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Stealth Laser Dicing Process Improvement via Shuffled Frog Leaping Algorithm

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Abstract**—**In this paper, performances of shuffled frog leaping algorithm was investigated on the stealth laser dicing process. Effect of problem on the performance of the algorithm was based on the tolerance of meandering data. From the customer specification it could be less than five microns with the target of zero microns. Currently, the meandering levels are unsatisfactory when compared to the customer specification. Firstly, the two-level factorial design was applied to preliminarily study the statistically significant effects of five process variables. In this study one influential process variable is integer. From the experimental results, the new operating condition from the algorithm was superior when compared to the current manufacturing condition.

Keywords**—**Stealth Laser Dicing Process, Meandering, Metaheuristics, Shuffled Frog Leaping Algorithm.

I. Introduction

A laser-based technique of stealth laser dicing process is one among various widely used silicon wafers dicing systems. There are two stages on the stealth laser dicing process [1]. Firstly, the beam is scanned with specific wavelengths along intended cutting lines. In the wafer there are defect regions with different levels of depths. Secondly, an underlying carrier membrane is radially expanded to induce fracture (Fig. 1). A high distortion density at the bottom is provided. In the stealth dicing process there are some advantages of no requirement of a cooling liquid and no debris generated.

On the stealth laser dicing process, the level of meandering is of interest. The current meandering levels are slightly higher than the customer specification. This situation leads to high levels of product inspection with a large sample size with a high frequency. This brings the high levels of production cost and also consumed time and labor. Therefore, it is necessary to enhance the meandering quality in the stealth laser dicing process. This problem has still existed when there is an application of high technology machines. In this case, the deep detail of stealth dicing process should be investigated so that the optimal working condition would be determined. Consequently, the problem of interest would be dissolved.

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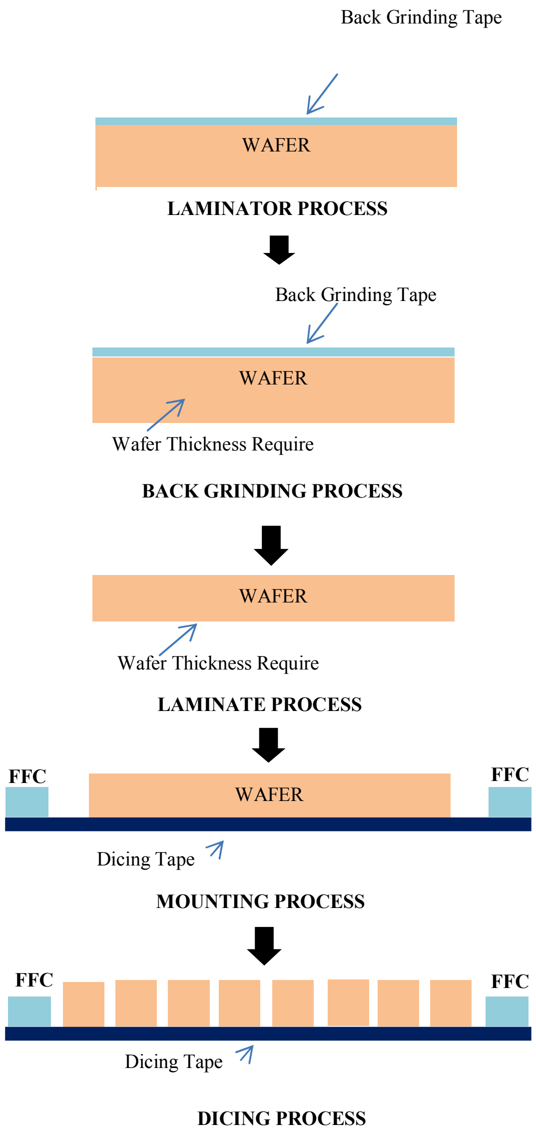


Fig. 1 Stealth laser dicing process

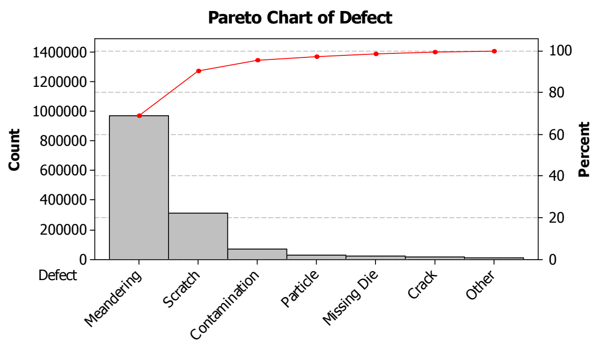
II. Stealth Laser Dicing Process (SLDP)

From processing the laser to wafers of the stealth laser dicing process (SLDP) there is no requirement of any cleaning subprocedure with water or other fluids. Consequently, there is no debris contamination on the wafer. The SLDP completely enables the dry processing with three major advantages of thinner wafer without chipping; no debris contamination and the completely dry process. In the SLDP, there are two operations on wafers. They are laser and wafer separation processing steps. In this research we focus only on the first step of laser processing. In this step, the laser beam is focused on the interior of wafer work pieces. It follows by scanning along the dicing line. In the wafer the modified layers or SLDP layers are formed along the scanned line. At this step, the wafer still has not splitted into chips after the laser processing [2].

The data of defect of this process were summarized as in Table I accompanying with the pareto diagram as shown in Fig. 2. It was found that the highest defect data was the tolerance of meandering data. These result in higher level of cost from high defect rate. In this case, this research will aim to reduce the potential defect. By brainstorming from teams who work for the SLDP, e.g. quality engineer, product and process engineers found that the five process variables are declared and all of them can separate in two types as shown in Table II.

TABLE I
SUMMARIZATION OF DEFECT ITEMS OF INTEREST

Defect	Piece	Proportion
Meandering	967,983	68.74
Scratch	308,006	21.87
Contamination	68,447	4.86
Particle	25,753	1.83
Missing Die	21,147	1.5
Crack	9,177	0.65
Front Side Chipping	3,872	0.27
Back Side Chipping	3,779	0.26



Count	967983	308006	68447	25753	21147	9177	7651
Percent	68.7	21.9	4.9	1.8	1.5	0.7	0.5
Cum %	68.7	90.6	95.5	97.3	98.8	99.5	100.0

Fig. 2 Pareto of defect items of interest

TABLE II
FIVE PROCESS VARIABLES AND THEIR TYPES

Process Variable	Description	Type of Data
A	Scanning High	Qualitative
B	Scanning Power 1	Quantitative
C	Scanning Power 2	Quantitative
D	Beam Shape	Qualitative
E	Scanning Speed	Quantitative

The problem of interest is the drift of meandering data in the stealth laser dicing process. The meandering data is then measured and compared with the customer specification. The tolerance has to be less than five microns with the target of zero microns. In order to optimize the response of meandering that might be influenced by several process variables the shuffled frog leaping algorithm is then applied to determine the preferable levels of these process variables. In this research, there are five process variables and the objective is to focus on the only one response of meandering data. However, in this study there are some qualitative process variables of A and D that need to be in forms of integer whereas the remaining process variables are quantitative.

III. SHUFFLED FROG LEAPING ALGORITHM

There are some difficulties associated with solving large-scale mathematical optimization problems. Alternatives have been proposed to solve these problems. They are based on simulations, learning, adaptation and evolution. Biologically-based algorithms of metaheuristics are introduced. One among them is shuffled frog leaping algorithm (SFLA) recently introduced by Eusuff and Lansey [3]. It is a stochastic search process and mimics group of frog behavior. There are some combined benefits from both algorithms of the genetic-based memetics (MAs) and the social behavior-based particle swarm (PSO) [4]. In the SFLA there is a balance between a deep search of promising locations and a wide search of a large solution space for a global optimum.

In the SFLA, the whole population or candidate solutions in optimization consist of a set of P frogs. Each frog has a fitness value. The frogs are then ranked in a descending order according to their fitness values. They are divided into M subgroup or memeplexes. Each frog has the same solution structure as in the genetic algorithm (GA) technique. Each subgroup has different cultures by performing a local search. These different memeplexes are then considered as different cultures at different places and they will perform their own deep local search. Within each memeplex, each frog has its own idea and can be influenced by the ideas of other frogs within their memeplex during the iterative shuffling process of memetic evolution. In each memeplex, the position of any frog is adjusted according to the different between the worst and the best frogs.

The reposition process is used to produce a new frog. If there is a frog with better fitness from the repositioning process, it replaces the worst frog. Otherwise, the process is repeated with respect to the global best frog with the best fitness value across the memeplexes. When there is no improvement, a new frog is randomly generated to replace the worst frog. The local stochastic search and the shuffling process or a global relocation continue until a preset convergence criteria is satisfied. The pseudo code of the SFLA is briefly provided in Fig. 3. As stated before, the recommended algorithm parameter levels of P, I, M and G are in the ranges of [50,150], [10000, 100000], [15, 30] and [15], respectively.

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Procedure of ***SFLA()***
Begin;
Define algorithm parameters:
P: preset number of frog (population)
M: preset number of memeplexes
I: preset number of shuffling iterations
Randomly generate a P population of frogs
For each individual i-frog; evaluate the i-frog fitness value
Sort the P population in descending order of their fitness values
Partition P into Mmemeplexes
For *each memeplex*
For *j = 1 to I*
Determine the best and worst frogs
Modify the worst frog position via position change and new position
If *better, then replace this worst frog with the new one*
Else
Randomly generate the new frog
End if
End for
End for
Combine the evolved memeplexes
Sort the P population in descending order of their fitness values
Check for the convergence termination
End
End procedure

Fig. 3 Pseudo code of the SFLA metaheuristic [4]

IV. Experimental Results

In the preliminary study, a 2^k experimental design was performed to determine the statistically significant from five process variables which consist of the scanning height (A), scanning power # 1 (B), scanning power # 2 (C), beam shape (D) and scanning speed (E). The feasible ranges, the current operating condition and type of process variables are provided in Table III.

TABLE III
Process Variables, Feasible Ranges and the Current Operating Condition

Process Variable	Feasible Range		Current	Type
	Lower	Upper		
A	(10,9)	(16,3)	(13,6)	Qualitative
B	0.12	0.48	0.24	Quantitative
C	0.18	0.72	0.36	Quantitative
D	1	3	1	Qualitative
E	100	300	300	Quantitative

At this step, the objective of using a factorial experimental design is to analyze both main and interaction effects of all process variables. The 2^5 experimental designs with two replicates provide 64 treatments. The two level of low and high were selected cover values of feasible ranges from the actual operating conditions in production line and the responses were measured from the meandering data average of each cutting line. By using a general linear model from the analysis of variance (ANOVA), sources of variation focusing on the main and interaction effects are shown in Table IV and the residual analysis for all model assumptions of the normality, independence and constant variance is shown in Fig. 4 [5]. The significant process variables or associated main effect consist of A, B, C and D as the p-value is less than at 95% confidence interval.

On the numerical experiments, SFLA parameters of number of frog and number of memeplexes were 10 and 2, respectively. The process variable of E is now fixed at the current operating condition of 300. The algorithmic procedures of the SFLA as shown in the pseudo code are then applied for statistically significant process variables of A, B, C and D to determine the most preferable levels to the response of meandering (Table V). In this study as mentioned before there are some qualitative influential process variables of A and D that need to be in forms of integer whereas the remaining influential process variables of B and C are quantitative. The feasible region of influential process variables including the limitation of integer for process variables of A and D are carefully considered throughout the process improvement of three iterations.

TABLE IV
Process Variables and Their P-Values

Process Variable	P-value
A	0.000
B	0.000
C	0.000
D	0.000
E	0.093

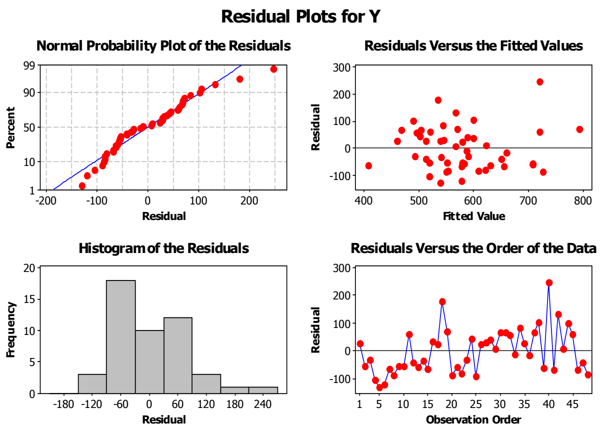

Fig. 4 Model adequacy checking

From the process settings for all influential process variables in Table V, the performance after the improvement for three iterations of the SFLA can be evaluated from the meandering data. After an implementation, it has been found that the average of the response from the new operating condition (NEW) is lower than the current manufacturing system (CUR) as described in a box-whisker plot (Fig. 5). ANOVA is applied to confirm experimental results in which a response of the meandering tolerance is measured under both operating conditions. It can also be seen that these experimental results on both scenarios were statistically significant with 95% confidence interval. The numerical results suggested that NEW provided the better performance in terms of the average meandering tolerance. The goodness of the linear statistical model via experimental errors or residuals is also adequate. As the results, NEW is then applied to the manufacturing system under a consideration of the reduction of meandering tolerance achieved.

TABLE V
PREFERABLE LEVELS OF INFLUENTIAL PROCESS VARIABLE FROM THE CURRENT AND NEW SCENARIOS

Process Variable	Description	Feasible Range	
		Lower	Upper
A	Scanning Height	(13,6)	(13,6)
B	Scanning Power 1	0.24	0.41
C	Scanning Power 2	0.36	0.50
D	Beam Shape	1	1

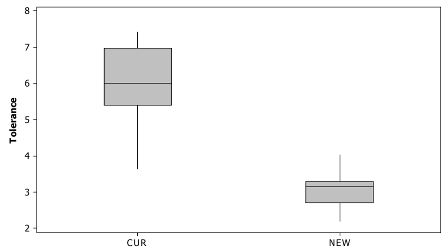

Fig. 5 Box-Whisker plot of meandering data from both scenarios

V. CONCLUSIONS AND DISCUSSIONS

From the SFLA, there are some qualitative process variables that need to be in forms of integer whereas the remaining variables are quantitative and one is fixed at the current operating condition. The experiments in this research were restricted to only three iterations. Consequently conclusions may not be the global process optimum. From the new process settings for all influential process variables shown in Table V, the process performance after the improvement can be evaluated from the defect and it brings the meandering close to the target and within specification. The tolerance is changed from 5.82899 microns to 3.16413 microns. Consequently, this reduces the level of production cost and also time and labor.

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