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Status and ambitions for data-driven asset management in Scandinavian hydropower companies

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This paper reports results from surveys among Scandinavian hydropower producers within three areas. The first part of the survey covers the acquisition and use of hydropower component condition data in asset management decision making. This part of the survey has been conducted previously in both 2015 and 2019, enabling analysis of respondents' development over the last ten years. We discuss findings and present possible explanations. The second part of the survey focuses on the use of models to predict the condition and failure probability of hydropower components. Barriers to increased use of these types of models are also explored. The final part of the survey investigates the status of data quality and metadata among the respondents. An important aim of the survey was to gain a better understanding of the needs of hydropower producers for models to estimate the development of component condition and failure probability. Such models are fundamental to enabling data-driven asset management, not only among hydropower producers but also in other asset-intensive industries.

Keywords: Data-driven asset management, collection and use of condition data, survey number three among hydro power companies, use of models in condition development and failure probability estimations, data quality and metadata, hydropower plant (HPP).

1. Background

According to ISO 55001:2024, any organization shall establish asset management objectives that consider, among other factors, risks and opportunities, as well as the condition, performance, and capabilities of its assets. Data from, e.g., inspections and sensors can provide information about the technical condition of components and, further, the component failure probability and remaining life. Models are needed to convert data into information, predict component condition, support asset management decision-making, and fulfil asset management objectives. Based on a study of the hydropower industry in the 2000s, Welte (2008) describes a situation in which a lack of data leads to a lack of incentive for model development, and again, a lack of models leads to a lack of incentive for data collection. In other words, a vicious circle of data collection and model development, as shown in Fig. 1.

However, several examples, from other industry sectors, of increasing access to condition monitoring data have been presented since then, e.g., (Bokrantz and Skoogh 2023; Pedersen et al. 2021; Roda and Macchi 2021). We aim in this study to investigate whether the vicious cycle described by Welte is still hindering the application of data-driven asset management in Scandinavian hydropower companies, or whether they have been able to transition to a virtuous cycle where increased access to data incentivizes model development, and increased access to models provides incentives for even more data collection (see Fig. 2).

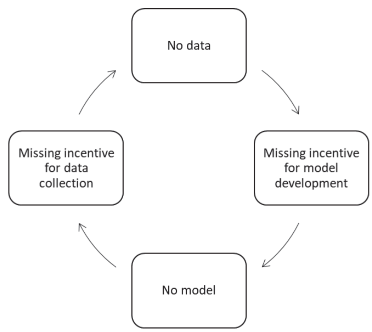

Fig. 1. The vicious circle of data collection and model development.

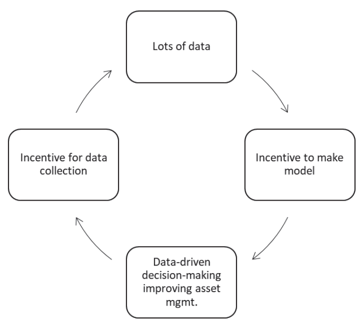

Fig. 2. The virtuous cycle of data collection and model development.

1.1. *Surveys conducted in 2015 and 2019*

In the research project MonitorX[a] (2015-2019), surveys were conducted at the beginning and the end of the project to investigate the development throughout the project. Results from these surveys are presented in (Welte et al. 2016), (Welte et al. 2018) and (Welte and Foros 2019). In the latter, the results from 2015 and 2019 are compared.

Surprisingly, there was a negative trend from 2015 to 2019 in respondents' evaluation of whether they were collecting the necessary data. In (Welte and Foros 2019) this was explained as a consequence of the respondents' improved overview of what is actually the necessary data for enabling data-driven asset management. Several of the questions from the 2015 and 2019 surveys were included in the 2025 survey.

1.2. *Data acquisition and model development*

There appear to be three trends in data acquisition and model development for asset management, based on a literature review reported below:

1. It seems to be increasing access to condition monitoring data, and use of models for supporting asset management decisions in the Scandinavian hydro power industry after 2019.
2. There seems to be an increase in the use of hybrid models, where data-driven models are supported by physics-based models, worldwide.
3. Explainable models with an option for feedback to improve the performance of the models seem to be preferred.

In the SmartKraft[b] project, sensors for the collection of component condition data were tested along with physics-based models to evaluate the condition of components at a given operational pattern (M. Hauki et al. 2024). Experience has shown that this can provide high value, even with few sensors and limited data, but only if the data is high-quality and accurate. Data from visual inspection, initiated by the modelling results, can be used for validation and model adjustments. Hence, such work can contribute to a virtuous circle. Ægir Predictive Maintenance (K. Vereide et al. 2020) and (A. Abelsen 2022) developed by the Norwegian hydropower company SiraKvina, also contributes to the creation of a virtuous cycle of data collection and model development, as the tool provides decision support based on sensor data, artificial intelligence, and data from condition monitoring (like inspections), so that assessments and experiences from maintenance personnel are also included. The predictions made by Ægir are presented to company experts, who evaluate whether any action is needed and, if so, which action to take. Hence, feedback on whether the predictions are correct is provided, enabling the models to be improved.

In (Xing et al. 2022) the status and plans for predictive maintenance of the Norwegian hydropower company, TrønderEnergi, are provided. This source suggests that using strictly data-driven models is not advised due to the lack of failure data and the quality of the available data. The source suggests transfer learning, hybrid artificial intelligence, or a combination of these. Explainability is important because company experts must understand why a model indicates a problem. In (A.-M. Giroux et al. 2023) Institut de recherche d'Hydro-Québec (IREQ) has published a literature review and experiences with digital twins for the operation and maintenance of hydropower generators. The paper states that over 80% of the articles in a 2018 review involved data-driven models, while the corresponding percentage was 58% in 2020. Data-driven models supported by physics-based models, described as hybrid models, have increased from 8% to 34% between 2018 and 2020. This suggests a change in the model preferences from purely data-driven to hybrid models. In another literature review (Sartor et al. 2024) an increase in the use of stochastic models to detect the condition of components was found. This was due to a preference for explainable models.

2 Method and Respondents

The survey in this study was organized as an anonymous self-administered questionnaire (A. Bryman 2016) using Microsoft Forms. A convenience sample of hydropower companies that are partners in the research projects AssetLife and RenewHydro were invited to participate in the survey. Email invitations were sent to the contact persons for the two research projects at the respective companies. Three reminders were sent by email to companies that had not replied to previous invitations. Of the 16 companies invited, 14 responded. In the invitation to the survey, the involvement of multiple experts within each company when completing the questionnaire was encouraged, but only one response per company was included in the final dataset.

Respondents were from both Norway and Sweden. To ensure content validity (C. Forza 2002), a draft version of the survey was sent to a selection of experts from academia and the hydropower industry to assess whether the terminology and question formulations were understandable to respondents from the hydropower sector with domain knowledge in asset management. Suggestions for improvements from these experts were incorporated into the final version of the survey.

The respondents in this survey are a convenience sample recruited based on their involvement in two research projects. A disadvantage of this type of non-random sampling is that the respondents are not necessarily representative of larger populations (A. Bryman 2016), for example, all hydropower producers in Scandinavia. It is reasonable to assume that hydropower producers who choose to participate in research projects such as RenewHydro and AssetLife place greater emphasis on research and development and therefore have a higher level of maturity in the topics covered in this survey than other producers. However, a large proportion of the large

[a] https://www.sintef.no/en/projects/2015/monitorx/
[b] https://smartgrids.no/smartkraft/#publikasjoner

and medium-sized hydropower producers in Norway and Sweden are represented among the respondents. The total annual production from the respondents amounts to just under 70% (140 of 204 TWh/year[c]) of the combined annual hydropower production in Norway and Sweden. Based on this, we believe that any bias arising from the non-random sampling strategy is limited and that the survey results provide a reasonable representation of the actual situation among large and medium-sized hydropower producers in Norway and Sweden.

A clear majority (12 out of 14) of respondents had not responded to either the 2015 or the 2019 survey of the MonitorX-project. While the remaining two had answered both surveys. Thus, there are differences between the people representing the respondent companies in the 2015 and 2019 surveys and those representing them in the current 2025 survey. Because only two people answered both the current and previous surveys, statistical analysis of differences in responses between the groups is not feasible. However, as none of the respondents had worked for fewer than 6 years in the hydropower sector, and the majority had worked over 11 years, it is reasonable to assume that the responses accurately reflect the actual situation in the hydropower companies they represent.

3. Results

This section compares the surveys conducted in 2015, 2019, and 2025 to analyze the development in data acquisition and the use of condition data in the hydropower sector over the last 10 years. Further, responses to questions on models for condition development and failure probability for hydropower components are analyzed, and finally, results related to metadata and data quality are presented.

3.1. *Comparison of 2015, 2019, and 2025 results*

In Fig. 3 the average of the replies to the survey in 2015, 2019, and 2025 is shown. The respondents were asked to rate their agreement with a statement on a Likert scale from 1 (disagree) to 5 (agree). The 2025 respondents had a higher score (agreement) compared to the 2019 respondents for 11 out of 14 questions. However, this is not the case when comparing results from 2015 and 2019, in which half of the questions showed negative development. The final MonitorX report (Welte and Foros 2019) suggested the following explanations for this negative development: differences in respondents across the two surveys and/or greater awareness of what constitutes a good situation for the different topics. As expressed by (Welte and Foros 2019, 16): *"for example, an instrumentation with sensors and measurement equipment that in 2015 was considered as good, may not be considered as good today, because new technologies and possibilities appeared since 2015. When no big changes of instrumentation were made, i.e. the status regarding sensors and instrumentation is in 2019 the same as in 2015, the relative status has worsened compared to a changing and developing "reference" (i.e. the state-of-the-art within the field, which is continuously developing)."*

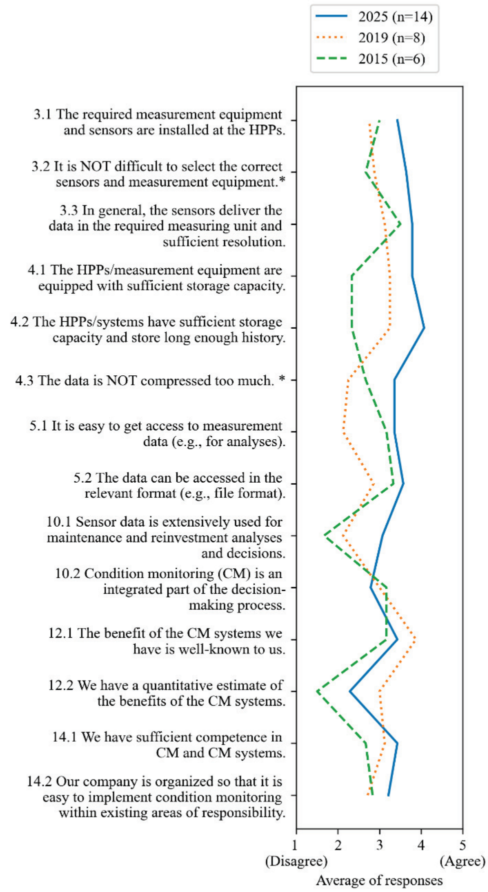

Fig. 3 Comparison of results from the 2015, 2019, and 2025 surveys. Questions marked with * are reversed.

3.1.1. *Barriers against the use of condition monitoring and condition monitoring systems*

The respondents were asked to rank 12 potential barriers against the use of condition monitoring and condition monitoring systems from 1 (unimportant) to 5 (important). The same question was asked in 2019, but unfortunately not in 2015. Fig. 4 shows the mean response, with error bars indicating ±1 standard deviation (SD).

Question 15.08 "Lack of standardization of IT-systems and sensor installations" has the highest score, but this question was unfortunately not included in the 2019 survey. Apart from this, the perceived importance of the different barriers, as ranked by the respondents, are quite

[c] Based on https://energifaktanorge.no/norsk-energiforsyning/kraftforsyningen/ and http://energimyndigheten.se/energisystem-och-analys/nulaget-i-energisystemet/energilaget/

similar in 2019 and 2025. In 2019, barriers related to the development of measurement methods and measurement setups were reported as an important barrier but were less important in 2025. This may be because competence in these topics is higher, or because these methods have matured. The lack of integration across different company internal systems is an important barrier in both 2019 and 2025.

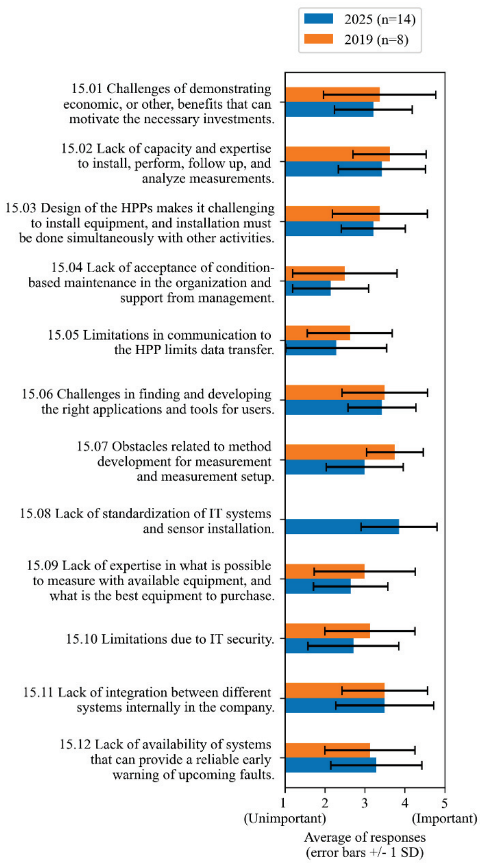

Fig. 4 Barriers against the use of condition monitoring and condition monitoring systems

3.1.2. *Data access and data use*

In order to analyze correlations between data access and the use of data, the questions shown in Fig. 3 was divided into two constructs: *data access* (questions 3.1 through 5.2) and *data use* (questions 10.1 through 14.2). The first construct comprises questions about the acquisition, storage, and availability of data. The second construct comprises questions related to the use of data to support decision-making that is valuable to the companies, as well as competence and organizational issues. Cronbach's α was used to measure the internal consistency of both constructs (see Table 1). For 2015, the Cronbach's α was found to be negative for both constructs. This may be because, as suggested in Sec. 3.1, the respondents at that time had limited awareness of the survey's topics. On the other hand, Cronbach's α was above 0.6 for both 2019 and 2025 for both constructs, which is often regarded as an acceptable level of internal consistency (A. Bryman 2016).

The average reply to the construct "*Data access*" increases significantly from 2019 to 2015, whereas this is not the case for "*Data use*" (see Table 2 and Fig. 5).

Table 1. Cronbach's α for the constructs "*Data access*" and "*Data use*".

Construct/year	2015	2019	2025
Data access	-0.5	0.82	0.76
Data use	-0.8	0.77	0.61

Table 2. Statistical test for change in the average of responses to the categories "*Data access*" and "*Data use*" from 2019 to 2025

Construct	Test	p-Value
Data access	t-test	$2.3 \cdot 10^{-5}$
	Mann-Whitney U	$2.3 \cdot 10^{-5}$
Data use	t-test	0.78
	Mann-Whitney U	0.80

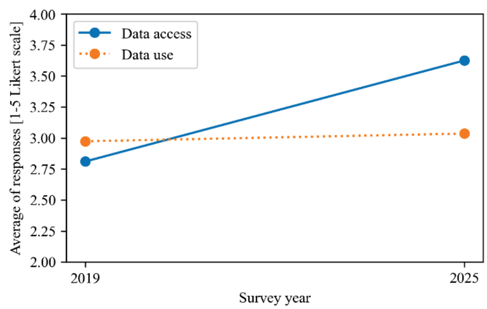

Fig. 5. Trend for the constructs "D*ata access*" and "D*ata use*" from 2019 to 2025.

3.2. *Use of models for the estimation of condition development and failure probability*

The share of respondents who can conduct advanced data analysis (artificial intelligence, self-taught systems, etc.) has increased from 15% in 2015 to 50% in 2025.

As shown in Table 3, several respondents are quite mature when it comes to identifying components in need of maintenance, as over 50% use "*automated analyses of trends in development of specific condition parameters*" and "*lifetime estimates based on simple physical or empirical models*". Further on, 35 % of the respondents are using "*data-driven models for anomaly detection, based on several condition parameters*". The respondents are also mature in methods and models for estimating future condition development and component failure probability in hydropower plants (HPPs). Approximately 30% use statistical models and numerical methods. Finally, 14% use machine learning models trained on historical data; see Table 4.

Table 3. Replies to the question: “Which methods and models does your company use today to identify components with a need for maintenance?” (n = 14).

Question	Yes	No
Condition assessments based on visual inspections	100%	0%
Condition assessments based on periodic "off-line" measurements	100%	0%
Alarm levels defined in the SCADA system or other IT solutions primarily developed for operation.	93%	7%
Alarm levels defined in dashboards or IT solutions developed primarily for condition-based maintenance.	50%	50%
Eyeballing of graphs/time series from sensor measurements and their development	100%	0%
Automated analysis of trends in some health parameters	57%	43%
Remaining useful life estimates based on simple physics-based or empirical models	57%	43%
Data-driven models for anomaly detection that are based on multiple state parameters	36%	64%

Table 4. Replies to the question: “Which methods and models does your company use today to estimate future condition development and failure probability for hydropower components?” (n = 14).

Question	Yes	No
We do not use these types of methods or models today.	0%	100%
Expert assessments (free text or reports).	86%	14%
Expert assessments systematized into condition classes (e.g., 1 – 5, with associated life expectancies).	79%	21%
Eyeballing of graphs/time series from sensor measurements and their development (e.g., vibration measurements).	79%	21%
Simple physics-based or empirical models (e.g., S-N curves and Miner's law for estimating time to fatigue of components).	43%	57%
Models that account for future operating loads (e.g., expected number of start/stop cycles).	21%	79%
Numerical methods (Finite element (FE) and/or Computational Fluid Dynamics (CFD) analyses).	29%	71%
Statistical models for estimation of future condition development and failure probability (e.g., the "Maintenance Toolbox" models developed by SINTEF Energy Research).	29%	71%
Machine learning models trained on historical degradation data.	14%	86%

The survey also asks who has developed methods and models that the company uses to estimate future condition development and failure probability (Table 5). As many as 86% of respondents have developed methods and models internally within the company, followed by development in cooperation with R&D projects (64%) and with consultancy companies (50%). Only 14% of respondents use condition development and failure probability models developed by, or in cooperation with, component vendors. Why so many have chosen to develop their own models and methods is a topic that may be worth exploring in further studies. Is there a lack of relevant methods and models offered in the market? Or do commercially available models not satisfy the requirements of the hydro power producer? Another reason may be that the producers do not want to become dependent on specific vendors. Furthermore, substantial differences across HPPs may make it challenging to build models that suit sufficiently many HPPs to make their development commercially viable.

Table 5. Replies to the question: “Who developed the methods and models that the company uses today to estimate future condition development and failure probability?” (n = 14).

Question	Yes	No
We do not use these types of methods or models today.	14%	86%
They are developed internally in the company.	86%	14%
They are developed by or in collaboration with consulting companies.	50%	50%
They are developed by or in collaboration with component suppliers.	14%	86%
They are developed by or in collaboration with R&D projects.	64%	36%
They came as part of IT solutions.	7%	93%

All respondents stated that new operational patterns, which lead to increased/different forms of degradation, are an important driver of increased use of models to estimate future condition development and failure probability. Other important driving forces are ageing equipment and improved access to models. Cheaper sensor technology is regarded as less important, see Table 6.

Table 6. Replies to the question: “What do you think are the most important drivers for increased use of models for estimating condition development and failure probability”? (n = 14).

Questions	Yes	No
There are no important drivers for this in the future.	0%	100%
Aging HPP assets.	71%	29%
New operating patterns that result in increased/different wear and tear on components.	100%	0%
Cheaper and better sensor technology reduces the cost of data collection.	29%	71%
Better access to IT solutions for compiling data that reduces the cost of using these types of models.	43%	57%
Better access to models for condition development and failure probability.	86%	14%
High power prices increase the value of HPP availability.	43%	57%

About one third of the respondents believed that a lack of models that fit the needs of the hydropower producers is “*the most important barrier to increased use of models for* *estimating condition development and/or failure probability for hydropower components*" in their companies in both the short term and in the long run (Table 7). Moreover, none of the respondents believe that the lack of data will be the most important barrier in the long run. Interestingly, a larger share of respondents believes that a lack of expertise in using these models will be the most important barrier in the long run (29%) than in the short term (14%). The opposite is the case for "*lack of culture, routines and/or procedures*", which is believed to be the most important barrier by 21% of respondents in the short term, but only by 14% in the long run (see Table 7).

All respondents agree with the statement: "*We want to increase the use of condition development and failure probability models in the future in our company*".

Table 7. Replies to the question: "What is the most important barrier to increased use of models for estimating condition development and/or failure probability for hydropower components in your company in the …" (n = 14).

Question	"… short term?"	"… long run?"
Lack of access to relevant data (asset data, condition data, operational loads).	14%	0%
Lack of access to models for estimating condition development and/or failure probability adapted to the needs of hydropower producers.	36%	36%
Lack of access to expertise in the use of this type of models and interpretation of the results.	14%	29%
Lack of culture, routines and/or procedures for the use of this type of model in decision-making processes.	21%	14%
The costs associated with increased use of this type of model exceed the expected benefit (lack of business case).	0%	7%
Other	7%	7%
SUM	100%	100%

3.3. *Models meeting the needs of the hydropower industry*

We have also explored which types of condition-development and failure-probability models best meet the hydropower industry's needs. As part of this effort, three questions assess whether respondents believe that simple models, primarily for relative ranking of individual components, or more advanced models for more accurate estimation of the condition and failure probability of individual components, best meet the needs of the industry. As Fig. 6 shows the respondents are divided on this matter.

When asked to prioritize between the following four types of analysis:

1. "Condition monitoring of most components using a traffic light model or similar",
2. "Condition monitoring with advanced models for estimating remaining useful life and maintenance intervals,"
3. "Hydraulic status (efficiency, head loss, etc.)",
4. "Electrical status (windings, magnetic fields, etc.)",

eight of the 14 respondents ranked option 1) as the highest priority, while the remaining six respondents ranked option 2) as the highest priority. Again, the respondents are divided when asked whether they prefer simple models for relative ranking of component conditions or more advanced models that provide more absolute outputs, e.g., remaining useful life.

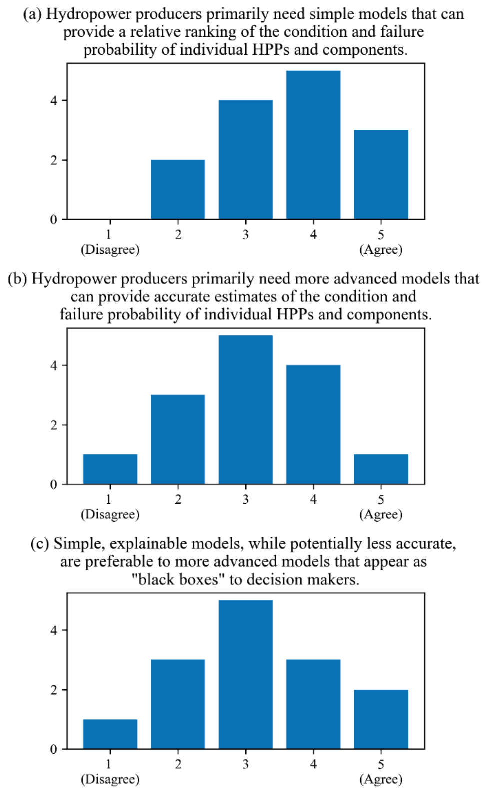

Fig. 6. Answers to questions about what types of models hydropower producers primarily need (n = 14).

It is not surprising that respondents hold differing views on which types of models best meet the industry's needs, given differences in the survey population with respect to both data availability and the models they use today.

To explore whether there are characteristics that separate respondents who prefer simple over advanced models, we have made a construct named "*Simple models*" and looked for correlations between this construct and some other constructs based on the 2025 survey.

The construct "Simple models" (Cronbach's $\alpha = 0.65$) comprises the three questions shown in Fig. 6, with question (b) reversed such that a higher score on the Likert scale indicates greater agreement with the statement that the industry primarily needs simple models. Moreover, a construct named "*Digital solutions*" (Cronbach's $\alpha = 0.80$) is a merger of the questions "*Compared to other hydro power producers in Norway, we are leading when it comes to taking new digital solutions into use*" and "*Compared to other hydropower producers in Norway, we are leading when it comes to realizing value from digital solutions*".

There is a positive correlation between "Digital solutions" and a preference for "Simple models" ($\boldsymbol{r} = \mathbf{0.61}, \boldsymbol{p} = \mathbf{0.02}$). However, there is no clear correlation between the categories "Simple models", and "Data access" or "Data use". See Table 8.

Moreover, there is a positive correlation ($\boldsymbol{r} = \mathbf{0.65}, \boldsymbol{p} = \mathbf{0.01}$) between the "Digital solutions" construct, and the construct "Data access" of chapter 3.1.2, see Table 8. This seems logical as digital solutions are necessary to enable the acquisition and sharing of data. However, it is surprising that there is no sign of correlation between "Digital solutions" and "Data use" ($\boldsymbol{r} = \mathbf{0.12}, \boldsymbol{p} = \mathbf{0.68}$) or between "Data access" and "Data use" ($\boldsymbol{r} = \mathbf{0.27}, \boldsymbol{p} = \mathbf{0.35}$). This indicates that digitally mature hydropower producers have better access to condition data, but that good access to data does not necessarily mean these data are used in asset management.

Table 8. Pearson correlation between the constructs "*Digital solutions*", "*Simple models*", "*Data access*", and "*Data use*".

	r	**CI95%**	**p**
	Digital solutions		
Data access	0.65	[0.18, 0.88]	0.01
Data use	0.12	[-0.44, 0.61]	0.68
Simple models	0.61	[0.11, 0.86]	0.02
	Data access		
Data use	0.27	[-0.30,0.70]	0.35
Simple models	0.14	[-0.42,0.62]	0.63
	Data use		
Simple models	-0.11	[-0.6,0.45]	0.71

In further work, it may be interesting to investigate further the categories "Digital solution", "Data access", and "Data use" and the modelling preferences for condition and failure probability. Are there, for instance, any differences in which department within companies has been involved in implementing digital solutions? Are there companies where the IT department has been responsible for data access, but a lack of competence or resources in the asset management department hampers the use of this data in asset management decision-making?

3.4. *Status on data quality and metadata*

Today, 9 out of 14 respondents are using edge processing. This implies processing high-frequency signals in the HPP rather than in a central location. Nearly half (6 of 14) respondents have implemented or are implementing the Reference Designation System (RDS), based on ISO/IEC 81346[d] or a similar standard, for naming data streams and metadata. Furthermore, 6 of 14 have a company-specific asset- and data-stream naming system. Hence, most respondents (12 of 14) have implemented, or are in the process of implementing, a standardized system for naming data streams and metadata.

In further work it would be interesting to investigate any correlations between use of RDS or similar standards and success in use of models for estimating condition development and failure probability.

4. Conclusions

It has historically been challenging to implement quantitative models for predicting condition development and failure probability in the hydropower sector and other industries. Welte (2008) characterizes this challenge as a vicious circle, in which insufficient condition data reduces the incentive to develop quantitative models for condition development and failure probability. Conversely, the absence of such models also reduces the motivation to collect component condition data. Findings from the 2025 survey indicate a substantial improvement in data availability since 2019. Furthermore, all respondents report that they intend to increase the use of condition development and failure probability models in the future. This suggests that the hydropower sector may now be positioned to enter a virtuous circle, in which greater data availability enhances the utility of quantitative models, and expanded model use further increases the value of data collection.

Nevertheless, further research is required to determine the conditions under which hydropower producers can successfully initiate such a virtuous circle. About one-third of the respondents rank the availability of models adapted to the needs of hydropower producers as the most important barrier, both in the short term and the long run. However, the survey results diverge on how these needs can be met. The responses are, e.g., approximately evenly split between simple models for relative ranking of component conditions and more advanced models for absolute estimation of component conditions and failure probability. The survey results also reveal no significant correlation between data access and the use of such data in asset management. While a few respondents identified a lack of data as a barrier, many highlighted insufficient standardization of IT systems and insufficient competence as major barriers. These challenges cannot be resolved by individual asset-management departments alone; they require collaboration with other internal organizational units and external partners.

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[d] https://www.iso.org/standard/75471.html

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