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Machine learning applied to quality management—A study in ship repair domain

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Abstract

The awareness about the importance of knowledge within the quality management community is increasing. For example, the Malcolm Baldrige Criteria for Performance Excellence recently included knowledge management into one of its categories. However, the emphasis in research related to knowledge management is mostly on knowledge creation and dissemination, and not knowledge formalisation process. On the other hand, identifying the expert knowledge and experience as crucial for the output quality, especially in dynamic industries with high share of incomplete and unreliable information such as ship repair, this paper argues how important it is to have such knowledge formalised. The paper demonstrates by example of delivery time estimate how for that purpose the deep quality concept (DQC)—a novel knowledge-focused quality management framework, and machine learning methodology could be effectively used. In the concluding part of the paper, the accuracy of the obtained prediction models is analysed, and the chosen model is discussed. The research indicates that standardisation of problem domain notions and expertly designed databases with possible interface to machine learning algorithms need to be considered as an integral part of any quality management system in the future, in addition to conventional quality management concepts.

Keywords: Quality management; Knowledge acquisition; Deep quality concept; Delivery time estimate; Dock works

1. Introduction

Ship repair is a complex, highly dynamic and stochastic process with high interdependencies. The process is also characterised with a high share of incomplete and unreliable information that is particularly expressed in some stages of the process. In such processes output quality is significantly influenced by the quality of assessments and decisions that cannot be ensured only by adherence to certain predefined procedures and instructions, on which, e.g. the standard ISO 9001 is based. In such systems expert knowledge and experience play a decisive role, and they are often of the nature that makes it practically impossible for them to be formalised with traditional methods. Also, because of so expressed technological complexity, and too many inter and intra dependent variables of influence, it is not easy (or even possible) to define efficient analytical models. Delivery time estimate in ship repair is one of typical examples of such processes. It includes the overall repair time estimate, as well as the estimate of duration of repair works in dock. The accuracy of these estimates significantly influences the quality of ship repair service. Also, it is critical for the business results of the shipyard. If the estimated times are too long, the shipyard will not be competitive. And if they are estimated too short, a production schedule may fail due to unrealistically estimated activity durations, which may result in final delivery time delay and penalties. Also, the quality of performed job might be influenced negatively given that delay often means doing things in hurry. This particularly goes for the overall repair time estimates.

On the other hand, developments in artificial intelligence provide powerful means for modelling expert knowledge. They also allow the automatic acquisition of such knowledge by means of machine learning or data mining techniques. Unfortunately,

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the use of such techniques in quality management context is not of systematic but rather of an *ad hoc* manner. In industry this is caused by at least two main reasons. The first is Taylorian philosophy of manufacturing that still prevails in the current quality management models. Determinism of operations, predictable behaviour of the system, and a priori information that is reliable, complete and accurate, identified as the basic Taylorian presumptions of manufacturing systems by Peklenik [1], are still the main presumptions of the most well known quality management models (total quality management model (TQM), Malcolm Baldrige Criteria for Performance Excellence, EFQM Excellence Model, and standard ISO 9001). For example, fact-based management, i.e. the factual approach to decision making, are still listed among core quality concepts in the frame of all these models. Also, the use of information technology is not sufficiently systematic. One of the consequences of this is the lack of accurate and standardised bases of organisational as well as of technological data in some manufacturing organisations and domains. The second reason why the use of artificial intelligence techniques in quality management context is not of systematic but rather of an *ad hoc* manner is that knowledge of artificial intelligence techniques is typically modest. On the other hand, although the Malcolm Baldrige criteria included recently knowledge management into one of its categories, the emphasis in related research is mostly on learning, i.e. on knowledge creation and knowledge sharing, and not knowledge formalisation process (see, e.g. [2]). Also, distinction between the terms 'knowledge' and 'information' is not always clear in such research (see, e.g. [3]). A more detailed explanation of these limitations, as well as the DQC model—a new theoretical framework how to overcome these deficiencies are presented by Srdoc et al. [4]. In difference to other quality models that are typically concerned only with shallow knowledge, in this model particular attention is paid to standardisation of domain concepts, and domain deep knowledge. Integration of information systems, defined as systems whose purpose is to acquire and represent knowledge, and quality systems is also proposed in [5]. Dooley [6] also suggests that TQM paradigm based on predictability, control and linearity may be insufficient. How TQM approaches are inadequate because they do not address the uncertainties that impact significantly on results in some industries, is also described in [7]. On the other hand, a review of the use of intelligent systems in manufacturing can be found in, e.g. [8]. The review shows variety in the use of these techniques.

Concerning the use of machine learning algorithms for quality management in manufacturing, there are also several approaches. For example, Shigaki and Narazaki [9] demonstrated an approximate summarisation method of process data for acquiring knowledge to improve product quality based on the induction of decision trees, one of machine learning techniques. They also demonstrated a machine learning approach for a sintering process using a neural network [10]. Concerning the ship repair domain there has been no work reported on the use of artificial intelligence for quality management. Thus the use of machine learning algorithms has also not been reported. Instead, approaches based mainly on statistical techniques and ISO 9000 standards can be found (e.g. [11,12]). On the other hand, some work concerning manufacturing databases in the ship repair domain has been reported (e.g. [13]).

In this study, the approach as suggested within the DQC model is applied. The mechanisms investigated are: (1) systematic recording of data into expertly designed database, (2) standardisation of the data, and (3) transformation of the data into a knowledge base by means of machine learning. The data studied in the research and collected from a real ship repair yard are: (1) parameters defining repair activities that were described within each repair project (attribute values), and (2) related times estimated by the human expert (the target attribute). The data are limited to dock works. The reasons for that are: (1) dock works are technologically self contained subset of repair works, present in almost every ship repair project, (2) dock works often contain activities that influence the overall delivery time the most, such as anti-corrosive and steel works, and (3) since docks appertain to the most valuable and bottleneck resources of any shipyard the duration of these works is always important, and estimated separately. The goal of machine learning from these data was to construct comprehensible delivery time predictors, such as regression or model trees for computer-supported estimate, eliciting the hidden implicit knowledge from the data. Attribute selection and data refinement are done manually, based on the deep understanding of the learning problem and what the attributes actually mean. Given that in the inquiries-answering stage detailed technical data typically are not known, they are not included into this study.

2. Delivery time estimate in ship repair

The correct estimate of delivery time largely influences the quality and cost of the ship repair service. The delivery time depends generally on factors concerning: (1) the particular works that have to be done within the ship repair project, (2) the features of the shipyard, such as, e.g. physical capacities and capacity loading, facilities, technologies, tools and manpower available, experience and skill of people, (3) delivery time of materials and components, and (4) the situation on the market, such as the corresponding delivery times of competitors. Although within the operations planning, shipyards define works dependencies for almost each ship repair project, and there have been some efforts to improve the situation (see, e.g. [14]), a satisfying generic and computerised model that would support time estimates in the inquiries-answering stage when a large amount of data are still not known, and has capabilities to learn with time, has not been developed. Instead, mainly software packages that allow the user to construct a hierarchical model of the shipyard's facilities and their workload based on the user knowledge and information are available (see, e.g. Chryssolouris et al. [15]). Also, a ship-owner typically contacts a number of shipyards in order to submit the initial work list. Therefore, shipyards accept a large number of enquiries that have to be evaluated. Consequently, the situations in which shipyards model ship repair works separately for each project, and on a relatively high level, are not rare.