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AN OPTIMIZATION-BASED FRAMEWORK FOR INSPECTION PLANNING

M. MOHAMMADI^{1,2}, J.Y. DANTAN¹, A. SIADAT¹

¹LCFC, CER Metz - Arts et Métiers Paris Tech, Metz,
France

²School of Industrial Engineering, College of
Engineering, University of Tehran, Tehran, Iran
mehrddad.mohammadi@ensam.eu

jean-yves.dantan@ensam.eu, ali.siadat@ensam.eu

R. TAVAKKOLI-MOGHADDAM

School of Industrial Engineering, College of
Engineering, University of Tehran, Tehran, Iran
tavakoli@ut.ac.ir

ABSTRACT: *This paper proposes an optimization framework for inspection planning based on a mixed-integer non-linear programming (MINLP) model, in which decisions are made on which quality characteristics need what kind of inspections and when these inspections should be performed such that total cost of manufacturing is minimized. Two different types of inspections containing Monitoring Inspection (MI) and Conformity Inspection (CI) are taken into account. In order to validate the correctness of the model, a real industrial case is studied. Since the size of problems is large, a genetic-based algorithm is developed to solve the real industrial case.*

KEYWORDS: *Optimization, Inspection planning, Mathematical formulation, Meta-heuristic algorithm.*

1. INTRODUCTION

Since many production processes are technologically incapable of producing high-quality products, a quality management system (QMS) has gained increasingly high importance at each modern production system, in which incapable production techniques, defective equipment and inferior raw materials are some of the external factors resulting in the quality problem. Accordingly, production managers are attempting to provide a quality control system (QCS) to gain high-quality products in the presence of such pesky external factors. In order to get more effective QCS under such conditions, in-line quality control measures are employed more intensively, and if workable, automatically. In such situations, firms invest large amounts in inspection systems, and inspection planning problems become more significant. Inspection allocation and selection decisions are actually made by quality managers; however, they lack an overall framework for their decisions when they should decide which quality characteristics in the process need to be inspected and when (Shiau, 2003).

One of the most effective approaches to design an inspection framework and cope with quality issues is creating a capable production metrology system. Production metrology is all activities by which manufacturers try to ensure that their product conforms to specifications and meets customer expectations, connected with measurement and testing functions to be provided in the industrial development process of the product. The main objective of production metrology is the recording of a feature's quality criteria measurements (Savio, 2012). Since a production system is judged based on its efficiency, an efficient technique is required to measure the cost of the system. On the other hand, cost measurement has be-

come an important issue in product and process design; in fact it becomes a key activity to improve the tolerance allocation, to select fittest manufacturing resources or inspection allocation planning (Mirdamadi et al., 2011). Therefore, a precise cost measurement is one of the prerequisites for having a reliable production metrology (Tolio et al., 2007; Burdick et al., 2003; Niazi et al., 2006).

For having enhanced production metrology, quality control has become a matter of great importance in recent years. The possibility for offering high-quality products at lower costs has become an essence for a manufacturer to keep in a competitive edge. One of the most efficient tools for decreasing wastes and meeting customer expectations is inspection planning. Inspection planning is an activity determines how an inspection of a product is to take place and what characteristics must be tested in order to ensure the quality of the product, as well as specific metrics and measurements that must be met in compliance of the product with standards (Lee and Unnikrishnan, 1998).

Two kinds of inspection can be performed in an efficient production metrology namely conformity (CI) and monitoring (MI) inspections. In the CI, the production process is halted and all products are checked whether quality characteristics have met standard specifications while nonconforming products are scrapped. Since stopping production process may not be cost-efficient, MI can be taken into account as an online inspection where corresponding features of the process (e.g., feed speed of a drilling machine, temperature etc) which significantly affect related characteristics of the products are checked not to deviate from their set value. In spite of CI, MI is

carried out after a specific number of products which results in lower inspection cost.

Manufacturers consider CI and/or MI in their production processes based on the importance of the quality characteristics. For example, for characteristics which directly correspond to the product function and a malfunction may decrease the customer satisfaction, a CI is recommended. On the other hand, considering MI absolutely increases the capability of the processes and consequently, the deviation from standard tolerances as well as number of defective characteristics is deduced. Both CI and MI are eventually for enhancing customer satisfaction degree where considering both CI and MI for all processes is the most reliable way to decrease the number of scraps and correspondingly increase customer satisfaction as much as possible. Due to recourse limitations, this approach is not practical and the cost of production as well as final cost of products is enormously increased. Therefore, a trade-off between customer satisfaction and cost of production should be conducted whether setting inspections is cost-effective or not. Broadly speaking, decision on what characteristics need inspection and where inspections should be considered in the production process is an action that all manufacturers are looking for, in which both production costs and customer satisfaction are taken into account.

With regard to the above-mentioned issues, this article tries to develop an optimization framework for inspection planning based on a mixed-integer non-linear programming (MINLP) model, in which decisions are required on what kinds of different quality characteristics need which kind of inspections and where these inspections should be take place. To the best of our knowledge, there is no paper in the literature that has carried out these decisions on the bases of mathematical model. On the other hand, due to the complexity of the proposed mathematical model, a genetic algorithm (GA) is developed for solving large sized problem especially real industrial cases.

The rest of the paper is organized as follow. A brief literature review is presented in Section 2. Section 3 explains the proposed MINLP model. Section 4 describes proposed GA with new solution representation. The correctness and validity of the proposed MINLP model is shown in Section 5 by a real industrial case. Finally, conclusion is provided in Section 6.

2. LITERATURE REVIEW

Savio (2012) presented a methodology for the assessment of the economic impact of metrology in production, in which several mathematical formulations to evaluate costs and benefits were developed. Although the evaluation of costs is facile, but the calculation of benefits is challenging, due to the nature of benefits such as improvement of product reliability and related reduction of warranty costs. Corresponding to this difficulty, a

review of micro-economic facets in metrology was also conducted emphasizing on the fact that while costs are easy to calculate, benefits are more complex to assess and should be taken into account in the context of the entire production process (Kunzmann et al., 2005).

Hanne and Nickel (2005) developed a multi-objective inspection planning model considering objectives with respect to the quality (no. of defects), project makespan, and costs within a software development (SD) project. The developed model of SD processes includes different phases as coding, inspection, test, and rework and comprises the assignment of operations to persons and the generation of a project schedule. They also used a discrete-event simulation model for supporting project managers in the software industry (see Neu et al., 2002, 2003; Munch et al., 2002). Besides, an evolutionary algorithm (EA) was presented to solve the proposed multi-objective inspection planning model.

Unlike other papers in the literature, Shiao (2003) studied an inspection allocation planning (IAP) for a multiple quality characteristic manufacturing, in which the production recourses are restricted and the limited number of inspection stations, of each inspection station class, is considered for solving IAP. This paper solved IAP using a unit cost model in which the manufacturing capability, inspection capability, and tolerance specified are simultaneously considered as well as situation of unbalanced tolerance design. In a similar work, Shiao et al. (2007) integrated production process and inspection planning while higher performance of a production industry can be realized if process planning and inspection planning become integrated to cope with the limited manufacturing resources. They also developed a genetic evolutionary algorithm for solving large size problems.

3. MATHEMATICAL FORMULATION

In this section a mixed-integer non-linear programming (MINLP) model is presented in order to decide which quality characteristics need what kind of inspections (i.e., MI or CI) and when these inspections should be performed. The cost-based objective function of the proposed model is separated into different parts such as cost of production, scrap, inspections (i.e., fixed and variable costs) and warranty when a nonconforming product is sold. Hereafter, main assumptions of the proposed model are listed as follows:

- A multi-process manufacturing production as a flow shop production is studied.
- Some of sequential processes may be dependent (i.e., they are performed on the same machine).
- Both kind of inspections (i.e., conformity and monitoring) are simultaneously considered.
- Different characteristics for the product are assumed, in which each characteristic belongs to a specific process.

- Each characteristic/process needs conformity or monitoring inspection.
- Frequency of inspections is different for CI and MI.
- Cost of CI and MI includes two parts of variable and fixed costs.
- A fixed cost for each station of inspection is assumed.

The required notations and mathematical model are provided as follows.

Sets:

$p, p' = \{1, 2, \dots, P+1\}$	Set of process
$k = \{1, 2, \dots, K\}$	Set of different characteristics

Parameters:

FR_{pk}^1	Failure rate of process p for characteristic k with MI.
FR_{pk}^2	Failure rate of process p for characteristic k without MI.
DR_{pk}	Detection rate of CI of process p for characteristic k .
α_{pk}	Error type I of CI of process p for characteristic k .
β_{pk}	Error type II of CI of process p for characteristic k ($\beta_{pk} = 1 - DR_{pk}$).
N_T	Total number of input parts to the production line.
CP_p	Production cost at process p .
CS_p	Scrap cost of products just after process p .
CD_k	Cost of defective product in the market due to characteristic k (i.e., Warranty cost).
FI_p	Fixed cost of inspection after process p .
FM_{pk}	Fixed cost of MI after process p for characteristic k .
FC_{pk}	Fixed cost of CI after process p for characteristic k .
VM_{pk}	Variable cost of MI after process p for characteristic k .
VC_{pk}	Variable cost of CI after process p for characteristic k .
$PI_{p'p}$	1 if two processes p' and p are dependent; 0 otherwise.
PK_{pk}	1 if characteristic k belongs to process p ; 0 otherwise.
KBP_{kp}	Equal to p . Means that inspection of characteristic k (i.e., MI and CI) must be done before process number p where k belongs to process p' and $p' \leq p$.
MF_k	Monitoring frequency for characteristic k .
CF_k	Conformity frequency for characteristic k .
M	A big number.

Decision Variables:

FR_{pk}	Failure rate of process p for characteristic k .
AC_{pk}	1 if process p needs CI for characteristic k ; 0 otherwise.
AM_{pk}	1 if process p needs MI for characteristic k ; 0 otherwise.
$XC_{p'p}^k$	1 if CI of process p' for characteristic k is performed after process p ($p' \leq p$); 0 otherwise.
$XM_{p'p}^k$	1 if MI of process p' for characteristic k is performed after process p ($p' \leq p$); 0 otherwise.
NI_p	1 if there is an inspection station after process p .
N_p	Input number of parts entering process p .
NM_{pk}	Number of MI after process p for characteristic k .
NC_{pk}	Number of CI after process p for characteristic k .
S_{pk}	Number of scrapped part after process p for characteristic k .
S_p	Total number of scrapped parts after process p .
$NXC_{p'p}^k$	Auxiliary variable.
$NXM_{p'p}^k$	Auxiliary variable.
O_{pk}	Auxiliary variable.
$OXC_{p'p}^k$	Auxiliary variable.

The proposed MINLP is as follows:

$$\begin{aligned} \min & \sum_p CP_p N_p + \sum_p CS_p S_p + \sum_p \sum_k FC_{pk} NC_{pk} + \\ & \sum_p \sum_k CF_k VC_{pk} N_p + \sum_p \sum_k FM_{pk} NM_{pk} + \\ & \sum_p \sum_k MF_k VM_{pk} N_p + \sum_p FI_p NI_p + \\ & \sum_p \sum_k CD_k (N_p FR_{pk}^2 \beta_{pk} AC_{pk} + N_p FR_{pk}^1 AM_{pk}) \end{aligned} \quad (1)$$

s.t.

$$\sum_{p=p'}^{KBP_{kp}} XC_{p',p}^k = AC_{p',k} \quad \forall p', k; p' \leq P \quad (2)$$

$$\sum_{p=p'}^{KBP_{kp}} PI_{p',p} XM_{p',p}^k = PK_{p',k} AM_{p',k} \quad \forall p', k; p' \leq P \quad (3)$$

$$AC_{pk} + AM_{pk} = PK_{pk} \quad \forall p, k \quad (4)$$

$$FR_{pk} = AM_{pk} FR_{pk}^1 + (1 - AM_{pk}) FR_{pk}^2 \quad \forall p, k; p \leq P \quad (5)$$

$$\begin{aligned} O_{pk} = & [N_p FR_{pk} DR_{pk}] + [N_p (1 - FR_{pk}) \alpha_{pk}] \\ & - [N_p FR_{pk} \beta_{pk}] \quad \forall p, k; p \leq P \end{aligned} \quad (6)$$

$$S_{pk} \geq O_{p',k} XC_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (7)$$

$$S_{pk} \leq [N_p FR_{pk} DR_{pk}] + [N_p (1 - FR_{pk}) \alpha_{pk}] \quad \forall p, k; p \leq P \quad (8)$$

$$S_p \geq S_{pk} \quad \forall p, k; p \leq P \quad (9)$$

$$N_p = N_{p-1} - S_{p-1} \quad \forall p, k; p \quad (10)$$

$$N_0 = N_T \quad (11)$$

$$M \times NIS_p \geq \sum_{p'} \sum_k (XC_{p',p}^k + XM_{p',p}^k) \quad \forall p; p \leq P \quad (12)$$

$$OXC_{p',p}^k \leq M \times XC_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (13)$$

$$OXC_{p',p}^k \leq O_{pk} \quad \forall p, p', k; p, p' \leq P \quad (14)$$

$$OXC_{p',p}^k \geq O_{pk} - (1 - M) XC_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (15)$$

$$NXC_{p',p}^k \leq M \times XC_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (16)$$

$$NXC_{p',p}^k \leq N_{pk} \quad \forall p, p', k; p, p' \leq P \quad (17)$$

$$NXC_{p',p}^k \geq N_{pk} - (1 - M) XC_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (18)$$

$$NXM_{p',p}^k \leq M \times XM_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (19)$$

$$NXM_{p',p}^k \leq N_{pk} \quad \forall p, p', k; p, p' \leq P \quad (20)$$

$$NXM_{p',p}^k \geq N_{pk} - (1 - M) XM_{p',p}^k \quad \forall p, p', k; p, p' \leq P \quad (21)$$

$$XC_{p',p}^k, XM_{p',p}^k, NS_p, AC_{p',k}, AM_{p',k} \in \{0,1\} \quad \forall p, p', k; p, p' \leq P \quad (22)$$

$$N_p \geq 0 \quad \forall p \quad (23)$$

$$\begin{aligned} Scrap_{pk}, Scrap_p, O_{pk}, NIS_p, OXC_{p',p}^k, \\ NXC_{p',p}^k, NXM_{p',p}^k, FR_{pk} \geq 0 \quad \forall p, k; p \leq P \end{aligned} \quad (24)$$

Objective function (1) summarizes different sources of cost of production, scrap, inspections and warranty. Equations (2) and (3) ensure that CI and MI of a characteristic must be done in one place, respectively. Equation (4) forces that one kind of inspection is needed for each characteristic. Equation (5) assures that failure rate of a process depends on the selected inspection. Constraints (6) to (9) determine the number of scraps after each process. Equations (10) and (11) calculate number of output products at from each process. Constraint (12) determines the number of different required inspection places. Constraints (13) to (21) are provided to linearize the

product of some variables. Constraints (22) to (24) are domain constraint.

4. PROPOSED SOLUTION METHODOLOGY

In order to solve the proposed process inspection planning model with stochastic complexity, the solution algorithm must be capable to obtain optimal or near optimal solution within the reasonable computational time. There are several methods in the literature for providing an optimal solution for small size problems such as simplex and dynamic programming based optimization algorithms (Taha 2006; Shukla et al., 2013). However, most of real problems are in higher sizes and solving them by the mathematical programming approaches takes the huge computational time. Therefore, to cope with this challenging issue, a well-known evolutionary algorithm, namely genetic algorithm (GA), is used to solve the proposed process inspection planning. It has been shown that evolutionary algorithms such as genetic algorithms (Holland, 1975) or evolution strategies (Back et al., 1991) are capable and robust approaches to solve a wide range of optimization problems. Application of these algorithms in the area of inspection planning and allocation can, for instance, be found in Hanne and Nickel (2005), Shiau (2003), Alam et al. (2003) and Shiau et al. (2007).

GA is an algorithm inspired by natural evolution to solve optimization problems (Holland 1975, Goldberg 1989). Each solution of a given problem is represented in the form of a string, called chromosome, which is a combination of several genes that hold a set of information of the problem (Goldberg 1989). GA starts with a random generated population of individual solutions (i.e., chromosomes). The fitness of each chromosome reflects the value the objective function. To find better solutions (offspring), best chromosomes share their information through crossover and mutation operators. The new created solutions are then evaluated and are used to create new generation if they provide better fitness. This process is repeated for a given number of iteration to obtain a best individual. For better understanding of GA, the interested readers are referred to Deb (1995).

4.1. Solution representation

The solution representation of the proposed inspection planning model is provided as follow. In the proposed MINLP of inspection planning, the aim is deciding on type and position of inspections for each process. For this purpose, a new solution representation is developed which includes two different parts as determining 1) type of inspections (DTI) and 2) position of inspections (DPI). Figs. 1 and 2, respectively, show the DTI and DPI parts of solution representation for a problem with 6 characteristics.

In Figure 1, each column corresponds to a characteristic. Also, at each column, value 1 at first row means the related characteristic needs monitoring inspection and needs conformity inspection otherwise. For example, in Figure 1, characteristic numbers 1, 2 and 4 need conformity inspection and characteristics 3, 5 and 6 need monitoring inspection. In Figure 2, columns explain processes and rows show characteristics. Therefore, value 1 at each array, indicates the inspection of related characteristic (i.e., row number of array) is carried out after the determined process (i.e., column number of array). For example, MI of characteristics number 3, 5 and 6 are carried out after processes number 3, 5 and 6, respectively. Besides, CI of characteristics number 1, 2 and 4 are carried out after processes number 3, 6 and 6, respectively.

		Characteristics					
		1	2	3	4	5	6
Monitoring		0	0	1	0	1	1
Conformity		1	1	0	1	0	0

Figure 1: Type of Inspection

		Processes					
		1	2	3	4	5	6
Characteristics	1	0	0	1	0	0	0
	2	0	0	0	0	0	1
	3	0	0	1	0	0	0
	4	0	0	0	0	0	1
	5	0	0	0	0	1	0
	6	0	0	0	0	0	1

Figure 2: Place of Inspections

4.2. Selection process

A binary tournament selection technique is adopted for the proposed GA in which the two selected chromosomes from the population are compared based on their fitness value and the fitter chromosome is selected for undergoing the crossover operator. This procedure is continued till the number of all selected chromosomes is reached a certain amount (i.e., $R_C \times PopSize$; where R_C and $PopSize$ are the given cross over rate and population size of the proposed GA).

4.3. Genetic operators

The new generation is created using the genetic operators. However, when creating the new population using genetic operators, some of the best found chromosomes may be removed from the population. To prevent this from happening, an elitism mechanism with rate of R_E is applied which copies the fittest chromosome at each iteration to the next generation. Meanwhile, elitism is more effective when the mutation rate is high and may cause the loss of good solutions in the next generation. In order to develop an algorithm with effective exploration and exploitation operators, the proposed GA contains two novel operators namely, multi-choice crossover and mutation operators.

4.3.1. Multi-choice crossover operator

In this step, selected chromosomes (parents) from section 4.2 share their information by using crossover operator to improve themselves. Chromosomes with lower objective function cost have more chance than others for sharing their information under a binary tournament selection (Section 4.2). For applying multi-choice crossover on the solutions, four different kinds of crossover are adopted, including: a) one point crossover, b) two points crossover, c) continuous uniform crossover, and d) discrete uniform crossover as shown in Figure 3. At each use of crossover operator, one of these mechanisms is applied on the parents.

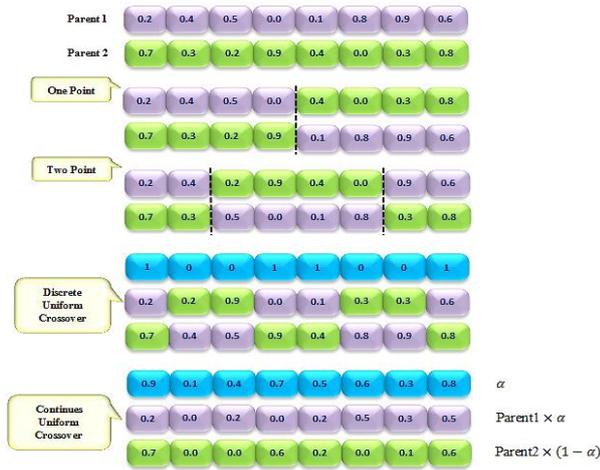


Figure 3. Sharing information between chromosomes

4.3.2. Multi-choice mutation operator

In order to develop an efficient exploration algorithm, some random selected chromosomes with rate of R_M go through the multi-choice mutation operator which contains: a) swap, b) reversion and c) inversion operators as shown in Figure 4. In the swap operator, places of two random selected bits are exchanged. In the reversion operator, a random part of a colony is selected and its permutation is reversed. Finally, in the inversion operator, one bit is chosen randomly and its value is replaced with new random value.

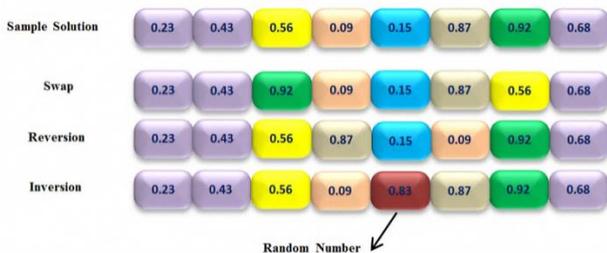


Figure 4. Multi-choice mutation operator

4.4. Termination

Unfortunately, in all optimization methods, it is always difficult to prove the convergence of the optimal solution and therefore a termination point must be set to stop the algorithm. In the proposed GA, Number of Function Calls-NFC mechanism is considered.

5. EXPERIMENTAL RESULTS

In order to validate the correctness of the proposed MINLP for inspection planning, an industrial case with similar 15 quality characteristics and different process capabilities has been provided, in which the effect of misadjustment has been neglected. First, parameter setting is done in the next section to enhance the performance of the proposed GA. Next, some information about the industrial case is provided. Then, the results of the proposed model for the industrial case are explained.

5.1. Parameters setting

GA, like other meta-heuristics, does not have any special criteria to set parameters. Therefore, we try to set the parameters of the proposed genetic algorithm. In order to design an efficient GA, parameters like crossover and mutation rates, population size, and iteration numbers should be tuned correctly. It is also well known that quality of an algorithm is influenced significantly by the values of its parameters. In this section, for optimizing behavior of the proposed GA, appropriate tuning of its parameters has been carried out. For this purpose, response surface methodology (RSM) is employed. RSM is defined as a collection of mathematical and statistical method-based experiments, which can be used to optimize processes. Regression equation analysis is used to evaluate the response surface model. First of all, those parameters that affect statistically on algorithm results are significantly recognized. To select the values that result in solutions with high quality, we consider problems in two different sizes including Small- S and Large- L sizes. To identify significant parameters, two levels for each parameter are considered. Each factor is measured at two levels, which can be coded as -1 when the factor is at its low level (L) and $+1$ when the factor is at its high level (H). The coded variable can be defined as follows:

$$X_i = \frac{r_i - \left(\frac{h+l}{2}\right)}{\left(\frac{h-l}{2}\right)} \quad (25)$$

where x_i and r_i are coded and real variable, respectively. h and l represent high level and low level of factor. Factors and their levels are shown in Table 1. After developing regression models for each problem size separately, tuned parameters of the proposed GA have been obtained and shown in Table 2. Finally, for the proposed GA, the NFCs stopping criteria was set on 40000 and 120000 for small and large size problems, respectively.

Factors	Coded Level					
	-1		0		+1	
	S	L	S	L	S	L
PopSize	100	150	150	225	200	300
P_E	0.1	0.2	0.2	0.3	0.3	0.4
P_C	0.6	0.7	0.7	0.8	0.8	0.9
P_M	0.1	0.2	0.2	0.3	0.3	0.4

Table 1. Parameters and their levels for small and large sizes

Factors	Optimal coded value		Optimal real value	
	S	L	S	L
	PopSize	0.85	1	193
P_E	0	-0.5	0.2	0.25
P_C	0	0.5	0.7	0.85
P_M	-1	+1	0.1	0.4

Table 2. Tuned parameters of the proposed GA

5.2. Industrial case study

In order to validate the proposed MINLP model, a car manufacturer has been selected. A special part with 15 different characteristics, which should be analyzed to make decision on the inspection plan, is chosen. Figures 5 and 6 show the part and different characteristics, respectively. In addition, details of the industrial case have been tabulated as Table 3, in which first to sixth columns explain name of processes, production time, process capability C_p and C_{pk} and failure rate of the processes with and without monitoring inspection. Besides, the allowable positions (AP) that inspections (i.e., CI and MI) of each characteristic can take place have been declared in the last column of Table 3. For example, for characteristic number 4 which belongs to process number 4, MI or CI can take place after processes number 4 to 10. Figure 7 illustrates the results of industrial case including decision on type and position of inspection for each characteristic.

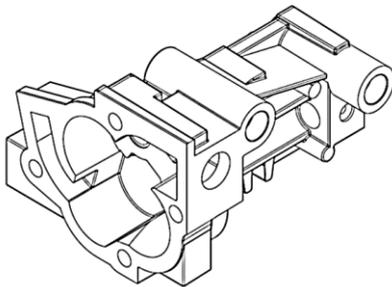


Figure 5: Under study part

In the real industrial case, the all characteristics go under monitoring inspection and no conformity inspection takes place. Therefore, monitoring inspection of characteristics number 1, 4 and 6 take place after process number 6; monitoring inspection of characteristics number 2, 3 and 5 take place after process number 8; monitoring inspection of characteristics number 7 to 10 take place after process number 10 and finally monitoring inspection of characteristics number 11 to 15 take place after process number 15. The details of cost objective function have been reported as Table 4.

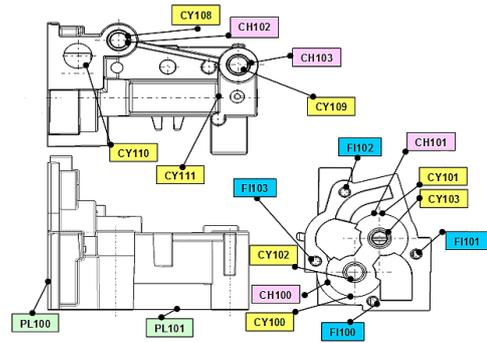


Figure 6: Characteristics of the under study part

Process name	Details					
	PT	C_p	C_{pk}	FR ¹	FR ²	AP
Rough milling PL100	0.148	2	1.50	1.97e-9	6.79e-6	1→13
Rough milling PL100	0.166	2	1.50	1.97e-9	6.79e-6	2→14
Rough milling PL101	0.133	2	1.66	1.97e-9	6.35e-7	3→15
Boring CY110	0.154	1.60	1.33	1.58e-6	6.60e-5	4→10
Rough drilling CY108 & CY109	0.09	2	1.66	1.97e-9	6.35e-7	5→10
Chamfering CY108 & CY109	0.25	2	1.66	1.97e-9	6.35e-7	6→6
Chamfering CY100 & CY101	0.257	1.50	1.20	6.79e-6	3.18e-4	7→15
Boring CY100	0.257	1.50	1.20	6.79e-6	3.18e-4	8→15
Boring CY101	0.122	1.66	1.30	6.35e-7	9.61e-5	9→12
Rough drilling CY102 & CY103	0.109	1.66	1.40	6.35e-7	2.66e-5	10→12
Rough drilling CY111	0.134	1.66	1.40	6.35e-7	2.66e-5	11→15
Boring CY108 & CY109	0.122	1.30	1.10	9.61e-5	9.66e-4	12→15
Boring CY102 & CY103	0.122	1.30	1	9.61e-5	2.69e-3	13→15
Boring CY111	0.117	1.66	1.33	6.35e-7	6.60e-5	14→15
Finish milling PL100	0.129	1.66	1.33	6.35e-7	6.60e-5	15→15

Table 3: Details of industrial case

		Characteristics														
MI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 7a: Type of Inspection

		Processes														
Characteristics	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 7b: Place of Inspections

Figure 7: Result of the industrial case

Total Cost	5132635	Production Cost	4812500
Fixed Conformity Cost	0	Fixed Monitoring Cost	9000
Variable Conformity Cost	0	Variable Monitoring Cost	419400
Scrap Cost	3665	Warranty Cost	24200

Table 4: Detail of cost objective function for real industrial case

6. CONCLUSION

This paper developed an optimization framework for inspection planning based on a mixed-integer non-linear programming (MINLP) model, in which decisions are required on which quality characteristics need what kind of inspections and when these inspections should be performed. In the proposed MINLP model, two different kinds of inspection, namely monitoring (MI) and conformity (CI) inspections were taken into account. The objective function minimized the sum of production cost, scraps cost, fixed and variable cost of CI and MI, fixed cost of overall position for both inspections and cost of warranty when a defective product is sold. In order to validate the correctness of the model, a real industrial case is studied. Since the size of problem was large, a genetic-based algorithm was developed to solve the real cases. The results show that almost of the characteristics need monitoring inspection and just for two or three of them a conformity inspection should be planned due to the low capability of their corresponding process.

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