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QFD WITH STATISTICAL RANKING – A HYDROPOWER TURBINE CASE STUDY

Rihar, L. & Jenko, M.
University of Ljubljana, Faculty of Mechanical Engineering, Department of Cybernetics, Mechatronics and Manufacturing Engineering, Aškerčeva 6, 1000 Ljubljana, Slovenia
E-Mail: marjan.jenko@fs.uni-lj.si

Abstract
Influences of hydropower plant water turbine operational parameters on turbine operational economics, reliability and lifetime are ranged with a new type of QFD method that includes parameter distribution densities and probabilities. In our method, each dominant i.e., main parameter coexists with associated side parameters. Their contribution to effects, usually attributed to the main parameter only, is modelled by a) probability density of the side parameter contribution to the main parameter effects, and by b) side parameters' Bernoulli distribution since association of side parameter to the dominant parameter effects is in the realm of probability and not all side parameter effects are associated with the main parameter effects at all times. Analysis results are probability densities of dominant parameters influence measure on the turbine operating attributes. A simulation tool was built to establish relations amongst influential parameters and turbine's economics, reliability and lifetime. We obtained technical data associated with turbine operation attributes from turbine senior designers having led successful projects within last 30 years. Simulation results have been validated with existing turbine-projects maintenance data.
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Key Words: Hydropower Turbine Maintenance, Parameter Probability Density, Predictive Analysis, QFD, QFD SR, Sensitivity Analysis

1. INTRODUCTION

Hydropower, which is most useful renewable energy source, converts water flow energy into electrical energy via turbine and generator systems. Efficiency and reliability are crucial as they influence large quantity energy conversions. Optimizations and predictions are most important in this industry [1-3].

Turbines in hydropower plants face various challenges during their lifetime. Among them are physical degradation (erosion and cavitation) and operational problems (overloads and maintenance issues). These challenges impact turbine performance. Technical, environmental, economic characteristics, and their influence on reliability and safety are primary concerns [4-6]. Relations amongst turbine operational parameters and turbine lifetime attributes need to be well understood for reliable and safe hydropower plant operation. Main challenge is variability of operational parameters coexistence through time. Power dynamics, external environmental and regulatory factors impact hydropower plant operation [6-8]. Collected data, including turbine records, maintenance logs, measurement results and environmental assessments, are analysed in [9, 10]. They emphasise importance of recognizing data diversity in analysing turbine system complexity. Some authors [11, 12] report extensive research on statistical correlations and data analysis methods for turbine system performance assessment. Researchers [13-15] elaborate on different statistical techniques that can be used in turbine system performance prediction. Authors of [16, 17] weigh up parameters that influence turbine performance the most.

Purpose of our work is establishing relations amongst concurrently present influential parameters and turbine's operation attributes. Results have value in improving turbine system maintenance protocols and procedures, which effects in enhanced operating reliability, lower operating costs and somewhat prolonged lifetimes, when needed.

We first collected and analysed different hydropower plants data, including turbine records, maintenance logs, measurement results and environmental assessments. Then we established mapping of turbine operating parameters to turbine operating attributes with help of a new type QFD (Quality Function Deployment) method where dominant parameters coexist with associated side parameters. Associations between both parameter types are defined by probability densities and Bernoulli distribution. Analysis results are probability densities of dominant parameters influence measure on the turbine operating attributes.

Methods for hydropower plant turbine preventive maintenance benefit from results of this study. The developed method produces new information, an input to decision making processes. Preventive maintenance and risk mitigation are enriched by the new information. Improved decision-making processes result in higher levels of hydropower economics, reliability and potentially somewhat prolonged turbine lifetime, which all contribute to development of sustainable energy exploration.

2. METHODS USED

Holistic approach is crucial when planning, building and exploring hydropower plant turbines. Planning starts with a comprehensive synthesis of system requirements – economic efficiency, operational stability, required lifetime and others. Early identification of most influential parameters on turbine performance is crucial to ensure long-term sustainability and efficiency. Experience and references from previous projects are essential in planning. Lead engineers are enhancing their knowledge and precious intuition through years, but quality planning cannot be based on intuition only. Adhering to structure of time-limited tasks, critical design reviews and simulation modelling improves design quality and increases planning objectivity which is a precursor to reliable industrial undertakings [18]. Quantitative methods in [18] make possible to go beyond intuition and plan more accurately in costly projects. Iterative planning, continuous training and adherence to industry standards and practices, as well as effective risk management and flexibility are key to success, even for less experienced engineers.

Design methods must go beyond subjective judgements. They must rely on effective quantification tools and metrics. Objective evaluation and standardisation with quantification tools adds to quality of solutions. Studies, such as about impact of collaborative robots on production line quality [19], and e.g., on production of simulation environment, that supplements real-time application with diagnostic data [20], show importance of quantitative assessments. Development of metrics for complex projects, where many factors play a role [21], and use of simulation models improve understanding and management of large projects [22]. Additionally, precise methods such as selective modelling of assembly processes [23] are essential for improvement of critical details in design, production and life-time maintenance.

We use Quality Function Deployment (QFD) methodology [17, 24], which ensures systematics in identification of most influential parameters and their influence on turbine operating attributes. This is precursor for effective decision-making process. The Quality Function Method (QFM) [16] in QFD methodology helps to identify key influential parameters and key technical system characteristics in order to make decisions.

In modelling and analysis of complex projects, use of algebra only cannot suffice due to uncertainty about presence and influence of many parameters [12]. One must consider and quantify this uncertainty to arrive at more reliable estimates. Industry 4.0 technologies [12, 25], such as Advanced simulations and Digital twins [25] improve modelling and analysis techniques, which increase planning efficiency and reduce costs, while creating a better balance between different objectives and constraints [12].

Statistical methods and analyses are powerful mathematical tools in optimization of planning and decision-making in complex projects. These methods provide better understanding of risk, associated with project uncertainties. They can use integral data from past projects to make better predictions. Research on statistics supported process control in service industry [26] shows better complexity management and increased project quality.

We analysed past projects of hydroelectric turbine system exploration. We mapped intensity of operation parameters influence on turbine operation attributes via probability density, which maps non-complete, but available knowledge into input data for use in analysis and prediction.

Our approach combines algebraic expressions and probability densities to generate data for predictive maintenance of a turbine system. Most defined data from past projects have fixed values, other data are represented with their probability densities. We made simulation environment which produces results that are presented by their probability density.

Our method considers uncertainty in parameter's contribution to effect, and uncertainty in co-presence of different parameters. This method gives means to increase forecasting accuracy. It reflects complexity of real world and provides a robust basis for decision-making.

3. EXPERIMENTAL WORK

3.1 The adapted QFD method

QFD method is recognised as a key tool for transforming customer requirements – design parameters – into technical specifications – product attributes. One uses QFD method in product and service design. Given the specific challenges in operation of turbine systems, where operational risks and potential adverse effects play an important role, adaptation of the classic QFD method has become appropriate. Our adapted version of the QFD method focuses specifically on the analysis and quantification of harmful impacts on turbine operating attributes. This approach allows accurate assessment of these impacts using simulation modelling and thus improves the design and maintenance processes of turbine systems.

The adapted QFD matrix introduces a two-tier evaluation system that qualitatively and quantitatively distinguishes between main i.e., dominant, and dominant-associated side impacts. Dominant impacts, that are continuously present in a turbine's operating environment, are given a maximum impact score of 1 and concurrence probability of 100 %. This reflects their direct impact – 1, that is present at all times – 100 % presence, on turbine's critical operation attributes – economic efficiency, operational stability and lifetime. In contrast, associated side impacts arising from dynamics of primary impacts have an impact score of less than 1 and concurrence probability of less than 100 %, both reflecting their associated nature.

This tailored approach allows for more precise analysis and highlights importance of understanding the cause-and-effect relationship amongst various operational stressors and their cumulative impact on a turbine system.

Measure of dominant, i.e., main impact factor influence on the turbine operating attribute is calculated by Eq. (1):

$$MIF_{\mathrm{II}} = \sum_{i=1}^{\mathrm{N}} IF_{\mathrm{CP}\,i}\, IF_{\mathrm{IS}\,i} / 100 \quad (1)$$

where:

MIF_{II} – Main Impact Factor's impact index,

$IF_{\mathrm{CP}\,i}$ – i^{th} Impact Factor's concurrence probability,

$IF_{\mathrm{IS}\,i}$ – i^{th} Impact Factor's impact score.

By Eq. (1), all impacts, from the dominant and from the associated harm factors, are properly quantified and considered in cumulative indicators, that are used in turbine design and maintenance processes. Table I shows matrix of main vs. all impact factors.

Table I: Structure of adapted QFD method for sustainable hydropower turbine preventive maintenance.

Effects on turbine attributes								
	Main Impact Factor's impact index $MIF_{\mathrm{II}\,j}$, $j = 1, \ldots, m$							
	Main impact factor 1		…	Main impact factor k		…	Main impact factor m	
Impact factor IF_i, $i = 1, \ldots, n$	Concurrence Probability CP_1	Impact Score IS_1		Concurrence Probability CP_k	Impact Score IS_k		Concurrence Probability CP_m	Impact Score IS_m
Impact factor 1	CP_{11}	IS_{11}		CP_{k1}	IS_{k1}		CP_{m1}	IS_{m1}
…	…	…		…	…		…	…
Impact factor i	CP_{1i}	IS_{1i}		CP_{ki}	IS_{ki}		CP_{mi}	IS_{mi}
…	…	…		…	…		…	…
Impact factor n	CP_{1n}	IS_{1n}		CP_{kn}	IS_{kn}		CP_{mn}	IS_{mn}
Main Impact Factor j's impact index $MIF_{\mathrm{II}\,j}$	$\sum_{i=1}^{n} CP_{1i}\, IS_{1i}$		…	$\sum_{i=1}^{n} CP_{ki}\, IS_{ki}$		…	$\sum_{i=1}^{n} CP_{mi}\, IS_{mi}$	

We integrate the modified QFD matrix in Table I with probabilistic simulation modelling. This generates probability density of the adverse reaction's indicator. Using different probability distributions - normal, skew-normal, and uniform, we consider inherent variability and unpredictability of operating environment and transform QFD from a static analysis tool into a stochastics forecasting framework.

3.2 Simulation with probability densities

To weigh uncertainties that are inherent in turbine harmful processes, and that exist in available maintenance data, we designed a simulation framework for systematic assessment of various impacts significance on the turbine exploration attributes – operating cost, operating reliability and lifetime.

It follows from the very nature of assessment process that no assessment could result in precise numbers that could thoroughly assess – predict operation attributes of a turbine over its service time. Any assessment, however, must reliably predict probability range of individual impacts significance. It must classify influential quantities by their influence on the turbine performance attributes – in this case, on cost, reliability and turbine's service time.

Evaluation must include a mechanism, which makes possible to determine cumulative influence of several factors, where one may be dominant and others are associated to a greater or lesser extent. Such association can be valued by:

1: factor of association strength, other than only a real number but density of the association strength probability to the dominant factor, and by

2: presence incidence of associated factor with the dominant factor.

Calculations with probability densities and with presence incidences of associated factors are in statistics domain. In order to calculate effects of the influential factors, which are defined by Eqs. (1) and (2), we have developed a custom simulation tool. It calculates probability density of the influence of dominant and dominant-associated parameters on performance attributes of a turbine in a selected number of computational iterations. Result is ranking dominant influence factors – erosion, cavitation, corrosion, lack of maintenance, and aging by strength of their influence on selected attributes of turbine operation. In our case, these are operation cost, reliability and turbine lifetime.

Let us describe structure and operation of the software tool for determining influence of the statistically defined influence factors on the turbine performance attributes.

Each dominant influence factor (erosion, cavitation, corrosion, lack of maintenance, aging) can coexist with its associated side-influence factors. These can be some of other dominant factors and additionally, some of side-influence factors, which are material defects, installation defects, water quality, non-existent spare parts, operational changes, defective SCADA system and overload.

In calculation of dominant parameter influence on the turbine operation attribute, this factor occurs with a weight of 1, and associated side-factors have weights less than one. These weights are not given as real numbers. Each weight is given by its probability density. We choose between normal, skew-normal and uniform distributions for that effect and define the characteristic distribution parameters (μ, σ; ξ, ω, α; a, b).

In addition, each side-factor has its probability [0 % – 100 %] of occurring simultaneously with the dominant factor.

Both properties of side-factors – the weight defined by its probability density, and the occurrence probability – give the necessary flexibility in modelling impact of side parameters in calculation of their influence on turbine performance attributes.

Sum of dominant and side parameters contribution is a measure of their integral impact on the particular turbine performance attribute. The sum is calculated in a virtual case, where each influence has a value from its distribution. This number is produced by a random number generator in the selected distribution (normal, or skew-normal or uniform distribution). In addition, we use a random number generator in Bernoulli distribution (a binary distribution – yes, no), which in a given virtual case does or does not associate particular side parameter to the dominant parameter.

By simulating many virtual cases, we obtain a large quantity of impact values on the selected attribute of turbine operation. These values form influence density of the dominant factor to the turbine operation attribute. This density we most often represent with calculated parameters of normal distribution (μ and σ). Mean values μ are used to rank influence of the dominant factors (erosion, cavitation, corrosion, lack of maintenance, aging), accompanied by their associated side-factors, on selected attributes of turbine operation (operating costs, operating reliability and operation time).

We experimentally determined the necessary amount of simulated virtual cases to determine the probability density of parameters influence measure on the turbine performance attributes. Our programming environment enables up to 3 million iterations of virtual case simulations without need for dynamic memory allocation. Most simulations we carried out with 100 000 iterations.

We found lowest limit of iterations, where the result is still comparable to the result achieved with a large number of iterations. The general understanding is that any statistic starts at a minimum of 30 samples. Our simulation gives comparable results of the calculated parameters of the normal result distribution approximation (μ, σ) from 30 samples – iterations of virtual case – onwards. The reason for such simulation robustness is that we determine nature of each parameter's distribution in advance. Namely, the problem of a small number of samples in the statistical calculation arises when it is difficult to determine – due to small sample size, which distribution type is best for the sample representation. We do not have this problem here.

Fig. 1 shows influence of cavitation and cavitation-side impact factors on turbine economic efficiency index. Fig. 1, left, shows histograms involved into influence of cavitation on the turbine economic efficiency index. On the left, there are histograms of main parameter – cavitation (1) and of 8 cavitation-associated parameters: erosion (2), inadequate maintenance (3), unforeseen overloads (4), operational changes (5), corrosion (6), material defects (7), lack of spare parts (8), and improper installation (9).

Cavitation impact score is 1, cavitation-associated impact scores are expressed in their probability densities: erosion – Skew-Normal (SN) (0.95, 0.09, 8); inadequate maintenance –

Normal (N) (0.80, 0.08); unforeseen overloads – SN (0.90, 0.08, 8), operational changes – SN (0.80, 0.08, -8), corrosion – SN (0.60, 0.06, 8), material defects – N (050, 0.05), lack of spare parts – N (0.40, 0.04), improper installation – SN (0.20, 0.02, -8).

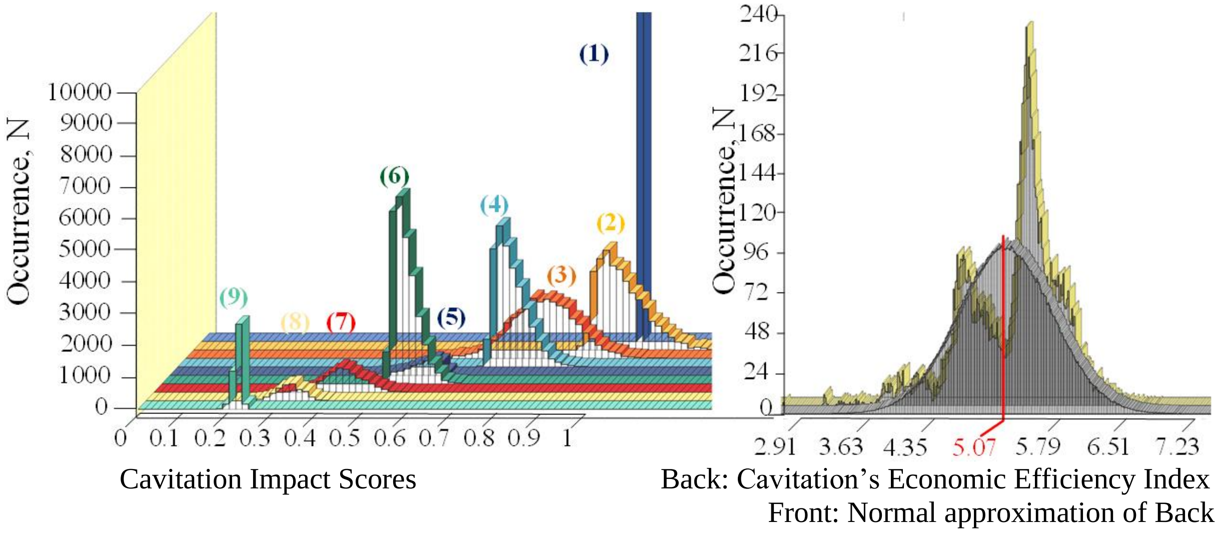


Figure 1: Influence of cavitation and cavitation side-impact factors on turbine economic efficiency index.

Cavitation concurrence probability is 100 % since cavitation is always present in the cavitation study. Concurrence probabilities of the cavitation-associated parameters are: erosion – 90 %, inadequate maintenance – 85 %, unforeseen overloads – 85 %, operational changes – 80 %, corrosion – 90 %, material defects – 20 %, lack of spare parts – 80 %, improper installation – 15 %.

Fig. 1, right back, shows histogram of cavitation – and associated impact factors – influence on the turbine economic efficiency index. Right front is its approximation in normal distribution with μ = 5.07 and σ = 0.72. This approximation could be improved, as e.g. by calculating parameters of Weibull distribution. We decided to model all influence indices in normal distribution.

Histograms in Fig. 1 are produced by 10000 runs of a virtual case where we calculate influence of cavitation on the turbine economic efficiency index.

4. RESULTS AND DISCUSSION

Cavitation influences turbine economic efficiency most, follow importance of erosion, inadequate maintenance and wear and aging in about same amount, and corrosion. Relative QFD SR (QFD with Statistical Ranking) influence indices are: cavitation N (1.94, 0.28), erosion N (1.51, 0.22), inadequate maintenance N (1.19, 0.17), wear and aging N (1.18, 0.15), and corrosion N (1.00, 0.19). Influence indices ranking is detailed in Table II. Table III displays QFD SR ranking of influences on turbine operational stability and lifetime.

Fig. 2 shows simulation results and normal approximations of QFD SR turbine economic efficiency, operational stability, and lifetime indices.

Figs. 3 and 4 show histograms involved into calculation of corrosion influence on the turbine operational stability index. On the left, there are histograms of main parameter – corrosion (1) and of 8 corrosion-associated parameters: wear and aging (2), unforeseen overloads (3), material defects (4), inadequate maintenance (5), improper installation (6), water quality (7), incorrect diagnostic information (8), and erosion (9).

Table II: Ranking influence indices on turbine economic efficiency in QFD with statistical ranking.

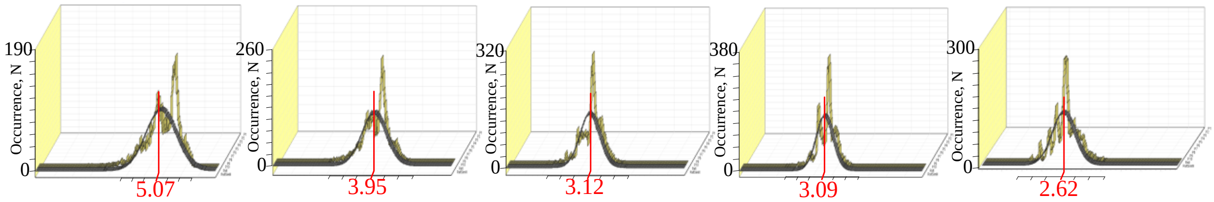
	Turbine economic efficiency				
	Main influence: cavitation	Main influence: corrosion	Main influence: erosion	Main influence: inadequate maintenance	Main influence: wear and aging
Cavitation	100 % | 1.00 1.00		90 % | 0.80 SN (0.80, 0.08, 8)	90 % | 0.50 SN (0.50, 0.05, 8)	90 % | 0.50 SN (0.50, 0.05, 8)
Corrosion	90 % | 0.60 SN (0.60, 0.06, 8)	100 % | 1.00 1.00		90 % | 0.50 SN (0.50, 0.05, 8)	90 % | 0.30 SN (0.30, 0.03, 8)
Erosion	90 % | 0.95 SN (0.95, 0.09, 8)		100 % | 1.00 1.00		90 % | 0.40 SN (0,40, 0.04, 8)
Inadequate maintenance	85 % | 0.80 N (0.80, 0.08)	85 % | 0.40 N (0.40, 0.04)	85 % | 0.65 N (0.65, 0.06)	100 % | 1.00 1.00	85 % | 0.50 N (0.50, 0.05)
Wear and aging of equipment		85 % | 0.70 N (0.70, 0.07)	85 % | 0.50 N 0.50, 0.05	85 % | 0.70 N 0.70, 0.07	100 % | 1.00 1.00
Incorrect diagnostic information		20 % | 0.30 U (0.25, 0.35)	20 % | 0.20 U (0.16, 0.25)	20 % | 0.20 U (0.16, 0.25)	20 % | 0.40 U (0.32, 0.50)
Improper installation	15 % | 0.20 SN (0.20, 0.02,−8)	15 % | 0.50 SN (0.50, 0.05,−8)	15 % | 0.30 SN (0.30, 0.03,−8)	15 % | 0.40 SN (0.40, 0.04,−8)	15 % | 0.20 SN (0.20, 0.02, −8)
Lack of spare parts	80 % | 0.40 N (0.40, 0.04)			10 % | 0.30 N (0.30, 0.03)	
Material defects	20 % | 0.50 N (0.50, 0.05)	20 % | 0.70 N (0.70, 0.07)	20 % | 0.60 N (0.60, 0.06)	20 % | 0.50 N (0.50, 0.05)	20 % | 0.30 N (0.30, 0.03)
Operational changes	80 % | 0.80 SN (0.80, 0.08,−8)				
Unforeseen overloads	85 % | 0.90 SN (0.90, 0.08, 8)	85 % | 0.10 SN (0.10, 0.01, 8)	85 % | 0.70 SN (0.70, 0.07, 8)	85 % | 0.30 SN (0.30, 0.03, 8)	85 % | 0.40 SN (0.40, 0.04, 8)
Water quality		80 % | 0.40 SN (0.40, 0.04,−8)	80 % | 0.40 SN (0.40, 0.04,−8)		
QFD influence index	4.93	2.62	3.82	2.98	3.02
QFD rank	1.	5.	2.	4.	3.
QFD SR influence index	N (5.07, 0.72)	N (2.62, 0.49)	N (3.95, 0.59)	N (3.12, 0.46)	N (3.09, 0.40)
Relative QFD SR influence index	N (1.94, 0.28)	N (1.00, 0.19)	N (1.51, 0.22)	N (1.19, 0.17)	N (1.18, 0.15)
QFD SR rank	1.	5.	2.	3.	4.

Legend:

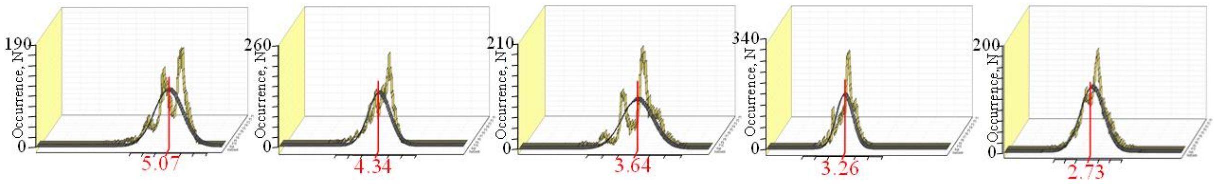
N – Normal distribution (μ, σ)	SN – Skew Normal distribution (ξ, ω, α)	U – uniform distribution (min, max)

Table III: QFD SR ranking of influences on turbine operational stability and lifetime.

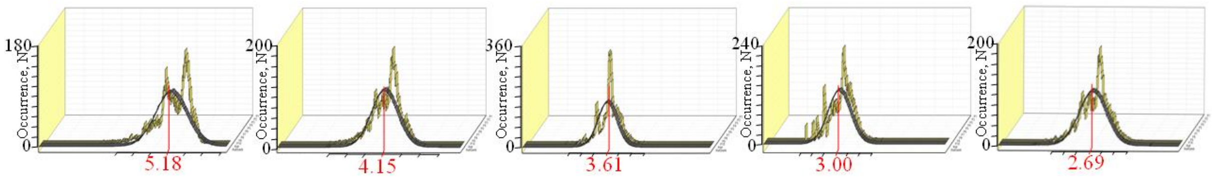
Turbine operational stability					
Main influence	Cavitation	Inadequate maintenance	Erosion	Corrosion	Wear and aging
Relative QFD SR influence index	N (1.85, 0.23)	N (1.59, 0.25)	N (1.33, 0.18)	N (1.19, 0.20)	N (1.00, 0.14)
Rank	1	2	3	4	5
Turbine lifetime					
Main influence	Cavitation	Erosion	Corrosion	Inadequate maintenance	Wear and aging
Relative QFD SR influence index	N (1.92, 0.27)	N (1.54, 0.23)	N (1.34, 0.24)	N (1.11, 0.16)	N (1.00, 0.20)
Rank	1	2	3	4	5



Economic efficiency indices: cavitation, erosion, corrosion, inadequate maintenance, wear and aging

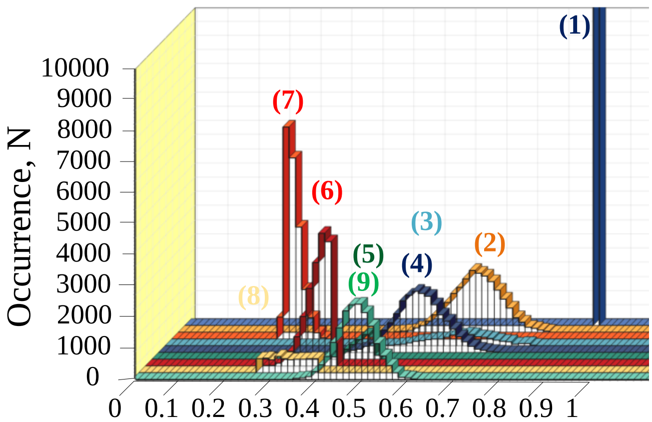


Operational stability indices: cavitation, inadequate maintenance, erosion, corrosion, wear and aging

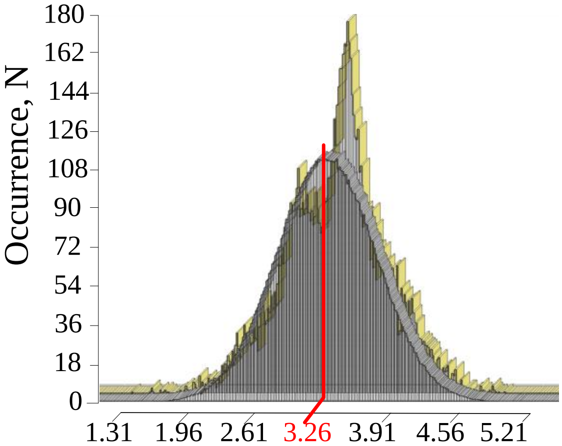


Lifetime indices: cavitation, erosion, corrosion, inadequate maintenance, wear and aging

Figure 2: QFD SR turbine economic efficiency, operational stability, and lifetime indices – back: simulation result, front: normal approximation.



Corrosion Impact Scores
10000 virtual-case iterations

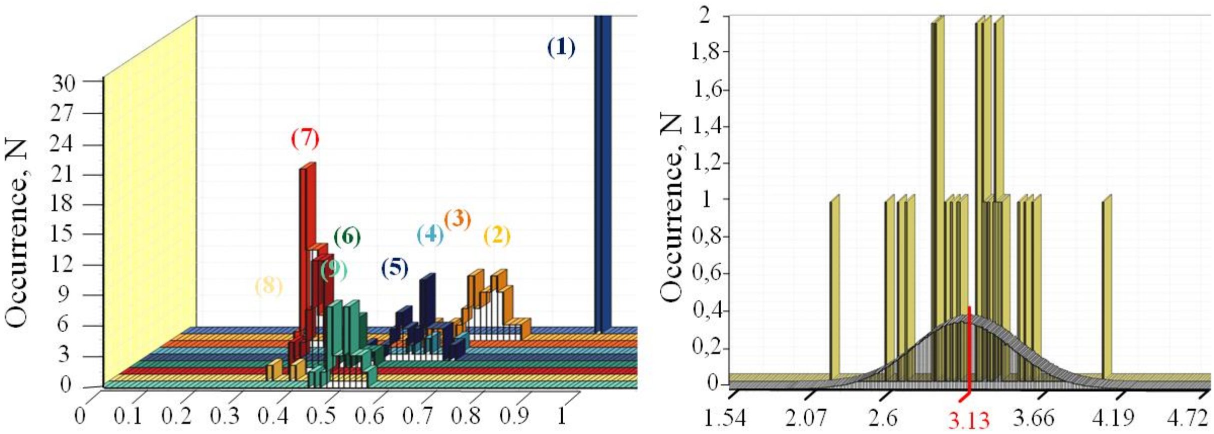


Back: Corrosion's Operational Stability Index
Front: Normal approximation of Back

Figure 3: Influence of corrosion and corrosion-associated parameters on turbine operational stability index from simulation of 10000 virtual cases.

Corrosion impact score is 1, corrosion-associated impact scores are expressed in their probability densities: wear and aging N (0.70, 0.07), unforeseen overloads SN (0.20, 0.03, 8), material defects N (0.70, 0.08), inadequate maintenance N (0.60, 0.07), improper installation SN (0.50, 0.05, -8), water quality SN (0.40, 0.05, -8), incorrect diagnostic information U (0.22, 0.38), and erosion N (0.50 0.05).

Corrosion concurrence probability is 100 % since corrosion is always present in the corrosion study. Concurrence probabilities of the corrosion-associated parameters are: wear and aging – 85 %, unforeseen overloads – 85 %, material defects – 20 %, inadequate maintenance – 85 %, improper installation – 15 %, water quality – 80 %, incorrect diagnostic information – 20 %, and erosion – 80 %.



Corrosion Impact Scores
30 virtual-case iterations

Back: Corrosion's Operational Stability Index
Front: Normal approximation of Back

Figure 4: Influence of corrosion and corrosion-associated parameters on turbine operational stability index from simulation of 30 virtual cases.

Fig. 3 shows histogram of corrosion (and associated harm parameters) influence on the turbine operational stability index after 10000 virtual case iterations. Right front is its approximation in normal distribution - N (3.26, 0.56).

Fig. 4 shows histogram of corrosion (and associated harm parameters) influence on the turbine operational stability index after 30 virtual case iterations. Right front is its approximation in normal distribution - N (3.13, 0.53).

Both QFD SR ranking indices – N (3.26, 0.56) and N (3.13, 0.53) have enough similar μ values that both can be used in influence ranking. 10000 simulation iterations obviously produce smoother histograms than 30 simulation iterations, but – from ranking perspective – induced ranking indices practically do not differ. Implication of this finding is that even data from a relatively small number of finished projects suffice for use of QFD SR method in ranking parameters influence on the process attributes. However, results at any number of iterations are sensitive to user's definition of side parameters distribution and concurrence probability. These definitions need to match influential parameters nature to most extent.

Input data, and control experiment data which confirms or invalidates research findings, were provided from specialists in the turbine field, listed in the Acknowledgements. Cumulative data used in this study is from about 400 hydropower projects in last 30 years.

This study helped to better understanding and classification of harmful process concurrency in turbine lifetime. In decision making, we depend on certain modelling and anticipations. There are 2 general directions in process modelling: behavioural modelling, which builds on observations, and physical modelling, which builds on understanding of process inner working. The latter modelling is preferred and used where possible. This work helps to shift from behavioural to physical modelling of turbine lifetime processes.

The QFD SR method introduces improvements in risk analysis and in quality design process, especially for turbine systems. With a stochastic rating scale – impact score, understanding of conditional coexistence of different operational factors – concurrence probability, and integration of simulation modelling into weighing process, this approach provides a thorough predictive analysis of adverse effects.

The simulation application is written in C++ Builder environment. It is available for download from [27].

5. CONCLUSION

In this study, we designed, implemented and verified a comprehensive ranking framework that significantly improves our understanding and prediction of turbine operation attributes that are influenced by both dominant and subordinate parameters. By innovatively modelling the influence of parameters through normal, skew-normal and uniform distributions and their presence through a Bernoulli distribution, we have developed a nuanced and detailed approach to mapping of parameters to attributes of a complex system.

The resulting ranking, expressed by probability densities of parameter influence measures on turbine operating attributes, not only improves our predictive capabilities, but offers for practical applications in predictive maintenance planning and scheduling. It enables a more refined and accurate identification of critical parameters that impact system performance, facilitating more efficient and targeted maintenance interventions.

The customisability of our framework extends beyond turbines, offering potential applications to a wide range of complex systems where impact of numerous parameters is best represented by precise probability densities. This adaptability underlines the versatility of the framework and its potential to help optimise operational efficiency and reliability across different sectors.

The availability of our project data for public download [28] emphasises our commitment to transparency and collaboration in the scientific community. It provides the opportunity for continuous refinement and adaptation of the presented framework, fostering wider applicability to other complex systems.

We anticipate that the continued development of this framework can lead to advances in operational efficiency, cost reduction and system reliability across a range of industries.

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REFERENCES

[1] Kaunda, C. S.; Kimambo, C. Z.; Nielsen, T. K. (2012). Hydropower in the context of sustainable energy supply: a review of technologies and challenges, *International Scholarly Research Notices*, Vol. 2012, Paper 730631, 15 pages, doi:10.5402/2012/730631

[2] Oral, A. E.; Akay, O. E. (2022). Prediction of vibration in the discharge ring of a river type hydroelectric power plant with bulb turbine using artificial neural networks and support vector machine, *Technical Gazette*, Vol. 29, No. 5, 1726-1732, doi:10.17559/TV-20210906114213

[3] Kougias, I. (2020). *Hydropower – Technology Development Report 2020*, European Commission, Joint Research Centre, Ispra, doi:10.2760/60451

[4] Kumar, R.; Singal, S. K. (2015). Operation and maintenance problems in hydro turbine material in small hydro power plan, *Materials Today: Proceedings*, Vol. 2, No. 4-5, 2323-2331, doi:10.1016/j.matpr.2015.07.284

[5] Liu, X.; Luo, Y.; Wang, Z. (2016). A review on fatigue damage mechanism in hydro turbines, *Renewable and Sustainable Energy Reviews*, Vol. 54, 1-14, doi:10.1016/j.rser.2015.09.025

[6] Jayaram, V.; Bavanish, B. (2022). Design and analysis of Gorlov helical hydro turbine on index of revolution, *International Journal of Hydrogen Energy*, Vol. 47, No. 77, 32804-32821, doi:10.1016/j.ijhydene.2022.07.181

[7] Moran, E. F.; Lopez, M. C.; Moore, N.; Müller, N.; Hyndman, D. W. (2018). Sustainable hydropower in the 21st century, *Proceedings of the National Academy of Sciences*, Vol. 115, No. 47, 11891-11898, doi:10.1073/pnas.1809426115
[8] Bogaart, P. (2023). The potential for sustainable hydropower, *Nature Water*, Vol. 1, 22-23, doi:10.1038/s44221-022-00018-9
[9] Bernardes, J.; Santos, M.; Abreu, T.; Prado, L.; Miranda, D.; Julio, R.; Viana, P.; Fonseca, M.; Bortoni, E.; Bastos, G. S. (2022). Hydropower operation optimization using machine learning: a systematic review, *AI*, Vol. 3, No. 1, 78-99, doi:10.3390/ai3010006
[10] Tsuanyo, D.; Amougou, B.; Aziz, A.; Nka Nnomo, B.; Fioriti, D.; Kenfack, J. (2023). Design models for small run-of-river hydropower plants: a review, *Sustainable Energy Research*, Vol. 10, No. 1, Paper 3, 23 pages, doi:10.1186/s40807-023-00072-1
[11] Limpert, E.; Stahel, W. A. (2011). Problems with using the normal distribution – and ways to improve quality and efficiency of data analysis, *PLoS One*, Vol. 6, No. 7, Paper e21403, 8 pages, doi:10.1371/journal.pone.0021403
[12] Rodriguez, L.; Loyo, J.; Silva, U. (2023). Layout evaluation with the Industry 4.0 approach for a manufacturing laboratory, *International Journal of Simulation Modelling*, Vol. 22, No. 4, 551-561, doi:10.2507/IJSIMM22-4-642
[13] Hariri, A.; Domingues, P.; Sampaio, P. (2023). Integration of multi-criteria decision-making approaches adapted for quality function deployment: an analytical literature review and future research agenda, *International Journal of Quality & Reliability Management*, Vol. 40, No. 10, 2326-2350, doi:10.1108/IJQRM-02-2022-0058
[14] Chuang, P. (2002). A QFD approach for distribution’s location model, *International Journal of Quality & Reliability Management*, Vol. 19, No. 8-9, 1037-1054, doi:10.1108/02656710210438113
[15] Nekoonam, A.; Nasab, R. F.; Jafari, S.; Nikolaidis, T.; Ebrahim, N. A.; Fashandi, S. A. M. (2023). A scientometric methodology based on co-word analysis in gas turbine maintenance, *Technical Gazette*, Vol. 30, No. 1, 361-372, doi:10.17559/TV-20220118165828
[16] Chan, L.-K.; Wu, M.-L. (2005). A systematic approach to quality function deployment with a full illustrative example, *Omega*, Vol. 33, No. 2, 119-139, doi:10.1016/j.omega.2004.03.010
[17] Carnevalli, J. A.; Miguel, P. A. C.; Calarge, F. A. (2010). Axiomatic design application for minimising the difficulties of QFD usage, *International Journal of Production Economics*, Vol. 125, No. 1, 1-12, doi:10.1016/j.ijpe.2010.01.002
[18] Breznik, M.; Buchmeister, B.; Vujica Herzog, N. (2023). Assembly line optimization using MTM time standard and simulation modelling – a case study, *Applied Sciences*, Vol. 13, No. 10, Paper 6265, 18 pages, doi:10.3390/app13106265
[19] Javernik, A.; Ojstersek, R.; Buchmeister, B. (2023). The impact of collaborative robot on production line efficiency and sustainability, *Technical Journal*, Vol. 17, No. 2, 237-243, doi:10.31803/tg-20230425171431
[20] Ojstersek, R.; Javernik, A.; Buchmeister, B. (2021). The impact of the collaborative workplace on the production system capacity: simulation modelling vs. real-world application approach, *Advances in Production Engineering & Management*, Vol. 16, No. 4, 431-442, doi:10.14743/apem2021.4.411
[21] San Cristóbal, J. R.; Diaz, E.; Carral, L.; Fraguela, J. A.; Iglesias, G. (2019). Complexity and project management: challenges, opportunities, and future research, *Complexity*, Vol. 2019, Paper 6979721 (Editorial), 2 pages, doi:10.1155/2019/6979721
[22] Ojstersek, R.; Buchmeister, B. (2020). Simulation modeling approach for collaborative workplaces' assessment in sustainable manufacturing, *Sustainability*, Vol. 12, No. 10, Paper 4103, 18 pages, doi:10.3390/su12104103
[23] Wang, W. M.; Li, D. B.; He, F.; Tong, Y. F. (2018). Modelling and optimization for a selective assembly process of parts with non-normal distribution, *International Journal of Simulation Modelling*, Vol. 17, No. 1, 133-146, doi:10.2507/IJSIMM17(1)CO1
[24] Rihar, L.; Kusar, J. (2021) Implementing concurrent engineering and QFD method to achieve realization of sustainable project, *Sustainability*, Vol. 13, No. 3, Paper 1091, 28 pages, doi:10.3390/su13031091

[25] Debevec, M.; Šimic, M.; Jovanović, V.; Herakovič, N. (2020). Virtual factory as a useful tool for improving production processes, *Journal of Manufacturing Systems*, Vol. 57, 379-389, doi:10.1016/j.jmsy.2020.10.018
[26] Khorshidi, H. A.; Nikfalazar, S.; Gunawan, I. (2016). Statistical process control application on service quality using SERVQUAL and QFD with a case study in trains' services, *The TQM Journal*, Vol. 28, No. 2, 195-215, doi:10.1108/TQM-02-2014-0026
[27] Rihar, L.; Jenko, M. Index of /~project/QFD-SR/app, from *http://www2.arnes.si/~project/QFD-SR/app/*, accessed on 15-01-2024
[28] Rihar, L.; Jenko, M. Index of /~project/QFD-SR/data, from *http://www2.arnes.si/~project/QFD-SR/data/*, accessed on 15-01-2024