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ScienceDirect

Procedia Manufacturing 38 (2019) 1600–1607

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2019), June 24-28, 2019, Limerick, Ireland.

Integrating quality costs and real time data to define quality control

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Abstract

The control of critical to quality (CTQ) parameters can be done in a given process or in a downstream process. Companies must decide which CTQ parameters will be controlled, in which process, and define the control method: statistical process control (SPC) or 100% inspection. However, operational constraints can influence its definition. Overall, the control for a given process can be excessive or insufficient, resulting in a non-optimal quality cost. This paper discusses the relevance of different factors that can influence the selection of a quality control method. Then, it assesses the likelihood of companies having reliable data on such factors and it is proposed a model to minimize the total quality costs of a given process. The model uses information like SPC efficiency in detecting potential process variations, false alarms, measurement system error, inspection cost, repair cost and the cost of passing defective units to the next process. The quality control method can be updated whenever recent data on the 18 parameters are available. Through an application example, quality control mechanisms are selected to minimize quality costs.

Keywords: Industry 4.0; process quality planning; quality costs; real-time data; statistical process control.

1. Introduction

To be competitive, manufacturing companies control processes to avoid producing and delivering defective units. "For this reason, more attention has been paid by operations managers and academics to the design of quality

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10.1016/j.promfg.2020.01.125

assurance strategies, acceptance sampling plans and inspection allocation problems" [1]. To develop quality assurance strategies, models and methodologies have been proposed to minimize the total costs of quality [1-8]. Quality costs can be organized into three categories: prevention costs, appraisal costs and failure costs [2]. The cost of quality is of more strategic and economic importance than previously conceived [9].

The definition of quality costs categories is the basis for the development of quality cost programs [3]. The basic assumption is that there is a minimum value (optimal) of total quality costs. Generally, an increase in prevention costs would result in a decrease in failure costs. However, there is not a consensus on the relation between cost categories [5] and, consequently, in the way of achieving that optimum minimum [7, 10].

Quality control involves two steps: (i) inspecting CTQ characteristics and (ii) when the process is out of control or the units are out of specifications acting on the process to put it stable and/or repairing/separating defective units. Much research has been made in the use of statistical process control (SPC) that define SPC parameters considering required quality levels and chart efficiency. Chart efficiency is typically assessed through the average run length (ARL) of the number of samples required to detect potential process variations. Other indices such as the process capability or the risk of providing false warnings (type I error) are also relevant.

The control of CTQ characteristics can be done in a given process or in a downstream process. The longer time to detect defects results in greater quality costs [11]. Companies must decide (within process quality planning activities) which CTQ variables will be controlled and define the control method. Control can range from 100% of produced units to a sample corresponding to a fraction of the production volume. To identify the optimal control solution under different scenarios, several authors have proposed different approaches:

- Oppermann et al. [12] developed a mathematical model to cope with the peculiarities with the inspection and repair processes, but do not model measurement system error or proportion of repairable defects;
- Abdul-Kader et al. [13] proposed a model to optimize the cost of reworking/scrapping, but the model is only adequate for one variable normally distributed;
- Shetwan et al. [14] used a heuristic to allocate control stations to manufacturing systems, but only consider as alternatives no control or 100% inspection and also includes production costs, adding (unnecessary) model complexity;
- Lari and Asllani [15] proposed a management system that associate quality costs to operational processes to measure overall organizational performance, but it is based on a single case study and requires much effort from employees;
- Lim et al. [7] used mixed integer linear programming applicable to a prevention-appraisal-failure framework, but do not model measurement systems errors and the model has parameters that can be difficult to estimate;
- Zhu et al. [16] used Markov chain method to find optimal inspection policies for the multi-station manufacturing system (MMS) subjected to quality shifts to minimize total quality-related cost, but only consider as alternatives attribute control charts;
- Farooq et al. [10] proposed an inspection strategy based on estimated quality costs, but the model is developed for specific conditions such as equal batch sizes throughout the year, the cost of a unit is very small and rework is never performed.

These approaches require reliable data and/or expert classification regarding the inspection process, the proportion of defective units, cost of inspection, cost of repair, inspection/SPC effectiveness. Nevertheless, either because the models are complex, or inadequate or simply difficult to apply in reality, there is "hardly any assent to the implementation of formal mechanisms for planning and control of quality related costs, and to the explicit identification and segregation of those costs in management reports" [6]. It can be concluded that there is a need to develop more effective and cost management mechanisms of quality control [8].

Considering technological evolution, availability of sensors, and powerful information and communications' systems, in industry 4.0 era, companies may decide to increase the number of processes or product variables monitored, by putting in place systems to acquire and manage data, and thus it can be discussed which data is relevant to collect and use to efficiently control processes at minimum cost. Overall, the planned control for a given process can be excessive or insufficient [2] resulting in a quality cost bigger than optimal.

This paper's objective is to develop a model to select the control strategy that minimizes quality costs. It studies the relevance of different factors that can influence the selection of a control/inspection method, considering the effectiveness of the control procedure and the costs associated with inspecting, unplanned inspection, repair, delivering defective units, scrap and not delivering units.

The relevance of this study, for research in the context of industry 4.0 and quality management, evidences companies' internal context factors when designing and updating quality control plans. This study, for practitioners, can contribute to companies' adoption of new strategies of quality control that minimize quality costs.

The remaining of this paper is organized as follows. Section 2 determines the appraisal and failure costs associated with three quality control strategies and describes its related factors. Afterward, a discussion is made on the accuracy of data required to calculate the costs, followed by the methodology to determine the optimal quality control strategy. The paper ends with an application example and conclusions.

Nomenclature

ARL	average run length for a typical shift in process mean (used in SPC strategy)
Ci	estimated average unitary inspection cost
Cir	estimated average unitary re-inspecting cost
Co	estimated average unitary cost of not delivering a unit according to plan/customer order
Cn	estimated average cost of passing a defective unit to the next process
Cr	estimated average cost of repairing a defective unit
Cs	estimated average cost of scrap (can be negative if the product has positive value)
f	estimated frequency of inspection (proportion of inspected *vs* produced, used in SPC strategy)
Fd	estimated proportion of false defectives given by the measurement system
Fn	estimated proportion of false non-defectives given by the measurement system
L	control limits distance from central line (in standard deviations) in $\bar{X}$ chart (used in SPC strategy)
n	sample size (used in SPC strategy)
Ni	number of inspected units in a period T (100% inspection)
Np	number of produced units in a period T
Dc	estimated proportion of defective units in a controlled process
Du	estimated proportion of defective units when assignable causes are present in the process
Ps	estimated probability of a controlled process become un-controlled in a period T
Pw	estimated probability of a controlled process providing a false warning
R	estimated proportion of defective units repairable

2. Quality cost in control strategies

There is a variety of manufacturing systems and products and the definition of system's variables must be tailored to its specific context. In specific manufacturing systems there are details, that, to be analyzed, may require the definition of more variables, making the resulting model more close to reality but also more complex.

In this work, a general scenario of a manufacturing system is discussed: a production line with sequential processes that manufacture batches of individual products. In some of those processes, there is a viable solution and a control station, to carry on inspection of a CTQ variable or to statistically control that process. Each control can reduce the likelihood of certain defects pass to the next process but each one increases appraisal costs. When a defective product is found, it is extracted from the production line for scrap or it is repaired and returned to the production line.

It is usual to do a preliminary analysis of process capability of CTQ variables, before manufacturing a product. At the stage of process quality planning, the control strategy must be defined. In general, three types of control strategies can be considered: No inspection; 100% inspection; and sampling inspection, typically using SPC techniques.

To contribute to company competitiveness, the control strategy should minimize inspection and failure costs. The costs depend on factors such as process capability, SPC efficiency in detecting potential process variations, false alarms, inspection cost, repair cost, the proportion of repairable defects, cost of defective units passing to the next process.

2.1. No Inspection

Knowing that a CTQ variable has a capacity gap, it may be decided not controlling it for a given period of time. In this case, there are no inspection costs. The cost associated with this strategy is the cost of sending defective units to the next process. Assuming the process is stable the failure cost is $Np \times Cn \times Dc$.

To represent a situation where the process proportion of defective output varies when the process is out of control, let *Ps* be the estimated probability of having a process shift of magnitude *delta* that would result in a new proportion of defective units (*Du*). It is assumed that these events are rare and are not expected more than one in a period T (e.g. one week). The quality cost can be determined by eq. 1, where Du*Ps+Dc*(1-Ps) represents the average proportion of defective units (*Pd*).

$$C_1 = Np \times Cn\big(Du \times Ps + Dc(1 - Ps)\big) \tag{1}$$

2.2. 100% inspection

In this case, one variable is measured at 100% (i.e. all the units produced). Whenever defective units are identified, if possible and economically feasible, an action to repair it can be made. Alternatively, the unit can go to scrap or sent defective to the customer. According to Teixeira et al. [11], it is cheaper to fix a problem at the source than in subsequent processes, the worst case being when the end customer detects the problem.

Assuming that a fraction of defective units is repairable, the cost of adopting this strategy is depends of Ni*Ci (inspection cost of Ni units), Np*Pd* R*Cr (repair cost of repairable defective units), Np*Pd*(1-R)*Min(Co, Cn) (cost of not delivering or delivering defective units), and Np*Pd*(1-R)*Cs (cost of scrap for the proportion of un-repairable defective units).

Any measurement/inspection system has an intrinsic error [17]. The error may be relevant (a unit within the specifications may be considered out of specification or an out-of-spec unit may be considered OK), resulting in false defectives (type I error) or incorrect classification of good units (type II error), respectively. In some scenarios, the measurement procedure can determine the repetition of the measurement, resulting in Ni>=Np. The cost of using 100% inspection, considering the measurement error is expressed by eq. 2, where, Ni*Ci is the cost of 100% inspection, Np*Fn*Cn is the cost of passing defective units to the next process, Np*max(0,Pd-Fn+Fd)*R*Cr is the cost of repair, Np*Max(0,Pd-Fn+Fd)*(1-R)*Min(Co, Cn) is the cost of not delivering units or delivering defective units, and Np*Max(0,Pd-Fn+Fd)*(1-R)*Cs is the cost of scrap.

$$C_2 = Ni \times Ci + Np \times Fn \times Cn + Np \times Max(0, Pd - Fn + Fd) \times R \times Cr + Np \times Max(0, Pd - Fn + Fd) \times (1 - R) \times Min(Co, Cn) + Np \times Max(0, Pd - Fn + Fd) \times (1 - R) \times Cs \tag{2}$$

2.3. Statistical Process Control

The control aims to reduce variability in process output. To do this, it monitors the output of a process allowing the identification of excessive variability compared to predefined limits. When such a variation reaches a certain value, it is necessary to act on the process to reduce its variability to acceptable levels. In this work, the costs of acting in the process will be considered zero.

In a stable process, it is assumed that the process capability and the proportion of defective units are acceptable. In six sigma projects, when calculating the process sigma-level, it is considered that stable processes can, over time, exhibit change in the process mean until 1.5 standard deviations [18]. When such deviations are identified, the proportion of defectives may increase, an inspection to the recent production is made. Thus, let us assume the company has a procedure that, when detects a point is out of control limits, inspects the recently produced ARL*n/f units. In this case, the proportion of defective units will be separated to be repaired (repairable units) or scrapped.

After defining the CTQ variable to be controlled through SPC, the measurement process and type of control chart to be used (with associated type I and type II errors), it is necessary to define sample size (n) and estimated frequency of inspection *(f)*. The increase of n or f reduces the type II error and increases chart effectiveness, but also increase the sampling costs. The quality cost (appraisal plus failures), can be characterized in three situations: (i) process is stable without influence of assignable causes; (ii) process suffers changes from an assignable cause; and (iii) process is stable but the chart indicates a false warning.

When the process is stable and predictable, *Dc* depends on the process capability value. The costs associated with using SPC are Ci*Np*f (sampling costs) and Cn*Dc*Np (the cost of delivering defective units). The expected cost of passing defective units to the next process is represented by eq. 3. The expected value of units to be 100% inspected is Ps*ARL*n/f and its percentage of defective units (*Dc*) will not pass directly to the next process. Thus, eq. 4 includes the fact that some units will be repaired in period T.

$$C_3 = Np \times f \times Ci + (Np - Ps \times ARL \times n/f)Dc \times Cn \quad (3)$$

The expected costs associated with an assignable cause are given by eq. 4, where, ARL*n/f is the average units inspected 100% due to out of control point in a control chart, Cir*ARL*n/f is the cost of inspection 100% the units likely to be produced under unstable process, Cr*Du *ARL*n/f *R represents repair costs, Min(Cn, Co)*Du*ARL*n/f*(1-R) is the minimum cost between delivering defective units or not delivering planned units and Cs*ARL*n/f*(1-R)*Du is the cost of scrap.

$$C_4 = Ps\left(Cir\frac{n}{f}ARL + Cr \times Du \times R\frac{n}{f}ARL + \mathrm{Min}(Cn, Co)\,Du \times (1-R)\frac{n}{f}ARL + Cs(1-R)Du\frac{n}{f}ARL\right) \quad (4)$$

The cost associated with a false warning (eq. 5) is similar to the cost of an assignable cause (see eq. 4), except that the proportion of defective units is not changed. In a period T, assuming that no more than one process shift occurs, and no more than one false warning occurs, the expected quality cost of using SPC is given by eq. 6.

$$C_5 = Pw\left(Cir\frac{n}{f}ARL + Cr \times Dc \times ARL\frac{n}{f}R + Min(Cn, Co)\,Dc \times (1-R)\frac{n}{f}ARL + Dc(1-R)\frac{n}{f}ARL \times Cs\right) \quad (5)$$

$$C_6 = C_3 + C_4 + C_5 \quad (6)$$

3. Data quality and cost

Each parameter described needs to be estimated to be used in the model to quantify quality costs, allowing to identify the control strategy with lower cost. The use of this model can contribute to organizational learning since the estimation of the model's input variables is recorded and updated, acting as Organizational Memory (the strength and intensity that organizations' members can pass on their knowledge in the form written documents) [19].

Each variable will be discussed focusing on its estimated accuracy, since using the model with low accuracy values can present misleading results [20], increasing the risk of not selecting the optimal control strategy [21]. Accuracy is one attribute of information quality (like the origin, granularity, collection frequency and actuality, and consistency) that influences data quality [22]. Accuracy is defined as the closeness between a value *v* and a *w*, considered as the correct representation of the real-life phenomenon that the value *w* aims to represent [23]. Thus, the errors associated with the measurement system and the uncertainty associated with the estimated values of process variables influence the accuracy of results.

Table 1 presents a discussion on the accuracy of the factors used to determine the quality costs in the previous section. Overall, it seems that through experts' opinion, historical data and calculations based on probability distributions, the proposed factors can be used in the model to provide the minimum cost solution. Furthermore, if new aggregated data on quality costs contradicts model outputs, it means model parameters should be updated to better represent reality.

Table 1. Discussion on model variables accuracy.

Variable	Discussion on accuracy
Ci	This cost can be estimated based on the average time of inspection and the average cost of materials/equipment usage. These can be estimated with historical data, typically available in the company.
Cir	It can be estimated based on the average time of inspection and the average cost of materials/equipment usage. These can be estimated with historical data, typically available in the company. This cost can be greater than Ci, because it corresponds to unplanned work, may use overtime, can cause delays in production, etc.
Co	This cost is defined in contracts or estimated/updated based on historical data.
Cn	This factor can be estimated based historical data or expert opinion. It depends on: the probability of having defective units at the customer; the probability of sending defective units to the next process; the cost of repairing defective units after sending defective units to the next process; and the consequences of arriving defective products to the customer (can be defined in customer contracts and historical data of costs related with defective units based on similar products and customers).
Cr	It depends on the average time of repair, the average cost of materials and equipment usage. It can be estimated with historical data, typically available in the company.
Fd	For calibrated equipment there is a maximum error under specific conditions of measurement. Based on the probability distribution of products it can be estimated the proportion of false defectives. For non-calibrated equipment, R&R studies can be made to estimate the precision of the measurement system and obtain an estimation of the measurement error.
Fn	Similar to Fd. A company can define product specifications tighter than initial customer specifications so that errors are forced in one side of the specification. This can make Fd increase while reducing Fn.
Ni	This variable may be influenced by measurement failures that impede new measurements or that cause repetition of measurements. It can also be affected by delays between the time of the measurement and the time when data is available.
Np	The location in the process sequence where the measurement is made may influence this value. Planned work orders may be influenced by unexpected changes on the shop floor. This data is available in the company's information system.
Pd	Du*Ps+Dc*(1-Ps). If reality does not confirm this result, Du, Dc and/or Ps should be updated.
Dc	This factor can be estimated based on historical data for similar components and similar specification tolerances.
Du	It can be estimated based on historical data for similar components and similar specification tolerances. For new products and processes, process capability studies allow estimating this probability.
Ps	This factor can be estimated based historical data or Expert's opinion.
Pw	This factor can be estimated based control chart characteristics.
R	This factor is based on the proportion of different defects types and each one's reparability.

4. Methodology to determine optimal Quality control Strategy

This section proposes a methodology to minimize the quality (appraisal plus failures) costs of a given process, based on different control strategies. For each potential inspection/control station that can monitor/control a CTQ variable, the following method can be defined:

1. Estimate/update variables: Np, Ni, Ci, Cir, Dc, Du, Cn, Cr, Co, R, Fd, Fn, Ps, Pw, Cs, n, f, ARL, and L.
2. Calculate the cost of 0% inspection: use eq. 1
3. Calculate the cost of 100% inspection: use eq. 2
4. Calculate the cost of SPC: use eq. 6
5. Select the control strategy with lower cost: Min (C1, C2, C6).

The method consists of, based on estimated and updated process variables, selecting the control strategy with minimum cost. It determines the absolute costs of appraisal and failure for a given scenario among studied control strategies. This can be done before mass production and can be updated whenever recent data on parameters is available. Thus, assuming that the industry 4.0 context provides more data on process variables, the quality control method can use that data in real time to select the control method with minimum cost.

5. Application Example

An application example demonstrates the applicability of this method based on a real manufacturing system. The product considered in this application is part of the vehicle induction braking system, also known as electromagnetic retarder, is obtained by cutting sheet metal undergoing various machining operations. It has to fulfil a set of dimensional and surface finish requirements, among others. Considering a CTQ dimension as described in [24], the process that does one drill in one component may or not be controlled for that dimension, before sending it for the next operation. Based on pre-production capability studies and on experts' opinion, the estimation of process variables used in the proposed model is presented in Table 2, Line 1. By acknowledging that changes in process values would result in different values of cost and consequently to different control solutions to minimize quality costs, several scenarios are presented. Each line represents a scenario i.e. an update to one or two variables, as the system where the process belongs is dynamic. These changes compared to values of scenario 1 are in bold. For example, in scenario 6, column Ci represents the new value of Ci if a new measurement system is adopted.

Table 2. Process variables estimation for different scenarios.

Scenario	Np	Ni	Ci	Cir	Dc	Du	Cn	Cr	Co	R	Fd	Fn	*Ps*	Cs	n	f	ARL	L
1	250	270	0.07	0.14	0.8%	10%	20	1	10	90%	1.0%	0.5%	0.1	-2	4	20%	3.2	3
2	250	270	0.07	0.14	**2.0%**	10%	20	1	10	90%	1.0%	0.5%	0.1	-2	4	20%	3.2	3
3	250	270	0.07	0.14	0.8%	10%	20	1	10	90%	1.0%	0.5%	**0.5**	-2	4	20%	3.2	3
4	250	270	0.07	0.14	0.8%	10%	**90**	1	**50**	90%	1.0%	0.5%	0.1	-2	4	20%	3.2	3
5	250	270	0.07	0.14	**0.2%**	**1%**	20	1	10	90%	1.0%	0.5%	0.1	-2	4	20%	3.2	3
6	250	270	**0.01**	0.02	0.8%	10%	20	1	10	90%	1.0%	0.5%	0.1	-2	4	20%	3.2	3

Table 3 presents the expected cost of each control strategy considering the process variables. The minimum cost solution is in bold. For scenario 1 the best control strategy is SPC, however, just by changing *Dc* from 0.8% to 2% (scenario 2) the best strategy becomes 100% inspection. This would be expected since the 100% inspection has one procedure in place to repair repairable units. With a greater proportion of defectives units, would be costlier to send defective parts either without inspection or just by using SPC, which is not an adequate solution for processes with low capability. If the proportion of defective units is smaller (e.g. scenario 5), the least expensive solution would be no control strategy. These examples support [25] findings that in manufacturing companies, higher levels of quality are associated with lower quality cost. The remaining scenarios show additional examples of model application.

Table 3. Expected cost (and gain compared to worst control strategy) for each control strategy *vs* scenario.

Control strategy	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
No inspection	86.0 (0.0%)	140.0 (0.0%)	270.0 (0.0%)	387.0 (0.0%)	**14.0 (70.3%)**	86.0 (0.0%)
100% inspection	53.3 (38.0%)	**57.9 (58.6%)**	69.0 (74.5%)	**163.0 (57.9%)**	47.2 (0.0%)	**37.1 (56.9%)**
SPC	**44.3 (48.5%)**	102.8 (26.6%)	**46.0 (83.0%)**	183.3 (52.6%)	14.5 (69.3%)	40.2 (53.3%)

6. Conclusions

The model developed represents reality on the selection of a control strategy of a given process, determining the quality cost solution considering: (i) measurement system error, when measuring/classifying units; (ii) SPC effectiveness in detecting assignable causes; (iii) SPC false alarms; (iv) fraction of repairable defective units; (v) units are repaired in the 100% inspection and in SPC (if an assignable cause is detected, the last units likely produced when the process became out of control are inspected and potentially repaired) (vi) different costs of inspection can be defined for planned inspection *vs* unplanned inspection; and (vii) different costs for defective units can be defined (delivering the defective unit or not delivering the unit, cost of repair and cost of scrap).

The use of this model can contribute to the development of a cost management mechanism based on quality costs, bridging a gap between theory and practice, as reported by [6] and [8].

The proposed model determines the sum of appraisal and failure costs for each control process analyzed. Thus, by determining shop-floor quality costs facilitates the deployment of quality cost programs, which is an opportunity few companies use [6]. This model also allows capturing knowledge that workers may have about possibility of defects contributing to organizational memory, one feature of organizational learning [26].

As future research directions, sensitivity analysis could be performed to ascertain the solution robustness. To provide more insights into the manufacturing system, for each control alternative, the expected number of defectives units can be determined. Case studies in different contexts could be done to validate or refute the proposed model.

Acknowledgements

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2019.

References

[1] D. Battini, M. Faccio, A. Persona, F. Sgarbossa, Design of an integrated quality assurance strategy in production systems, International Journal of Production Research, 50 (2012) 1682-1701.
[2] J. Juran, A. B. Godfrey, Quality handbook, (1999) McGraw-Hill.
[3] J. Campanella, Principles of quality costs: Principles, implementation, and use, (1999) American Society for Quality.
[4] C. C. Yang, Improving the definition and quantification of quality costs. Total Quality Management, 19, (2008) 175-191.
[5] Q. Su, J. Shi, S. Lai, Research on the trade-off relationship within quality costs: A case study, Total Quality Management & Business Excellence, 20 (2009) 1395-1405.
[6] A. R. Pires, A. Cociorva, M. Saraiva, J. Novas, Á. Rosa, Management of quality-related costs. The case of Portuguese companies, Total Quality Management & Business Excellence, 24 (2013) 782-796.
[7] C. Lim, H. Sherali, T. Glickman, Cost-of-quality optimization via zero-one polynomial programming. IIE Trans., 47(3), (2015) 258-273.
[8] A. V. Gorbunova, O. N. Maximova, V. A. Ekova, Developing methods of controlling quality costs. In SHS Web of Conferences 35, (2017) EDP Sciences.
[9] K. K. Castillo-Villar, N. R. Smith, J. L. Simonton, A model for supply chain design considering the cost of quality, Applied Mathematical Modelling, 36 (2012) 5920-5935.
[10] M. A. Farooq, R. Kirchain, H. Novoa, A. Araujo, Cost of quality: Evaluating cost-quality trade-offs for inspection strategies of manufacturing processes, International Journal of Production Economics, 188 (2017) 156-166.
[11] H. Teixeira, I. Lopes, S. Sousa, Prioritizing quality problems in SMEs: a methodology, The TQM Journal, 27 (2015) 2-21.
[12] M. Oppermann, W. Sauer, H. Wohlrabe, T. Zerna, New quality cost models to optimize inspection strategies. IEEE Transactions on Electronics Packaging Manufacturing, 26, (2003) 328-337.
[13] W. Abdul-Kader, O. Ganjavi, A. Solaiman, An integrated model for optimisation of production and quality costs. International Journal of Production Research, 48 (2010) 7357-7370.
[14] A. G. Shetwan, V. I. Vitanov, B. Tjahjono, Allocation of quality control stations in multistage manufacturing systems. Computers & Industrial Engineering, 60 (2011) 473-484.
[15] A. Lari, A. Asllani, Quality cost management support system: an effective tool for organisational performance improvement, Total Quality Management & Business Excellence, 24 (2013) 432-451.
[16] H. Zhu, C. Zhang, Y. Deng, Optimisation design of attribute control charts for multi-station manufacturing system subjected to quality shifts, International Journal of Production Research, 54 (2016) 1804-1821.
[17] Automotive Industry Action Group (AIAG), Measurement systems analysis (4th ed.) (2010) ISBN: 978-1-60-534211-5
[18] T. Pyzdek, P. A. Keller, The six sigma handbook (2003) New York: McGraw-Hill Education.
[19] G. F. Templeton, B. R. Lewis, C. A. Snyder, Development of a measure for the organizational learning construct, Journal of Management Information Systems, 19 (2002) 175-218.
[20] I. Lopes, S. Sousa, E. Nunes, Methodology for Uncertainty Characterization of Performance Measures, International Journal of Quality & Reliability Management, 33 (2016) 1346-1363.
[21] S. Sousa, E. Nunes, I. Lopes, Measuring and Managing Operational Risk in Industrial Processes, FME Transactions, 43 (2015) 295-302.
[22] S. Sousa, E. Nunes, I Lopes, Uncertainty Components in Performance Measures. In: Yang, Ao, Gelman (Hrsg.): IAENG Transactions on Engineering Technologies. Dordrecht: Springer Netherlands, 229 (2013) 753-765.
[23] F. Gehlhoff, T. Busert, M. Lewin, A. Fay, Incorporating imperfect information in decentralized agent-based dynamic and integrated scheduling. In 2018 IEEE 23rd Int. Conf. on Emerging Technologies and Factory Automation (ETFA), IEEE, 1 (2018) 816-823.
[24] S. Sousa, N. Rodrigues, E. Nunes, Evolution of process capability in a manufacturing process, Journal of Mgmt. Analytics, 5 (2018) 95-115.
[25] M. Plewa, G. Kaiser, E. Hartmann, Is quality still free? Empirical evidence on quality cost in modern manufacturing. International Journal of Quality & Reliability Management, 33 (2016) 1270-1285.
[26] R. Souza, S. Sousa, E. Nunes, Developing organisational learning through QC story, Total Quality Management & Business Excellence, (*in press*) DOI: 10.1080/14783363.2018.1490641.