

METHODOLOGY

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Machine learning-based interactive dynamic resilience assessment for complex hydropower systems

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Abstract

Complex hydropower systems are vital infrastructure in modern societies. Because of the risks associated with the operation of hydropower plants and dam structures, it is necessary to assess the dynamic resilience of these systems by considering the effects of faulty equipment and/or extreme environmental events. Common approach is to evaluate the performance of system components when exposed to a set of scenarios, combining various equipment faults in adverse conditions (e.g. flooding, earthquake). The evaluation is usually carried out with specific needs: (1) establishing design criteria; (2) providing real-time operation of the hydropower system. However, these specific needs may limit the application in complex circumstances, as they require repetition of evaluation system performance with a wide-spread of input datasets. The authors propose a novel methodology for interactive dynamic resilience assessment based on machine learning techniques and big data. The methodology is based on producing an extensive computational dataset for various scenario assessment and providing a machine learning-based tool for rapid search within the dataset previously simulated. These scenarios are then evaluated interactively, without subsequent simulations, against user-defined resilience metrics. This way, an operation manager may evaluate the dynamic resilience of the hydropower system for various operational constraints in timely manner. The Pirot hydropower system located in Serbia is analysed and findings are presented. The results indicate that the proposed search methodology enhances the traditional simulation model for dynamic resilience assessment by reducing the time required for series of simulation runs, thereby enabling faster improvements in system resilience.

Keywords: Dynamic resilience, Hydropower system, Machine learning, Approximate nearest neighbour, Flood protection

Introduction

Large dams are man-made structures that are vital for modern economy and society. By forming reservoirs that are used for electricity generation, water supply, irrigation, and other purposes, they provide many benefits with relatively low cost of maintenance. However, they also bring considerable risks to nearby environment and populated areas,

due to possible damage or breakage that may have catastrophic effects. With most of the dams being in operation for many decades, certain changes in dams, such as damage in the structure, damage in the rock mass, and other potentially adverse effects on the safety of the dam inevitably appear, further increasing the intrinsic risks dams already present. Dams are susceptible to risks from natural hazards, mostly to intensive floods, earthquakes, landslides, and other extreme events. It is common practice that dam owners have risk management procedures in place concerning most probable risks. Recent incidents showed that, when extreme events do happen, sometimes even those procedures may not guarantee the safety of the dam and related structures. In the case of Wadi Derna Dam [25], where heavy flooding caused structural failure and collapse of the dam, the risks were not properly managed, due to lack of maintenance and proper response. The other notable incident in recent history is the case of Oroville Dam [13], where heavy rainfall produced a flood wave well within operating limits [17]. However, the main spillway suffered structural damage when put in use, starting a chain of events that endangered the dam structure.

Although dam failures are not that common, it is essential to assess dynamic resilience of dams, as well as related water systems [31]. The resilience of a system is a measure of its capability to recover from the disturbance event [12, 37]. In terms of water systems' resilience, various approaches are applicable to assess the resilience of water resources [5, 18, 23], while the assessment of resilience of dams and related water bodies is less studied [9]. Usually multiple scenarios, e.g. climate change [32], population increase, cyberattacks etc., are analysed by means of simulation models of underlying process and their interdependencies [27] in order to assess the resilience of a water system. However, by including scenarios of failure of the dam or related structures and equipment, the complexity of resilience assessment increases considerably. Earthquake scenarios may be the most important for dams in seismically active regions. Such scenarios usually include computationally intensive simulations, which provide valuable data that may not be observed otherwise. These simulations may be based on a historic event [28], or a hypothetical one [26].

On the other hand, multipurpose reservoirs are facing increasing demands and less predictable inflows due to the climate change. It is necessary to assess the resilience of water systems, not only to extreme hazardous events, but to conflicting demands and operational issues. These problems are usually referred to as water-energy nexus and are also important for complex water and hydropower systems [38]. There are also examples of reservoirs being repurposed through their life-cycle because of industrial and demographical development, which changes the operational rules and constraints [22].

Problem definition

A complex hydropower system consists of multi-purpose reservoir created by the construction of a dam, and a hydropower plant which uses the head between the reservoir and the recipient river. The complexity arises from multi-purpose reservoir operation, where water is being used for water hydropower generation or other uses, while preserving at all times the flood-management capability of the reservoir [21]. The demands for water use are often conflicting and may further raise the risks from natural causes (e.g., hydropower generation may favour larger head, which in turn

reduces freeboard volume and increases the risk from flood wave overtopping the dam). The resilience of such systems is usually difficult to determine since multiple risks should be considered and the observed data is not available (i.e., the most harmful events may have not happened yet). Instead, multiple models are used to simulate the response of diverse components of the system: hydrological models for flood waves assessment, hydraulic models for water intake and outflow, hydropower models for powerplant operation, and even elaborate structural analysis models for earthquake damage assessment to the dam structure [33]. The results provided by various models are usually run through system dynamics (SD) simulation models [16], which combine the outputs from other models and decision-making in casual loop diagrams. These models provide assessments of behaviour of system's components, while taking into account the operational rules that govern the system [30]. While providing valuable insights into system's behaviour, these models rely on computationally demanding simulations, therefore requiring considerable resources for execution. System dynamics simulations often rely on multiple scenarios assessment, where diverse components failures are considered in order to assess the resulting risks. The common approach is to perform a significant number of simulations, which provide the necessary dataset for resilience analysis. Some simulations may include very complex problems, such as earthquake damage assessment, which is usually performed using Finite Element Analysis [26]. Preparing the dataset for resilience analysis is a demanding task, especially in terms of computing time. Therefore, the authors of this paper have used the datasets from previous research, which dealt with resilience of Pirot Water system [33].

The Pirot Water system is shown in Fig. 1. It consists of Zavoj Reservoir and Pirot hydropower plant. It is located in south-eastern Serbia, with its drainage basin spanning over Serbia-Bulgaria border. Largest populated places in the vicinity of the reservoir are Pirot and Bela Palanka. Due to the influence of reservoir discharge and hydropower plant outflow into Nišava River, the relevant catchment area is considerably larger than that of the reservoir (approximately 570 km²). The flow of following rivers needed to be modelled: Visočica, on which the reservoir has been formed, Dojkinačka, Gaberska, Jerma, Toplodolska, Temštica, and Nišava. In total, nearly 3000 km² was modelled hydrologically, to provide various flood hydrographs.

The usable storage of Zavoj is 140 million m³, while total storage is nearly 170 million m³. It is formed by impoundment of Visočica River by Zavoj dam. The dam is equipped with 3 gated spillways, with total capacity of 1,820 m³/s. The water is discharged through spillways to Visočica River, which, together with Toplodolska River, create Temštica River, the largest tributary of Nišava River.

The water from the reservoir is used by Pirot hydropower plant (HPP), located near the town of Pirot. The plant houses two turbines, with total capacity of 45 m³/s. The water is diverted from Zavoj reservoir through the pressurized tunnel, 9 km in length. The tailrace of the HPP Pirot ends with compensation reservoir on Nišava River.

The operation of Pirot Water system needs to balance the electricity generation with flood protection. This is achieved through HPP Pirot operation in normal operating conditions. In case of high inflow in Zavoj Reservoir, one or all spillways may be used. The release of water through spillways needs to be controlled, since it may cause flooding

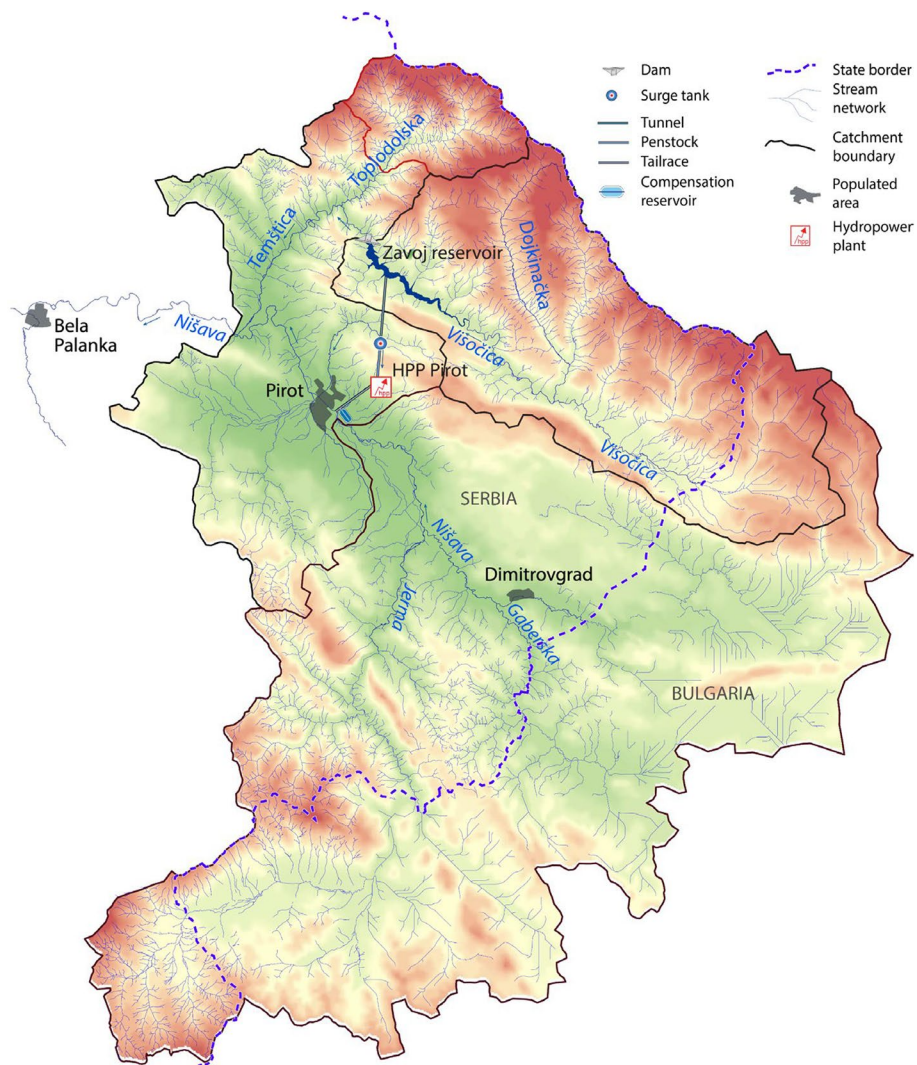


Fig. 1 Pirot reservoir system with associated drainage basin

downstream. Also, the release of water through HPP Pirot may cause high waters in Nišava River, thus endangering the city of Pirot.

Dynamic resilience quantification of the presented system relies on system dynamics simulation model used in previous research [33]. The model was developed using Vensim DSS software, where Stock and Flow diagram has been used to evaluate the response of unaltered system, as well as single- or multi-failure scenarios. For failure scenarios, a performance of system component is degraded for a certain period. In case of spillway gates, it is possible that one or more gates may be jammed when flood wave fills the reservoir, thus reducing the spillway performance. The indicator of performance α is introduced, where 0 value denotes total loss of performance and 1 represents full performance. The values between 0 and 1 are discrete, where each value represents partial performance degradation due to a certain failure scenario (i.e., 0.5 value for HPP Pirot represents single power unit failure). Therefore, for each of the system components in a certain failure scenario, an appropriate α value is defined:

$$\alpha \in [0, \dots, 1] \quad (1)$$

For every scenario, at the beginning of the simulation, the system performance is intact. That is, all components are associated with $\alpha = 1$. At the occurrence of risk event, a corresponding component's performance will be degraded, and α value will be reduced. After a designated recovery period, the value of α will be restored.

At any given time t , the state of the system may be 0 (failure) or 1 (success). In case of multipurpose reservoir [31], this can be noted as:

$$X_t = \begin{cases} 1, & R_t \geq D_t \\ 0, & R_t < D_t \end{cases} \quad (2)$$

where R_t stands for release at time t , and D_t stands for demand at t .

Resilience represents the measure of the system's ability to recover from a failure, and can be described as conditional probability of success state superseding failure state [31]:

$$\gamma = \{X_{t+1} \in SS | X_t \in FS\} \quad (3)$$

where SS denotes success state, and FS denotes failure state.

To understand the failure states of a complex hydropower system, all measures of performance need to be considered. As mentioned earlier, complex hydropower systems are confronted with conflicting demands: electricity generation and flood protection. These demands are limited by the volume of water available in the reservoir.

For hydropower generation, minimum volume is related to minimum operational level for hydropower plant V_{minHPP} , while maximum volume relates to maximum allowable head for turbines, V_{maxHPP} . Minimum volume is defined by hydropower plant design but may be subjected to change because of operational constraints [21]. Performance measure of the reservoir regarding hydropower generation is given as:

$$P_{HPP} = \begin{cases} 1, & V_t > V_{minHPP} \\ 0, & V_t \leq V_{minHPP} \end{cases} \quad (4)$$

where V_t denotes the reservoir volume at given time t , and P_{HPP} denotes performance measure.

Flood protection, on the other hand, requires a volume for receiving the flood wave (flood control volume), which corresponds to maximum volume with retarding capability, given as V_{maxFP} . Although the amount of storage reserved for flood control is defined at the design level for the reservoir, it may also be modified to take into account the effects of climate change. Performance measure of the reservoir regarding flood protection (P_{FP}) is given as:

$$P_{FP} = \begin{cases} 0, & V_t > V_{maxFP} \\ 1, & V_t \leq V_{maxFP} \end{cases} \quad (5)$$

The operation of the system inevitably affects the flow-regimes in the receiving rivers, so flow-related performance measures also need to be considered: Q_{RFD} —regular flood defence flow, and Q_{EFD} —emergency flood defence flow. The actual values for

these flows are usually declared in flood emergency plans. Two performance measures P_{RFD} and P_{EFD} are given as:

$$P_{RFD} = \begin{cases} 0, & Q_t \geq Q_{RFD} \\ 1, & Q_t < Q_{RFD} \end{cases} \quad (6)$$

$$P_{EFD} = \begin{cases} 0, & Q_t \geq Q_{EFD} \\ 1, & Q_t < Q_{EFD} \end{cases} \quad (7)$$

where Q_t is flow in river at a given time t .

The loss of system performance ρ at time t is defined as [31]:

$$\rho(t) = P_0(t - t_0) - \sum_{t_0}^t P \quad (8)$$

where t_0 denotes the starting time of component failure.

Dynamic resilience r at a given time t is defined as:

$$r(t) = 1 - \frac{\rho(t)}{P_0(t - t_0)}, r(t) \in [0,1] \quad (9)$$

Multi-parameter dynamic resilience is therefore given as:

$$r_m(t) = \sqrt[4]{r_{HPP}(t)r_{FP}(t)r_{RFD}(t)r_{EFD}(t)} \quad (10)$$

where $r_{HPP}(t)$ is dynamic resilience of hydropower generation, $r_{FP}(t)$ is dynamic resilience of flood protection, while $r_{RFD}(t)$ and $r_{EFD}(t)$ are dynamic resilience of regular and emergency flood defence, respectively.

The problem with dynamic resilience defined this way is that some of the performance measures depend on arbitrary parameters, especially in the case of flood protection measures, which are subject to change because of the rising global temperatures and more intensive weather events. Even if thousands of scenarios are simulated and worst-case scenario is used for resilience metrics, the problem with performance measures relying on variable parameters imply that the resilience needs to be calculated repeatedly [9]. Using conventional approaches, the process of reassessing the resilience may be resource- and time-consuming. It is necessary to reasonably reuse the available data and perform resilience metrics in cost-effective and timely manner.

Existing solutions

Trends in resilience research are notable in various scientific areas: socioeconomics, engineering, information technology, etc. Many authors are trying to improve existing resilience metrics and apply them to new problems. In terms of structural resilience, significant efforts are made to improve resilience metrics and provide more information on recovery phase. One example is cost-based resilience assessment of bridges in case of an earthquake [3]. The approach in that example is to determine dynamic resilience in both deterministic and stochastic ways. The authors state that stochastic approach (Monte Carlo) is more accurate than deterministic, especially for complete damage scenarios. The proposed framework encapsulates direct and indirect losses and recovery process in

two indices, providing the engineers a tool to select appropriate thresholds for the resilience indices, according to their needs and priorities.

An approach to resilience assessment using multi-objective genetic algorithms is presented in [24]. A multi-purpose reservoir in Czech Republic is analysed in conditions of uncertain climate change. The emphasis is on drought-prevention, where Pareto-optimal set of resilience vs. net present value allowed for creation of operation rules for better handling the water demand in dry periods. However, the authors note that several points of methodology are specific to case study and may not be applicable to other dams.

Another approach to dynamic resilience quantification is presented in [4]. A SD model of dam and hydropower plant was established to quantify dynamic resilience in multihazard environments. A total of 256,000 simulations was conducted for multihazard scenarios and the resilience of spillway and hydropower generation was assessed. All simulations are based on fixed parameters for performance measures.

One way to improve resilience assessment is to implement machine learning in the process. In [29] a fuzzy rule-based system is established using the data from 900 failure scenarios simulations with SD model of hydropower plant and multipurpose reservoir. A genetic algorithm is used to estimate fuzzy rules which may be later employed to instantaneously assess resilience of the system for a certain failure scenario. The other benefit of using fuzzy rule-based system is the explainability of system's resilience using natural language. However, the explainability in this study is somewhat reduced due to the use of genetic algorithm, which may introduce its own underlying logic into the rule set.

The use of machine learning for resilience metrics in a novel framework for evaluation of flood dynamic resilience is also presented in [33]. The output from hazardous models was supplied to SD model of multipurpose reservoir to obtain the dataset for training of artificial neural network (ANN). A feed-forward neural network was used to model dependencies between hazardous events and resilience metrics: robustness and rapidity. The authors conclude that ANNs can approximate the robustness and rapidity values with reasonable accuracy. Still, the performance measures that were defined for the training set limit the application for other cases.

Proposed solution

The presented problem may be solved using the traditional approach of repeatedly performing simulations when resilience analysis is performed. Due to the emergence of big data techniques in various fields, the authors here propose a novel methodology that employs the approach of implantation [6]. It relies on previous research and introduces big data techniques into analysis of dynamic resilience of complex hydropower systems.

Dataset generation

The basis for the solution presented in this paper is a large dataset consisting of pre-realized calculations for different values of the input parameters of the model. The dataset was generated by combining a system dynamics model [33] that mimics the nonlinear nature of the system, an earthquake disturbance model [26] and a flood hydrograph model which defines a flood wave of a certain return period. The combination of the last two models defines hazardous phenomena in the system dynamics model. By varying the input parameters of the system within the given ranges

Table 1 Input variables for dynamic resilience assessment of the hydropower system

Input	Description	Range	Units
Q_{\max}	The flood hydrograph peak value	[500—3500]	m ³ /s
T	Return period	[10 – 10,000]	Year
V_{init}	Initial reservoir volume	[1.33e + 08 – 1.90e + 08]	m ³
α	Seismic intensity	[0–15]	–
T_{dist}	Time distance between flood peak and earthquake	[0–12]	Day
T_e	Duration of functional degradation due to earthquake	[0–100]	Day

(Table 1) and by applying the Monte Carlo method, a database with about 300,000 different calculations was obtained. Each calculation simulates the operation of the system on an hourly basis for a period of 10 years.

The system dynamics model was developed in the Python programming language, using the PySD library [19]. PySD is an open-source library intended for working with system dynamics models, one of the main development goals of which is the integration of Big Data and Machine Learning in the SD workflow.

Generating a large number of calculations requires significant computer resources as well as the time required for execution. Dataset generation was done using WorkBinder service, a part of WoBINGO software platform [15]. Work binder service provides almost instant access to distributed resources of a computation cluster and increases their utilization by automatic and elastic allocation, depending on current and recent client behaviour.

The importance of generating such dataset and with this number of scenarios lies in the fact that the generation process takes place only once, while all subsequent analyses are carried out always starting from the same base of available scenarios.

Interactive dynamic resilience analysis

The interactive analysis of dynamic resilience is based on changing the parameters of the performance measures, which affect the assessment of resilience without changing the dynamics of the system itself. In other words, the behaviour of the system remains unchanged, and the indicators of the system's resilience are calculated without affecting the input variables and the states of the model. This approach excludes the need to rerun simulations for each individual change in the limit value, which achieves a significant saving in the time required to obtain results. The dataset needs to be extensive, though, to provide enough variable scenarios to evaluate. The interactive analysis of dynamic resilience consists of 3 steps, as shown in Fig. 2.

In the first step, a number of similar scenarios is selected by searching the predefined dataset. To perform this action, the Approximate Nearest Neighbour algorithm has been used. This algorithm uses the concept of indexing to efficiently search a large set of data in an N-dimensional space [2, 14, 36]. According to this concept, for each element of the data set (scenario) an index is determined which is unique for that combination of values (tuple) and by which the search is further carried out. The similarity of neighbouring scenarios is defined by the distance function. To implement

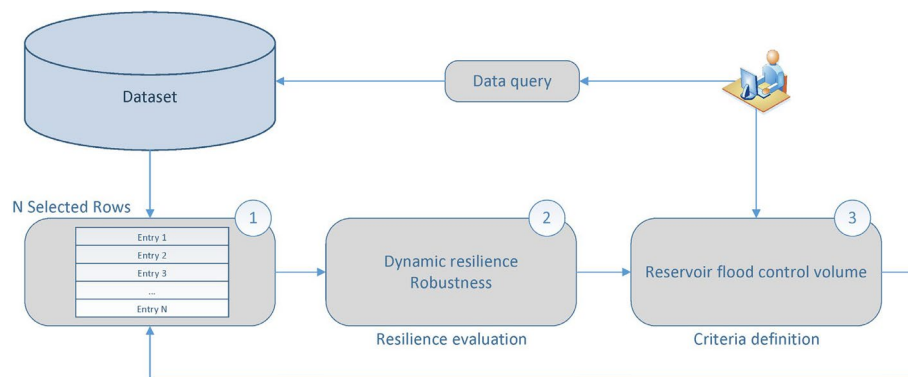


Fig. 2 Interactive dynamic resilience workflow used in the study

the algorithm, the PyNNDescend library was used, which also contains a significant number of predefined distance functions [20].

A proper build of index is crucial for the success of the search. Taking into account that the input data set is of different order of magnitude (hydrograph peak value, volume and other parameters), normalization of values in the range [0–1] was carried out. In that way, all scenarios are equally included without favouring any of them. In order to fine tune search algorithm some parameters related to indexing and searching should be adjusted. For indexing those parameters are: *n_neighbor*, *diversify_prob* and *pruning_degree_multiplier*. *Diversify_probe* defines the probability that, while constructing the graph-based index, the edge identified as redundant would get pruned. Thus, reducing this value will result in denser graph. Default algorithm value is 1.0. Since there is no clear recommendation in the algorithm documentation for choosing this value, but rather it depends on the specific problem, by analyzing the algorithm's performance for different values, the value 0.2 was adopted. The values less than 0.2 had no impact on accuracy except making graph denser. *Pruning_degree_multiplier* gives the multiple of the number of neighbours many edges that any given vertex in the search graph is allowed to have. The selected value is 2.0 which is consistent with similar algorithms presented in [10, 34]. Number of nearest neighbours used to build index differs from case to case. It is known that the larger the number of neighbours the search is more accurate, but slower. In order to gain an insight into the time needed to create an index, a small experiment was conducted. On proposed dataset, the index was built 20 times for 5 different number of neighbours and the time was measured. It is suggested that computational complexity can increase exponentially as the number of neighbors continues to grow. The other parameters remained constant. According to obtained results, the number of nearest neighbours is set to 50.

In the second step, for selected scenarios, partial indicators of robustness of the system parts are calculated. Two indicators are used to assess system resilience: robustness and rapidity [33]. The first is an indicator of minimum performance over time, while the second is an indicator of the rate of system recovery after hazardous events. In this paper, the focus will be on the analysis of the robustness of the system, considering that this parameter can be used when analysing and defining the rules of the system as well as designing certain parts of the system. However, the performance measures of the

system in itself sublimates the performance measures of its parts so that it can lead to the concealment of the real state. For this reason, in the interactive analysis, in addition to the overall performance of the system, performance measures of all its components are used. In this way, it is possible to take a better look at all the advantages and disadvantages of changing the robustness criteria.

In the third step, a set of combinations of limit values of functions for assessing the resilience of parts of the system is defined. After that the procedure of calculating partial performance measures is repeated on previously selected scenarios. Within the observed Pirot hydropower system, functions for the assessment of the resilience of the hydropower plant and reservoir are defined. The performance of the hydroelectric power plant is determined by the function of the minimum working level (P_{HPP}) in the reservoir and the flow downstream of the power plant (P_{RFD}). The reservoir performance is determined by the maximum water level for flood protection (P_{FP}) and the discharge downstream of the reservoir (P_{EFD}).

The proposed solution deals with some issues regarding to research gaps and opportunities presented in [1]. From the utility’s perspective, proactively addressing the issue of resilience could reduce the impact of an upcoming event or assist in faster recovery what is an advance of interactive analysis. Considering two hazards, flood and earthquake, within the same problem, made effort to evaluate system resilience upon independent occurrence of extreme events. Hazard characterization consists of two main parameters: probability and intensity of event. Large number of possible combinations lead to forming big data set and making such problem suitable for machine learning and big data analytics (Fig. 3).

Elaboration

In this chapter the results obtained using the proposed method of interactive analysis of dynamic resilience have been presented for the case of flood protection performance measure. It is noted that, due to the large number of possible different

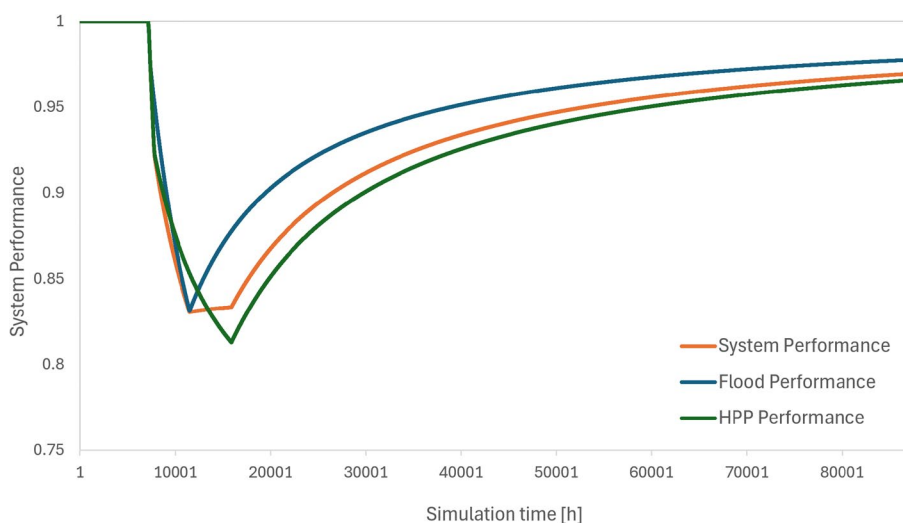


Fig. 3 Overall system performance (HPP Pirot) at the beginning of analysis

Table 2 Index build time: Different number of neighbours and the time measured

Number of neighbours	Build time [s]
10	72.6
25	77.4
50	79.5
75	120.7
100	164.6

Table 3 Query and results from dataset: 5 Nearest Neighbours

		Q_{\max}	T	V_{init}	α	T_{dist}	T_e	r_m
Data query		920.0	220	145000000	0.400	11	59	0.7000
Nearest Neighbours	1	905.3	216	144000000	0.670	7	33	0.8307
	2	916.3	223	148958770	0.402	6	60	0.1250
	3	929.9	233	147703460	0.519	7	48	0.8085
	4	929.6	232	144226400	0.479	5	53	0.3333
	5	948.6	246	150247920	0.529	7	47	0.2000

combinations of parameters, it is not feasible to show all the analyses that can be carried out, and that they will only be marked as guidelines for further research.

As previously shown in problem definition, flood protection performance measure of the reservoir is considered to be success when volume of the reservoir is at all times less than the corresponding flood control volume. Flood protection relies on a volume for receiving the flood wave in such a way that reservoir outflow is controllable. The flood control volume may be changed from the designed value in order to accommodate larger flood waves than previously predicted (Table 2).

In order to analyse the effect of changing the flood protection criteria, it is necessary to select the solution that has a good initial performance from the predefined dataset. It is not justified to start the analysis from a case that has a poor starting performance, because increasing the controllable volume for flood defence degrades the existing performance. Likewise, there is no need to analyse the case where a hazardous event degrades the performance of the system so much that no further degradation is required. This primarily refers to the magnitude of the earthquake and its duration.

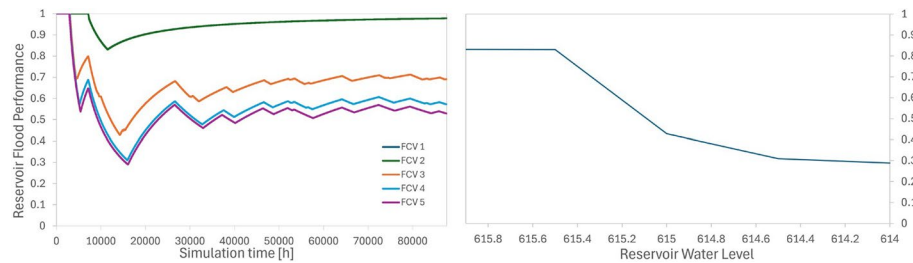
Taking into account the previously stated assumptions, a query was made over the dataset on the basis of which the algorithm proposed its solutions (Table 3).

Given that the desired selection criterion is the highest possible initial performance of the system, solution No. 1 was chosen for the analysis.

Flood protection system performance includes two separate performances: P_{FP} and P_{EFD} . The first is determined by the water level in the reservoir, while the second is defined by the flow rate in the river downstream. In this particular case, the impact of changing the emergency flood criteria on the overall performance of the flood defence system is negligible. On the other hand, the impact of the change in the reservoir level is examined in detail.

Table 4 Boundary water level for flood control volume of the HPP Pirot

Water Level [m.a.s.l]	Volume [million m ³]	FCV Label
615.9	162.140	FCV 1
615.5	159.944	FCV 2
615	157.200	FCV 3
614.5	154.558	FCV 4
614	151.919	FCV 5

**Fig. 4** Reservoir flood performance for different water levels (left), flood protection performance decrease (right)

In addition to the initial state, 4 more levels were considered as limit values for the mandatory flood protection reserve (Table 4).

For each of the considered levels, data from time-series is assessed for flood protection performance measure, providing the values of system performance for each time step. From the obtained results (Fig. 4) several conclusions can be drawn. Decreasing the level to 615.5 m.a.s.l. does not significantly affect the observed performance of the system. For levels less than or equal to 615 m.a.s.l., the flood protection performance takes a different form. A saw-tooth behaviour is pronounced which, to a certain extent, is alleviated for level 615, while for the other two levels it persists throughout the whole time. This is a consequence of the hydropower management and the rule according to which the level, due to the production of electricity, should be maximized. Therefore, in this case, when decreasing the level for the mandatory flood protection reserve, an adjustment of the operating rules of the power plant should also be considered. Levels 614.5 and 614 are close to each other and indicate a flattening of the curve that describes the decline in performance due to a change in levels.

Conclusion

The results of proposed methodology presented in previous chapter show the applicability of various resilience metrics based on an extensive dataset. The possible application of this approach is in operational management of complex hydropower systems, where decision-makers are usually confronted with everchanging conditions and demands. Due to the effects of climate change many operational rules that were previously established need to be reassessed and adapted. The example presented in this paper may provide decision-makers with cost-effective means to check the adapted operational rules against vast amount of failure scenarios and assess the resilience of the system in new conditions. Furthermore, the flood protection measures may include construction of levees and other structures within

the complex systems with reservoirs and hydropower plants, changing the flood emergency plans and corresponding performance measures. When designing new flood protection structures, the planners may easily assess the effect of those structures on resilience of the system and may adapt the design values accordingly.

There is a downside to the proposed methodology that one should consider when applying it to a specific case: if the performance measure is based on a value that may influence either the parameters or the states of SD model, the simulation needs to be performed to take into account the new behaviour. This, in some way, limits the application of the proposed methodology, but the potential for application recognizing this limit is still considerable, as is presented for the case of flood protection resilience.

The search algorithm used in the proposed solution is just one of many algorithms suitable for searching in N-dimensional space [8]. The further research would consider implementation and performance some of those algorithms. In addition to other algorithms, different indexing techniques [11] as well as proposed improvements of Approximate Nearest Neighbour [35] should be examined.

The intensive processing of time-series data using this methodology allows for application of feature extraction algorithms [7], which may provide valuable insights in underlying phenomena of failure scenarios and bring out the “hidden” aspects of resilience metrics.

Abbreviations

ANN	Artificial neural network
SD	System dynamics
HPP	Hydropower plant
m.a.s.l.	Meters above sea level

Author contributions

VM, NM and BS conceptualized the paper. VM and NM provided the background research. VM and VC drafted the paper. MS and NM provided the datasets from previous research. VC performed the analysis for elaboration. MS, UM, and VK reviewed the paper. VM and VC made the final edit. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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