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A bi-objective robust inspection planning model in a multi-stage serial production system

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In this paper, we present a bi-objective mixed-integer linear programming (BOMILP) model for planning an inspection process used to detect nonconforming products and malfunctioning processors in a multi-stage serial production system. The model involves two inter-related decisions: (1) *which* quality characteristics need *what* kind of inspections (i.e. *which-what* decision) and (2) *when* the inspection of these characteristics should be performed (i.e. *when* decision). These decisions require a trade-off between the cost of manufacturing (i.e. production, inspection and scrap costs) and the customer satisfaction. Due to inevitable variations in manufacturing systems, a global robust BOMILP (RBOMILP) is developed to tackle the inherent uncertainty of the concerned parameters (i.e. production and inspection times, errors type I and II, misadjustment and dispersion of the process). In order to optimally solve the presented RBOMILP model, a meta-heuristic algorithm, namely differential evolution (DE) algorithm, is combined with the Taguchi and Monte Carlo methods. The proposed model and solution algorithm are validated through a real industrial case from a leading automotive industry in France.

Keywords: multi-stage production system; conformity inspection; monitoring inspection; multi-objective optimisation; robust optimisation; differential evolution

1. Introduction

Since many production processes are technologically incapable of producing high-quality products, a quality management system has gained increasingly high importance in many modern production systems. In most of the production processes, incapable production techniques, defective equipment and inferior raw materials are some of the external factors resulting in quality problems (Alfares and Attia 2017). Accordingly, production managers are constantly attempting to provide a quality control system (QCS) to obtain high-quality products in the presence of such adverse external factors. In order to secure an effective QCS under such conditions, in-line quality control measures are employed more intensively, and if workable, automatically. For having an effective QCS, firms invest large amounts in inspection systems, and inspection planning problems stay on top of the manager's concerns. Inspection allocation and selection decisions are actually made by quality managers; however, an overall framework for their decisions when they should decide *which* quality characteristics of the products need to be inspected and *when* to be inspected through the process and *how* to be inspected (i.e. which type of inspection) is almost missing.

Decisions regarding the inspection of products to detect the nonconforming parts before being sold are made in every production system (Sun, Ren, and Yin 2017). In particular, planning of inspection in a multi-stage production system (MPS), in which raw materials are transformed into the final product through a series of distinct and consecutive processing stages, has been recognised as one of the major necessities in production systems. Since an MPS presents various possibilities for inspection, inspection activities in an MPS may be performed after some or every processing step. Therefore, inspection planning (IP) in an MPS is to determine the must-inspect quality characteristics as well as time and type of the inspections.

In an inspection planning process, conformity (CI) and monitoring (MI) inspections are integrated with production processes (Mohammadi et al. 2014, 2015). CI is a collective term used for a number of activities (e.g. testing, inspection and certification) to specify whether the final product meets designed characteristics. In other words, CI determines whether the product has correctly been manufactured based on a process plan and it complies with design specifications. More importantly, in CI no deviation from the design specifications is allowed and nonconforming products might be

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reproduced or reworked to bring them into conformance. Therefore, the main aim of CI is to minimise the production cost by early detection of nonconforming products and to maximise customer satisfaction through removing defective products before being sold (Hinrichs 2011; Etienne et al. 2017). During CI, the production process is temporarily stopped and all products (i.e. 100% frequency) or a sample of products are inspected to verify whether the most important quality characteristics meet design specifications. Since stopping the production process results in a significant decrease in both yield and productivity, MI, with a lower frequency than CI, can be performed as a process status verifier. By MI, critical processing features (e.g. feed speed of a drilling machine, force, temperature ant, etc.) are monitored not to deviate from their set value (Yu and Chen 2016).

Decisions regarding the implementation of CI and/or MI highly depend on the importance of quality characteristics. For example, CI is implemented on those quality characteristics that directly correspond to the product function, where even a small malfunction may highly decrease the customer satisfaction. On the other hand, MI is performed to increase the capability of the processes and to reduce the deviation from standard tolerances and ultimately, to minimise the number of defective/nonconforming products. Simultaneous implementation of both CI and MI to secure quality characteristics is the most reliable way to decrease the number of defectives and, respectively, reach the highest customer satisfaction level. However, due to recourse limitations, simultaneous implementation is mainly impractical as the total production cost increases significantly. Therefore, a trade-off between production cost and customer satisfaction should be made to find the most preferable inspection plan.

In addition to the elaborated concerns in planning an inspection process, lack of information about production processes and several environmental factors imposes a degree of uncertainty to inspection planning decisions (Galbraith 1973; Ho 1989; Han et al. 2016). Although uncertainty and manufacturing variations (e.g. performance degradation and non-conformance to specifications) are almost inevitable in practice, classical methods mainly consider deterministic conditions during the planning of an inspection process; while manufacturing processes are stochastic in nature. Consequently, a per cent of the manufactured products do not conform design specifications and the corresponding process becomes sensitive to manufacturing variations. Traditionally, tight tolerance or higher precision manufacturing process was being applied to cope with uncertainty, which mainly led to a huge manufacturing cost. Hence, manufacturers are interested in less sensitive manufacturing processes. These manufacturing processes are called robust processes that are relatively insensitive to alteration of uncertain parameters.

Finally, robust planning of an inspection process to pick out the critical quality characteristics and to determine the type and the location of the inspections is the main problem that this paper attempts to address.

The rest of this paper is organised as follow. Section 2 reviews the relevant papers in the literature. Section 3 explains the proposed BOMILP model. Section 4 describes the global robust optimisation approach. The solution algorithm is explained in Section 5. The experimental results of the real industrial case are provided in Section 6, and finally the paper is concluded in Section 7.

2. Literature review

This section updates our previous work (Mohammadi et al. 2015) by adding more relevant papers published in inspection planning problem. Inspection planning problems have been studied by many researchers since the 1960s. A basic conceptual model was proposed by Lindsay and Bishop (1964) and the authors considered perfect inspection accuracy for workstations of attribute data (WAD), in which all rejected items are scrapped. They also assumed that the inspection station could only check the outcome of the immediately preceding workstation. The extension of their study was proposed by White (1966), in which the rejected items are replaced with conforming ones. Hurst (1973) first planned an inspection process by considering both inspection errors type I and type II. Peters and Williams (1984) proposed five heuristic decision rules to find the location of the inspections. This work was extended later by Yum and McDowell (1987) in form of a mixed-integer linear programming model by adding the consideration of a rework activity. Chakravarty and Shtub (1987) investigated the impact of set-up and inventory costs on inspection strategies such as ‘all or none’ versus ‘partial’ inspection. The authors proposed a shortest path heuristic algorithm to determine the strategic location of inspections and production lot sizes. Barad (1990) provided a solution-oriented technique based on the concept of break-even quality level. Viswanadham, Sharma, and Taneja (1996) mathematically modelled the location problem of inspections in an MPS and developed two stochastic search algorithms for solving the problem, one based on simulated annealing (SA) and the other on genetic algorithm (GA). Similarly, Bai and Yun (1996) developed a cost model and an algorithm to find optimal locations of inspections and inspection level in an MPS. Lee and Unnikrishnan (1998) proposed a mathematical model to solve the inspection allocation problem in an MPS, in which various parts with distinctive machinery steps are processed and inspections can be performed on one of the several inspection stations with corresponding inspection errors. Verduzco, Rene Villalobos, and Vega (2001) presented real-time inspection allocation that is based on the information gained by inspecting one additional component. They modelled the selection of which components to be inspected as an information maximisation problem. Besides, a modified knapsack greedy heuristic method was used to find near-optimal solutions to this optimisation problem within the required time constraints.

Regarding the integration of the production process and the inspection plan, Lee and Kim (2001) proposed an optimisation model to integrate the inspection planning and scheduling using simulation-based genetic algorithms. The performance measures based on the process plan combinations calculated by a simulation module instead of process plan alternatives and the calculated measures are fed into a GA in order to improve the solution quality until the scheduling objectives are satisfied. Emmons and Rabinowitz (2002) studied the planning of the layout and operation of an inspection process used to detect malfunctioning processors in an MPS. Their planning involved three inter-related decisions: (i) overall inspection capacity, (ii) assignment of inspection activities to the inspectors and (iii) scheduling of the inspector's tasks. Kogan and Raz (2002) proposed a mathematical model of managing the intensity, sequence and timing of inspections in an N-stage production system with M inspection activities possible at each stage in order to minimise the sum of inspection costs and penalties caused by undetected defects. Shiau (2002, 2003a) studied the inspection resource assignment problem in an MPS by considering the inspection errors. They considered a limited number of inspections to be assigned through the production process. The author also considered the inspection errors that happen due to rapid changes of tolerances to satisfy the customer requirements.

Additionally, Shiau (2003b) studied an inspection-allocation planning (IAP) problem for MPS, in which the production recourses are restricted and the limited number of inspections is considered for solving the IAP problem. This paper solved the IAP problem using a unit cost model, in which manufacturing capability, inspection capability and specified tolerances are simultaneously considered. Rau and Chu (2005) considered inspection allocation problems for an MPS with two types of workstations, workstation of attribute data (WAD) and workstation of variable data (WVD), in which three strategies are adopted to treat nonconforming parts (i.e. repair, rework and scrap). They developed a profit model for optimally allocating inspections and a heuristic solution method to solve the model. Hanne and Nickel (2005) developed a multi-objective inspection planning model considering objectives with respect to 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 the operators and the generation of a project schedule. By integrating the production process and the inspection planning, Shiau, Lin, and Chuang (2007) declared that higher performance of a production industry can be realised if the process and the inspection plans become integrated to cope with the limited manufacturing resources. They also developed a GA for solving large-sized problems. In another work, Ferreira, Almeida, and Cavalcante (2009) proposed an optimisation model to determine the inspection intervals for MI in case of equipment's failure.

Colledani and Tolio (2006) proposed an approach to evaluate the overall performance of a system considering both quality and production logistics. The results obtained by the application of the method provided new insight in the relations among the two areas and paved the way to the joint design of production logistics and QCSs. In a similar work, Colledani and Tolio (2012) presented a general theory to combine quality, maintenance and production control contexts in an MPS in order to analyse the production rate of conforming products in manufacturing systems with progressively deteriorating machines and preventive maintenance. In addition, due to increasing pressure on high precision manufacturing and development of on-line measurement technologies, Colledani, Ebrahimi, and Tolio (2014) presented an integrated quality and production logistics model to profitably manage the trade-off between selective and adaptive assembly systems in emerging sectors, such as micro-production, biomedical and e-mobility industry. In another work, Colledani et al. (2014) proposed the production quality as a new paradigm aiming at going beyond traditional six-sigma approaches. Their new paradigm is extremely relevant in various technology intensive and emerging strategic manufacturing sectors. They claimed that the traditional six-sigma techniques show strong limitations in highly changeable production contexts, characterised by small batch productions, customised, or even one-of-a-kind products, and in-line product inspections. Therefore, innovative and integrated quality, production logistics and maintenance design, management and control methods as well as advanced technological enablers have a key role to achieve the overall production quality goal. Finally, they revised problems, methods and tools to support this paradigm.

Mohammadi et al. (2014) developed an optimisation framework for process inspection planning of an MPS with multiple quality characteristics. They developed a single-objective mixed-integer programming model to minimise the sum of manufacturing and warranty costs. By summing up, the warranty cost might be dominated by the manufacturing cost in cases when the warranty cost is low. This domination may lead to transferring higher number of scraps to the customers and consequently lower customer satisfaction. The authors also investigated the effect of uncertainty in misadjustment and attempted to provide a robust inspection plan. Mousavi et al. (2015) proposed an intuitionistic fuzzy grey model for selecting an inspection plan among different inspection scenarios considering conflicting criteria as inspection cost and customer satisfaction. Accordingly, they introduced a distance-based decision model for the multi-attributes analysis by considering the concepts of intuitionistic fuzzy sets (IFSs), grey relations and compromise ratio approaches. Their approach needs a priori set of inspection scenarios to be selected. Having such a priori set is impossible when the decision-maker has not enough knowledge about the manufacturing and inspection processes as well as the consequence of each decision. There is also no guarantee that the priori set consists of an optimal feasible inspection plan. Their approach can be applied on the Pareto solutions obtained by the proposed mathematical model in Section 3.4.

Regarding the uncertainty of input parameters, Kanyamibwa and Ord (2000) developed a form of the loss function considering variability of a production process, decision loss, and costs of sampling and inspection. Specifically, they considered monitoring a production process, which may undergo continuous mean shift and variance deterioration during a production run. Kallgren et al. (2003) reviewed the present status of the role of measurement uncertainty in conformity assessment. Macii, Carbone, and Petri (2003) studied a theoretical analysis aimed at estimating the growth in decisional risks due to both random and systematic errors. Also, they provided some useful guidelines about how to choose the test uncertainty ratio of industry-rated measurement instruments in order to limit the risk of making wrong decisions below a maximum preset value. Pajula and Ritala (2006) illustrated through a case study, how the control a structure design that has been affected by uncertainty and how the corresponding dynamic problem is defined and solved with rather regular tools. The interested readers are referred to the recent review of impact of uncertainty in production inspection done by Desimoni and Brunetti (2011).

From the other aspects, some researchers have considered uncertainty in terms of risk in manufacturing processes. Bassetto, Siadat, and Tollenaere (2011) presented the concept of risk typology and its use in the management of process control deployment at a fab-wide level. They provided a comprehensive method based on the failure mode effect and criticality analysis (FMECA) to control failures that count throughout an organisation. Khan and Haddara (2003) presented a new methodology for risk-based maintenance-inspection planning. They proposed a comprehensive and quantitative methodology that comprises three main modules; namely, risk estimation module, risk evaluation module and maintenance-inspection planning module.

Regardless of the context, several approaches have been developed to cope with the inherent uncertainty of the input parameters (see Zahiri, Tavakkoli-Moghaddam, and Pishvaee 2014; Zahiri, Torabi, and Tavakkoli-Moghaddam 2017; Zahiri, Zhuang, and Mohammadi 2017), out of which, the robust design has been shown to be the most effective technique in a manufacturing process to better address the manufacturing variations and uncertainty of the corresponding input parameters (Chen et al. 1996; Xiaoping and Chen 2000; Gyung-Jin and Lee 2002; Beiqing and Du 2006; Hans-Georg and Sendho 2007; Arvidsson and Gremyr 2008; Torben, Arvidsson, and Gremyr 2009; Khalaj, Makui, and Tavakkoli-Moghaddam 2012; Mechri et al. 2013; Trosset 1997).

Almost all of the above-reviewed papers have only focused on allocating the inspection activities during the production process without considering other decisions, such as picking out the critical quality characteristics to be inspected and selecting the type of inspection activities (i.e. MI and/or CI). Despite the literature, this paper integrates the inspection plan with the production process to simultaneously pick out the critical quality characteristics and to determine the type and the location of the inspections. Additionally, this paper takes into account the uncertainty of the input parameters and investigates the effect of uncertainty on the final decisions. Comprehensively, this integration problem under uncertainty is presented as a new robust bi-objective MILP model with a trade-off between production cost and customer satisfaction as two conflicting objective functions. To the best of our knowledge, there is no model in the literature that is able to effectively and efficiently address all of these challenges. The proposed model and the solution approaches are validated through a real industrial case from one of the leading automotive industries in France. Finally, the sensitivity of the objective functions to the uncertain parameters is investigated to draw valuable managerial insights.

Showing the gaps of the literature, the main contributions of this paper, which differentiate our efforts from those already published on the subject, are as follows:

- Effectively integrating inspection plan with the production plan by performing inspection activities during the process instead of having an acceptance or a rejection check at the end. This integration minimises the production cost by early detection of the nonconforming products.
- Considering the monitoring inspection alongside the conformity inspection to monitor the processing parameters and avoid the creation of nonconforming products.
- Proposing a new bi-objective mixed-integer linear programming (BOMILP) model for planning an inspection process.

- Making trade-off between two important targets in almost all industries as manufacturing cost and customer satisfaction. These targets have been formulated as the objective functions of the proposed mathematical model.
- Taking into account the uncertainty of the input parameters by developing a global robust approach based on the Taguchi loss function and the Monte Carlo simulation method.
- Studying a real industrial case from a leading automotive industry in France to validate the performance of the proposed model and the robust solution approach.
- Developing a tailored meta-heuristic algorithm, namely differential evolution (DE), to solve the real industrial case.
- Investigating the sensitivity of the objective functions to the input parameters and extracting valuable managerial insights.

3. Problem description and mathematical formulation

This section, first, describes the problem and main operational decisions; and second, develops the mathematical formulation based on a BOMILP model.

3.1 *Problem description*

Consider a flow shop production system consisting of N serial stages with unlimited buffers, in which in-process parts pass through all stages 1 to N sequentially and inspections are performed at m stages where $m \leq N$. The in-process parts are transported between stages manually and the transportation does not create any non-conformity in the part. It should be noted that each stage can be an operation and a set of operations can be performed on the same machine. At each stage, a unique operation is performed on the part and a new quality characteristic is created in the part. The output of this stage is transferred to an inspection station or to the next processing stage. Suppose that a part consists of K quality characteristics and all these characteristics are created during the production process. A part is 'nonconforming' if at least one quality characteristic does not meet the design specifications. If a CI is performed between stages i and $i + 1$, there is an opportunity to detect the nonconforming parts originated from the i-th stage or at some of the earlier stages. The detected nonconforming parts are scrapped and no further rework is allowed. On the other hand, if an MI is performed between stages i and $i + 1$, the processing features are monitored after a specific number of parts. An inspection activity may involve two types of errors: misclassification of a conforming part as nonconforming (error type I) and nonconforming one as conforming (error type II).

Adopted from Mohammadi et al. (2015), this paper plans the inspection process through two main decisions as (1) *which* quality characteristics need *what* kind of CI or/and MI inspections (i.e. *which-what* decision) and (2) *when* the inspection of these characteristics should be performed (i.e. *when* decision). For the first decision, although those characteristics that have more impact on the product functionality and significantly affect the customer satisfaction should be picked out, but all the characteristics cannot be inspected while the inspection cost is highly increased. The second decision about the location of the inspections is also challenging, in which the inspection of a characteristic can be done only at particular stages throughout the production process. For example, the process cannot be stopped or accessibility to and measuring that characteristic is impossible unless in some further stages (Mohammadi et al. 2015). In addition, finding and removing nonconforming parts at initial stages is desired where nonconforming parts do not unnecessarily go through further operations and the cost of production is consequently decreased. Hence, it is more sensible to detect non-conformity immediately after its originating stage and before the next operation starts, but the number of inspection stations and the process interruptions as well as the total cost of inspection are increased. As an example, consider a situation that each characteristic is inspected immediately after its creation. Since each inspection activity includes three steps as: (1) removing the part from the machine, (2) inspecting and (3) setting up the part for the next operation; these steps are unnecessarily repeated for each characteristic. On the other hand, when a set of characteristics is inspected at a same allowable stage, the removing and setting up steps are needed only once (Mohammadi et al. 2015). Therefore, making right and optimal *which-what* and *when* decisions are challenging and that this paper aims at coping with this challenge. Figure 1 shows the flowchart of the inspection planning decisions.

3.2 *Assumptions*

The considered assumptions of the proposed BOMILP are listed as follows:

- The production system contains N manufacturing stages arranged serially, wherein one part type is processed with K identical quality characteristics;

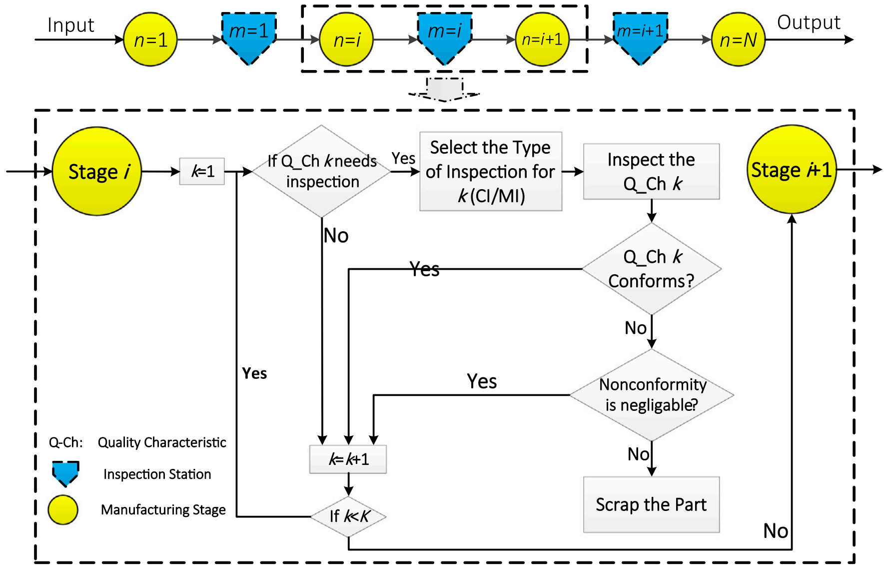

Figure 1. Inspection planning flowchart.

- Different quality characteristics may be processed in a same manufacturing stage;
- Non-conformities are generated only at the manufacturing processes and other activities (e.g. movement, set-up and inspection activities) do not make non-conformity;
- Each manufacturing stage has a failure rate of producing nonconforming parts;
- Two types of conformity (CI) and monitoring (MI) inspections are considered, while considering MI for a manufacturing stage decreases the failure rate of that stage;
- CI subjects to both errors type I and II;
- The frequency of MI is fixed;
- MI affects the mean value of the process capability statistics such as P_{pk};
- Detected nonconforming items from CI are directly scrapped and no rework or repair operation is considered;
- A unit scrap cost is imposed to the system in case of detecting a nonconforming part. The scrap cost depends on both the number of manufacturing stage and the quality characteristics;
- The production system reaches a steady state and system breakdown is not assumed;
- Input parameters of the problem are considered to be uncertain;
- In the robust model, we consider misadjustment that affects C_{pk} and P_{pk} as well as failure and scrap rates.

3.3 *Notations*

Necessary notations for the proposed mathematical formulation are provided as follows:

Sets

$p, p' \in \{1, 2, \ldots, P+1\}$	Set of operations
$k \in \{1, 2, \ldots, K\}$	Set of different quality characteristics

Parameters

fr^1_{pk}	Failure rate of operation p for characteristic k with monitoring inspection
fr^2_{pk}	Failure rate of operation p for characteristic k without monitoring inspection
d_{pk}	Detection rate of conformity inspection assigned to operation p for characteristic k
α_{pk}	Type I error of conformity inspection assigned to operation p for characteristic k
β_{pk}	Type II error of conformity inspection assigned to operation p for characteristic k ($\beta_{pk} = 1 - d_{pk}$)
n_T	Total number of parts fed to the production process

pc_p	Unit production cost per time for operation p
pt_p	Production time of operation p
sc_p	Scrap cost of parts immediately after operation p
nc_k	Cost of nonconforming part in the market due to characteristic k
fm_{pk}	Fixed cost of an MI station after operation p for characteristic k
fc_{pk}	Fixed cost of a CI station after operation p for characteristic k
vm_{pk}	Unit variable cost of MI per time performed after operation p for characteristic k
vc_{pk}	Unit variable cost of CI per time performed after operation p for characteristic k
mt_{pk}	Time of MI performed after operation p for characteristic k
ct_{pk}	Time of CI performed after operation p for characteristic k
fs_p	Fixed space cost per part of establishing inspection stations just after operation p
$\zeta_{p'p}$	1 if two operations p' and p are dependent; and 0, otherwise
ψ_{pk}	1 if characteristic k belongs to operation p; and 0, otherwise
mf_k	Monitoring frequency for characteristic k
cf_k	Conformity frequency for characteristic k
G_k	Relative importance of characteristic k
M	A big number

Decision variables

NP_{pk}	Number of nonconforming parts due to characteristic k from operation p
YC_{pk}	1 if operation p needs CI for characteristic k; and 0, otherwise
YM_{pk}	1 if operation p needs MI for characteristic k; and 0, otherwise
$XC^k_{p'p}$	1 if CI of operation p' for characteristic k is performed immediately after operation p ($p' \le p$); and 0, otherwise
$XM^k_{p'p}$	1 if MI of operation p' for characteristic k is performed immediately after operation p ($p' \le p$); and 0, otherwise
N_p	Number of parts entering operation p
NM_{pk}	Number of MI performed between operations p and $p+1$ for characteristic k
NC_{pk}	Number of CI performed between operations p and $p+1$ for characteristic k
NS_p	Is 1 if there is an inspection station between operations p and $p+1$
$\mathcal{S}_{pk}$	Number of the scrapped part between operations p and $p+1$ due to characteristic k
S_p	Total number of the scrapped parts between operations p and $p+1$
OFV_τ	The τ-th objective function value

3.4 *Mathematical formulation*

This section develops the proposed BOMILP model by mathematically representing the *which-what* and *when* decisions. The first objective function of the model minimises the total manufacturing cost which includes costs associated with production (*TCP*), scrap (*TCS*) and inspection (*TCI*). Total inspection cost contains total fixed inspection cost (*TCIF*) and total variable inspection cost (*TCIV*), where $TCI = TCIF + TCIV$. The second objective function minimises the customer satisfaction. Since customer satisfaction is typically a qualitative factor, in this paper, minimising the total warranty cost (*TCW*) is considered to capture customer satisfaction. Warranty cost is the cost when a nonconforming part reaches the customer and the company has to compensate the damages.

Through an inspection process plan, two different strategies can be adopted as well. First, a strategy considers that all characteristics need inspection and at most one kind of inspection (i.e. MI or CI) should be performed. Second, by relaxing some restrictions of the first strategy, it is considered that none, one or both of MI and CI (i.e. MI or/and CI) can be performed for each characteristic. Hereafter, the first and second strategies are called MI-or-CI and MI-and-CI strategies, respectively.

3.4.1 *Objective functions*

The objective functions of the model are mathematically formulated as Equations (1) and (2), respectively. Hereafter, the first and second objective functions are called as internal and external costs, respectively.

$$OFV_1 = \min\{TCW + TCW + TCIF + TCIV\} \tag{1}$$

$$OFV_2 = \min\{TCW\} \tag{2}$$

where,

$$TCW = \sum_{p=1}^{P} pc_p pt_p N_p \tag{3}$$

$$TCW = \sum_{p=1}^{P} sc_p S_p \tag{4}$$

$$TCIF = \sum_{p=1}^{P}\sum_{k=1}^{K} fc_{pk} NC_{pk} + \sum_{p=1}^{P}\sum_{k=1}^{K} fm_{pk} NM_{pk} + \sum_{p=1}^{P} fs_p NS_p N_p \tag{5}$$

$$TCIV = \sum_{p=1}^{P}\sum_{k=1}^{K} cf_k ct_{pk} vc_{pk} N_p XC^k_{p'p} + \sum_{p=1}^{P}\sum_{k=1}^{K} mf_k mt_{pk} vm_{pk} N_p XM^k_{p'p} \tag{6}$$

$$TCW = \sum_{p=1}^{P}\sum_{k=1}^{K} G_k nc_k \left(NP_{pk} YC_{pk} \beta_{pk} + NP_{pk} \times YM_{pk}\right) \tag{7}$$

3.4.2 *Constraints*

The constraints of the model have been provided as Constraints (8) to (18).

$$\sum_{p=p'}^{P} \zeta_{p'p} XC^k_{p'p} = \psi_{p'k} YC_{p'k} \quad \forall p', k;\ p' \le P \tag{8}$$

$$\sum_{p=p'}^{P} \zeta_{p'p} XM^k_{p'p} = \psi_{p'k} YM_{p'k} \quad p', k;\ p' \le P \tag{9}$$

$$YC_{p'k} + YM_{p'k} = \psi_{p'k} \quad p', k \tag{10}$$

$$NP_{pk} = N_p \times YM_{pk} fr^1_{pk} + N_p \times YC_{pk} fr^2_{pk} \quad p, k;\ p \le P \tag{11}$$

$$\mathcal{S}_{pk} \ge \left[XC^k_{p'p} \times NP_{p'k} \times d_{pk}\right] + \left[XC^k_{p'p} \times N_p \times \alpha_{pk} - XC^k_{p'p} \times NP_{p'k} \times \alpha_{pk}\right] - \left[XC^k_{p'p} \times NP_{p'k} \times \beta_{pk}\right] \quad p, p', k;\ p, p' \le P \tag{12}$$

$$S_p \ge \mathcal{S}_{pk} \quad p, k;\ p \le P \tag{13}$$

$$N_p = N_{p-1} - S_{p-1} \quad p; p \le P + 1 \tag{14}$$

$$N_0 = n_T \tag{15}$$

$$NM_{pk} \geq \sum_{p'=1}^{P} XM_{p'p}^{k} \quad \forall p, k;\ p \leq P \tag{16}$$

$$NC_{pk} \geq \sum_{p'=1}^{P} XC_{p'p}^{k} \quad p, k;\ p \leq P \tag{17}$$

$$M \times NS_p \geq \sum_{p'=1}^{P} \sum_{k=1}^{K} \left(XC_{p'p}^{k} + XM_{p'p}^{k} \right) \quad p, p', k;\ p, p' \leq P \tag{18}$$

Equations (8) and (9) ensure that CI and MI of a quality characteristic should be done for all part just in one inspection stage, respectively. Equation (10) forces that one kind of inspection is needed for each quality characteristic. This equation is directly related to the MI-or-CI strategy. Equation (11) relates that the failure rate of an operation to the decision whether the MI is considered for that characteristic or not. Constraints (12) and (13) calculate the number of scraps after each inspection stage based on type I and type II errors. Constraints (14) and (15) determine the in-process part after each operation, where the number of parts is decreased in presence of any inspection due to scrap detection and removal. Equations (16) and (17) calculate total number of MIs and CIs throughout the whole production system. Constraint (18) calculates different inspection stage among the whole process.

3.4.3 *Linearisation*

As it can be seen, the objective functions and some of the constraints include non-linear terms and this issue makes the model difficult to solve. In order to address that, a linearisation technique is applied to linearise the non-linear terms. In this technique, the product of each pair of variables is replaced by a new auxiliary variable and three extra constraints are added to the model for each pair. It must be noted that this technique is used when at least one of the variables is binary variable. For example, consider a binary variable X and a real variable Y. The problem is to linearise the product of these two variables (i.e. $X \times Y$). Therefore, a new real auxiliary variable Z is considered. Next, the term $X \times Y$ is replaced by Z in the whole model. Finally, the following three constraints should be added accordingly.

$$Z \leq M \times X,$$

$$Z \leq Y,$$

$$Z \geq Y - M(1 - X).$$

Necessary auxiliary variables are provided as follows.

Auxiliary variables

$\mathbb{A}_{p'p}^{k}$	Linear form of $XC_{p'p}^{k} \times N_{p'}$
$\mathbb{B}_{p'p}^{k}$	Linear form of $XM_{p'p}^{k} \times N_{p'}$
$\mathbb{D}_{p'p}^{k}$	Linear form of $XC_{p'p}^{k} \times NP_{p'k}$
$\mathbb{E}_{pk}$	Linear form of $NP_{pk} \times YC_{pk}$
$\mathbb{F}_{pk}$	Linear form of $NP_{pk} \times YM_{pk}$
$\mathbb{L}_{p}$	Linear form of $NS_p \times N_p$
$\mathbb{U}_{pk}$	Linear form of $N_p \times YC_{pk}$
$\mathbb{V}_{pk}$	Linear form of $N_p \times YM_{pk}$

3.4.4 *Proposed BOMILP model under the MI-or-CI strategy*

After adding the linearisation constraints (i.e. Constraints (23) to (46)), the final proposed BOMILP model under the MI-or-CI strategy is proposed as follows.

BOMILP (MI-or-CI):

$$\begin{aligned}\operatorname{Min} OFV_1 \quad &= \sum_{p=1}^{P} pc_p pt_p N_p + \sum_{p=1}^{P} sc_p S_p + \sum_{p=1}^{P}\sum_{k=1}^{K} fc_{pk} NC_{pk} \\ &+ \sum_{p=1}^{P}\sum_{k=1}^{K} cf_k ct_{pk} vc_{pk} \mathbb{A}_p + \sum_{p=1}^{P}\sum_{k=1}^{K} fm_{pk} NM_{pk} + \sum_{p=1}^{P}\sum_{k=1}^{K} mf_k mt_{pk} vm_{pk} \mathbb{B}_p + \sum_{p=1}^{P} fs_p \mathbb{L}_p\end{aligned} \tag{19}$$

$$\operatorname{Min} OFV_2 = \sum_{p=1}^{P}\sum_{k=1}^{K} G_k nc_k \left(\mathbb{E}_{pk}\beta_{pk} + \mathbb{F}_{pk}\right) \tag{20}$$

s.t.

Constraints (8)–(11), (13)–(18)

$$NP_{pk} = \mathbb{V}_{pk} fr^1_{pk} + \mathbb{U}_{pk} fr^2_{pk} \quad \forall p,k;\ p \le P \tag{21}$$

$$\mathcal{S}_{pk} \ge \left[\mathbb{D}^k_{p'p} \times d_{pk}\right] + \left[\mathbb{A}^k_{p'p} \times \alpha_{pk} - \mathbb{D}^k_{p'p} \times \alpha_{pk}\right] - \left[\mathbb{D}^k_{p'p} \times \beta_{pk}\right] \quad \forall p,p',k;\ p,p' \le P \tag{22}$$

$$\mathbb{A}^k_{p'p} \le M \times XC^k_{p'p} \quad \forall p,p',k;\ p,p' \le P \tag{23}$$

$$\mathbb{A}^k_{p'p} \le N_{p'} \quad \forall p,p',k;\ p,p' \le P \tag{24}$$

$$\mathbb{A}^k_{p'p} \ge N_{p'} - M\left(1 - XC^k_{p'p}\right) \quad \forall p,p',k;\ p,p' \le P \tag{25}$$

$$\mathbb{B}^k_{p'p} \le M \times XM^k_{p'p} \quad \forall p,p',k;\ p,p' \le P \tag{26}$$

$$\mathbb{B}^k_{p'p} \le N_{p'} \quad \forall p,p',k;\ p,p' \le P \tag{27}$$

$$\mathbb{B}^k_{p'p} \ge N_{p'} - M\left(1 - XM^k_{p'p}\right) \quad \forall p,p',k;\ p,p' \le P \tag{28}$$

$$\mathbb{V}_{p'k} \le M \times YM_{p'k} \quad \forall p,p',k;\ p,p' \le P \tag{29}$$

$$\mathbb{V}_{p'k} \le N_{p'} \quad \forall p,p',k;\ p,p' \le P \tag{30}$$

$$\mathbb{V}_{p'k} \ge N_{p'} - M\left(1 - YM_{p'k}\right) \quad \forall p,p',k;\ p,p' \le P \tag{31}$$

$$\mathbb{U}_{p'k} \le M \times YC_{p'k} \quad \forall p,p',k;\ p,p' \le P \tag{32}$$

$$\mathbb{U}_{p'k} \le N_{p'} \quad \forall p,p',k;\ p,p' \le P \tag{33}$$

$$\mathbb{U}_{p'k} \ge N_{p'} - M\left(1 - YC_{p'k}\right) \quad \forall p,p',k;\ p,p' \le P \tag{34}$$

$$\mathbb{D}^k_{p'p} \le M \times XC^k_{p'p} \quad \forall p,p',k;\ p,p' \le P \tag{35}$$

$$\mathbb{D}^k_{p'p} \le NP_{p'k} \quad \forall p,p',k;\ p,p' \le P \tag{36}$$

$$\mathbb{D}^k_{p'p} \ge NP_{p'k} - M\left(1 - XC^k_{p'p}\right) \quad \forall p,p',k;\ p,p' \le P \tag{37}$$

$$\mathbb{E}_{p'k} \le M \times YC_{p'k} \quad \forall p',k;\ p' \le P \tag{38}$$

$$\mathbb{E}_{p'k} \leq NP_{p'k} \quad \forall p', k;\ p' \leq P \tag{39}$$

$$\mathbb{E}_{p'k} \geq NP_{p'k} - M\left(1 - YC_{p'k}\right) \quad \forall p', k;\ p' \leq P \tag{40}$$

$$\mathbb{F}_{p'k} \leq M \times YM_{p'k} \quad \forall p', k;\ p' \leq P \tag{41}$$

$$\mathbb{F}_{p'k} \leq NP_{p'k} \quad \forall p', k;\ p' \leq P \tag{42}$$

$$\mathbb{F}_{p'k} \geq NP_{p'} - M\left(1 - YM_{p'k}\right) \quad \forall p', k;\ p' \leq P \tag{43}$$

$$\mathbb{L}_{p} \leq M \times NS_{p} \quad \forall p; p \leq P \tag{44}$$

$$\mathbb{L}_{p} \leq N_{p} \quad \forall p; p \leq P \tag{45}$$

$$\mathbb{L}_{p} \geq N_{p} - M\left(1 - NS_{p}\right) \quad \forall p; p \leq P \tag{46}$$

$$XC^{k}_{p'p}, XM^{k}_{p'p}, NS_{p}, Y_{p}, YC_{p'k}, YM_{p'k} \in \{0, 1\} \quad \forall p, p'; p, p' \leq P \tag{47}$$

$$\mathcal{S}_{pk}, S_{p}, \mathbb{D}^{k}_{p'p}, NM_{pk}, NC_{pk}, \mathbb{A}^{k}_{p'p}, \mathbb{B}^{k}_{p'p}, NP_{pk}\mathbb{E}_{p'k}, \mathbb{E}_{p'k}, \mathbb{L}_{p}, N_{p} \geq 0 \quad \forall p', p, k;\ p', p \leq P \tag{48}$$

where, Constraints (47) and (48) are domain constraint.

3.4.5 *Proposed BOMILP model under the MI-and-CI strategy*

This section develops a BOMILP under the MI-and-CI strategy.

BOMILP (MI-and-CI):

$$\begin{aligned}\text{Min}OFV_1 = &\sum_{p=1}^{P} pc_p pt_p N_p + \sum_{p=1}^{P} sc_p S_p + \sum_{p=1}^{P}\sum_{k=1}^{K} fc_{pk} NC_{pk} + \sum_{p=1}^{P}\sum_{k=1}^{K} cf_k ct_{pk} vc_{pk} \mathbb{A}_p + \sum_{p=1}^{P}\sum_{k=1}^{K} fm_{pk} NM_{pk} \\ &+ \sum_{p=1}^{P}\sum_{k=1}^{K} mf_k mt_{pk} vm_{pk} \mathbb{B}_p + \sum_{p=1}^{P} fs_p \mathbb{L}_p\end{aligned} \tag{19}$$

$$\text{Min}OFV_2 = \sum_{p=1}^{P}\sum_{k=1}^{K} G_k nc_k \left(\mathbb{E}_{pk}\beta_{pk} + \mathbb{F}_{pk}\right) \tag{20}$$

s.t.

Constraints (8), (9), (11), (13)–(18), (21)–(48)

$$YC_{p'k} + YM_{p'k} \leq 2\psi_{p'k} \quad \forall p', k \tag{49}$$

4. Global robust optimisation

As mentioned in Section 1, the lack of information about production processes and several environmental factors imposes a degree of uncertainty to the planning parameters, which directly affect other decisions relating to the inspection process (Galbraith, 1973; Ho, 1989). In most of the manufacturing industries, a minimum level of uncertainty is inevitable. There are several parameters in the proposed BOMILP model that are affected by environmental factors and may fluctuate over the time. These parameters are production and inspection times, errors type I and II of the inspection activities, dispersion and misadjustment of the production processes. It should be noted that uncertainty in errors type I and II directly affects the number and cost of scraps and indirectly influences the warranty cost. In addition, uncertainty in dispersion and misadjustment of a process affects the failure rate and the number of scraps as depicted in Figures 2 and 3, respectively.

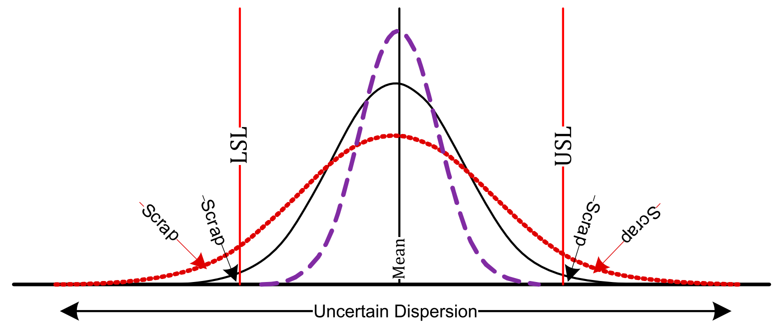

Figure 2. Uncertainty in dispersion.

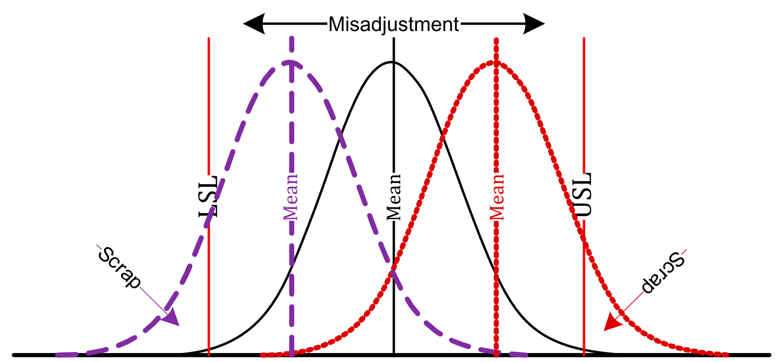

Figure 3. Uncertainty in misadjustment (Mohammadi et al. 2015).

Hence, manufacturers are interested in less sensitive manufacturing processes to the uncertain parameters. These manufacturing processes are called robust processes, which are relatively insensitive to alteration of the uncertain parameters. The main goal of this section is to take into account the uncertainty in the BOMILP's parameters and to design a global robust BOMILP (RBOMILP) model.

In order to design a robust inspection process, two methods have been proposed as follows (Das 2000; Beyer, Olhofer, and Sendhoff 2002):

- Optimising the expected value of the objective function under different alterations in the uncertain input parameters.
- Minimising the variance of the objective function under different alterations in the uncertain input parameters.

It is noteworthy that not only the expectation-based measure does not sufficiently take care of fluctuations of the objective function while these fluctuations are symmetric around the average value, but also a purely variance-based measure does not also take the absolute value of the solution into account. Hence, an optimisation problem minimising both expected value and variance of the objective function is desired to search the robust optimal solution. For these purposes, the Taguchi method is applied as the objective function (50) that should be minimised (Gyung-Jin et al. 2006). First, the necessary notations are provided below:

Parameters

MCR	Number of Monte Carlo runs
ω	Weight factor of standard deviation in the Taguchi method
CP_p	Process Capability. A simple and straightforward indicator of process capability
CPk_p	Process Capability Index. Adjustment of CP for the effect of a non-centred distribution
ρ_{MI}	Uncertainty factor of the process misadjustment under MI
ρ_{CI}	Uncertainty factor of process misadjustment under CI
ρ_{σ}	Uncertainty factor of process dispersion

ρ_{TP}	Uncertainty factor of production time
ρ_{TMI}	Uncertainty factor of MI time
ρ_{TCI}	Uncertainty factor of CI time
ρ_{e_I}	Uncertainty factor of type I error
ρ_{e_II}	Uncertainty factor of type II error

Variables

μ_{OFV_τ}	Expected value of the τ-th objective function
σ_{OFV_τ}	Standard deviation of the objective function
R_OFV_τ	Robust value of the τ-th objective function

$$R\_OFV_\tau = \mu_{OFV_\tau} + \omega\sigma_{OFV_\tau} \quad \forall\tau = 1, 2 \tag{50}$$

The alteration range for each uncertain parameter has been provided as Table 1.

where $P\{z \leq Z\}$ is the cumulative probability of standard normal distribution. In order to alter the uncertain parameters over their alteration range, a Monte Carlo simulation technique is performed.

5. Proposed solution algorithm

In order to solve the proposed RBOMILP model with uncertain parameters, the solution algorithm should be capable to obtain optimal or near-optimal non-dominated Pareto solutions within a reasonable time. There are several methods in the literature for providing an optimal solution for small-sized and single-objective problems, such as simplex and dynamic programming-based optimisation algorithms (Taha 2006; Shukla, Tiwari, and Ceglarek 2013). However, most of real problems not only are in higher sizes and solving them by mathematical programming approaches takes the huge computational time (Rostami, Dantan, and Homri 2015; Niakan, Vahdani, and Mohammadi 2014; Vahdani and Mohammadi 2015; Azizmohammadi et al. 2013; Mohammadi, Dehbari, and Vahdani 2014; Mohammadi et al. 2016), but also they need to be treated as the multi-objective problems (MOPs).

Traditionally, there are several methods available in the literature for solving MOPs as such as goal programming (Brandenburg 2015), weighted sum method (Mohammadi, Tavakkoli-Moghaddam, and Rostami 2011), and the iso-resource–cost solution method (Zeleny 1998). A negligible drawback of these methods is that none of them treats all the objectives simultaneously, except the iso-resource–cost solution method, which is a basic requirement in most MOPs (Abbass, Sarker, and Newton 2001). Accordingly, the solutions may be far away from the optimal ones. Despite the single-objective problems, solving MOPs lead to a set of optimal alternative solutions and no other solutions in the search

Table 1. Alteration range of the uncertain parameters.

Parameters		Uniform alteration range
Misadjustment	fr_{pk}^{MI}	$\left[1 - P\{z \leq 3 \times CP_p\} + P\{z \leq -3 \times CP_p\}, 1 - P\{z \leq 3 \times CP_p - \rho_{MI}\} + P\{z \leq -3 \times CP_p - \rho_{MI}\}\right]$
	fr_{pk}^{CI}	$\left[1 - P\{z \leq 3 \times CPK_p\} + P\{z \leq -3 \times CPK_p\}, 1 - P\{z \leq 3 \times CPK_p - \rho_{CI}\} + P\{z \leq -3 \times CPK_p - \rho_{CI}\}\right]$
Dispersion	fr_{pk}^{MI}	$\left[1 - P\left\{z \leq 3 \times \frac{CP_p}{1-\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CP_p}{1-\rho_\sigma}\right\}, 1 - P\left\{z \leq 3 \times \frac{CP_p}{1+\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CP_p}{1+\rho_\sigma}\right\}\right]$
	fr_{pk}^{CI}	$\left[1 - P\left\{z \leq 3 \times \frac{CPK_p}{1-\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CPK_p}{1-\rho_\sigma}\right\}, 1 - P\left\{z \leq 3 \times \frac{CPK_p}{1+\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CPK_p}{1+\rho_\sigma}\right\}\right]$
pt_p		$\left[pt_p(1 - \rho_{TP}), pt_p(1 + \rho_{TP})\right]$
mt_{pk}		$\left[mt_{pk}(1 - \rho_{TMI}), mt_{pk}(1 + \rho_{TMI})\right]$
ct_{pk}		$\left[ct_{pk}(1 - \rho_{TCI}), ct_{pk}(1 + \rho_{TCI})\right]$
α_{pk}		$\left[\alpha_{pk}(1 - \rho_{e-I}), \alpha_{pk}(1 + \rho_{e-I})\right]$
β_{pk}		$\left[\beta_{pk}(1 - \rho_{e-II}), \beta_{pk}(1 + \rho_{e-II})\right]$
Misadjustment & Dispersion	fr_{pk}^{MI}	$\left[1 - P\left\{z \leq 3 \times \frac{CP_p}{1-\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CP_p}{1-\rho_\sigma}\right\}, 1 - P\left\{z \leq 3 \times \frac{CP_p}{1+\rho_\sigma} - r_{MI}\right\} + P\left\{z \leq -3 \times \frac{CP_p}{1+\rho_\sigma} - r_{MI}\right\}\right]$
	fr_{pk}^{CI}	$\left[1 - P\left\{z \leq 3 \times \frac{CPK_p}{1-\rho_\sigma}\right\} + P\left\{z \leq -3 \times \frac{CPK_p}{1-\rho_\sigma}\right\}, 1 - P\left\{z \leq 3 \times \frac{CPK_p}{1+\rho_\sigma} - r_{CI}\right\} + P\left\{z \leq -3 \times \frac{CPK_p}{1+\rho_\sigma} - r_{CI}\right\}\right]$

space are superior to (dominate) them when all objectives are simultaneously considered. The literature calls these alternative solutions as Pareto-optimal solutions. Having a set of solutions instead of a single solution provides flexibility for the decision-maker (Mohammadi, Jula, and Tavakkoli-Moghaddam 2017).

Recently, evolutionary algorithms (EAs) have been well applied for solving MOPs (Zhalechian et al. 2016; Asl-Najafi et al. 2015; Zahiri et al. 2014; Mohammadi, Torabi, and Tavakkoli-Moghaddam 2014). EAs have some advantages comparing to traditional mathematical programming approaches. For instance, in the mathematical programming approaches, a real concern is that the functions must be convex/concave and/or continuous, whereas, these are not necessary in EAs (Abbass, Sarker, and Newton 2001). Although EAs are successful in solving MOPs, the proposed algorithms in the literature vary a lot in terms of their solutions and the way of benchmarking them with other existing algorithms. By the other words, there is no unique method for MOPs resulting to a good set of solutions for all problems.

5.1 *Differential evolution (DE) algorithm*

In this paper, we apply a well-known EA called differential evolution (DE) algorithm (Storn and Price 1997; Rahimi et al. 2016) for solving the proposed RBOMILP model. The approach showed promising results when compared with the imperialist competitive algorithm (Mohammadi, Jolai, and Rostami 2011), simulated annealing (Lin and Ying 2015), particle swarm optimisation (Fathi et al. 2016) and genetic algorithm (Mohammadi et al. 2014), for solving the RBOMILP problem. Due to space limitations, this comparison is not included in the paper.

Like other evolutionary computational algorithms, DE involves the evolution of a population of solutions with a size of PS using mutation, crossover and selection operators (Calégari et al. 1999). The initial population is often randomly generated over the variables domain. Each solution vector in the population has to be selected once as the target vector so that totally PS competitions take place in one generation. A new solution vector is generated by the DE's mutation operator, in which the weighted difference between two population vectors is added to the third vector. Hence, this algorithm is named as differential evolution. Note that these three vectors are randomly selected and must be different from the target vector; therefore, PS must be at least 4. Let e_i, $i = 1, \ldots, PS$, be the target vector, a mutated vector is generated according to Equation (51).

$$\mu_i = e_{v1} + F(e_{v2} - e_{v3}), \tag{51}$$

where $v1$, $v2$, and $v3$ are mutually different random indices taking from {1, 2, …, PS}, and are not equal to i. F in Equation (51) is a constant real value ∈ [0, 2], which controls the amplification of the differential variation (i.e. $e_{v2} - e_{v3}$) between the second and third randomly chosen population vectors. Each mutated vector shares its information with a target vector using the crossover operation in order to create new solution $\tau_i = \{\tau_{i1}, \ldots, \tau_{ij}, \ldots, \tau_{iD}\}$ as the condition set (52).

$$\tau_{ij} = \begin{cases} \mu_{ij} \; if \; rand\,(j) \le CR \text{ and } \; j = rnbr(i) \\ e_{ij} \; if \; rand\,(j) > CR \text{ and } \; j \ne rnbr(i) \end{cases}, \tag{52}$$

where rand(j) is the j-th component of a D-dimensional uniform random number ∈ [0, 1] and $rnbr(i)$ is a randomly chosen index ∈ {1, … ,D} to ensure that at least one mutated dimensional value is used in the new created solution.

If the newly created solution dominates the target vector in terms of both objective functions, then the new solution is replaced by the target vector in the next generation. After each generation, the non-dominated solutions are extracted from the population by applying a non-dominance technique (Niakan, Vahdani, and Mohammadi 2015).

5.2 *Non-dominance technique*

Suppose that there are τ objective functions. When the following conditions are satisfied, the solution x_1 dominates another solution x_2. If x_1 and x_2 do not dominate each other, they are placed in the same front.

(1) For all the objective functions, solution x_1 is not worse than another solution x_2.

(2) For at least one of the k objective functions x_1 is exactly better than x_2.

Front number 1 is made by all solutions that are not dominated by any other solutions. This front is called Pareto frontier. Also front number 2 is built by all solutions that are only dominated by solutions in front number 1.

5.3 *Termination criteria*

The algorithm can be terminated with a pre-specified maximum number of generations and/or a pre-specified maximum number of function evaluations. Figure 4 shows the flowchart of the DE algorithm, and Figure 5 illustrates how Taguchi

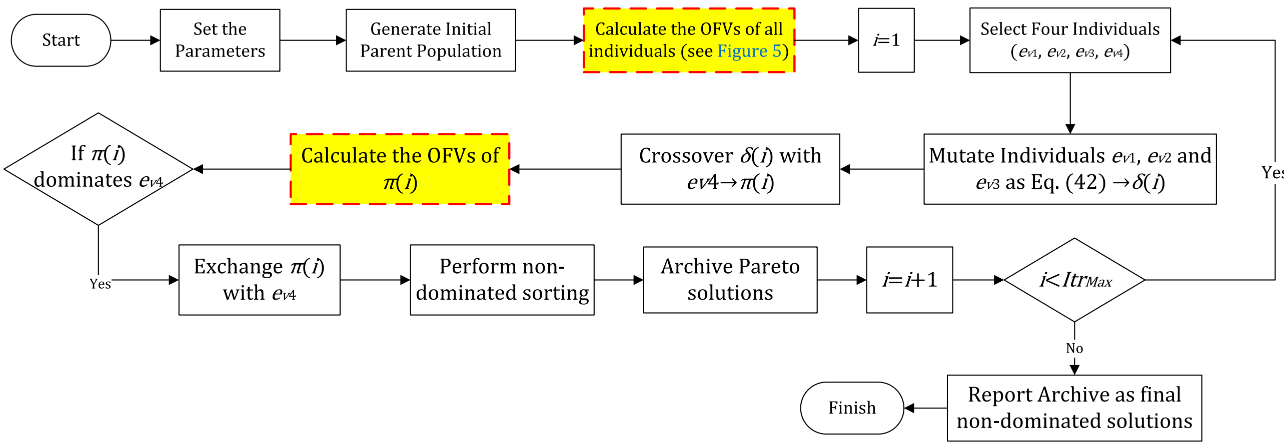

Figure 4. Main flowchart of the DE algorithm.

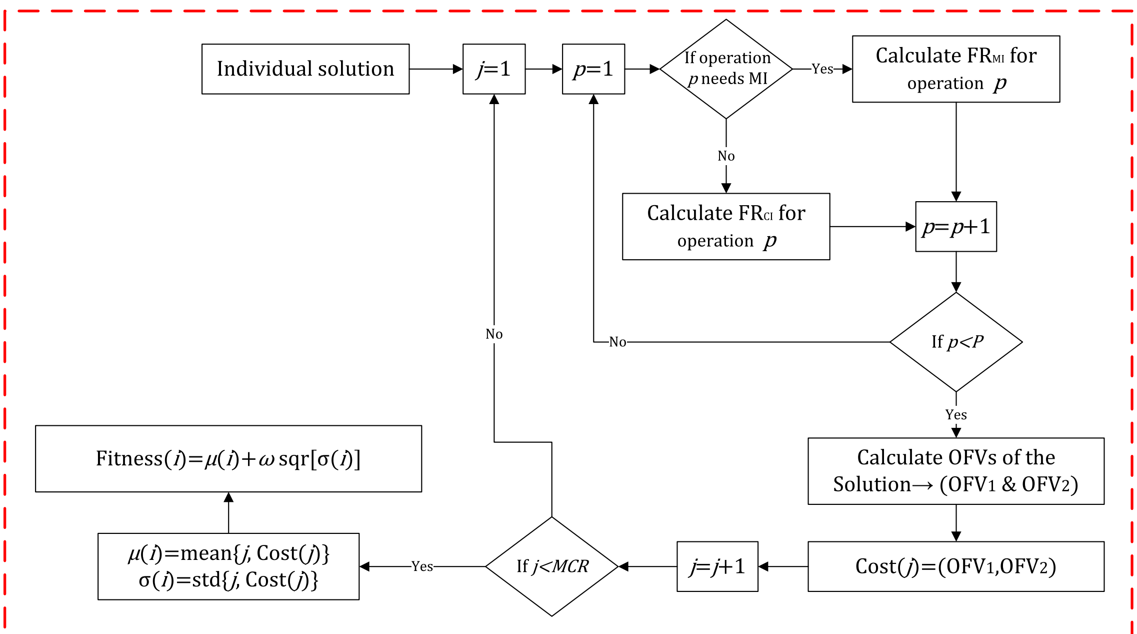

Figure 5. Taguchi and Monte Carlo methods in calculating *OFV*s.

and Monte Carlo methods are applied to take uncertainty of the parameters into account and calculated the robust objective functions.

6. Case study

6.1 *Experiment design*

In order to validate the correctness of the proposed RBOMILP model and the evolutionary solution algorithm, a real industrial case is studied from one of the leading automotive industries in France. This case is a hydraulic pump with 15 quality characteristics. Figures 6 and 7 show the solid frame of the part and labelled quality characteristics which need to be inspected, respectively (Mohammadi et al. 2015). Accordingly, some required deterministic information (i.e. without misadjustment) of the industrial case are tabulated in Table 2, in which the first to sixth columns explain the name of operations, the production time, the process capability C_p, the process performance P_{pk} and the failure rates with and without monitoring inspection, respectively. Finally, the last column shows the allowable places (AP) that the

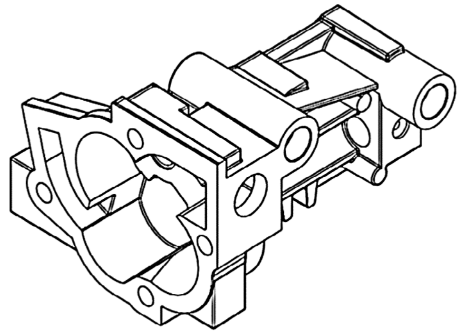

Figure 6. Solid frame of the industrial part.

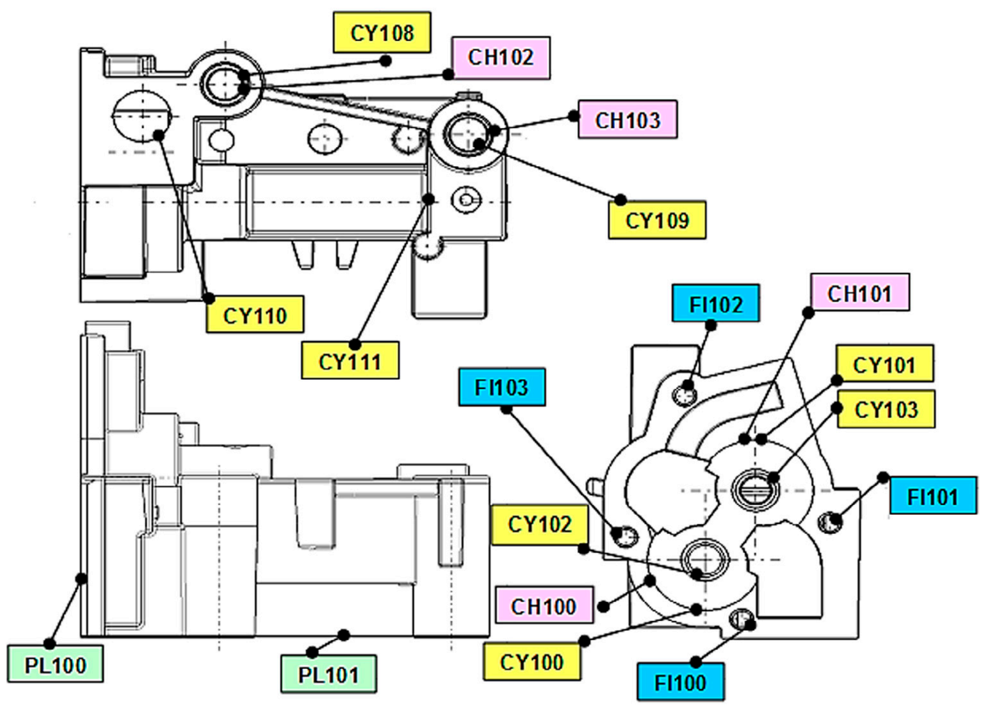

Figure 7. Labelled operations of the industrial part.

Table 2. Information of the industrial case.

Operation number	Operation name	Details					
		PT	C_p	P_{pk}	FR^1	FR^2	*AP*
1	Rough milling PL100	0.148	2.00	1.50	1.97e-9	6.79e-6	1→13
2	Rough milling PL100	0.166	2.00	1.50	1.97e-9	6.79e-6	2→14
3	Rough milling PL101	0.133	2.00	1.66	1.97e-9	6.35e-7	3→15
4	Boring CY110	0.154	1.60	1.33	1.58e-6	6.60e-5	4→10
5	Rough drilling CY108 & CY109	0.090	2.00	1.66	1.97e-9	6.35e-7	5→10
6	Chamfering CY108 & CY109	0.250	2.00	1.66	1.97e-9	6.35e-7	6→6
7	Chamfering CY100 & CY101	0.257	1.50	1.20	6.79e-6	3.18e-4	7→15
8	Boring CY100	0.257	1.50	1.20	6.79e-6	3.18e-4	8→15
9	Boring CY101	0.122	1.66	1.30	6.35e-7	9.61e-5	9→12
10	Rough drilling CY102 & CY103	0.109	1.66	1.40	6.35e-7	2.66e-5	10→12
11	Rough drilling CY111	0.134	1.66	1.40	6.35e-7	2.66e-5	11→15
12	Boring CY108 & CY109	0.122	1.30	1.10	9.61e-5	9.66e-4	12→15
13	Boring CY102 & CY103	0.122	1.30	1.00	9.61e-5	2.69e-3	13→15
14	Boring CY111	0.117	1.66	1.33	6.35e-7	6.60e-5	14→15
15	Finish milling PL100	0.129	1.66	1.33	6.35e-7	6.60e-5	15→15

inspections (i.e. CI and MI) can be performed at. For example, for the characteristic number 4 belonging to the operation 'Boring CY110', MI or CI can be performed only between operations 4 to 10. The DE algorithm is written in MATLAB 2014 and run using a computer with Intel Pentium 4, 2.3 GHz CPU and 4 GB RAM.

6.2 *Computational results*

This section provides the results of the proposed global robust RBOMILP model. After applying the DE algorithm on the data of the hydraulic pump, the Pareto frontier of the RBOMILP model under the MI-and-CI strategy has been provided as Table 3 for both deterministic and uncertain models. In the deterministic model, all the parameters are deterministic and no uncertainty is imposed to the model. In the uncertain model, the parameters are manipulated in their corresponding alteration range as Table 1. In Table 3, the first column shows the number of Pareto solutions. The second and the third columns represent the values of the first and the second objective functions for the deterministic model. Similarly, the fourth and the fifth columns show the values of the first and the second objective functions for the uncertain model. Accordingly, 21 and 6 Pareto solutions were obtained for deterministic and uncertain models, respectively.

The results of Table 3 have been illustrated in Figure 8, wherein dash and solid lines represent the Pareto frontier of the deterministic and the uncertain models, respectively. The inspection plans for different six Pareto solutions of the uncertain model have been depicted in Figure 9. As it can be seen, the solutions with the lower value of the first objective function, e.g. solutions number 5 and 6, represent the inspection plans with less number of MI and CI inspections. The reason is that the total internal cost (i.e. OFV_1) is decreased by reducing the total cost of inspections (i.e. TCI), while the lower the inspection cost, the lower the number of inspection stations during the production process. On the other hand, solutions with the lower values of the warranty cost (i.e. OFV_2) represent those inspection plans wherein the minimum nonconforming parts reach the customers. Accordingly, more numbers of inspections are performed in the inspection plans with lower values of OFV_2. These different plans show the conflict of the total internal cost and the warranty costs and highlight the applicability and validity of the proposed RBOMILP.

Since in the real industrial case, the cost of CI is the same for all the quality characteristics, a quality characteristic undergoes the CI if that characteristic corresponds to an operation with low value of process capability *CP*. Accordingly, the operations with the lowest *CP* undergo CI one by one once the trade-off between two objective functions is met and the global minimum solution is found. The order of the process capability for different operations is $CP_{12} = CP_{13} < CP_7 = CP_8 < CP_4 = CP_9 = CP_{10} = CP_{11} = CP_{14} = CP_{15} < CP_1 = CP_2 = CP_3 = CP_5 = CP_6$. Accordingly, the quality characteristics created by operations number 7, 8, 12 and 13 are more likely to undergo CI in every inspection plan.

Table 3. Pareto solutions of the RBOMILP model under MI-and-CI strategy.

	Deterministic parameters		Uncertain parameters	
Pareto solution #	OFV_1	OFV_2	OFV_1	OFV_2
1	6,077,043	20,900	6,288,260	44,440
2	6,076,760	30,800	5,342,750	322,410
3	6,076,160	32,340	5,219,250	1,649,230
4	6,075,560	55,220	5,130,050	2,328,370
5	5,970,993	142,670	5,029,200	5,473,050
6	5,240,900	165,440	5,014,600	6,467,010
7	5,240,300	166,980	–	–
8	5,185,450	170,060	–	–
9	5,164,850	171,600	–	–
10	5,154,250	179,300	–	–
11	5,143,650	190,740	–	–
12	5,143,050	213,620	–	–
13	5,138,450	302,500	–	–
14	5,097,000	412,830	–	–
15	5,066,400	546,150	–	–
16	5,055,800	877,470	–	–
17	5,054,200	1,357,290	–	–
18	5,039,600	2,351,250	–	–
19	4,964,950	3,630,610	–	–
20	4,929,750	5,561,930	–	–
21	4,910,150	6,555,890	–	–

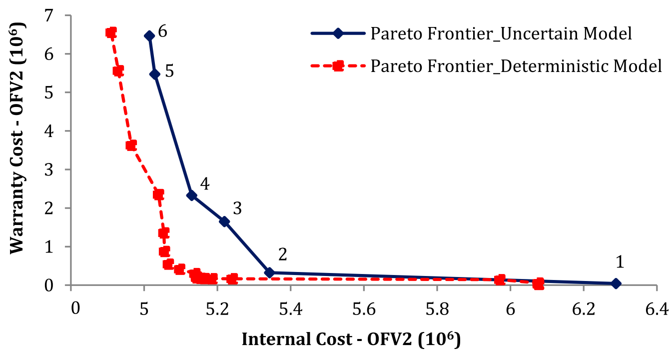

Figure 8. Pareto frontiers for deterministic and uncertain models.

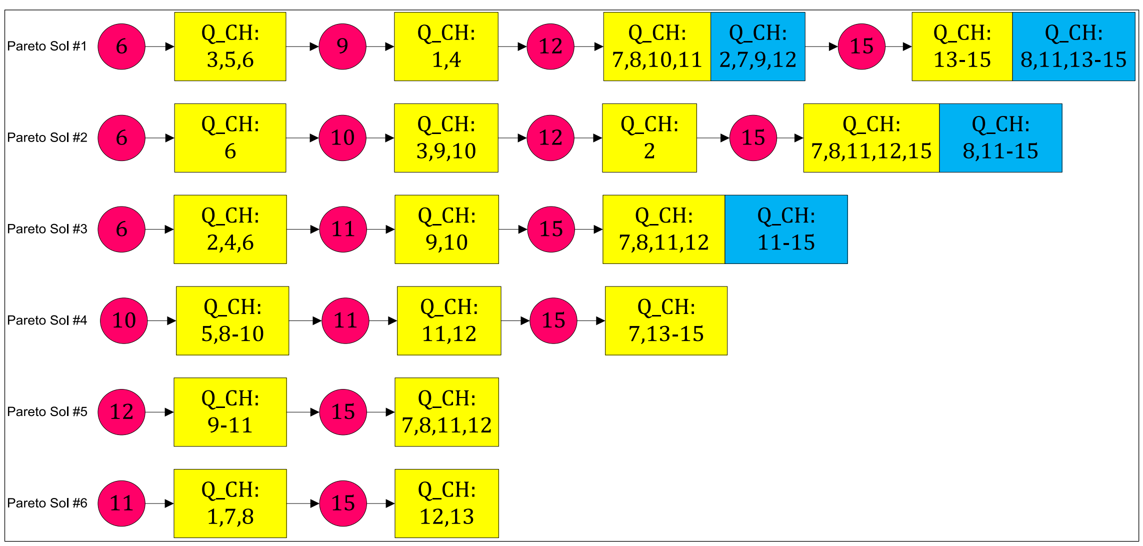

Figure 9. Inspection plans of the Pareto solutions for the robust BMILP_EP.

Through an experiment, the contribution of the uncertain parameters in the increase of the objective functions was investigated to extract those parameters that impose high sensitivity to the objective functions. The result of this experiment has been depicted as Figure 10. As it can be seen, misadjustment and dispersion have the highest contribution on

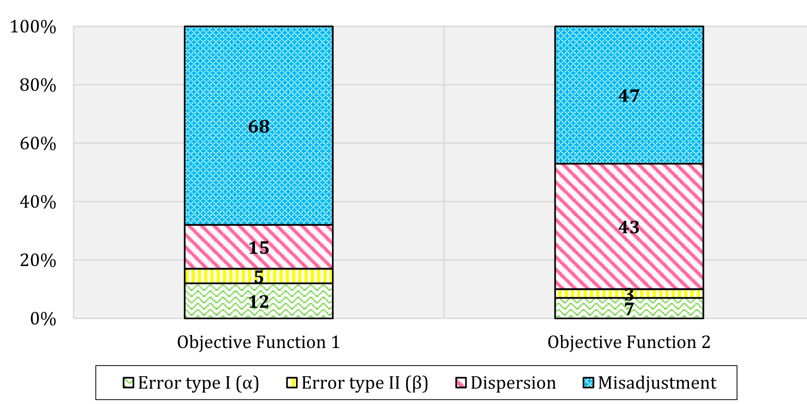

Figure 10. Effect of uncertain parameters on the objective functions.

the objective functions' sensitivity. In addition, misadjustment has higher effect on OFV_1 rather than OFV_2 and vice versa for dispersion. Therefore, the company of producing the hydraulic pump should have better control on the misadjustment if lower level of the internal cost is desired. It has been recommended to this company to limit the alteration and the uncertainty of the misadjustment as much as possible. On the other hand, if increasing the customer satisfaction (i.e. minimum warranty cost) is desired, limiting the variation of the both misadjustment and dispersion is recommended. Adragna, Samper, and Pillet (2010) and Thornton (2004) have also proved the significant impact of misadjustment and dispersion in calculating inertial tolerancing and process capability index.

6.3 *Sensitivity analysis*

Hereafter, the effect of uncertainty in different parameters on *which-what* and *when* decisions are separately investigated. In addition, since the failure rate is affected by both misadjustment and dispersion, the effect of uncertainty in both of these parameters is also examined on the inspection decisions. Finally, a global robust inspection plan is obtained by considering all the parameters under uncertainty. The results are tabulated in Table 4, in which the first to third columns show different sources of uncertainty, the inspection strategy, and the total cost of manufacturing ($\boldsymbol{OFV_1 + OFV_2}$), respectively. The 4th to 10th columns explain the contribution per cent of each component to the total cost of manufacturing. Finally, the last two columns present those quality characteristics that need monitoring and conformity inspection, respectively. It should be noted that the value inserted in the parenthesis corresponds the location where inspection should be performed. For example, for the case of uncertainty in misadjustment under MI-or-CI, quality characteristics 1 to 6 need MI after operation 6, quality characteristics 9 to 11 need MI after operation 11, and quality characteristics 7, 8, and 12 to 15 need CI after operation 15. The first row of each inspection strategy corresponds to the deterministic model, wherein the parameters are deterministic and no alteration is allowed.

According to Table 4, uncertainty in errors type I and II as well as dispersion has no effect on the final inspection decisions while their results are similar to the result of the deterministic model. This issue points out that at the current level of fluctuation intervals of errors type I and II and dispersion, the final decisions are not affected by the imposed uncertainty. In other words, the company does not need to decrease the variation of these parameters more than their current value, while adopting new strategies to limit the variations of errors type I and II and dispersion need a high investment.

Figures 11 and 12 illustrate the warranty (OFV_2) and internal costs (OFV_1) per part for different sources of uncertainty and the both inspection strategies. It is noteworthy that lower values of the internal and warranty costs, respectively, correspond to higher efficiency and higher responsiveness of the production system. Higher efficiency is desired by the manufacturers and higher responsiveness is desired by the customers. By the other words, although manufacturers are interested in more efficient production systems, customers are likely to interact with more responsive production systems. It can be seen from Figures 11 and 12 that the MI-or-CI strategy is more responsive; however, the MI-and-CI strategy is more efficient. In the MI-or-CI strategy, the worst cases in terms of responsiveness and efficiency belong to the situations with no uncertainty and uncertainty in all the parameters, respectively. On the other hand, in the MI-and-CI strategy, the worst cases in terms of responsiveness and efficiency belong to the situations with uncertainty in both misadjustment and dispersion and uncertainty in all the parameters, respectively. Hence, parameter variations and particularly misadjustment has significant effect on the inspection decisions and needs to be precisely determined and their alteration be decreased as much as possible.

In another analysis, the impact of each source of uncertainty (in %) has been illustrated in Figure 13, for both strategies. The maximum increase percentage belongs to a situation in which all parameters are uncertain with increase up to 24% for both strategies. In addition, errors type I and II and dispersion, separately, have no impact on the internal cost in their current values of uncertainty factor in MI-or-CI strategy. It can be also seen that impact of uncertain factors on the internal cost for the MI-and-CI strategy is more than the MI-or-CI strategy in almost all cases. Besides, Figure 14 illustrates the same results as Figure 13 but shows the monetary values of uncertainty. For instance, when all parameters are uncertain and we try to design a robust inspection plan, we need to spend extra 1.340€ and 1.341€ costs for the final price of each product under MI-or-CI and MI-and-CI strategies, respectively.

Additionally, the sensitivity of robustness cost versus alteration in the uncertain parameters is investigated for the MI-or-CI strategy as shown in Figures 15–18. It should be noted that in Figures 15–18, the lower bound of the uncertainty intervals for all parameters are considered equal to their current real value and only the upper bound is changed.

Figure 15 illustrates the effect of alteration of errors type I and II on the cost of robustness. The vertical axis shows the price of robustness per part. The vertical axis determines the increase in the errors type I and II. For instance, the value 7 in the horizontal axis means that the errors become 7 times greater than their mean values. As it can be seen, type I error has no effect on the robustness cost once $\rho_{e-I} \geq 5$, e.g. for $\rho_{e-I} = 9$, the robustness cost is equal to 0.25€ per

Table 4. Detail of cost objective function for different sources of uncertainty.

			Detail Costs (%)							Decisions	
			OFV_1 (% of Total)						OFV_2 (%)		
Source of uncertainty	Strategy	Total ($OFV_1 + OFV_2$)	*TCP*	*TCS*	*TCIF* for CI	*TCIF* for MI	*TCIV* for CI	*TCIV* for MI	*TCW*	MI	CI
Deterministic	MI-or-CI	5,160,250	93.26	0.00	0.00	0.17	0.00	6.10	0.47	1,2,4–6(6) 3,7–10,12(12) 11,13–15(15)	–
Type I error		5,160,250	93.26	0.00	0.00	0.17	0.00	6.10	0.47	1,2,4–6(6) 3,7–10,12(12) 11,13–15(15)	–
Type II error		5,160,250	93.26	0.00	0.00	0.17	0.00	6.10	0.47	1,2,4–6(6) 3,7–10,12(12) 11,13–15(15)	–
Time		5,369,950	89.62	0.00	0.00	0.17	0.00	9.76	0.45	1(2); 3,6(6) 2,4,5,7–10(10) 11–15(15)	–
Misadjustment		6,080,603	79.13	0.04	0.06	0.09	17.20	3.45	0.03	1–6(6) 9–11(11)	7,8,12–15(15)
Dispersion		5,160,250	93.26	0.00	0.00	0.17	0.00	6.10	0.47	1,2,4–6(6) 3,7–10,12(12) 11,13–15(15)	–
Misadjustment & dispersion		6,396,190	75.23	0.04	0.04	0.10	16.35	8.19	0.05	1–3,5,6(6) 9,10(10)	4,7,8,11–15 (15)
All parameters		6,500,003	74.03	0.04	0.06	0.08	16.09	9.68	0.03	1(1); 2–4(7) 5,6(6); 9–11(10)	7,8,12–15(15)
Deterministic	MI-and-CI	5,068,120	94.96	0.00	0.00	0.14	0.00	4.14	0.76	1,3,4,7–10(10) 11–15(15)	–
Type I error		5,079,900	94.74	0.00	0.00	0.12	0.00	4.13	1.02	1,3,4,7–10(10) 11–15(15)	–
Type II error		5,069,060	94.94	0.00	0.00	0.13	0.00	4.14	0.79	1,3,4,7–10(10) 11–15(15)	–
Time		5,173,170	93.03	0.00	0.00	0.09	0.00	6.08	0.80	4(6) 7–9(12) 12–15(15)	–
Misadjustment		6,000,253	80.19	0.04	0.07	0.03	17.43	1.75	0.49	4,9,10(10)	7,8,11–15(15)
Dispersion		5,079,900	94.74	0.00	0.00	0.12	0.00	4.13	1.02	1,3,4,7–10(10) 11–15(15)	–
Misadjustment & dispersion		6,253,453	76.95	0.04	0.05	0.06	16.72	5.03	1.15	3,4,6(6); 9(9) 10,11(11)	7,8,12–15(15)
All parameters		6,409,190	75.08	0.04	0.05	0.06	16.32	8.18	0.29	2(2); 4,9(9) 10,11(12); 7 (15)	8,12–15(15)

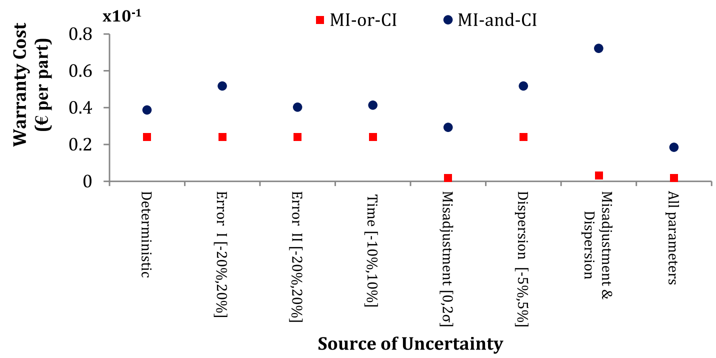

Figure 11. Warranty cost vs. different source of uncertainty.

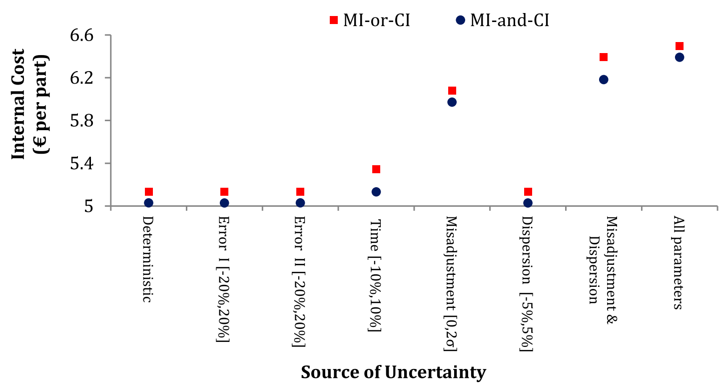

Figure 12. Internal cost vs. different source of uncertainty.

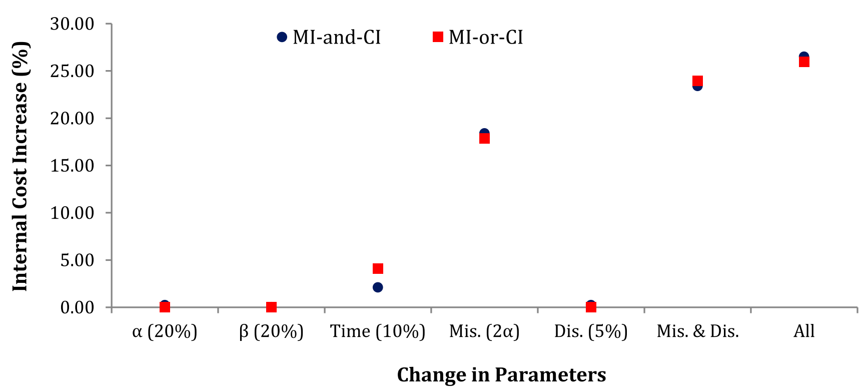

Figure 13. Internal cost increase vs. different source of uncertainty.

part. Despite error type I, error type II has no effect even for $\rho_{e-II} \cong 15$. Therefore, it can be concluded that the manufacturer should pay more attention to error type I rather than error type II. Since ρ_{e-I} is equal to 0.2 in the industrial case, the ρ_{e-I} is allowed to be altered and increased even up to 5 with no increase in the internal cost. On the other words, by increasing error type I, the inspection plan remains robust. On the other hand, the inspection plan remains robust when error type II becomes even 15 times greater.

Figure 16 depicts the alteration in the robustness cost versus increase in the production time's uncertainty factor. The vertical axis shows the increase percentage in the production time. It is noteworthy that by increasing the uncertainty factor of the production time (ρ_{TP}) from 0 to 0.4, the *which-what* decision does not change and all quality characteristics need MI; while for values bigger than 0.4, the *which-what* decision is changed as some quality characteristics

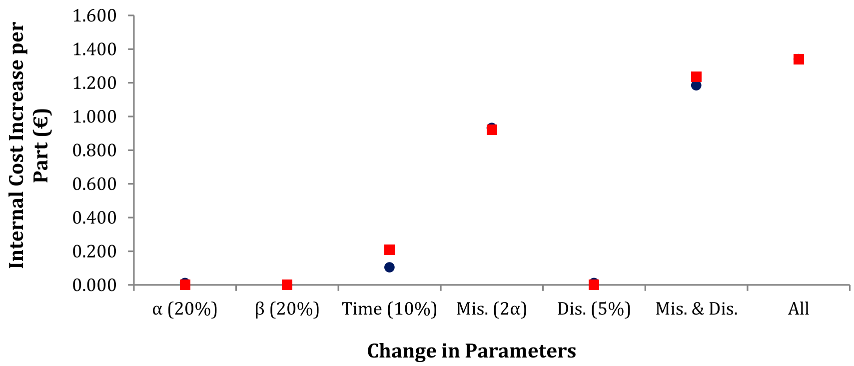

Figure 14. Price increase per part vs. different source of uncertainty.

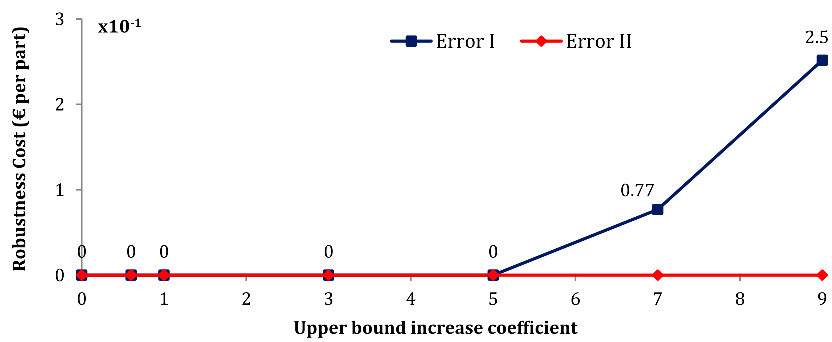

Figure 15. Cost of robustness vs. increase in ρ_{e-I} and ρ_{e-II}.

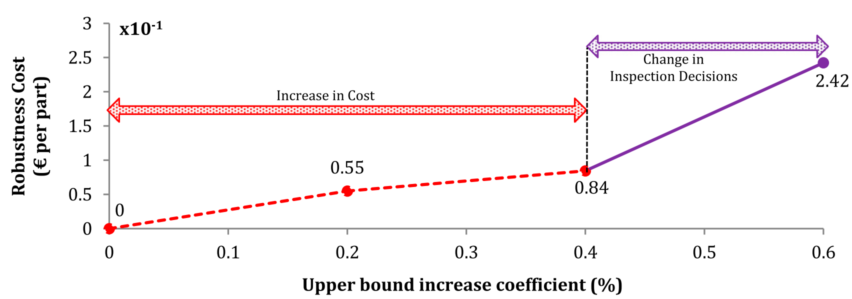

Figure 16. Cost of robustness vs. increase in the production time.

need CI. It can be stated that for values higher than 0.4, the costs of production and inspection are highly increased and the model decides to remove more nonconforming parts from the process to avoid unnecessary operations on these parts. Consequently, the costs of production and inspection are decreased and the way to remove the nonconforming parts is to perform CI during the process. Therefore, for the values of ρ_{TP} higher than 0.4, the model decides to perform CI for some of quality characteristics.

Figure 17 shows the effect of alteration in the misadjustment on the robustness cost, so that by increasing the misadjustment, the cost of creating a robust plan is extremely increased. It is noteworthy that the value of misadjustment can be increased up to 0.25σ with no increase in the robustness cost. Finally, Figure 18 illustrates the impact of increase in dispersion on the cost of robustness. As it is obvious, for the values of ρ_σ lower than 0.1, the robust plan is not changed. Since decreasing dispersion in the manufacturing processes is too expensive, hence, in the real industrial case, the company can let dispersion to alter up to 0.1.

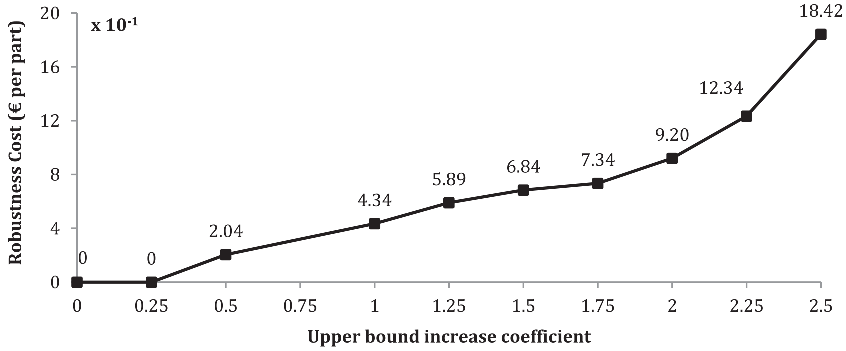

Figure 17. Cost of robustness vs. increase in the misadjustment.

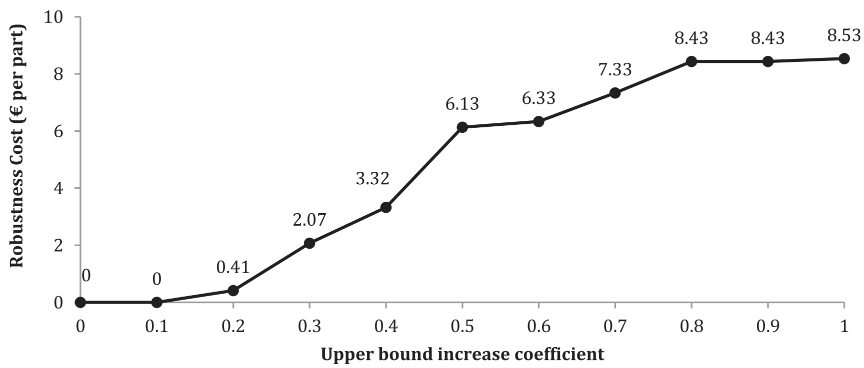

Figure 18. Cost of robustness vs. increase in the dispersion.

7. Conclusion

This paper integrates the inspection plan with a MPS to simultaneously pick out the critical quality characteristics and to determine the type and the location of the inspections where the planning parameters are uncertain. For this aim, a new robust bi-objective mixed integer linear programming (RBOMILP) model was developed with a trade-off between the production cost and the customer satisfaction as the two conflicting objective functions. The proposed RBOMILP model decides (1) *which* quality characteristics needed *what* kind of inspection and (2) *when* the inspection of these characteristics should be performed. Through the inspection plan, quality characteristics undergo two kinds of inspection as monitoring and conformity inspections. Uncertain parameters include production and inspection times, errors type I and II, misadjustment and dispersion of the operations. To cope with the uncertainty of the parameters, a robust optimisation approach based on the Taguchi and the Monte Carlo methods were developed. The proposed model and the solution approach were validated through a real industrial case study from one of the leading automotive industries in France. Finally, the sensitivity of the objective functions to the uncertain parameters was investigated to draw valuable managerial insights. It was resulted the misadjustment had the most effect on the final decisions. On the other hand, since eliminating the source of uncertainty is expensive, a maximum threshold for each parameter was extracted that allows a level of uncertainty in the parameters. It is our hope that this study could inspire additional in-depth research and discussions on this topic.

Considering the total production time of the parts as the third objective function and making trade-off between the production costs, the production time and the customer satisfaction may lead to interesting knowledge about the problem. On the other hand, taking into account the failure rate of the equipment and investigating the effect of breakdown on the production time objective function could be another further research direction. Finally, proposing the inspection plan for a multi-product manufacturing system could be an interesting perspective on this topic.

Disclosure statement

No potential conflict of interest was reported by the authors.

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