The Use of QFD for the Design of a Maintenance Service Support System

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Abstract. The development of machinery performance monitoring systems along with the prospect of intelligent factories developed under the concept of industrial revolution 4.0 affect dynamic changes in the field of maintenance. Therefore, based on an overview of the literature and observations of production enterprises, we propose a model of maintenance service support system with respect to failure prediction and decision making in the area of maintenance works. In the designing stage the QFD method was employed with a view to testing its usefulness for the process.

1 Introduction

The development of manufacturing companies resulting from the emergence of the Industry 4.0 sets high requirements for IT systems designed to support enterprises in most areas of their operation. A distinct tendency to design systems and applications that put more and more emphasis on replacing the human factor with IT solutions, especially at the stage of decision making, can be widely observed. In effect, this approach contributes to the creation of expert systems dedicated to manufacturing enterprises. Their advantage over human employees is the possibility of inference based on extensive knowledge databases and models, and the rules of inference [16, 24].

As a result of automation of data analysis processes and delegation of the responsibility for decision making in a production company to IT systems, it becomes necessary to use both programming and qualitative tools enabling proper determination of the functioning of these systems already at the conceptual stage.

A growing awareness of entrepreneurs regarding the need to create companies that are competitive both domestically and internationally results in the implementation of innovative solutions which improve both the activities carried out in the enterprise and the quality of products or services, and generate savings by eliminating the existing sources of waste. Besides overproduction or redundant operations, these sources include requirements, defects or quality losses due to the occurrence of failure. They must be limited to random events, as demonstrated by the constant development of predictive maintenance enabling the prediction of unexpected failures, resulting in reduced reliability of the company's stock of machinery.

Efforts regarding the development of machinery monitoring systems, analysis and inference expert system decision systems based on generated forecasts and database systems require thorough preparation of the initial designing stage. To this end, a range of available quality management tools can be implemented already at the conceptual stage.

2 Methods and tools for improving manufacturing processes

The need to meet a growing competition (more and more often on a global scale) requires continuous improvement of processes performed in every organization. To increase the competitiveness of manufactured products and the effectiveness of manufacturing processes, enterprises often resort to solutions widely described in the literature on operational management or quality management. A selected list of principles, methods, tools and techniques applicable in many organizations is given in Table 1.

Since this work aims to identify requirements in relation to a prediction and decision-making system supporting the operation of maintenance services, a decision was made to determine these requirements with the use of QFD, alternatively referred to as the "house of quality" [18].

The QFD (Quality Function Deployment) method was first used in the 1960s, and its original purpose was to transform customer demands into final product characteristics [8]. The method consists in associating engineering parameters of the designed or existing product/system with customer demands voiced in their natural language [6].

After [18], it is worth mentioning the most important benefits of using this method, including:

– limitation of main problems caused by time consumption and costs incurred at the product design stage,

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– focus on customer satisfaction,
– a competitive advantage by ensuring product development in accordance with customer demands,
– assurance of coherence between the planning stage and production.

From the list above, it becomes apparent that the QFD method allows satisfying customer requirements with respect to the entire process (starting from preparation, production design and the launch of new services to the development of new computer systems) [15].

The QFD analysis requires the use of a tool known as the house of quality. Fig. 1 shows the diagram of this tool consisting of the following fields:

I. customer requirements,
II. prioritised customer requirements
III. technical requirements
IV. relationship between customer and technical requirements
V. prioritised technical requirements
VI. correlation between technical requirements
VII. competitive assessment of designed product with other products
VIII. target technical requirements
IX. indicators of technical feasibility.

It is worth mentioning that there are different versions of QFD. The most popular and, at the same time, the simplest is the single-matrix QFD, which consists in the implementation of only the basic matrix. In this way, the relationship between customer demands and engineering characteristics of the developed product is studied.

The QFD method discussed in this paper is of a quantitative and qualitative nature, and requires the involvement of team at the preparatory stage.

3 Methods and tools for improving manufacturing processes

The demands of enterprises that increasingly make use of available modern technologies result in the development of new solutions that can support the human factor in the analytical and decision-making areas. Such support is of great importance in the context of development of monitoring systems and the creation of big data databases. The use of modern IT systems supporting the work of functional areas of a company greatly improves the actions implemented, among others, by the company's maintenance department, thereby leading to their increased efficiency, *e.g.* due to the possibility of failure time prediction.

Previous studies focused on the possibility of using different predictive models to support predictive maintenance.

In her work [4], Rogalska investigated the prediction of repair time of an L14 wheel excavator by the multiple regression method. The dependent variable was the cumulative repair time of the excavator, and the correctness of the prediction was verified by the partial correlation approach.

Multiple regression was also used by Luciferdi, Mazzieri and Rossi to predict the failure of a hydroelectric power system [11]. In their analysis, the authors also used Modified Kriging method and combined it with neural networks.

The use of artificial intelligence was also applied to design a system for monitoring the condition of a wind turbine gearbox [3], which enabled, *inter alia*, the integration of actions resulting from the employed predictive maintenance strategy, *i.e.*, continuous monitoring, detection and diagnosis of failures, planning of predictive maintenance and assessment of maintenance work effectiveness.

Artificial neural networks were used by Mazurkiewicz to predict the condition of conveyor belt joints in a mine [13]. The measurement of the changes in length of selected conveyor belt joints representing the time series from t-20 to t allowed for a selection of a unidirectional multi-layer network with the architecture of 1-4-4-1. The resulting reproduction error was equal to 0.06.

Tabaszewski undertook an investigation of multi-aspect prediction of status and time to failure using neural networks [17]. The tests were performed on 608 rolling bearings, and the measurement data were obtained with accelerated wear of said bearings. For the analysis, the author chose effective and peak values of vibration acceleration in two frequency bands (acoustic emission rate and kurtosis value in the band).

Table 1. Basic classification of quality management tools [12].

PRINCIPLES	METHODS	TOOLS	TECHNIQUES
– Team work, – KAIZEN, – POKA-YOKE, – Zero defects, – 8 principles of quality management, – Deming's 14 Points, – Quality management principles used for product study and design	– FMEA, – **QFD,** – SPC, – DOE – design of experiments, – 8D report, – 5S	– Six Sigma, – 5 Why, – Ishikawa diagram, – Pareto-Lorenz diagram, – Flow diagram, – Shewart control charts, – Histogram, – Brainstorming, – New tools for quality management	– Measurement, – Recording, – Organoleptic assessment, – Examination sheets

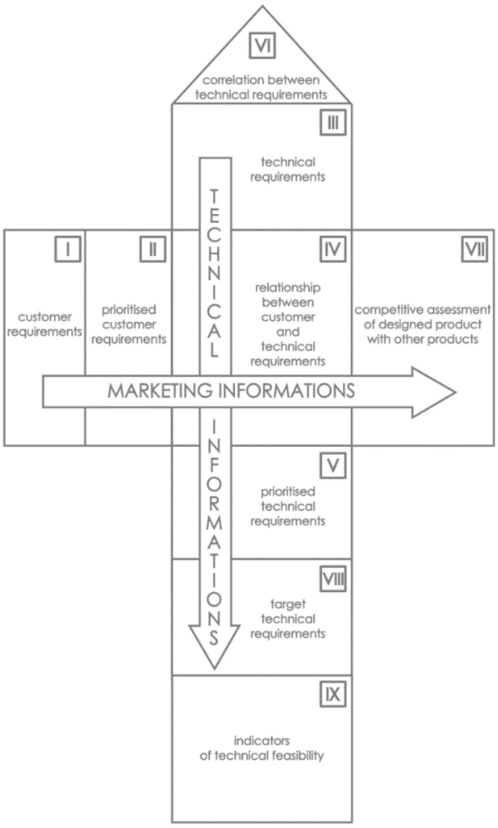

Fig. 1. House of quality (based on [15]).

Wu Sz., Gebraeel N., Lawley M.A. and Yih Y. conducted experimental investigations on thrust bearings in order to gather information about real-time vibration until failure [22]. The collected results were used to develop the model of a neural network for the prediction of bearing wear based on Feed Forward Back Propagation Neural Network (FFBPNN).

On the other hand, Wróblewski *et al.* [21] estimated the service life curve of some turbogenerator components using vibration symptoms to estimate the time of their work. The authors focused on the analysis of vibration speeds of the turbogenerator front joints, taking into account the frequency of damages.

Huang, Xi, Li, Liu, Qiu and Lee undertook research into the use of self-organizing maps and a neural network using back propagation neural network methods for the prediction of ball bearing failure, obtaining much better results than in previous studies based on nominal service life [5].

The above studies are only a small part of the research on the use of prediction methods for failure prediction, and they aim to show the universal application of various predictive models. The analysed works do not present the approach proposing the selection of a model depending on the changes in the monitored values of residual processes. Benefits resulting from predicting the moment of exceeding the limit values encourage further research on the use of predictive models and expert systems that support the decision-making staff in determining the moment of undertaking maintenance works.

The proposed solution (Fig. 2) consists of two parts: prediction and decision making. In the prediction part, data collected by the object monitoring system (*e.g.* temperature, vibration and noise, marked in the figure as observation vectors) are supplied to the intelligent system for prediction method selection. On their basis, drawing upon the IT and prediction criteria indications (by the ranking method), the system will select a suitable mathematical model:

- for stationary series [7,19]:
  - *autoregressive (AR)*,
  - *moving average (MA)*,
  - *autoregressive moving average (ARMA)*,

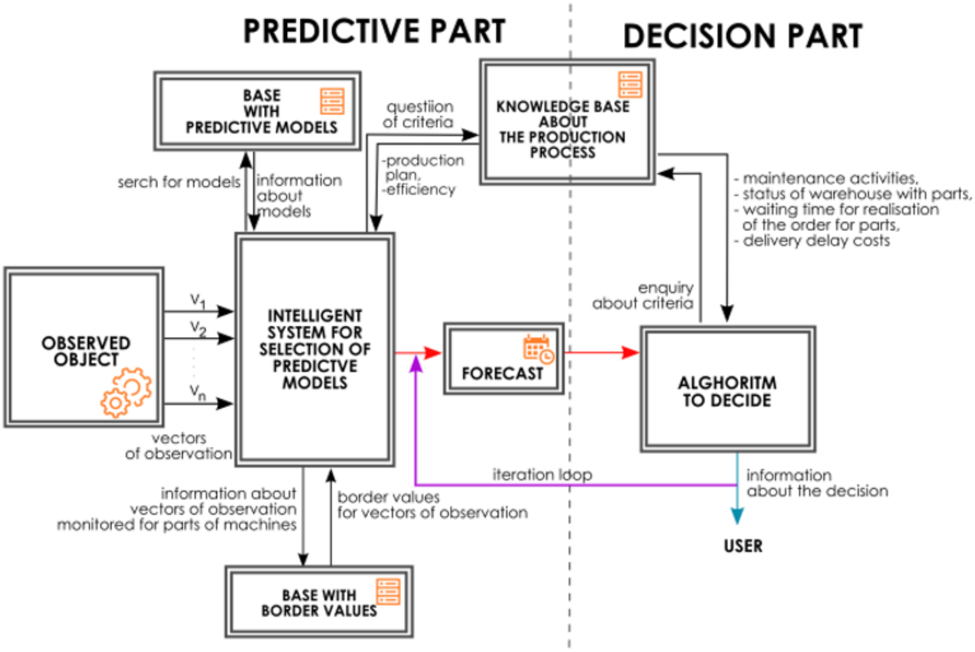

Fig. 2 Diagram of the prediction and decision-making algorithm in a maintenance service support system [9].

- for non-stationary series [1,7,20]:
  - *autoregressive integrated moving average (ARIMA),*
  - *seasonal ARIMA (SARIMA),*
  - *Autoregressive Conditional Heteroscedasticity (ARCH),*
  - *Generalized ARCH (GARCH),*
  - *Randomized GARCH (RGARCH),*
  - *Exponential GARCH (EGARCH),*
  - *Threshold ARCH (TARCH),*
  - *Heterogeneous interval ARCH (HARCH).*

The reason for selecting a mathematical model in real time is to obtain the most accurate prediction for a given time window. A detailed description of the operation of a prediction and decision making system is given in [9], which describes the procedure of model selection, [7] proposes a cyber-physical system, while [8] proposes the creation of a system consistent with the m-maintenance approach.

4 The application of QFD to design a maintenance service support system

The objective of transforming the target group demands regarding the machinery failure prediction is to support the design stage and affect its final shape. It is, therefore, justified to discuss with the prospective system user, among others, the indications of the system's functionality, so that they could be included them at the modelling stage as part of system engineering.

The preparation of the QFD scheme focused on the following:

1. Identification of requirements of the prospective system user,
2. Identification of prioritised customer requirements,
3. Determination of technical requirements,
4. Determination of the interrelations between technical requirements,
5. Determination of the relationship between system user requirements and technical requirements,
6. Determination of indicators for customer requirements,
7. Calculation of weights of the determined technical requirements.

The house of quality in a single-matrix version was created with the use of Excel's dynamic sheet downloaded from http://www.qfdonline.com [25].

Due to its large size, the generated house of quality is shown after the division into two diagrams – L and R.

Fig. 3 presents the L diagram describing the interrelations between the identified requirements of the prospective system user and technical requirements. The interrelations are shown graphically and divided into strong, medium and weak, assigning them with the values of 9.3 and 1, respectively.

Denotations are explained in Fig. 4.

Legend		
⊙	Strong Relationship	9
○	Moderate Relationship	3
▲	Weak Relationship	1
++	Strong Positive Correlation	
+	Positive Correlation	
−	Negative Correlation	
▼	Strong Negative Correlation	
▼	Objective Is To Minimize	
▲	Objective Is To Maximize	
x	Objective Is To Hit Target	

Fig. 4. Legend of the symbols describing the interrelations between customer requirements and technical requirements.

Row #	Max Relationship Value in Row	Relative Weight	Weight / Importance	Quality Characteristics (a.k.a. "Functional Requirements" or "Hows") / Demanded Quality (a.k.a. "Customer Requirements" or "Whats")	language of programming	computerization of other areas of the company	system modularity	compatibility with implemenetd systems	BYOD approach of the company	equipment potential of the company	logical structure of the system	responsiveness	system window loading time	update procedure	real-time mathematical operations
1	9	9,2	7,0	system access via Internet	○	▲	▲	▲	○	⊙	▲	○	○	⊙	○
2	9	9,2	7,0	system operation on mobile devices	○	▲	▲	▲	○	⊙	▲	⊙	○	○	▲
3	9	11,8	9,0	possibiolity of system development to monitor other devices	⊙	⊙	⊙	○	○	⊙	○	▲	○	○	○
4	9	13,2	10,0	failure alerts	○	▲	▲	○	▲	○	▲	▲	⊙	▲	⊙
5	9	11,8	9,0	intiutive interface	▲	▲	▲	▲	▲	▲	⊙	○	▲	▲	▲
6	3	10,5	8,0	authorized access	○	▲	○	▲	○	○	○	▲	○	○	▲
7	9	7,9	6,0	connection of the system with maintenance work schedule	○	○	▲	⊙	▲	▲	▲	▲	○	○	○
8	9	7,9	6,0	system integration with stock	○	○	▲	⊙	▲	▲	▲	▲	○	○	○
9	1	10,5	8,0	clear messages	▲	▲	▲	▲	▲	▲	▲	▲	▲	▲	▲
10	3	7,9	6,0	graphic visualization (charts, diagrams) of certain data	○	▲	▲	▲	▲	▲	▲	▲	○	▲	○

Fig. 3. L diagram describing the interrelations between identified customer requirements and technical requirements.

Fig. 5 shows the R diagram (which forms the roof of the house of quality) describing the interrelations between the above-mentioned 11 technical requirements (positive or negative). The determination of these interrelations will help satisfy customer requirements and allow the designer to determine the measure of freedom with which the design can be optimized.

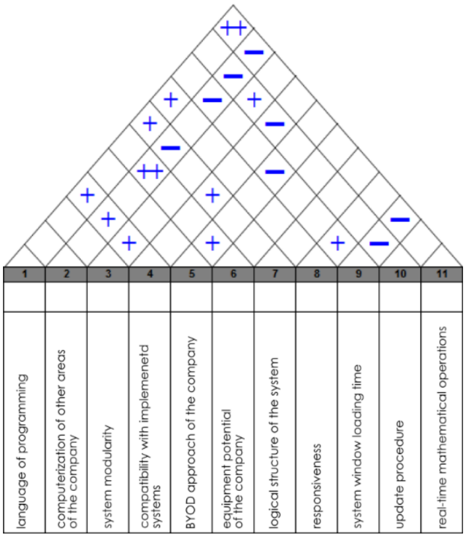

Fig. 5. Diagram R describing the interrelations between technical requirements of the system.

The matrix demonstrates that it will be necessary to find compromise solutions with respect to:

– system window loading time and the type of *Bring Your Own Device (BYOD)* approach used by the company,
– system window loading time and updates,
– system window loading time and real-time mathematical operations.

5 Summary and conclusions

The possibility of collecting information in real time about the production process, machinery work parameters as well as the quality of manufactured products has become an indispensable element of the upcoming transformation of production enterprises as part of the 4.0 industrial revolution [25]. As a result, implemented IT systems must meet high requirements – given the number of processed data as well as the ability to determine the impact of correlation between collected data (both quantitative and qualitative), inferring systems should also be expert systems supporting the user in the analytical and decision-making areas.

Based on the reported analysis, the following conclusions can be drawn:

– the use of the QFD method at the initial stage of works enables identification of the requirements posed for the system by defining its desired features,
– the customer opinion regarding the desired system characteristics, boosts the chance of achieving a high level satisfaction of the system's end-user increases,
– the development of an IT system entails cooperation between various functional units, whose task is to influence the system's final shape by specifying its functionality, without directly affecting its design,
– the use of qualitative tools for the design of a prediction and decision system is to be a step towards ensuring satisfaction of an entrepreneur using this system to support works carried out by the maintenance services, resulting from the benefits for the company due to the elimination of certain failures.

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