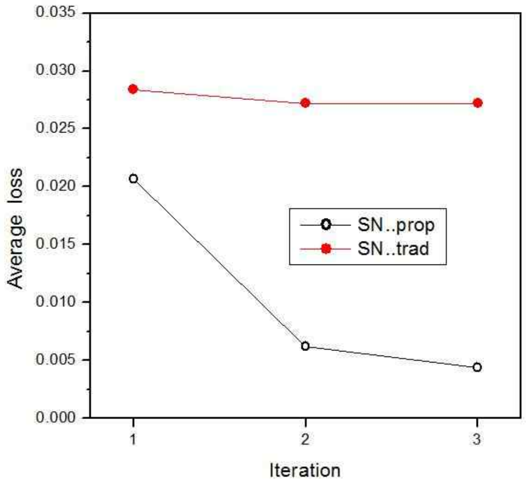


Fig 11. Average losses vs. iterations

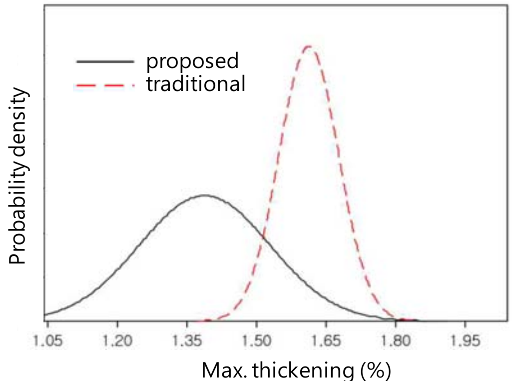
5. Verification

To compare the two optimal values obtained by the two different SN ratios, a Monte Carlo simulation is performed to check if the design attributes are actually improved by the proposed method under random noises. Assuming that the noise factors follow the normal distribution and that 99% of the population falls into the noise range in Table 2, the mean and the standard deviation of the noise factors can be estimated by equations μ = (level1 + level2)/2 and std=(level2 - level1)/6. Table 8 summarizes the estimated means and standard deviations of the noise distributions. From these noise distributions, 120 sets of noise conditions are generated for the comparison.

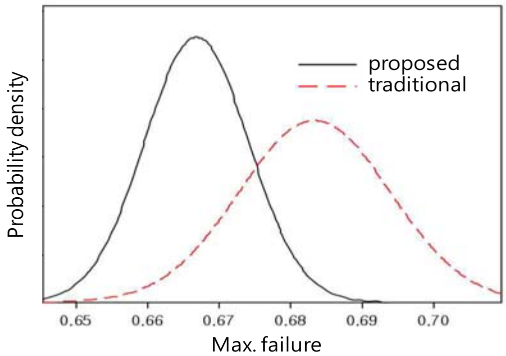
Table 8 Parameters of noise factor distributions

Design Variable	Mean (μ)	Standard Deviation (std)
K	547.00	5.47
n	0.24	0.0052
f	0.15	0.0050

With the optimization parameters in Table 7, simulations are run under the generated noises using the two SN ratios (SN_{prop} and SN_{trad}) separately.



(a) Distributions of maximum thickening



(b) Distributions of maximum failure

Fig. 12 Distributions of design attributes

Fig. 12 shows the fitted normal distributions of the two attributes from the simulation results. The graphs show that using the proposed SN ratio decreases both the maximum thickening and maximum failure as expected. The t-test on each design attribute is performed to verify the advantage of the proposed SN ratio over the traditional SN ratio. The null hypothesis of Eq. (10) was rejected with confidence level of 99% for each design attribute(the P-value of the test (calculated via Minitab) is 0.000, which means it is less than 0.0005), which shows that the proposed SN ratio gives lower value for each design attribute than the traditional SN ratio.

$$H_0 : \mu_{prop} = \mu_{trad} \;\; vs. \;\; H_1 : \mu_{prop} < \mu_{trad} \quad (10)$$

where μ_{prop} and μ_{trad} are the average maximum thickenings (or maximum failures) for the optimal solutions obtained from the proposed method and the traditional method respectively.

The less the values of the design attributes, the less the defect rates will be in this application. When the proposed SN ratio is used, the average maximum thickening is reduced by 15.72% and the average maximum failure is reduced by 2.63% as summarized in Table 9. The deviations of the design attributes to the target are also reduced as shown in Fig. 11. These mean that we can find more robust design when the proposed SN ratio (SN_{prop}) is used.

Table 9 Comparison of the two methods

Design Methods	Average Max. Thickening	Average Max. Failure
Traditional	1.603%	0.686
Proposed	1.351%	0.668
Improvements	-15.72%	-2.63%

6. Concluding Remarks

In this research, a new design method that reduces two conflicting defects under uncontrollable noises is proposed. A new SN ratio for the operating window is derived, and a sequential search procedure is described to determine the optimal robust conditions in the process design domain. Applying them to a sheet metal forming process, it has been verified that the proposed method can give a smaller average loss than the traditional method can do; hence a better robust design can be achieved. The main contribution of this research is improving the traditional SN ratio for the operating window approach.

Two-level orthogonal array is used in this study to reduce the number of experiments. If the simulation time is not an issue, then a three level orthogonal array is expected to give a better result. Other minor improvements may be achieved in the sequential optimization search process, by choosing the optimal candidate solution at the current level as the center point of the next new search space. Further study is needed to discuss the advantages or disadvantages of the current approach over the multi attribute design method that is an alternative approach to dealing with conflicting defects.

ACKNOWLEDGEMENTS

The authors appreciate Autoform Engineering Korea for providing us with the Autoform software for this research. This research has been performed while staying at California State University, Sacramento as visiting scholars.

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