APEM journal
Advances in Production Engineering & Management
Volume 11 | Number 3 | September 2016 | pp 159–172
http://dx.doi.org/10.14743/apem2016.3.217
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Production monitoring system for understanding product robustness

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ABSTRACT

In the current quality paradigm, the performance of a product is kept within specification by ensuring that its parts are within specification. Product performance is then validated after final assembly. However, this does not control how robust the product performance is, i.e. how much it will vary between the specification limits. In this paper, a model for predicting product performance is proposed, taking into account design, assembly and process parameters live from production. This empowers production to maintain final product performance, instead of part quality. The PRECI-IN case study is used to demonstrate how the monitoring system can be used to efficiently guide corrective action to improve product performance. It is claimed that the monitoring system can be used to dramatically cut the time taken to identify, plan and execute corrective action related to typical quality issues. To substantiate this claim, two further cases comparable to PRECI-IN, in terms of complexity, material and manufacturing process, were taken from different industries. The interviews with quality experts revealed that the typical time taken for corrective action for both cases was accounted to be seven days. Using the monitoring system for the PRECI-IN case, similar corrective action would have been achieved almost immediately.

ARTICLE INFO

Keywords:
Product robustness
Performance variation
Robustness monitoring system
Performance consistency
Unit to unit robustness

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Article history:
Received 27 May 2016
Revised 5 August 2016
Accepted 17 August 2016

1. Introduction

1.1 General

A robust product has consistent performance, showing little variation from one unit to the next. The variation in functional performance is determined by both design and production [1], as described by the Variation Management Framework (VMF) [2]. Several researchers have explained how to handle robustness during design [3-5]. Performance variation is driven by its sensitivity to design parameters and how much they vary. Many tools are available to help design engineers to manage design parameter variation and design sensitivity [6]. However, few methods have been developed to achieve robustness from a manufacturing perspective which currently has the focus on producing part to a specification determined by design. Quality estimations, monitoring and control in industry are driven by Statistical Quality Control (SQC) and Statistical Process Control (SPC) [7]. Common practice is to understand process variables through SPC techniques and change their process settings for reducing product variation. This is to much an extent reactive control of performances and the estimation accuracies are limited due to limited sampling. Technology enhancement with a high degree of automation, allowing 100 % in-line inspection, can improve the control of final product variation [8]. However these quality systems work on the principle of controlling the variables, not adjusting one to compensate another. Also performance estimations are of larger volumes can't currently be used to estimate the performance of a specific unit running on the line.

The current state of the art performance prediction can be exemplified by the Artificial Neural Network Performance prediction model [9], which suggests that batches of parts be produced and measured before assembly to allow for matching complementary variations in parts for better performance. Neural network principles are effectively applied in process manufacturing industries to estimate the final product performance with measured variables beginning of the cycle [10]. This method also considers the variables relationship. However this system is proactive to only assembly, not for manufacturing. Also does not address products with multiple functions and parameters interlinked.

This research focuses on method of reducing unit to unit product variation during mass production by complimenting variables with their relationships for each unit. This means that if all units of the product were to be functionally tested after production, there would be less variation between the performances of each unit. However the paper does not address the change in performance of a product through its life, or in different use condition/scenarios. Unit to unit performance variation of a product is the result of variations in its parts and processes. Fig. 1 shows the representation of variation inflow to the typical production process.

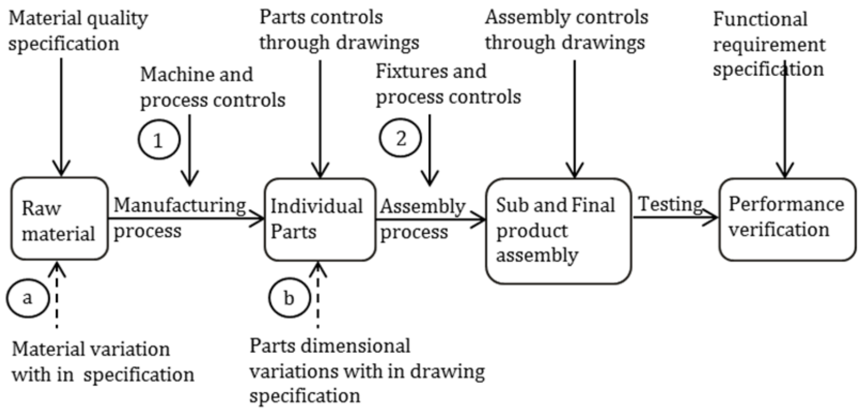

Fig. 1 A schematic representation of the production process with controls and variations

The research approach is to create a robustness monitoring system for production, which allows for understanding the incoming variation "a" and "b" (Fig. 1) and opportunities to compensate for them through "1" and "2" (Fig. 1). To create a model connecting the end product performance with all of the influencing variables, one needs to extract the relationships throughout, which are derived during product design and production tools development.

1.2 Parameter sensitivity

Variations of the part dimensions influence different product functions. Their degree of influence is known as sensitivity and can be non-linear and therefore dependent on nominal value. Sensitivity plays an important role while improving the parts and their design parameters in production to achieve consistency in final product performance.

1.3 Parameter interactions

It is not always the case that parameters influence product functions independently. Situations are present when the influence of a design parameter changes due to variations in the other design parameter. These interactions add more complexity when it comes to mapping influences of relationships in a design. However, good news is that the interaction effects are not as common as first order interactions and they also tend to have less influence than the first order interactions [11].

1.4 Axiomatic design

Complexity increases when each design parameter influences more than one function. For the design of a snap hook, the thickness of snap hook arm has an influence on the force required to deflect the arm and also the tensile strength of the hook once the snap has engaged. If we need to increase the tensile strength of the snap increasing the arm thickness will help but will create greater resistance to deflection.

1.5 Assembly process parameters

Assembly strategy gets defined along with product geometry concept. Variables in assembly can be dimensions of the parts and also fixtures in use [12, 13]. Sometimes even sub processes, like amount of glue applied, torque applied, etc. can be assembly variables. When these variables connect to product performance, applying them to compensate for parts variations is an opportunity in assembly to achieve performance constancy.

1.6 Manufacturing process parameters

The manufacturing process used for part production generates variation in part's dimensions. An injection moulding process relies on, pressure, temperature and cooling time, etc. as process parameters; similarly a machining process relies on speed, feed, tool size etc. as process variables. Those can be applied to generate the parts as needed. For example, in an outsourced part is made produced where the measurement report shows the batch to be close to the upper specification limit, a corresponding in-house part can be made closure to the lower specification limit to compensate.

The basic principle of this approach is "as we cannot eliminate the variations, apply them in order to compensate one another, nullify their effect on the final product". The monitoring system developed in this article allows this approach to be done more effectively.

2. Method for building robustness monitoring system

Engineering design philosophy builds the relationship of each design parameter to the final product functional requirements. Eq. 1, and Eq. 2 shows the simplest form of a product functional requirement and its variation, in which DP refers to Design Parameter and s refers to the Sensitivity of the function to variation of that DP.

$$\mathrm{Fn} = (s1 \times DP1) + (s1 \times DP2) + \ldots + (s\mathrm{n} \times DPn) \tag{1}$$

$$\Delta\mathrm{Fn} = (s1 \times \Delta DP1) + (s1 \times \Delta DP2) + \ldots + (s\mathrm{n} \times \Delta DPn) \tag{2}$$

DP variations (ΔDP) are caused by various process and equipment influences in manufacturing. Identifying all those Influencing Factors (IF) and quantifying the DP sensitivity to each of them is required to establish the link between variations in functional requirement to variations in manufacturing. The nature of the IFs derives the monitoring system requirements. The method followed to establish the monitoring system is shown in Fig. 2.

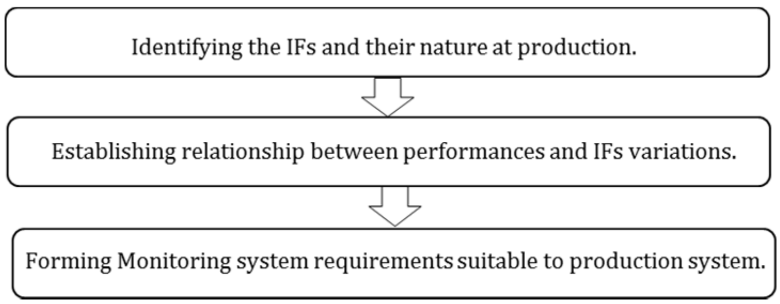

Fig. 2 Steps followed to establish monitoring system content and structure

2.1 Identifying IFs and their nature

Different influencing factors cause variations at various stages of production shown in the Fig. 3. The nature of all the IFs is not the same and production's ability to apply change differs. Compensating one IF by controlling another, is dependent on many aspects as outlined here:

Time: In the chain of production activities, the first generated variation becomes the base for later IF to be adjusted accordingly. Certain outsourced parts arrive at the assembly warehouse before may constitute the first IF.

Changeability: Certain influencers are rigid in nature. For example, a dimension in plastic mould is made 15 microns bigger is well within the machining tolerance, and cannot be changed in production.

Agility: How quick production can act on IF also differs. Changing a tightening torque is quick, and may take only a few seconds but mould temperature change takes an hour to stabilize. This limit's the application while choosing the IF for compensation.

Axiomatic conditions: When IFs affect the performance of multiple functions of the product, it becomes more complex to manage. Adjusting one IF to compensate for another, may bring the performance of one function back to the target value, but may have negative effects on other functions.

Degree of Control: All IFs will not completely be within production control. For example, raw material characteristics are specified with certain variation acceptance. As long as it is maintained within the range, material batches are quality passed, and cannot be asked to change. These are semi controlled. Ambient temperature and humidity etc. are often uncontrolled. However, both semi-controlled and uncontrolled can be measured and compensated by other controlled IFs.

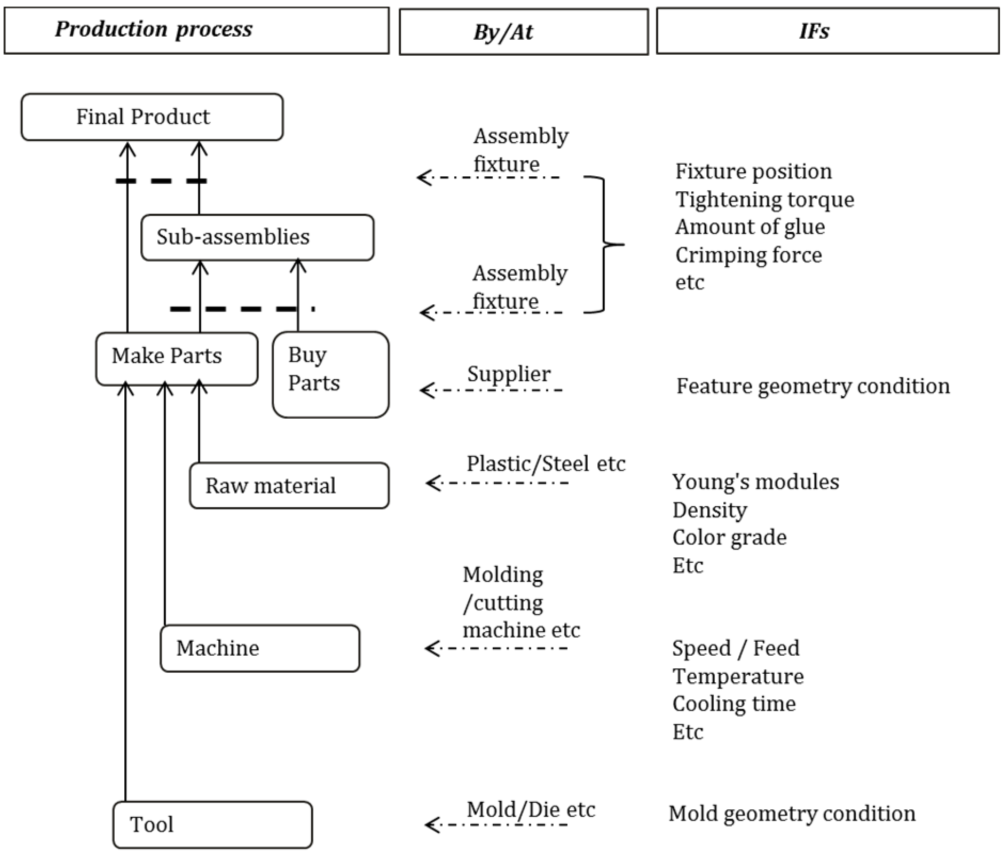

Fig. 3 Mapping of IFs over production process

2.2 Establishing relationships

Design Parameters (DPs) are identified at product design. Relationship equations of these design parameters to the Functional Requirements (FRs) are determined by the designed concept. Many products designs choose final assembly dimensions as targets to achieve FRs, e.g. spring compression length in final assembly is maintained in production to achieve push force function. These Dimensional Targets (DT) build with DPs to achieve FRs indirectly. Some cases DT itself can be FR, e.g. product length, flushness, gap uniformity, etc. Many assembly processes involve the use of fixtures to achieve DTs. In this case the dimensions of the fixture would be an assembly parameter (AP) which also influences on the FRs. However the relationship of manufacturing Process Parameters (PPs) to DPs is generated through the tools design (moulds, dies, fixtures, etc.)[14-16]. Fig. 4 shows the production process with variables identification. Here all APs and PPs are IFs.

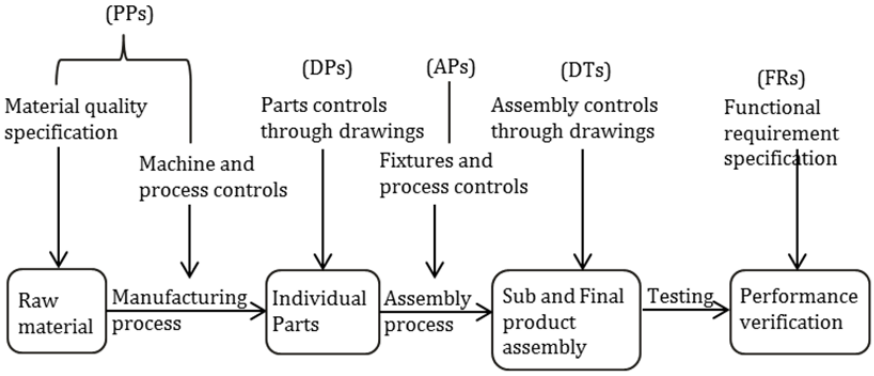

Fig. 4 Variables in discussion identified on production process

2.3 Monitoring system requirement

The intention of the monitoring system is to indicate which function is varying, by how much and due to which IFs. After identification, the relationship between those IFs and the function requirement helps in determine by how much they need to be adjusted to improve intended function.

Generic quality focused production approaches aim to maintain parts and assemblies as per drawing specifications. This ensures the functional requirements to achieve within specification. When unit to unit product robustness is in focus, FRs not only needs to be within specification, but they also need to be consistent from unit to unit. Product robustness as defined by John P King [17] is "*A system that is more ROBUST is less sensitive to the sources of variability in its performance*". To understand the robustness achievement, measuring and maintaining of performance variation is required. For this, production has to note, not only the DP achievement but also "how that DP is impacting on performance", requiring a change to the information flow from design to manufacturing. Table 1 shows the difference in both.

Sensitivity of an FR to a DP, describes the ratio of how much variation is induced in the FR by variation of DP. This allows the calculation of the DP's contribution to that specific FR achievement [18].

Transfer function describes how the sensitivity of the FR to the DP changes for different values of the DP. If the transfer function is linear then the sensitivity will remain constant for any value of the DP. This allows an estimation of the exact change required in DP to achieve the required improvement in FR.

Couplings/Axiomatic condition describes how all of the FRs are influenced by different DPs. This enables the FRs to be balanced while applying changes in DPs adding to the transparency of the effects of adjusting the DPs.

Table 1 Robustness focused organizations need more information flow than those with a traditional quality focus

Quality	*Robustness*	*Purpose*
1. 3D models	1. 3D models	For making tools and fixtures
2. Drawings with design parameter controls/ specifications	2. Drawings with design parameter controls/ specifications	To measure and maintain
3. Assembly process	3. Assembly process	To establish assembly line
	4. Sensitivity	Count the DP contribution
	5. Transfer functions	Act according to the DP position
	6. Couplings – Design parameters connected with more than one functional requirements	Balancing FRs while changing DPs.

It must be emphasised that individually, each of the above techniques are well researched and various tolerance analysis methods in practice allow for counting sensitivity and contribution of design parameters [19-24].

To calculate the performance of any product picked up from the end of the assembly line, one has to know the measurements of each part from the same assembly. Assembly lines of mass production work on different logistic principles, for example, in a Just In Sequence (JIS) system; parts from manufacturing units reach the assembly line in the same sequence as the assembly plan. In these systems part measurements happen at the part manufacturing location only. In the present globalized situation, often parts come from overseas. Measurement data captured at various locations needs to be bought together and analysed. Advancements in PDM/PLM tools in addition to part making and identification technology, make monitoring and adjustment approaches such as the one being proposed in this article, both a feasible and probable capability in the near future.

3. Results and discussion

The principle of robustness monitoring system is "predicting functional performance by calculating with actual parts and processes achievement using their relationships ". From design, FRs and DTs flow down the system to DPs. Further relationships from DPs to PPs are generated through tools and equipment design. The assembly process gets defined at design but APs are derived from assembly line design.

Linking PPs – DPs – APs – DTs – FRs of the product in an easy readable form is the backbone of the monitoring system. This also aims to display the variation contribution of each parameter. This indicates HOW product performances vary and directs WHICH parameter and HOWMUCH to adjust in order to compensate. Furthermore monitoring system gives the overview of HOW TO CHANGE by selecting the quickest and minimum number of parameters. A schematic representation of the robustness monitoring system is as shown in Fig. 5.

The robustness monitoring system communicates three levels of information.

Level1 – Shows the status of final product Dimensional Targets and Functional Requirement. Mathematical relationships of DTs and FRs are derived from design philosophy.

Level2 – Shows the status of Design parameters. The relationship between Level1 and Level2 is derived through Assembly parameters. These relationships are determined from assembly equipment design. Outsourced parts are maintained by suppliers within specified limits and join at this Level. These DPs are known only once they have arrived and cannot be changed further.

Level3 – Shows the status of Process Parameters as controlled, semi and uncontrolled. Controlled refers to production floor opportunities like, Speed, Feed, injection pressure, etc. Those can be varied within a set range of values anytime during production. Semi controlled refers to incoming variables like raw material characteristics which are within specified limits but cannot be changed every day or every instant of production. Uncontrolled refers to parameters that do not have any specifications like ambient temperature, humidity etc. the relationships with Level2 are derived during the Tool design process (Moulds, Dies, etc.) by virtual simulation or physical DOEs before the Start Of Production (SOP).

Fig. 6 shows the robustness monitoring system operating process flow and description of its steps.

This monitoring system is in principle suitable for any type of product and process. Performance variation can be minimised using this tool without the need to tighten parameter tolerances. Once the system established, product upgrades and design improvements can be easily applied. Identifying the robustness monitoring requirements and building its structure is the key step for successful adoption. By linking PPs to their time and cost criteria the monitoring system can incorporate algorithms for suggesting the quickest and cheapest adjustments. Higher measurement frequency and data alignment increases the prediction accuracy.

Higher complexity products, like automotive vehicle production, may need multiple monitoring systems, broken down in to different sets of relevant FRs. Whenever production tools and equipment is replaced, their PP sensitivities are to be updated.

Robustness monitoring to be initiated during design and continued by the development team. This demands a strategic document flow along with stage gate process from design to manufacturing. Alignment between design and process parameter verification at digital and physical levels is critical for system reliability.

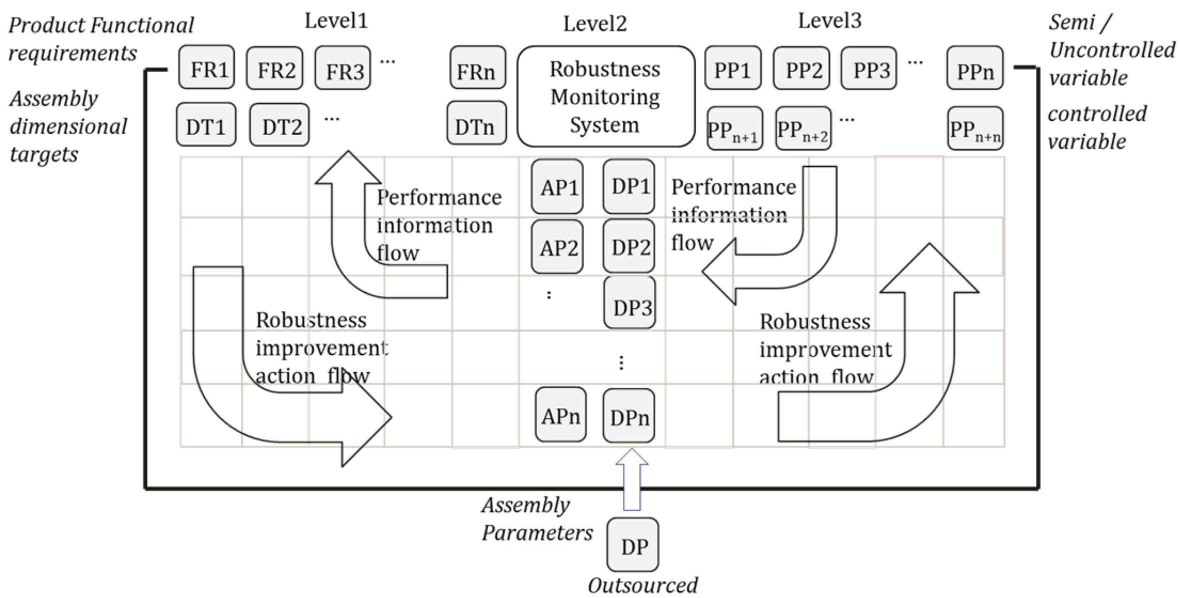

Fig. 5 A schematic representation of the robustness monitoring system connecting PPs and FRs

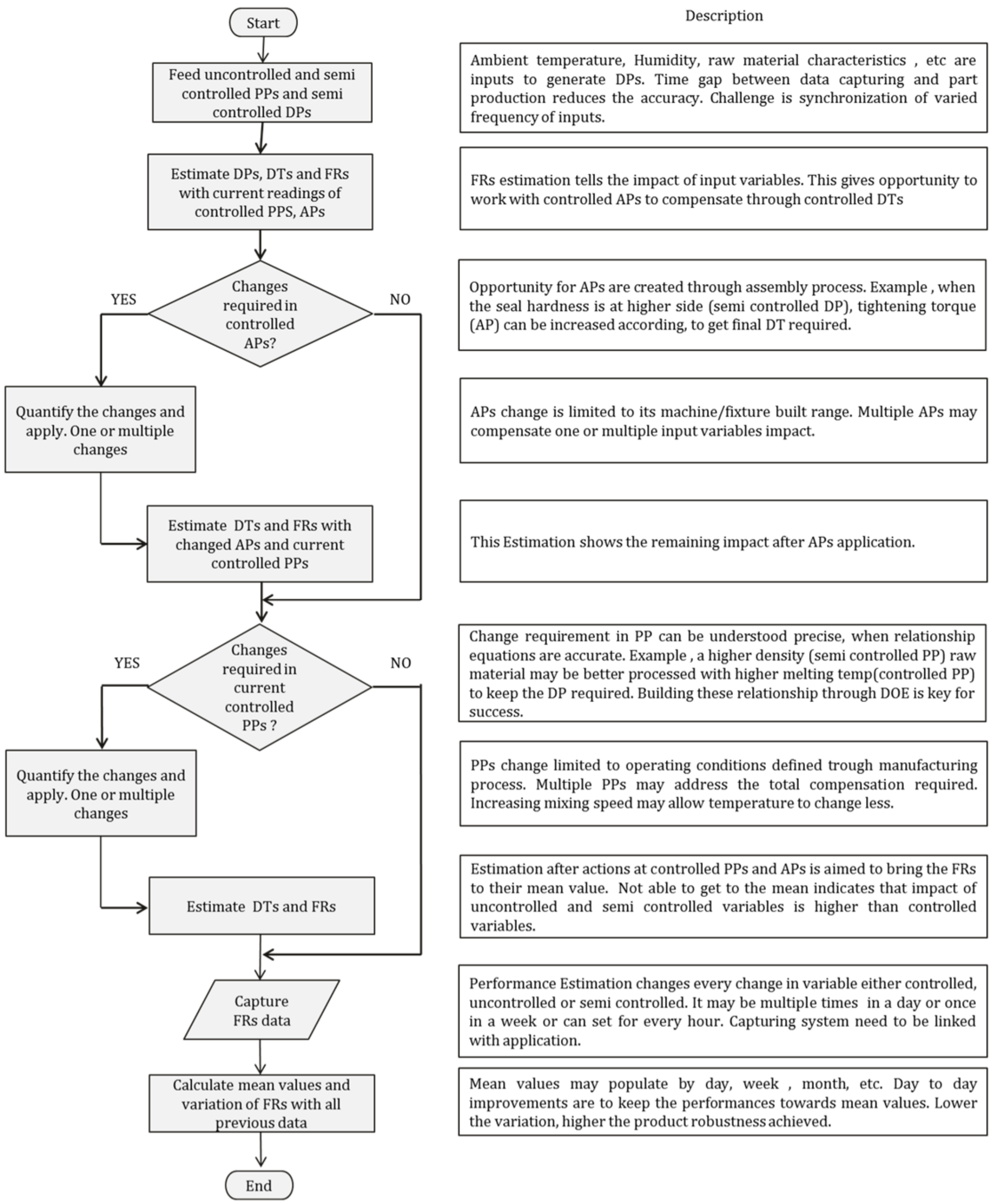

Fig. 6 Monitoring system application flow

4. Case study

A portion of the PRECI-IN injection device concept have been simplified and modelled as a case study to exemplify the application of robustness monitoring system.

4.1 Information from design

This module of injection device is attachable to various types of drug cartridges. A dose setting mechanism allows the user to dial a dose by rotating the scale, which in turn generates tension in a torsional spring. By pushing the button the spring tension is converted to axial movement of piston rod. Fig. 7 shows the assembly and parts with relevant design parameters.

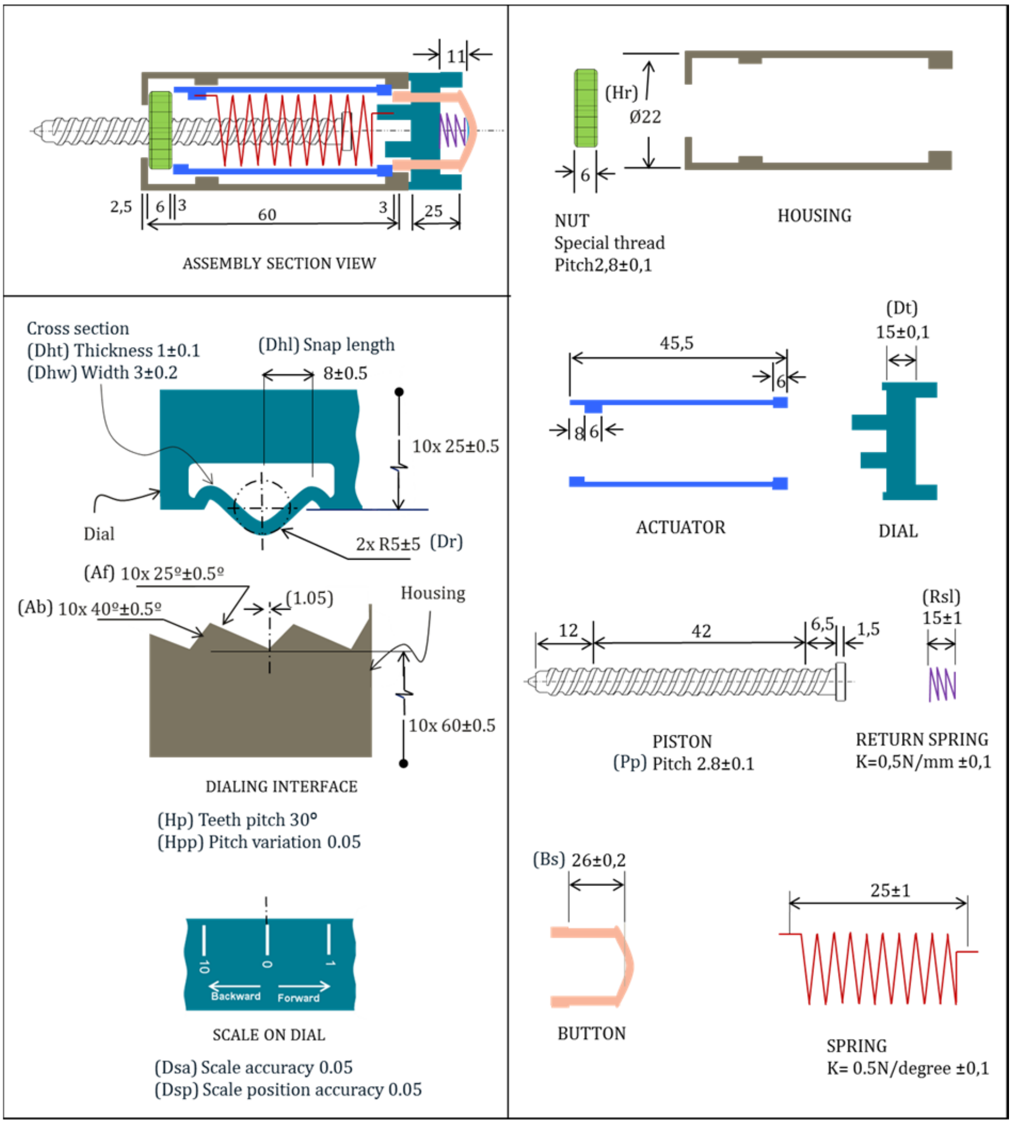

Fig 7 Design parameters information through 3D models and drawings

Functional requirements of Push Button Force (PBF), Dosage Accuracy (DA), Dialling Force (DF), Back Dialling Force (BDF), and Indicator Mismatch (IM) are considered for monitoring. Based on the design, the relationship equations of the FRs to DPs are imported from variation analysis to monitoring system.

4.2 Relationships of PPs to DPs

Data driven production departments will already have good methods to determine the relative influence of the different PPs to the DPs. Dimensional variation of mass produced, injection moulded parts can be modelled based on the analysis of previous experiments determining the influence of different factors. Such experiments are common practice in production departments, although the systematic recording and re-use of data is not done by many companies. All DPs produced in-house are related to their PPs. For e.g. The DP, Pitch of the piston (Pp) from Fig. 7 related to moulding process parameters for that specific tool and machine characteristics simplified as in Eq. 3 Similarly the DP, button snap (Bs) from the Fig. 7 in Eq. 4.

$$\Delta Pp = (2 \cdot 10^{-4} \cdot \Delta MT) + (3 \cdot 10^{-4} \cdot \Delta HP) - (2.5 \cdot 10^{-4} \cdot \Delta CT) + (3 \cdot 10^{-3} \cdot \Delta T) + (5 \cdot 10^{-3} \cdot \Delta H) \tag{3}$$

$$\Delta Bs = (1.4 \cdot 10^{-2} \cdot \Delta MT) + (6.4 \cdot 10^{-4} \cdot \Delta HP) - (1.65 \cdot 10^{-2} \cdot \Delta CT) - (2 \cdot 10^{-2} \cdot \Delta T) + (4 \cdot 10^{-2} \cdot \Delta H) \tag{4}$$

Where, ΔMT, ΔHP, ΔCT, ΔT, and ΔH are change in mould temperature, holding pressure, cooling time, ambient temperature, and ambient relative humidity, respectively.

4.3 The PRECI-IN robustness monitoring system

Fig. 8 shows the experimental monitoring system for six PRECI-IN functional requirements, related to their PPs through DPs.

As the concept does not contain assembly dimensional controls, no DTs are identified in Fig. 8. However the Indicator Mismatch (IM) is a final assembly dimension which is counted as an FR. As all the parts are assembled on to features of other parts, no Assembly Parameters (APs) are used and thus do not feature in Fig. 8. The captured status in Fig. 8 is a single instance of simulated production. The monitoring system treats all controlled variables (Yellow) as opportunities for change. The red cells are the measured but uncontrolled PPs, which can be entered as actual values. The orange cells are DPs of outsourced parts and therefore can only be entered as actual values based on measurement reports. Variation occurring in the FRs can be captured from Level1 cells. To decrease the FR variation, the contribution of each DP and their sensitivity /contribution direction (whether positive or negative correlation) helps to identify which DP to change and in turn, which PP to change. In the current status, BDF (one of FR circled in Fig. 8) is highly deviated by -5.47 N. Opportunities for decreasing the variation is through the DPs, Ab, Hp, Dhl, Dhw and Dht. These DPs are linked to three PPs, MT-S1, HP-S1 and CT-S1. The intention is to change as few PPs as possible to improve BDF, at the same time, affecting the other FRs positive or minimally. Fig. 9 shows the FR improvement after PP change application through the monitoring system. Variation of BDF is reduced to -0.14 by increasing one of PP, MT-S1 (circled) from 90 to 102.

PRECI-IN PRODUCT ROBUSTNESS MONITORING SYSTEM

Level1						Level2		Level3											
ΔPBF	ΔDA1	ΔDA2	ΔFDF	ΔBDF	ΔIM			MT-S1	HP-S1	CT-S1	MT-S2	HP-S2	CT02	MT-S3	HP-S3	CT-S3	T	H	TC
0,21	0,00	-0,01	-2,39	-5,47	-0,17	PRECI-IN		90	85	12	50	85	5	250	120	15	30	75	TC
			-1,60		0,02	25,070	Af	0,0000	0,0000	0,0000							0,0000	0,0000	0,0700
				-12,28	-0,24	44,950	Ab	0,0000	0,0000	0,0000							0,0000	0,0000	-0,0500
0,02	0,00	-0,01	5,67	14,31		36,200	Hp	0,0000	0,0000	0,0000							0,0000	0,0000	0,2000
					0,34	0,300	Hpp	0,0000	0,0000	0,0000							0,0000	0,0000	0,3000
					-0,08	11,178	Hr	-0,0114	0,0268	0,0023							-0,0900	0,1000	0,1500
					0,09	4,805	Dr	0,0000	0,0000	0,0000							-0,0450	0,0500	-0,2000
0,06						15,127	Dt	0,0000	0,0000	0,0000							-0,0135	0,0200	0,1200
			7,15	18,82		8,036	Dhl	-0,0081	0,2145	0,0292							0,0000	0,0000	-0,2000
			-9,89	-29,56		3,103	Dhw	0,0000	0,0000	0,0000							-0,0270	0,0300	0,1000
			-3,73	3,25		0,948	Dht	-0,0010	0,0268	0,0037							-0,0720	0,0400	-0,0500
0,13						25,747	Bs				-0,0004	0,0120	-0,1148				-0,1800	0,2000	-0,1700
	0,00	0,00				2,755	Pp							-0,0006	-0,0063	-0,0010	-0,0270	0,0250	-0,0350
0,00						15,000	Rsl												
					-0,17	0,200	Dsa												
					-0,11	0,100	Dsp												

Uncontrolled variables · Controlled variable · Contribution inversely proportionate to variables · Contribution directly proportionate to variable · Semi-controlled variable

Fig. 8 Monitoring system for six functions of PRECI-IN product concept

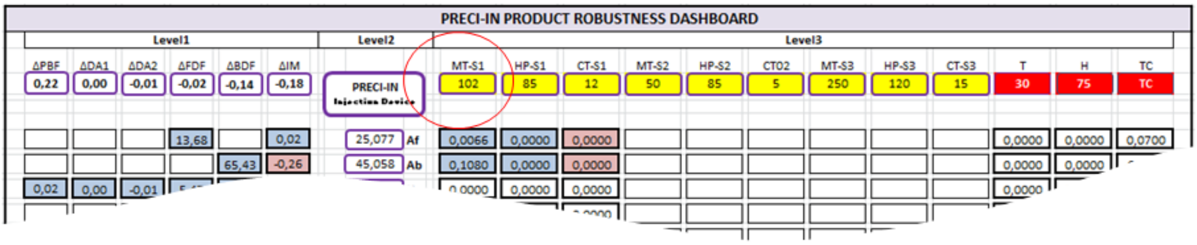

Fig. 9 Monitoring system after FR variation reduction

The robustness monitoring system helps to identify the most effective parameters to act on for FR improvement, which leads to the minimum number of changes. In traditional quality focused approach organizations tend to identify all possible improvements across the production value chain. Brief comparison of both approaches is shown in Table 2.

Table 2 Advantages of robustness focused approach over quality focused

Task	*Traditional quality focused approach*	*Robustness focused approach*
Performance improvement identification	Final inspection/testing	Predictive, before assembly/ manufacturing
Improvement action identification	Root cause analysis techniques	Monitoring system directs the action
Action focus	Applying all possible improvements	Changing minimum parameters
Action reliability	Less, being iterative process	More, due to calculated approach
Time for action identification	Final inspection + Root cause analysis time	Data filling time (instantaneous)

Depending on the quality issue and the complexity of the product, the time saving from using proposed monitoring system to guide corrective action could be anything from hours to months. To give some examples of the impact, two quality experts were interviewed from different industries to describe the procedure and the time required to achieve typical quality aims. To ensure a reasonable comparison, projects were chosen with similar characteristics to PRECI-IN, in terms of, the number of components, plastic components and the forces involved. The context were also similar, where the performance was with-in specification but improvement intended. Table 3 describes the main differences between the PRECI-IN case and those described in the interviews. The *industry* influences the analysis procedure and time for concluding actions. Assembly cycle time indicates the minimum time required to make a PP change visible in the final product for each iteration. The *production volume* impacts the time available for iteration, The percentage of *in-house manufacturing* determines the number of controlled PPs. The time to conclude action and the *# of DPs and PPs* acted on were recalled/estimated by the interviewees.

Analysing the nature of iterations in both the cases reveals the missing information, which can eliminate the iterations is shown in the Table 4.

Table 3 Average time taken and number of DPs and PPs acted on in various industries

Industry	*Production*	*Cycle time*	*In-house manufacturing*	*Time for concluding action*	*No. of DPs acted on*	*No. of PPs acted on*
Automotive	6000/day	4 h	10 %	7 days	2	7
Home appliances	300/day	3 h	10 %	7 days	1	3

Table 4 Iterations and their related information missing

Industry: Improved FR	*Concluding DPs*	*Concluding PPs*	*Missing information*
Automotive: Gap uniformity around the switch bezel found higher side in door trim assembly	Iterative process : First – Bezel hook position changed equal to the non-uniformity observed. Second – Higher pressure on snap opposite to the hook lifted the bezel up and flushness disturbed, to reduce the stress snap interference reduced. Third – Uniformity not improved as expected, once again hook position changed.	Iterative process: First – One uncontrolled PP has been changed Second – Second Uncontrolled PP has been changed Third – First changed PP is changed again. Along with three of controlled PPs also adjusted.	1. No DP to FR relationships are defined. 2. Specific DP change impact on other FRs is not known 3. Contribution of Uncontrolled and controlled PPs together in DPs is not clear.
Home appliances: Mixer-A load transmission gear life is noted lower side of its defined warranty.	Iterative process: First – Gear strength increased by changing the material grade. Second – As the gear life not increased as expected, material grade changed again for higher strength Third – Once again improved the material with latest grade.	Iterative process: At every time of grade change, three PPs are re-established.	1. No FR to DP relationships established, No DP contribution analysis could perform. 2. No performance linkages available for narrowing correct DP.

4.4 Predictability accuracy

The accuracy of prediction for any product at any instance of production depends on how frequent the uncontrolled and semi controlled variables measurements are available. If we are able to capture variation data for every part, with the monitoring system it is possible to predict the performance of every product coming off the line. When the variable represents a batch of parts, estimation accuracy is directly proportional to the batch variation. This is similar for uncontrolled PPs, such as ambient temperature and humidity. If the ambient temperature is noted for every 2 °C change, prediction accuracy is affected by 2 °C. Table 5 shows the list of variables influencing prediction accuracy.

Table 5 Prediction accuracy of various performances influenced due to semi controlled DPs and uncontrolled PPs

Performance variation	*DP variation acceptance within the batch*			*PP variation with in frequency*		*Total influence on prediction accuracy*
	Rsl 0.4 mm	Dsa 0.05 mm	Dsp 0.05 mm	AT 2 °C	AH 1 %	
ΔPBH	0.20	NA	NA	0.03	0.02	0.25
ΔDA1	NA	NA	NA	0.00	0.00	0.00
ΔDA2	NA	NA	NA	0.10	0.01	0.11
ΔFDF	NA	NA	NA	0.40	0.49	0.89
ΔBDF	NA	NA	NA	1.41	1.04	2.45
ΔIM	NA	0.10	0.10	0.10	0.00	0.30

5. Conclusion

Proposed monitoring system found capable to reduce final product performance variation dynamically by providing most effective adjustments in process parameters. This is analysed for injection moulded parts assembly case. Adapting this monitoring system as part of a project from the beginning allows ensuring the correct information flow from design. This shifts the present paradigm of quality control at mass production from part dimensions to product performance.

Same tool can be further extended to estimate customer / stakeholder perceived quality loss, due to variation which can be defined at the beginning of the product development [25].

Some challenges that left for future work are:

- Deriving relationship equations at the manufacturing stage demands conscious experiments and data validation. The challenge of applying uncontrolled variables in the experiments reduces the accuracy of relationship equations.
- Industry follows several approaches to calculate contribution and sensitivity. This may lead to different interpretations of the same information.

Acknowledgement

The authors would like to acknowledge Novo Nordisk for the research funding under the DTU-Novo Nordisk Robust Design Programme. Authors thank the quality engineers and their respective organizations that participated and evaluated the research proposal.

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