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A Quality Management Model Based on Databases and Knowledge

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Subject review

In the paper the results of the doctoral research in which a new knowledge-focused approach to quality management called *Deep Quality Concept* (DQC) is conceptualised, are presented in short. The main features of the new quality management model developed on that approach also are presented. Particular attention is paid to expert knowledge – especially tacit and deep domain knowledge, i.e. on knowledge that is not only decisive for quality, but also for the competitive advantage of an organisation. Given that such knowledge is hard or even impossible to be formalised by traditional methods, computer concepts – including artificial intelligence (AI) concepts, also are included in the model. The DQC model contains both, i.e. (1) the part concerning development of quality standard i.e. quality award criteria based on the developed approach; and (2) the part concerning implementation of the so obtained standard i.e. award criteria. The main points and potential of the model and approach are validated in the case study by example of delivery time estimate in ship-repair, aimed to get a more transparent assessment and decision structure through the use of machine learning – one of the AI's best known and efficient knowledge acquisition and representing techniques. The application results showed that the proposed approach can contribute significantly to the more reliable quality, particularly in complex and highly dynamic and stochastic domains. That confirmed that computer and AI concepts need to be considered as an integral part of quality management systems, as it is anticipated in the DQC model.

Model upravljanja kvalitetom temeljen na bazama podataka i znanju

Pregledni članak

U ovom su radu ukratko predstavljeni rezultati znanstvenog istraživanja u okviru izrade doktorske disertacije u okviru kojeg je osmišljen novi, na znanje usmjereni pristup upravljanju kvalitetom, nazvan *Deep Quality Concept* (DQC). Glavne značajke novog na temelju tog pristupa razvijenog modela upravljanja kvalitetom, također su predstavljene. Posebna pozornost pridana je pritom ekspertnom znanju – posebno tihom i dubokom znanju o domeni, tj. znanju koje nije samo odlučujuće za kvalitetu već i za komparativne prednosti neke organizacije. Budući je takvo znanje teško ili čak nemoguće formalizirati tradicionalnim metodama, računalni koncepti – uključujući koncepte umjetne inteligencije (UI), također su uključeni u model. Model sadrži oboje, tj. (1) dio koji se odnosi na razvoj standarda kvalitete, tj. kriterija nagrada kvalitete; te (2) dio koji se odnosi na implementaciju tako dobivenog standarda, odnosno kriterija nagrada. Glavne točke i potencijal modela potvrđeni su u studiji slučaja na primjeru procjene vremena isporuke u brodoremontu, kojeg je cilj bio dobiti treansparentniju strukturu ocjene i odlučivanja uporabom strojnog učenja – jedne od najpoznatijih i najučinkovitijih tehnika UI za stjecanje i prikaz znanja. Rezultati te primjene pokazali su da predloženi pristup može značajno doprinijeti pouzdanijoj kvaliteti, posebno u složenim i izrazito dinamičkim i stohastičkim domenama. Time je potvrđeno da računalni koncepti, kao i koncepti UI, trebaju biti smatrani sastavnim dijelom sustava upravljanja kvalitetom, kao što je to predviđeno u DQC modelu.

Keywords
DQC model
Knowledge management
Knowledge synthesis
Machine learning
Quality management
Ship-repair

Ključne riječi
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Sinteza znanja
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Upravljanje znanjem

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1. Foundations of the research

For the last quarter of the twentieth century one of the leading topics not only in industry has without doubt been quality. Nowadays, growing world market globalisation and ruthless competition have increased the importance of quality additionally. On the global market only the best can survive, and not only in the sense of the quality of their products and/or services, but in a much broader meaning of the word. That is now well-recognised in the majority of the available quality management models. However, although there are significant differences

Symbols/Oznake

AI	- artificial intelligence - umjetna inteligencija (UI)
CC	- correlation coefficient - koeficijent korelacije
DQC	- Deep quality concept - Koncept dubinske kvalitete
EFQM	- European foundation for quality management - Europska fondacija za upravljanje kvalitetom
HP	- high pressure - visoki tlak
ISO	- International organization for standardization - Međunarodna organizacija za standardizaciju
MAE	- mean absolute error - srednja apsolutna pogreška
MBCPE	- Malcolm Baldrige criteria for performance excellence - Malcolm Baldrige kriteriji za izvrsnost performansi
PF	- pruning factor - faktor rezanja
RAE	- relative absolute error - relativna apsolutna pogreška
RMSE	- root mean squared error - standardna devijacija srednje kvadratne pogreške
RRSE	- root relative squared error - kvadratni korijen relativne kvadratne pogreške
TQM	- Total quality management - Upravljanje potpunom kvalitetom

in those models, the problem is that although these frameworks give the guidelines for development of quality systems, they are found to be not entirely complete, even where the most advanced are concerned. Second, although certain proposals of how to integrate these models are found in literature, and some of them have significantly illuminated the issue (see e.g. [1 – 3]), they were assessed as not complete, and not completely acceptable. That has confirmed the report of Aravindan *et al*. (see [4]) of the lack of a generalised model which can integrate the various strategies adopted by numerous quality management and engineering experts, and can be focused towards quality.

The reasons we find these quality frameworks and integration receipts not completely acceptable lay in their concern only with the integration of standards series ISO 9000 and Total Quality Management (TQM), or *vice versa*, while other models, like business excellence models, were completely left out. Second, they all also depart mainly from the existing models as given dimensions that they then suggest to be integrated either unchanged, or very slightly changed. On the other hand, many studies showed serious deficiencies in the standards series ISO 9000, as well as in TQM. Some authors also found that the relationship between ISO 9000 and TQM is often poorly understood (see e.g. [4]). Managers also generally lack understanding of the concepts and principles of quality management (see e.g. [5]).

However, the most important reason why the explored frameworks and propositions were assessed as unacceptable lay in our finding that the existing quality models did not reflect, and did not utilise, the achievements and possibilities of other relevant sciences – especially not of computer and cognitive sciences. We also concluded that if this trend continues, there is a serious possibility that the existing gaps shall remain uncovered, or insufficiently systematically covered, particularly in the treatment of knowledge within the models. Thus, e.g. although the knowledge management concepts were in the meantime included in one of the explored models, it was found that all questions are not fully addressed. Our research also showed that the emphasis on research relating to knowledge management is focused mainly on knowledge creation and dissemination, while the knowledge formalisation process – which in our opinion deserves at least equal attention, is almost completely left out of such considerations.

On the other hand, according many references the differences in a firm's performances are attributed increasingly to tacit knowledge (see e.g. [6]). The mix of tacit knowledge – that is mainly based on experience, and the deep domain knowledge that is also very important for organisations, and based mainly on years of studying and learning, is particularly significant for experts. However, human experts are typically rare. Their knowledge can also be incomplete, and not always easy to be bought because it is highly context dependent. It is also difficult to be imitated, and it is often of a nature that makes it practically impossible for it to be formalised with traditional methods. This means that the processes depending on such knowledge, if the knowledge is not formalised, *de facto* depend on individual(s) that have that knowledge [7]. Given that it is also knowledge that is always decisive for the output quality of related processes, in the quality context the question is whether such a situation is allowable, and under what conditions. The second question is what its implications are. The uncertainty associated with humans makes these questions even more important [7].

The quality models before the DQC model was developed typically were not concerned with such questions. They knowledge related only to people, and looked at it as unquestionable. Also, they omitted to note that there are different types of knowledge. Our conclusion was that such a situation could be a consequence of the Taylorian philosophy of manufacturing, which these models are still mostly based on. The basic presumptions of Taylorian philosophy are: (1) determinism of operations; (2) predictable behaviour of the system; and (3) *a priori* information which is reliable, complete, and accurate (see e.g. [8, 9]). 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, not only the expert knowledge that is not formalised.

Developments in AI provide powerful means for modelling the expert type of knowledge. They also allow the synthesis, i.e. the automatic acquisition of such knowledge by the means of machine learning or data mining techniques. Unfortunately, the use of AI techniques in a quality management context is not of systematic, but rather of an *ad hoc* manner. In industry this is caused by the aforementioned Taylorian philosophy of manufacturing, but also with typically very limited knowledge on AI techniques and their possibilities [7]. Even though in quality management literature there is some progress in that sense, the dynamic and stochastic side of processes, as well as the uncertainty connected to humans, are still not included into considerations within the models existed before the DQC model [see 7]. On the other hand, these considerations are included in reflections of some other authors (see e.g. [9 – 11]). Although their work was not well articulated in the terms of its applicability in the time of this research, for the quality management theory and practice it was important – and still is – that the change of the TQM paradigm is also suggested by other authors. However, mechanisms that can ensure that crucial concepts for which we argue are systematically covered, in their work are not presented.

The quality management models being explored within our research are: (1) Total Quality Management (TQM) model; (2) the Malcolm Baldrige Criteria for Performance Excellence (MBCPE) model; (3) the European Foundation for Quality Management Excellence (EFQM) model; and (4) the standard ISO 9001. The terminology used concerning quality management models and quality management systems is well explained in [7], in which the DQC model is presented for the first time. On the other hand, full details of the example on which the DQC model is validated, and that represents the first application of machine learning concepts and techniques to ship-repair, can be found in [12].

2. Scope of the research and motivation

Based on the mentioned findings, as well as the known empirical observation that experts find it easier to produce good examples than to provide explicit and complete general theories [13], and that within AI there are now very powerful techniques and tools for extracting and representing knowledge from databases that can be effectively used in complex applications, the following theses of the dissertation are established:

1. In order to be considered as effective and reliable, besides documented procedures, working instructions and different documents and records, quality management systems have to contain formalised knowledge – particularly formalised expert knowledge, as well as general data on knowledge in organisations.
2. To make this possible, besides traditional methods of knowledge recording, e.g. by means of documents, and the like, and in organisations already established functions like quality engineers and quality managers, in designing, development, and maintenance of quality systems contemporary techniques and tools from computer technology and science for knowledge synthesis and representation – such as e.g. machine learning algorithms, should be also included, as well as knowledge engineers.

The objectives of the research therefore were: (1) to conceptualise a new approach to establishing quality systems; and (2) to define and validate the quality management model based on that approach. The approach, as well as the model we called *Deep Quality Concept*, given that in difference to other quality models typically concerned only with shallow knowledge, in our approach and the model particular attention is paid to tacit and domain deep knowledge. 'Deep knowledge' is a term from AI, and in the research was understood as deep principles from which shallow knowledge (another term from AI) can be derived logically. For this reason and because of the importance of AI concepts, as mentioned before, they are anticipated in the model. The same goes for domain specific concepts to which particular attention also is paid, while in other models they are not explicitly mentioned, and are understood only implicitly. Reasons why the example by which the developed approach and the model are validated is limited to dock works are explained in section 4.

The research has been motivated by the first author's experience with knowledge-intensive processes, as well as with implementation of the standard ISO 9001 in two big Croatian shipyards. One of the shipyards was of a repairing type, i.e. with strongly expressed characteristics of dynamic, as well as stochastic systems in which tacit i.e. expert type of knowledge plays a particularly important role. The positive results achieved using AI techniques in the first author's Master Thesis – also in the field of ship-repairing, contributed significantly to the chosen approach. Finally, although the emphasis of the research was on concepts dealing with knowledge formalisation and AI, the model is designed as opened with inbuilt possibility of including also other concepts from other relevant sciences and disciplines. That represents the next important particularity and contribution of the developed model, compared with the other models available. According to the research carried out, a significant part of possibilities for better and more reliable quality could lay exactly in concepts from areas outside the traditional quality management.

3. The DQC model

The core of the DQC model, originally consisting of twelve levels, is presented in Figure 1. As shown in the figure, the model contains: (1) the development of a quality standard i.e. award criteria; and (2) the implementation of the resultantly obtained quality standard, i.e. award criteria, which are both interrelated with the continuous improving processes. In the model these parts are marked as *Part I* and *Part II*. The fact that the model incorporates both - the quality standard i.e. criteria development part and the implementation part, while all other models are concerned only with implementation, is another of the important particularities and contributions of the DQC model. Other models typically contain only guidelines how to implement some standard or award criteria as a final product, while the methodology of their development that precede this process is typically not included in the models. For this reason they are untransparent, and are changing slowly.

On the other hand, customers' needs and criteria in the DQC model are marked as *Part 0*. Given that this is included also in all other models, in our research it is not specially discussed, although it is of course very important. The concepts listed in the double marked blocks, under each of the parts' titles, represent the expected outcomes.

However, given that each of the parts listed in Figure 1 consists of one ore more levels, it is to note that the most specific levels corresponding to the concepts being discussed previously are those of Part I. These levels are: (1) domain specific concepts; (2) computer concepts including AI concepts; (3) quality management concepts; and (4) other relevant concepts and social priorities. The last three are supposed to form the quality management framework that defines the philosophy and values, which then the quality standard i.e. award criteria are to be based on and developed.

The aims of the so conceived model are twofold:

- To help quality standardisation and award bodies to develop better and more sophisticated quality standards, i.e. quality award criteria; and
- To help organisations to develop better and more efficient quality systems.

It is to note that in the DQC model quality is defined as a four dimensional phenomenon, consisting of (see [7]):

- Business results i.e. results, including indicators and trends;
- Customer satisfaction;
- People - including managers, experts and other specialists - satisfaction, development and health; and
- A positive impact on society and environment.

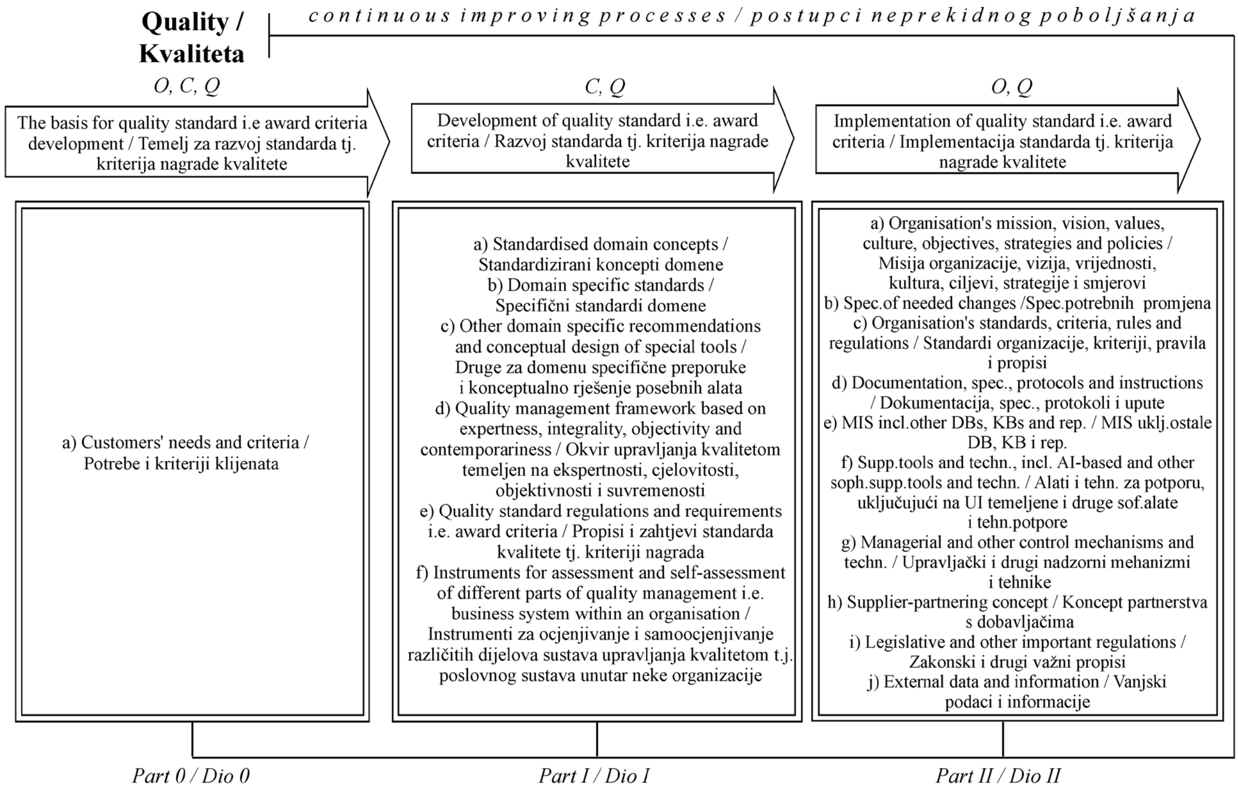
In addition to 'business results', 'results' are included as a possible version of the first dimension because the DQC model is also perfectly applicable to non-manufacturing and non-profit organisations, such as scientific, educational, or public institutions. On the other hand, indicators and trends are put also in this dimension, because to get reliable assessments, they could be even more important than the current results are. As it can be seen, this quality definition also incorporates people satisfaction, development and health. It also incorporates the impact that organisations have on society and environment. All these make this definition absolutely consistent with the newest demands for more rigorous corporate responsibility – reinforced also by the newest omnipresent and serious financial and economical crisis, but also with the emerging concern about environmental and sustainable development issues. Although in some other models we also found concepts regarding corporate responsibility and the like, the environment namely was found only in one model. Our newest research also revealed that although sustainable development is a growing issue within quality management community, and quality management frameworks are also understood as a possible catalyst for more effective sustainable development (see e.g. [14]), such efforts are still not incorporated in all official quality management models. We revealed also that the portion of such joined research *vs.* whole quality management and sustainable development research is still very limited. According the preliminary results of searching the ISI Web of Knowledge database, it is not likely to exceed much than few per cents. In absolute figures, on the other hand, it grows significantly.

What is also very important concerning the quality standard i.e. award criteria implementation process is that the most desirable features of all of the most important participants are also clearly denoted in the DQC model. In other models these features are mainly only implied, similarly as *a priory* knowledge. Thus e.g. among the most important features for managers, experts and other specialist, but also for the people are denoted their knowledge, integrity, and openness, but also willingness and capability to learn.

Main exponents of each of the parts - that correspond to the particular stage of the development process, also are denoted in the DQC model (see Figure 1). These exponents are: centres of knowledge (C); organisations (O); and quality standardisation and/or award bodies (Q), which is another of important differences comparing with all other models. For more details about the model, such as e.g. its core concepts and values, as well as recommendations considering the implementation of the model, see [7].

4. Validation of the DQC model

The theses set out in section 2 are tested and the model is validated using the example of a delivery time estimate of dock works in ship-repair. This particular problem was chosen for the case study because: (1) dock works are technologically a self-contained subset of repair works, present in almost each ship-repair project; (2) dock works often contain activities that influence the overall delivery time the most; 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 [12]. However, the most important reason was that ship-repair is a sufficiently complex, dynamic, and stochastic business system (see [15]), and the delivery time estimate significant enough for the quality of ship-repair service that the results and conclusions derived could be considered as relevant for the assessment of the new approach and the model.



Legend / Legenda: C - Centres of knowledge / Centri znanja; O - Organisations / Organizacije; Q - Quality standardisation and/or award bodies / Tijela koja se bave standardizacijom i/ili nagradama kvalitete; AI - Artificial intelligence / Umjetna inteligencija; DBs - Databases / Baze podataka; KBs - Knowledge bases / Baze znanja; MIS - Management information system / Upravljački informacijski sustav; incl. - including / uključujući; rep. - repositories / repozitoriji; soph. - sophisticated / sofisticirani; spec. - specifications / specifikacije; supp. - supporting / za potporu; techn. - techniques / tehnike.

Figure 1. The DQC model (adapted from [7])

Slika 1. DQC model (prilagođeno prema [7])

The basic concepts and mechanisms of the DQC model investigated by this example in the case study were:

1. Standardisation of the domain concepts;
2. Forming of the expertly designed database; and
3. Application of the AI techniques and tools for the estimating knowledge synthesis.

The particular AI techniques applied for transformation of the data into a knowledge base were from machine learning – particularly regression and model trees, and instance-based learning. For learning about model trees, as well as about regression trees, the system M5' [16] for continuous classes was used. M5' is a reimplementation of Quinlan's model tree learner M5 [17] within the software package *Weka* [18]. The aims of the knowledge synthesis were:

1. To make more transparent estimate structures;
2. To increase the reliability of the estimates, and thus the quality of the ship-repair service with lower costs and lower risks as well; and
3. To prevent the loss of the valuable knowledge and experience.

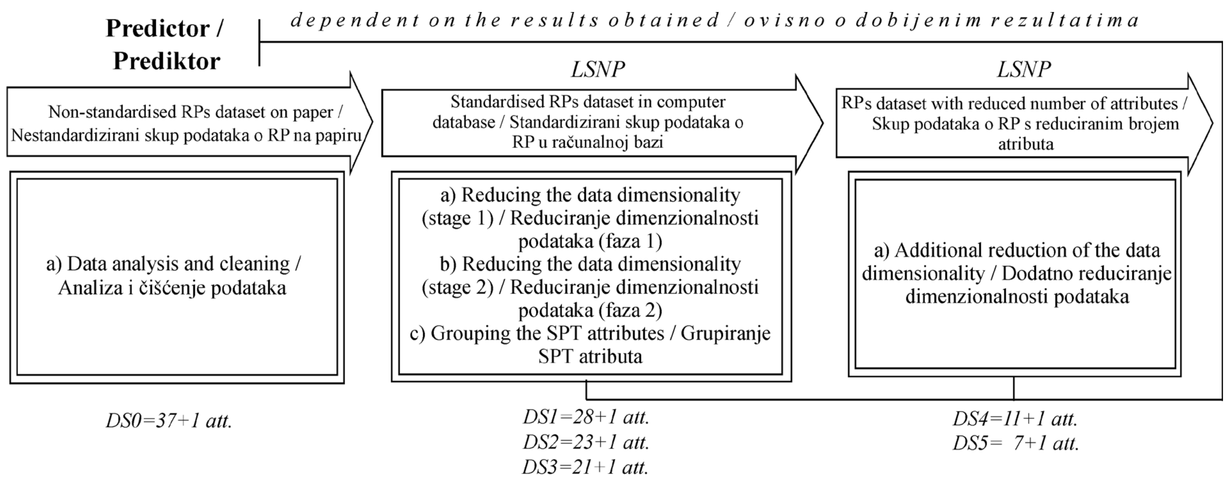
4.1. The experiments

In the experimental part of the research a total of 221 cases of ship-repair projects were collected. The first analyses showed that of this number a part of the cases was not appropriate for further analyses. For this reason only 197 cases containing relatively well-defined works in dock are used to define the appropriate data model. However, it is to note that of these 197 cases 13 were discarded later because they were with the same values as some other cases in the sample. After this preliminary cleaning of the data, the focus was put on the four groups of works that the domain expert assessed as the most important for the duration estimate of dock works, i.e. on:

1. Renewal of steel on shell plating;
2. Shell plating treatment;
3. Works on propeller and propeller shaft; and
4. Works on rudder.

That way finally the data model consisting of 37 most important dock works for a duration estimate was obtained. The main difficulty was that although the shipyard was already ISO certificated, the repair projects were described in a shortened non-standardised form on paper, and a lot of systematic analyses and consultations were necessary to get the final data model. By adding durations estimated by the domain expert in days as the target attribute (continuous class), and the column for the case ID, the pattern for dock works data entry into the database was finally defined (see [12]). That was followed by the careful data pre-processing procedures. Due to their possible influence on the efficiency of learning, particular attention was paid to missing values in the sample, and the reduction of the data space. Within the explored dataset, the values are missing mainly because a significant part of them is typically unknown in the stage of inquiries answering process.

After that, the machine learning algorithms were applied. However, there is no definite way to choose the most appropriate learning methods in a specific domain [19]. For this reason in the learning stage several learning tests were carried out. In different tests different prediction techniques were applied, using different attribute sets, and different options available. Because of so many possibilities discovered for the reduction of the data dimensionality, this process was realised in two stages (see Figure 2). Due to the predictors obtained and their accuracies, the grouping of attributes, as well as additional reduction of data dimensionality, was also performed (in the figure that is indicated in the double marked blocks).



Legend / Legenda: DS - Data set / Skup podataka; LSNP - Learning schemes for numeric prediction / Sheme učenja za numeričku predikciju; RPs - Repair projects / Remontni projekti; SPT - Shell plating treatment / Tretman vanjske oplate.

Figure 2. The outline of the learning experiments

Slika 2. Opći pregled pokusa učenja

4.2. The predictor chosen

The results confirmed that model trees and simple linear regression are the best methods for the delivery time estimate problem in ship-repair domain. To evaluate how different methods work and to compare results, five measures of performance were examined:

1. The multiple correlation coefficient (CC);
2. The mean absolute error (MAE);
3. The root mean squared error (RMSE);
4. The relative absolute error (RAE); and
5. The root relative squared error (RRSE).

Results are compared varying: (1) the learning method; (2) the dataset, i.e. the attributes used; and (3) the pruning factor. Good performance when measured with the correlation coefficient is indicated with large values. For all other methods good performance is indicated by small values.

Although the results compared are those achieved in terms of predictive accuracy of induced models on unseen cases, as estimated by 10-fold cross-validation, where appropriate, i.e. for regression and model trees and linear regression, to explore the performance bounds, models generated on the entire dataset of 184 instances also are analysed (see [12]). Generally, the 10-fold cross-validation results showed that in the case of model trees, as well as linear regression, varying pruning factor accuracy of the results influenced very little. In case of regression trees, on the other hand, it influenced significantly. Regarding datasets, predicting accuracy was much stronger influenced with the learning scheme applied, very little with the pruning factor applied. Finally, for predicting the durations of repair works in dock the model tree induced by M5' scheme from a dataset containing twenty one plus one attribute (DS3), and using the default pruning factor 2,0 was chosen. Although the corresponding linear regression model achieved similar accuracy (CC = 0,8376; MAE = 1,9701; RMSE = 3,1239; RAE = 57,2147 %; and RRSE = 55,8301 %), it was not chosen because it was not as readable as the model tree. To predict the value of the target attribute, it used all the variables, while the model trees (as well as regression trees) focus only on the variables that dock works duration influences the most [12].

The performance accuracy of the chosen predicting model on unseen cases as estimated by 10-fold cross validation is among the highest achieved (CC = 0,8439; MAE = 1,9898; RMSE = 3,0417; RAE = 57,7887 %, and RRSE = 54,3618 %). Also, it covers well almost the whole range in which dock works durations occurred. The chosen model tree induced by M5' on all the data of 184 instances is given in [12]. The experiments confirmed that total quantity of steel within the renewal of steel on shell plating, and shell plating treatment are the most important attributes, appearing in all generated models. On the other hand, high-pressure (HP) washing surface revealed as a more informative parameter than it is usually thought. The tree can be used to predict the duration of repair works in dock. Depending on the values of attributes that appear in the ship-owner's enquiry, one of the five corresponding linear models is to be used.

4.3. Comparison with the sample estimates

A comparison of values obtained by the chosen model tree, and those recorded in the database for the target attribute showed that 89,7 per cent of the results lay within the acceptable bounds of ±2-3 days of deviation or less, assessed by the domain expert as acceptable, while only 10,3 per cent were outside of that. The average deviation of the model compared to the expert's estimates was 1,83 days, and only 0,52 days after the values for the five cases containing inconsistencies in the expert estimates were discarded. It is to note that these inconsistencies were detected after the predicting model was synthesised, and the values compared. On the other hand, it is known that for small datasets the performance of the model could deviate sharply [12].

It was revealed that model estimates for these five examples appeared to be closer to the expert estimates for the similar cases, than the values recorded as expert estimates for these instances. The conclusion confirmed by the expert was that true estimates for these five cases were not recorded, thus not included into the dataset. In order to get the job, shipyards sometimes give even unrealistic offers to the ship-owners. Also, they could estimate delivery times having in mind the need for additional manpower. For these reasons for real-life applications it is always important to have notes considering the presumptions of the estimate (e.g. normal conditions or additional manpower anticipated, etc.), as well as data on the estimate itself (e.g. initials of the expert, the date of the estimate, etc.), included into the records [12].

All this demonstrated how additional justification of expert opinion could be critical [12]. It also demonstrated how a relatively small sample of historical cases could contribute significantly to this. In the case of employing such a basic concept as systematic recording of relevant data into expertly designed databases – preferably within quality systems, the higher estimating accuracy of machine learning predictors could be achieved, and be of great benefit to the efficiency and profitability of the ship-repair service. On the other hand, human experts need at least 10-15 years of experience to be able to give reliable estimates. For these reasons, the mechanisms, as suggested within the DQC approach, are so important to be recognised, and applied in quality systems. The feedback, however, although also important, for this particular problem has to be applied with caution (see [12]).

4.4. Statistical significance

To check whether there is a statistically significant difference between the two algorithms that achieved the best results, i.e. between the model tree and linear regression, both generated on the same dataset (DS3) with the default pruning factor (PF=2), a statistical test known as the *paired t-test* is applied. The test was performed according to the methodology and formulae found in [20]. It was found that the null hypothesis that the means are the same has to be rejected, and that there is a significant difference between the two learning methods on that dataset.

However, a statistically significant difference does not necessarily mean that the difference is large. In fact, from the graphs representing the predictive accuracy (error) obtained using different datasets was obvious that CC values for model trees and for linear regression are very close, for all datasets and pruning factors. For other measures for numeric prediction the *paired t-test* was not performed because from the graphs it was obvious that for these performance measures the differences between the corresponding pairs are much greater than for the CC.

5. Conclusions and acknowledgement

In the paper the results of the doctoral research in which a new knowledge-focused approach to quality management called *Deep Quality Concept* (DQC) is conceptualised, are presented in short (see [21]). Although in the research the emphasis was put on concepts regarding knowledge, the developed model is general and complete. The aim was twofold: (1) to examine the issue from a different angle – not to exploit the usual stereotypes with which a majority of currently available research in the field is mainly occupied (see e.g. conclusions of the research by Jack et al. [22]); and (2) to make the room for more in depth reasoning and finer understanding of elements that could influence and define quality, and that are usually omitted. The intention also was to help to overcome the existing gap between theory and practice in different, currently not sufficiently connected but logically close areas. For these reasons, the developed approach and the model represent the important shift in the relation to other approaches and models, which are described and used widely. The recent change that occurred in the MBCPE model considering the introduced knowledge management concept into one of its categories, confirmed the right direction suggested in our research.

Except in the MBCPE model, in literature also other attempts to link together concepts related to knowledge and quality management concepts were found. However, they are based mainly on narrative, and are difficult to understand, or are too academic to be applied in practice (see e.g. [11, 23]). The model that is developed within the presented research, on the other hand, is supported graphically, and it is easy to understand. This model also contains all elements necessary to achieve real integration of knowledge related concepts and quality management concepts. Also, it is much wider than other models, and opened to include all other knowledge that is also relevant for quality no matter which science or discipline it appertains to – of general type, as well as those of particular domains.

In the example studied, the most important points and concepts of the developed theoretical framework are validated on a real problem from ship-repair industry, using machine learning algorithms. That – as mentioned – represents the first application of machine learning to ship-repair. In spite of very limited sample available, as well as a high share of missing or unknown values in the sample, the results usable in real life are achieved. The experiments also demonstrated that machine learning methods can offer an advantage over approaches based on linear and network analysis that are usually employed for the time estimate problem in shipyards, because they do not need any prior assumptions or knowledge about the relationships between variables [12]. That demonstrated that concepts explored within our approach need to be included in quality management systems - as it is anticipated in our model - on a regular basis, as well as the mechanisms that make it possible that powerful techniques and tools for knowledge synthesis also are used. That is particularly important for dynamic and stochastic domains and processes where estimates based on expertness are particularly frequent.

Of course, all these do not mean that traditional quality management principles have to be set apart. As shown, it only means that these principles need to be re-examined and enriched with the new concepts and approaches with more courage and decision than it was the case till now. The courage and decision are particularly important in this time of crisis.

Finally, it is to note that such a complex work would not be possible to be accomplished successfully without a good example and significant domain expert help. For this reason we would like to underline our sincere thanks to Mr. Drago Brzac, who has helped us in that unselfishly.

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