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Uporaba vodnih virov za proizvajanje električne energije je ena najbolj učinkovitih oblik izkoriščanja obnovljive energije. Moč vode so sicer znali izkoriščati nekateri narodi že pred začetkom našega štetja. Prvi projekt hidroelektrarne na svetu je bil sicer uporabljen za napajanje ene same svetilke v podeželski hiši Cragside v Northumberlandu v Angliji leta 1878. Štiri leta pozneje je bila v Wisconsinu v ZDA odprta prva elektrarna, ki je služila sistemu zasebnih in komercialnih strank. Prvo hidroelektrarno na reki Niagari je zgradil George Westinghouse po načrtih Nikole Tesle leta 1895. To je bila prva večja elektrarna, ki je proizvajala izmenični električni tok. Le nekaj dni pozneje je začela delovati hidroelektrarna na reki Krki pri Šibeniku. Hidroelektrarna Fužine je hidroenergetski objekt na Ljubljanici, ki stoji ob južni steni gradu Fužine v ljubljanskem predelu Nove Fužine. Obratovati je začela 14. aprila 1897 kot prva slovenska elektrarna na izmenični tok. Razvoj hidroelektrarn po svetu je nato potekal izjemno hitro.

V svetu, pa tudi v Sloveniji, je hidroenergija pomemben vir, saj Slovenija okoli 25 % vse proizvedene električne energije pridobi iz hidroelektrarn, v svetu pa se pridobi približno 15 odstotkov vse električne energije s pomočjo potencialne energije vode. Takšen način pridobivanja energije je okolju prijazen, saj ne povzroča emisij toplogrednih plinov, vendar pa ima kljub temu vpliv na okolje. Čeprav hidroelektrarne ne povzročajo onesnaževanja zraka in vode, imajo lahko vpliv na okolje, zlasti pri postavitvi jezov.

V splošnem lahko rečemo, da hidroelektrarne prispevajo k trajnostnemu razvoju, z nadaljnjimi raziskavami pa lahko še izboljšamo učinkovitost in zmanjšamo njihov vpliv na okolje. Zato sta razvoj in izboljšanje obstoječih tehnologij na področju izkoriščanja vodne energije izjemnega pomena.

Bralcem želim zanimivo branje revije JET.

Jurij AVSEC
odgovorni urednik revije JET

Dear Readers of the Journal of Energy Technology (JET)

The use of water resources to produce electricity is one of the most efficient forms of renewable exploitation energy. Some nations have been able to harness the power of water since before the beginning of our era. The world's first hydroelectric power project was used to power a single lamp at the Cragside country house in Northumberland, England, in 1878. Four years later, the first power plant to serve a system of private and commercial customers was opened in Wisconsin, USA. The first hydroelectric power plant on the Niagara River was built by George Westinghouse according to plans by Nikola Tesla in 1895. It was the first major power plant to produce alternating current. Just a few days later, a hydroelectric power plant began operating on the Krka River near Šibenik. The Fužine Hydroelectric Power Plant is a hydroelectric power facility on the Ljubljanica River, located next to the southern wall of Fužine Castle in the Nova Fužine district of Ljubljana. RKD No. It began operating on 14 April 1897 as the first Slovenian alternating current power plant. The development of hydroelectric power plants around the world has been than extremely rapid….

In the world, as well as in Slovenia, hydropower represents an important source, as Slovenia obtains around 25% of all electricity produced from hydroelectric power plants, and, in the world, approximately 15% of all electricity is obtained using the potential energy of water. This method of generating energy is environmentally friendly, as it does not cause greenhouse gas emissions, but it still has an impact on the environment. Despite the fact that hydroelectric power plants do not cause air and water pollution, they can have an impact on the environment, especially when dams are built.

In general, we can say that hydroelectric power plants contribute to sustainable development, and, with further research, we can improve their efficiency further, as well as reduce their impact on the environment. Therefore, the development and improvement of existing technologies in the field of exploiting hydroelectric power is of the utmost importance..

I wish readers an interesting reading of the JET magazine.

Jurij AVSEC
Editor-in-chief of JET

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THEORETICAL AND EXPERIMENTAL INVESTIGATIONS OF A WATER HAMMER IN SAVA RIVER KAPLAN TURBINE HYDROPOWER PLANTS

TEORETIČNE IN EKSPERIMENTALNE RAZISKAVE VODNEGA UDARA V HIDROELEKTRNAH S KAPLANOVIMI TURBINAMI NA REKI SAVI

Anton Bergant[1,2ℜ], Jernej Mazij[1], Jošt Pekolj[1]

Keywords: hydropower plant, Kaplan turbine, Sava River, water hammer, validation

Abstract

This paper deals with critical flow regimes that may induce an unacceptable water hammer in the Sava River Kaplan turbine hydropower plants. The rigid water hammer model is introduced first. The computational results are then compared with the results of measurements in two distinct hydropower plants (HPP): (i) The refurbished and upgraded Medvode HPP, and (ii) The newest Brežice HPP. Comparisons of the computed and measured results are examined for normal operating regimes. The water hammer in the two power plants is controlled by appropriate adjustment of the wicket gates and runner blades closing/opening manoeuvres. The agreement between the computed and measured results is reasonable.

Povzetek

Prispevek obravnava kritične pretočne režime, ki lahko povzročijo nesprejemljiv vodni udar v hidroelektrarnah s Kaplanovo turbino na reki Savi. Najprej je predstavljen model togega vodnega udara. Računske rezultate nato primerjamo z rezultati meritev v dveh značilnih hidroelektrarnah

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(HE): (i) prenovljeni in nadgrajeni HE Medvode ter (ii) najnovejši HE Brežice. Primerjave izračunanih in izmerjenih rezultatov so podane za normalne režime obratovanja. Vodni udar v obeh elektrarnah je krmiljen z ustrezno nastavitvijo manevrov zapiranja oziroma odpiranja vodilnih in gonilnih lopatic turbine. Ujemanje med izračunanimi in izmerjenimi rezultati je dobro.

1 INTRODUCTION

Hydropower is a key renewable energy asset in Slovenia capable of meeting long term, and, in particular, intermittent electrical power demands. In the European Union it accounts for about 12 % of electricity production. In addition, it offers flexibility and storage of energy, which are important for maintaining the stability of the electrical grid system, due to the growing share of variable renewable energy sources [1]. In the light of safe and flexible operation of hydropower systems this paper deals with water hammer events in the Kaplan turbine hydropower plants installed on the Sava River in Slovenia. The Sava River basin is the largest in Slovenia and represents more than 50% of the total country area, but is the least utilised in terms of hydropower, with a total installed capacity of 230 MW [2]. The Sava River hydropower plants with Kaplan turbines are (from north to south): Mavčiče HPP (1968, 2x19 MW), Medvode HPP (1953, upgraded and refurbished 2004, 2×12.4 MW), Arto-Blanca HPP (2008, 3x13 MW), Krško HPP (2012, 3×13 MW) and Brežice HPP (2017, 3×15.2 MW). Completion of the chain on the lower Sava River is underway, and the start of the procedure for the design of the middle Sava River chain with 10 hydropower plants is foreseen in the near future.

Water hammer control is essential, to assure safe and flexible operation of the new, as well as the refurbished and upgraded hydropower plants. Large transient loads may disturb the overall operation of the plant (operational range) and damage the system components, for example, distributor vanes or runners. Hydraulic transients in hydropower plants with Kaplan turbines can be kept within the prescribed limits (pressure in the flow passage-system, turbine rotational speed, etc.) with the following methods [3], [4], [5]:

- *Alteration of operational regimes*. This method includes typically appropriate control of the wicket gate and runner blade manoeuvres (the turbine governor and servomotor mechanism). A two- or multi-speed wicket gate closing time function (adding a cushioning stroke) improves the safe operation of the plant significantly. Opening of the runner blades during the turbine shutdown (normal, mechanical quick stop, emergency) results in a favourable runner blade manoeuvring, improved over-speed performance and reduced negative axial hydraulic thrust.
- *Installation of surge control devices in the system*. A draft tube gate can be used to protect a Kaplan turbine against runaway. In addition, sluicing operation of the low-head Kaplan turbines can attenuate open channel waves during transient regimes. Surge control devices alter the system characteristics (shorten the active conduit length, reduce the liquid compressibility, increase the turbine inertia, etc.). The protective devices that may be installed along the inlet and outlet conduit or added to the system components are increased turbine unit inertia, a surge tank (in HPPs with long conduits), a pressure regulating valve, aeration pipe, air valve, etc.
- *Redesign of the flow passage system layout* includes a change of the conduit profile (high point) and dimensions (diameter, length), and different positioning of the system components (for example, valves).

A traditional water hammer control device, particularly in the case of refurbishment and upgrading of Kaplan turbines, is the turbine governor coupled to the wicket gate and runner blade servomotor mechanisms [6], [7], [8], [9]. The control devices should operate smoothly in the following normal operating conditions [4]: turbine start-up, load acceptance, load reduction and total load rejection (mechanical quick stop, electrical emergency shutdown). Emergency conditions are load rejections in which partial runaway occurs. The turbine runaway is considered as a catastrophic transient regime. Water hammer analysis should be performed for normal, emergency and catastrophic operating conditions.

The main objective of this paper is to identify critical flow regimes that may induce unacceptable water hammer in the Sava River Kaplan turbine hydropower plants. The rigid water hammer model [3], [10] is introduced first. The computational results are then compared with the results of measurements in two distinct HPPs: (i) The refurbished and upgraded Medvode HPP, and (ii) The newest Brežice HPP. Comparisons of the computed and measured results are examined for normal operating regimes.

2 THEORETICAL MODELLING

The water hammer in hydropower plants equipped with axial turbines (Kaplan, bulb) can be calculated using either the elastic [11] or rigid [10] water hammer theory. The run-of-river power plants are, traditionally, comprised of relatively short inlet and outlet conduits. The length of the conduit is of the same order as the cross-sectional dimensions, as is the case for the Medvode HPP and for Brežice HPP. The cross-sectional area is of a complex shape. The standard one-dimensional elastic water hammer model cannot predict the physics of wave transmissions and reflections accurately [12]. The rigid water hammer model is recommended to be used for this case [10]. Incompressible liquid and rigid pipe walls are assumed in the model. Rigid water hammer is described by the one-dimensional equation of motion for unsteady pipe flow [3]:

$$\frac{\partial H}{\partial x}+\frac{fQ|Q|}{2gDA^2}+\frac{1}{gA}\frac{dQ}{dt}=0 \tag{2.1}$$

in which H = pressure head, x = distance, f = Darcy-Weisbach friction factor, Q = discharge, g = gravitational acceleration, D = diameter, A = cross-sectional area, and t = time. Equation (2.1) is solved simultaneously with the dynamic equation of the turbine unit rotating masses, taking into account the discharge and torque turbine characteristics [10]:

$$T_x = I\frac{d\omega}{dt} \tag{2.2}$$

in which T_x = the net torque applied to the turbine unit shaft, I = the polar moment of inertia, and ω = the angular velocity. Steady-state turbine characteristics are used for a transient analysis [13]. There are some discrepancies between the steady and unsteady performance characteristics, due to unsteady flow effects and when the turbine operates in a cavitating region [10]. Transient regimes in the HPP are *relatively slow* (the wicket gates closure time is much slover than the wave reflection time); therefore, the unsteadiness should not affect the turbine's characteristics significantly. The complex axial turbine performance characteristics in zones of normal turbine operation and energy dissipation, and complex flow behaviour of the turbine, particularly at off-design operating conditions, led researchers to develop a full-three-dimensional model for water hammer analysis in axial turbines with relatively short inlet and outlet conduits [14], [15], [16]. The three-dimensional model enables the prediction of flow quantities at an arbitrary computational domain location. The first step was to develop a model for a bulb turbine, because of its *relatively simple* geometry in comparison to the Kaplan turbine geometry (scroll-case, draft tube with elbow). The development of a three-dimensional water hammer model for Kaplan turbines is the subject of the authors' further research in the field of Fluid Transients in Systems.

The geometric characteristics of the inlet (Gu) and outlet (Gd) conduits are decribed by the following equations:

$$G_u = \sum_i \frac{L_{ui}}{A_{ui}} \tag{2.3}$$

$$G_d = \sum_i \frac{L_{di}}{A_{di}} \tag{2.4}$$

in which L = the length of the conduit.

3 COMPARISONS OF THE COMPUTED AND MEASURED WATER HAMMER EVENTS IN MEDVODE HPP

Medvode HPP is located on the Sava River in the town Medvode, 15 km north of Ljubljana. There are two double-regulated Kaplan turbines, each with its own flow-passage system. The plant was built in 1953 with the rated output of each turbine of P_r = 9.3 MW. The diameter of the six-bladed runner was D = 3060 mm. A major refurbishment and upgrading of the two old turbines were performed in 2004. The old turbine runners have been replaced by new five-bladed runners of increased rated output, P_r = 12.43 MW, and increased runner diameter, D = 3250 mm [17]. During the development and design of the new runner special attention was given to reliable, sustainable and environmentally friendly constructional solutions, in order to minimise the unwanted impacts of lubricants on the river water's pollution.

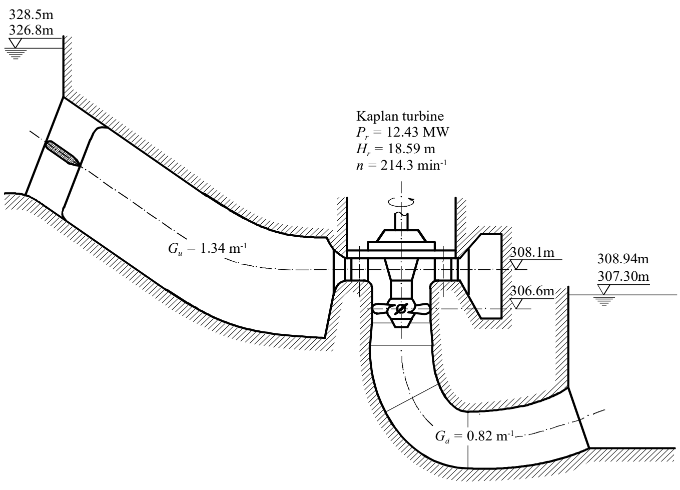

***Figure 1**: Medvode HPP flow-passage system of the Kaplan turbine unit*

The flow-passage system of the Medvode HPP is comprised of an upper basin (Lake Zbilje), two parallel inlet conduits, each with a Kaplan turbine unit and draft tube (Figure 1), and tailrace (Sava River). Dynamic loads during the transient regimes are controlled by appropriate adjustment of the wicket gate and runner blade closing/opening manoeuvres. The dimensions of the inlet conduit and scroll-case, and the draft tube, are expressed as the geometrical characteristics G_u = 1.34 m^{-1} and G_d = 0.82 m^{-1} (Equations (2.3) and (2.4)), respectively. The polar moment of inertia of the unit's rotating parts (turbine, shaft, generator) is I = 163×10^3 kgm^2.

A hydraulic transient analysis in the final design stage of the refurbished and upgraded turbine unit was performed for normal, emergency and catastrophic operating regimes [4]. The rigid water hammer model was used for all the computational runs. A number of experimental runs for various transient regimes were carried out in the plant, in order to verify the suitability of the wicket gate and the runner blade closing/opening procedures. The extreme values of the measured quantities during the transients were within the prescribed limits. This paper presents two emergency shutdown case studies [17]. The computational results are compared with the results of the measurements.

3.1 Emergency shutdown of the turbine unit from 13 MW

An emergency shutdown of the turbine unit from the maximum load of 13 MW is the most severe normal operating transient regime with respect to the extreme pressure heads and turbine rotational speed, and, consequently, the danger of full water column separation under the turbine head cover. The turbine is disconnected from the electrical grid, followed by a complete closure of the wicket gates (servomotor stroke (y_{wg})) (Figure 2a). The runner blades (servomotor stroke (y_{rb})) stay still at their fully open position (Figure 2b).

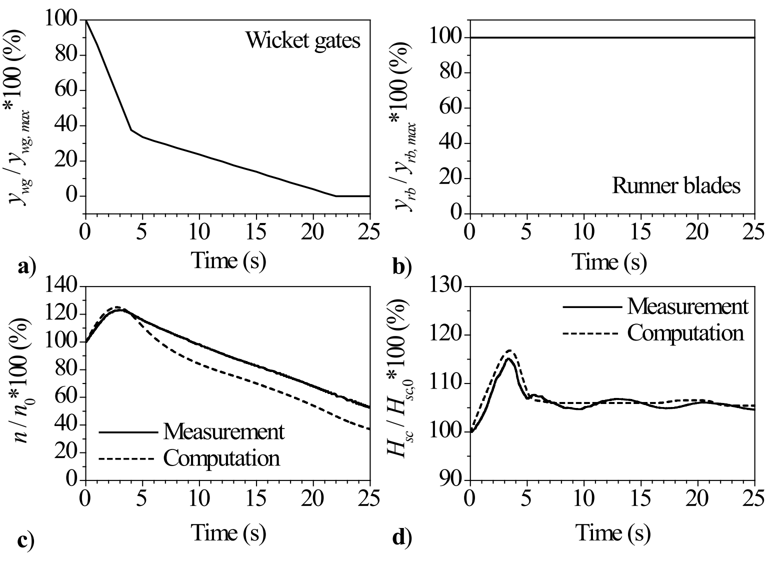

Figure 2: Emergency shutdown of the Kaplan turbine unit in the Medvode HPP from 13 MW – wicket gate servomotor stroke a), runner blade servomotor stroke b), rotational speed c) and scroll-case pressure head d)

The turbine rotational speed (n) (Figure 2c) and the pressure head in the scroll-case of the turbine (H_{sc}) (Figure 2d) were compared. There was a reasonable agreement between the computed and the measured maximum rotational speed rise of 25.9 % and 23.2 %, respectively (Figure 2c). The computed maximum scroll-case pressure head rise of 17.4 % was higher than the measured pressure head rise of 14.2 % (Figure 2d). The maximum speed rise and the maximum scroll-case pressure head rise were well below the prescribed limits (45 % of the nominal speed and 35% of the maximum gross head, respectively).

3.2 Emergency shutdown of the turbine unit from 6.8 MW

Emergency shutdown of the turbine unit from the half-load of 6.8 MW was investigated, in order to verify the model for a broader range of input parameters. The turbine was disconnected from the electrical grid, followed by a complete closure of the wicket gates (y_{wg}) (Figure 3a). The runner blades (y_{rb}) opened to their fully open position (Figure 3b).

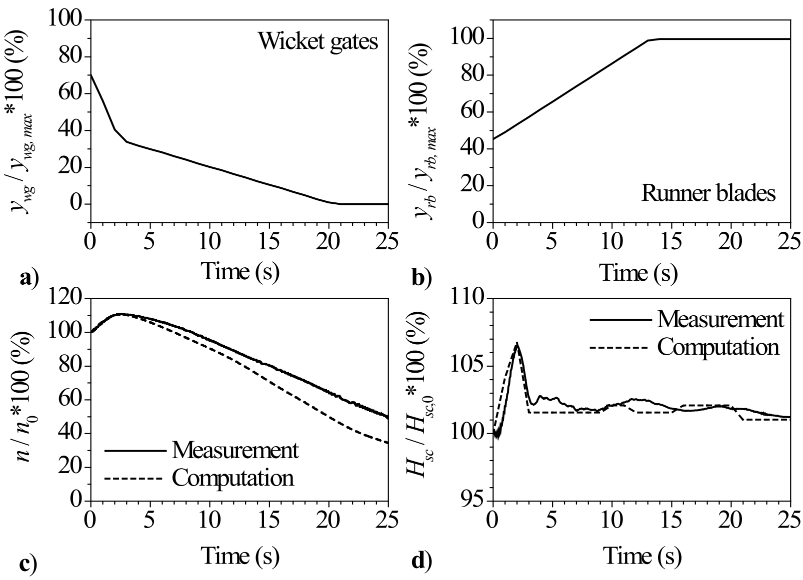

***Figure 3**: Emergency shutdown of the Kaplan turbine unit in the Medvode HPP from 6.8 MW – wicket gate servomotor stroke a), runner blade servomotor stroke b), rotational speed c) and scroll-case pressure head d)*

The turbine rotational speed (n) (Figure 3c) and the pressure head in the scroll-case of the turbine (H_{sc}) (Figure 3d) were compared. There was an excellent agreement between the computed and the measured maximum rotational speed rise of 10.9 % and 11.0 %, respectively (Figure 3c). The computed maximum scroll-case pressure head rise of 6.8 % was slightly higher than the measured pressure head rise of 6.5 % (Figure 3d). The maximum speed rise and the maximum scroll-case pressure head rise were well below the prescribed limits (45 % of the nominal speed and 35% of the maximum gross head, respectively).

4 COMPARISONS OF THE COMPUTED AND MEASURED WATER HAMMER EVENTS IN BREŽICE HPP

Brežice HPP is the fifth in a chain of six planned run-of-the river hydropower plants the Slovenian lower Sava River basin. When completed, the 6 hydropower plants will account for 20 % of hydropower energy production in Slovenia. The three Kaplan units, with a total installed discharge of 500 m^3/s and rated power of 15.2 MW each with yearly production of 161 GWh, are controlled by a remote centre in the nuclear power plant Krško. The runner diameter of the four-bladed double-regulated Kaplan turbine is D = 4900 mm. The three turbines have been opearting successfully since 2017. Major additional landscaping and municipal engineering work was performed, in order to provide flood protection, compensate for lost habitat, and make way for possible future tourist development. A fishway, that allows fish and other aquatic organisms to pass the hydropower structure, has been built on the left-hand-side river-bank (relative to the flow direction) – see Figure 4.

Figure 4: *Brežice HPP layout with clearly visible fishway located on the left-hand-side river-bank (relative to the river flow direction) (www.he-ss.si)*

The flow-passage system of Brežice HPP is comprised of an upper basin (Sava River forebay), three parallel inlet conduits, each with a Kaplan turbine unit and draft tube (Figure 5), and tailrace (Sava River). The dynamic loads during transient regimes are controlled by appropriate adjustment of the wicket gate and runner blade closing/opening manoeuvres. The dimensions of the inlet conduit and scroll-case, and the draft tube, are expressed as the geometrical characteristics G_u = 0.52 m^{-1} and G_d = 0.69 m^{-1} (Equations (2.3) and (2.4)), respectively. The polar moment of inertia of the unit's rotating parts (turbine, shaft, generator) is $I = 735 \times 10^3$ kgm^2.

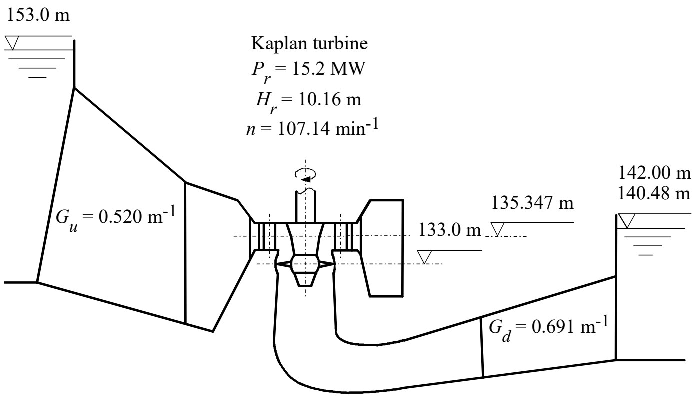

***Figure 5**: Brežice HPP flow-passage system of the Kaplan turbine unit*

Similar to Medvode HPP, the emergency shutdown of the Kaplan turbine unit from the maximum load of 21 MW is considered to be the most severe normal operating regime in Brežice HPP [18]. The maximum load is much larger than the rated one, because the turbine has been optimised for the complete lower Sava River chain, with a much higher tailrace water level. The turbine was disconnected from the electrical grid, followed by the complete closure of the wicket gates (Figure 6a), while the runner blades are opened to their fully open position (Figure 6b). The agreement between the computed and measured maximum unit rotational speed rise of 36.3 % and 35.3 % (Figure 6c), respectively, was very good. The same can be said for the maximum scroll-case pressure head rise; the computed value was 7 % and the measured one was 6.1 % (Figure 6d). The maximum speed rise and the maximum scroll-case pressure head rise were well below the prescribed limits (50 % of the nominal speed and 35% of the maximum gross head, respectively).

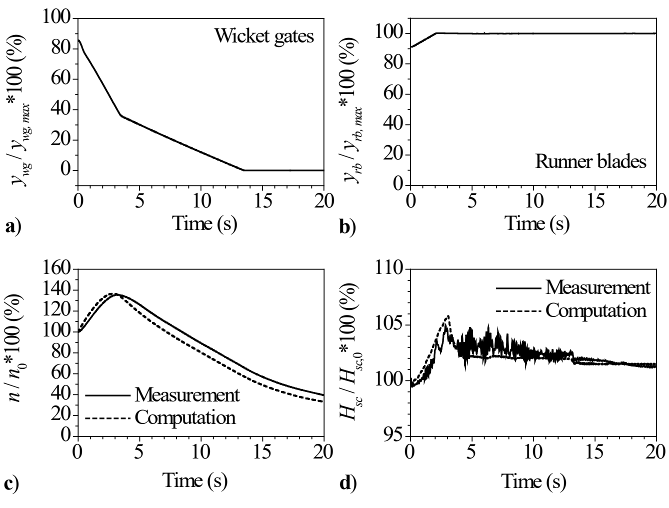

***Figure 6**: Emergency shutdown of the Kaplan turbine unit in Brežice HPP from 21 MW – wicket gate servomotor stroke a), runner blade servomotor stroke b), rotational speed c) and scroll-case pressure head d)*

5 CONCLUSIONS

The main objective of this paper is to identify the most critical normal transient flow regimes that may induce extreme water hammer loads in the Sava River Kaplan turbine hydropower plants. These powerplants are comprised of relatively short inlet and outlet conduits. Therefore, the rigid water hammer model has been used for hydraulic transient analysis. The computational results were compared with the results of measurements in two distinct hydropower plants (HPP): (i) The refurbished and upgraded Medvode HPP, and (ii) The newest Brežice HPP. Water hammer in the two power plants is controlled by appropriate adjustment of the wicket gates and runner blades closing/opening manoeuvres. The agreement between computed and measured results was reasonable.

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Nomenclature

(Symbols)	(Symbol meaning)
A	cross-sectional area
D	runner diameter, diameter
f	Darcy-Weisbach friction factor
G_d	geometric characteristic of the outlet conduit
G_u	geometric characteristic of the inlet conduit
g	gravitational acceleration
H	pressure head, head
H_r	rated net head
H_{sc}	scroll-case pressure head
I	polar moment of inertia
L	length
n	turbine rotational speed
P_r	rated turbine output
Q	discharge
t	time
x	distance
y_{gw}	wicket gate servomotor stroke
y_{rb}	runner blade servomotor stroke
ω	angular velocity

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ASSESSING THE EFFECTS OF A HYDROPOWER PLANT BASIN ON FISH SPAWNING IN AN UPSTREAM RIVER TRIBUTARY

OCENA VPLIVA JEZA HIDROELEKTRARNE NA DRSTENJE RIB V GORVODNEM PRITOKU

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Keywords: environmental impact; habitat sustainability; hydro-dynamic model

Abstract

This paper presents a combined modeling approach to evaluate the ecological effects on the habitat of an upstream tributary of a river with a series of hydropower plants. The influence is investigated of the last planned hydropower plant to be built, which has a large impact on the river ecosystem. The new hydropower plant basin will affect the tributary with hydropeaking in the upstream basin. A simulation was conducted of spawning conditions for two protected fish species. The analysis combined a hydro-morphological model with a fish module that considers the water depth and velocity necessary for fish reproduction. The different river discharge scenarios were simulated, incorporating the hydropeaking effects of the new hydropower plant basin on the upstream tributary. With the new hydropower plant, sustainable measures are planned to prevent the damaging negative impacts that could lead to the degradation of the river ecosystem and the destruction of the existing ecosystem at the river's confluence. The results indicate that, after the hydropower plant begins operation, the habitat`s suitability will decrease, and the planned sustainable measures will not provide a fully satisfactory solution.

Povzetek

Članek predstavlja kombinacijo modelov za oceno ekoloških učinkov na habitat reke, na kateri je že veriga hidroelektrarn. Načrtovana je zadnja hidroelektrarna v verigi in treba je raziskati njen vpliv na ekosistem reke, pravzaprav na pritok reke pred novim jezom. Novi jez hidroelektrarne

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bo močno vplival na zgornji pritok z nihanji gladine. Izvedena je bila simulacija pogojev drstitve za dve zaščiteni vrsti rib. Analiza je kombinacija hidromorfološkega modela in modela indeksa habitatov, ki upošteva predvsem globino in hitrost vode, potrebne za reprodukcijo rib. Simulirani so različni scenariji pretoka reke, pri čemer so bili upoštevani učinki spremembe gladine jeza zaradi obratovanja hidroelektrarne. Z novo hidroelektrarno so načrtovani tudi trajnostni ukrepi za preprečevanje negativnih vplivov, ki bi lahko pripeljali do degradacije ekosistema reke in uničenja obstoječega ekosistema na sotočju rek. Rezultati kažejo, da bo po začetku obratovanja hidroelektrarne ustreznost ekosistema padla, načrtovani trajnostni ukrepi pa ne bodo zagotovili povsem zadovoljive rešitve.

1 INTRODUCTION

Slovenia lies at the junction of four natural areas, the Alps, the Mediterranean, the Dinaric Mountains, and the Pannonian Basin. The Slovenian territory drains mainly through the Sava River and its tributaries into the Danube, and, finally, to the Black Sea (approximately 80%), while the rest drains into the Adriatic Sea. In the highland Alps and subalpine mountains there are many torrential streams in which flash flooding can occur during excessive rainfall [1]. Because of Slovenia's specific structure, its river basins, steep slopes, and impermeable bedrock, flash floods are the prevailing type of floods along most Slovenian watercourses [2].

The river ecosystems of the area undergo natural fluctuations in their hydrological cycle, with a variability ranging from floods to droughts. To deal with this variability, the common human response was to regulate rivers. Hydropower is a leading renewable energy resource in Europe, which has a "green image" due to its low greenhouse gas emissions. Hydropower plants (HPPs) are a synergy of river regulation and electricity generation, but they have negative impacts on aquatic ecosystems. The mitigation of the negative impacts on the environment is necessary.

Since their development, physical habitat models have become an essential tool for evaluating the habitat suitability for aquatic organisms, based on physical variables, such as depth, flow velocity, and substrate. This is particularly useful in assessing the impact of hydropower plants on the ecological state of the river, and the determination of the requirements for sustainable conditions for the aquatic population. Many rivers are characterized by structural disturbances, such as embankments and flood control weirs. As a significant migration barrier, these weirs alter habitat conditions, due to direct changes of the flow characteristic. Physical habitat models could enhance and evaluate the selection of options to reduce the impacts of water infrastructures on aquatic habitats in Slovenia and elsewhere.

The fish module of the habitat simulation model Computer-Aided Simulation Model for Instream Flow Requirements (CASiMiR) [3] was used to predict habitat availability and suitability for the fish species reproduction. PHABSIM is an alternative that must be supplemented with multiple observations of the same areas to develop a flow-habitat relation. In [4], the combination of HEC-RAS and PHABSIM carried a modeling framework comprised of hydrological, hydraulic, and habitat models for water management of unidirectional and tidal rivers. HEC-RAS is an integrated system of software, designed for interactive use by the Hydrologic Engineering Center of Engineers River Analysis [3]. This software allows researchers to perform one-dimensional steady flow, one and two-dimensional unsteady flow calculations, sediment transport/mobile bed computations, and water temperature/water quality modeling.

The evaluations of both models are presented in [5], showing strong and weak points in the simulations. The conclusions present sufficient coverage of the results, and, because CASiMiR is used commonly in Europe, it was suitable for our investigation. Habitat suitability is evaluated for the targeted life stage as in [6]: spawning in each cell with a direct method. The most used index of habitat is the Habitat Suitability Index (HSI), which is a tool to represent the preferences of different species for a combination of instream variables (water velocity and depth, the substrate, and cover, or shading with trees) [7]. The indices are in the range of 0–1 for each variable. Several suitability indices are combined to define a composite suitability index, assuming that all the variables are equally important, all the environmental variables are independent, and there is no interaction between them. Different methods could be used in CASiMiR to combine the different suitability indices obtained for each physical factor, and the indices are combined to calculate a composite HSI [8, 30]. The methods to obtain HSI are compared in [9]: the product method assumes that the most limiting factor determines the upper limit of habitat suitability, and the fact that high values cannot compensate for low values of other variables; the arithmetic-mean method is based on the assumption that the habitat variables are compensatory, and that the good habitat conditions on one variable can compensate for bad conditions on others [10]; the geometric-mean method also implies some compensation, but the product method yields zero suitability for any zero-valued indices. In the literature, CASiMiR is used often, and emphasized because of fuzzy rules to define the relationship between input variables and habitat suitability for certain species' life stages, which is not the case in PHABSIM. Different scenarios and their effects can be investigated, to find the most suitable conditions for species in all life stages [11]. Since the amounts of fish data available for this study were limited and the development of fuzzy rules for the description of habitat suitability was based on expert knowledge and the limited database (Table 1), a quantitative validation of the model could not be performed within this study. The outputs of CASiMiR were used to assess the changes in fish habitat availability and suitability. First, habitat suitability maps for fish species at each combination of river flow and HPP hydropeaking (normal and minimal basin levels) were generated, to visualize the areas within the river that provide certain physical conditions for fish under a steady flow situation.

In the simulation, we used the CASiMiR standard preference function method, in which the condition of an aquatic ecosystem is coupled directly with the physical conditions of the reference species, focusing on spawning. Changes to the flow rate result primarily in impacting the water depth, flow velocity, and substrate conditions, all of which are major factors in determining the habitat suitability for spawning, and are evaluated directly with numerical models [12, 13, 32].

This study aimed to assess the effect of a hydropower plant basin and hydropeaking on those river habitat descriptors that depend on flow characteristics. Based on this, we evaluated sustainable habitat measures that are planned to reduce the impact of the hydropower plant basin. This paper aims to apply the CASiMiR approach, to investigate the impact of the hydropower plant basin on the habitat suitability of an endangered species spawning in Slovenia. The current situation in the tributary stretch will be compared with a simulation of the planned sustainable measures situation after the hydropower plant basin implementation. The investigation results will apply to other rivers with similar ecological problems.

2 MATERIALS AND METHODS

Slovenia produces approximately one third of its electric energy by hydropower on its main rivers: the Drava, Soča and Sava. HESS (Hidroelektrarne na Spodnji Savi) is a Slovenian hydroelectric power company, with its core mission of producing and promoting the construction of hydropower plants, and of engaging in electricity generation that is sustainable, reliable, competitive, and environmentally friendly [14] on the lower Sava River, and of improving protection from the flooding that occurs in the area annually. The construction of a series of five HPPs on the lower Sava started in 1999. The penultimate HHP, Brežice, entered service in 2018, and the final HHP, Mokrice, should be active by 2026. Their total output shall account for 21% of the Slovenian hydropower production, and it is anticipated that they will meet 6% of the Slovenian energy needs. They are all designed and provided with bays, fish paths, channels and spawning grounds, additional animal habitats, birds nesting grounds, and maintained or improved farming conditions. The last planned HPP is positioned near the Croatian border, where the Sava River is enriched by the Krka River; it will have a smoothing reservoir role in the scheduled streaming and storage regime on the Sava River. In the area is the Krško Nuclear Power Plant, which uses the Sava water to dissipate excess heat. The plant began operating in January 1983. This study focuses on the lower part of the Sava, and particularly on its tributary the Krka, presented in Figure 1.

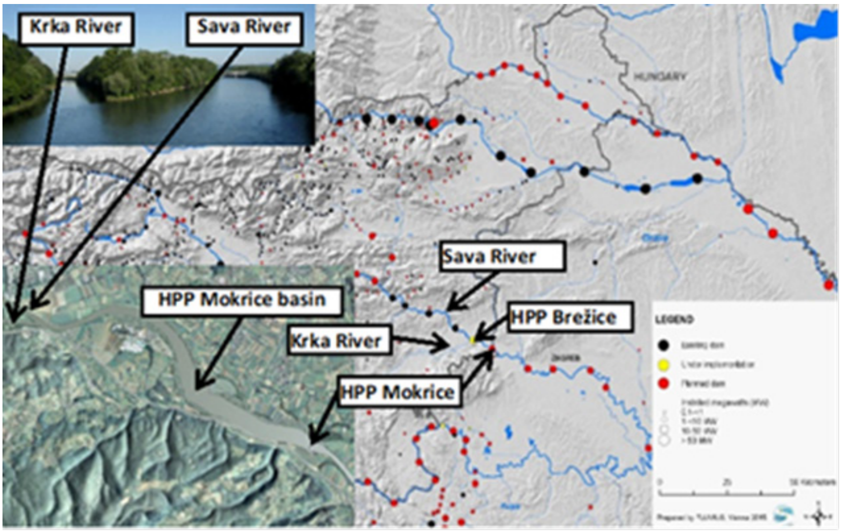


Figure 1: *Location of the study site. In the map of Slovenia are shown the existing and planned hydropower plants [15]. With arrows are marked HPP Brežice, that was put into service in 2018; the Sava River and tributary Krka River; their confluence and planned HPP Mokrice and its basin*

The region of the lower Sava is surrounded by hills. It is riddled with numerous permanent streams, as well as intermittent springs and streams. The two major rivers that cross the valley are the Sava and the Krka. The Sava is the longest river in Slovenia, and the Krka is its largest tributary. The area has experienced many flood events throughout its history, the biggest in 1990, and the last in 2010 [16]. The Sava River is sensitive to precipitation due to human impacts, such as urban development, and stream channel straightening. Intensive peak flows are observed several times a year, sometimes resulting in flooding of inhabited areas. It has to be pointed out that the ratio between the flow rates of the Sava and the Krka, especially when they exceed the average rate, is high. The power of the Sava's flow blocks (acting almost as a dam) the flow from the Krka and increases the floods upstream of the Krka drastically (Figure 1). Since 1999, the lower Sava has been the subject of human alterations, owing to the constructions of dams for hydropower production and embankments. The construction of a chain of hydroelectric power plants contributes to the reliable supply of electric power in Slovenia.

The functioning of the energy facilities and the related infrastructure also serve as flood preventers. However, the infrastructure impact on the environment causes the degradation of river ecosystems and biotic diversity, changing the hydro-morphological characteristics of the riverbeds [17] and their habitat suitability [18]. The infrastructure obstructs the connectivity of river habitats [19], and fish paths are implemented for the migration of fish; on high waters the fish swim down the river, and when the water level decreases the fish migrate upstream, which can be observed primarily in regulated rivers [20].

When the chain of HHPs are operating in peak time but in lower than the installed flow Qi=500m^3/s, the accumulation basins of the HPP Brežice and HPP Mokrice have the role of equalizing the daily Sava variability of water flow from the upstream HPPs. In the flow balancing, the fluctuation in the accumulation basin of HPP Mokrice is calculated to be up to 1.3 m, the normal water level at 141.7m above sea level, and minimum water level at 140.4m above sea level.

By fluctuating the level of the last two basins, the upstream HPPs will work with the full installed flow at peak time. Outside the peak time the upstream HPPs will operate at a lower flow, filling the basins, while the HPPs Brežice and Mokrice will have the opposite rhythm of operating conditions. The effect of the Sava River with the HPP Mokrice basin on the Krka River with the daily fluctuation of water level is hydrologically and morphologically tremendous: changing the drainage regime from the river to the regime of slowly running water in the river mouth, changing the natural dynamics of the river, changing the physical conditions of the aquatic habitat, and the river mouth is the spawning grounds of many species.

The hydrological data for all the Slovenian rivers and lakes are available on the web page of the Slovenian Environment Agency (ARSO) [21]. ARSO performs expert, analytical, regulatory, and administrative tasks related to the environment at the national level. The riverbed’s form and elevation were obtained from the project of the HPP basin provided by INFRA [22], which was established as a public company for the implementation and maintenance of the water infrastructure facilities in the lower Sava.

The hydraulic structures, such as hydropower plants, dams and wires, affect the water environment for plants and aquatic lives in and around rivers. Therefore, before the construction of such hydraulic structures, it is necessary to conduct environmental assessments [23]. The abiotic parameters, with the morphological characteristic of the river, determine the physical habitat for living organisms. Consequently, the availability and suitability of this habitat are altered by the modification of the abiotic parameters. Fish are very valuable aquatic organisms, and as good indicators of the environmental state of the ecosystem, they are often chosen as the target species to study the impact of HPPs on the environment [24]. The studies demonstrated that the fish populations are less abundant and have reduced population sizes in hydro-peaking rivers in the River Cabriel, Spain [25]. The results from [26] show how the overall habitat quality fluctuates daily due to the dam operation in a big river.

Table 1: *Fish spawning conditions*

fish	depth [cm]	substrate size [cm]	flow velocity [m/s]
Alburnoides bipunctatus	*14–20*	*2.0–10.0*	*0.2–0.5*
Squalius cephalus	*15–30*	*>0.5*	*0.2–0.5*
Barbus barbus	*15–50*	*2.0–5.0*	*0.3–0.5*
Vimba vimba	*<50*	*0.2–6.0*	*>0.2*
Rutilus rutilus	*15–45*	*5.0–15.0*	*>0.2*
Chondrostoma nasus	*15–30*	*2.0–6.3*	*0.9–1.1*
Romanogobio uranoscopus	*15–20*	*5.0–20.0*	*1.0–1.3*

The physical habitat conditions were assessed from the Fisheries Research Institute of Slovenia, that is a central, expert institution in the field of Fisheries in Slovenia. The institute is engaged in activities that contribute to the sustainable management of fish populations and the preservation of their diversity; it is very active in order to preserve or substitute fish area habitats. They prepared Table 1 on the spawning conditions for some fish species spawning in the Krka River. Most fish species in the Krka are spawning in the springtime, from March to May. The mean discharge for the previous ten years was calculated for both rivers. The spawning time often coincides with a low discharge of the Krka, so we also take into consideration the minimal mean discharge for the same period. The Fisheries Research Institute of Slovenia confirmed the selected discharges used in the simulations: mean discharge $Qs=54.5m^3/s$ and minimal mean discharge $nQs=10.9m^3/s$.

We obtained spawning data for seven fish species (Table 1). Considering the spawning conditions, we classified the seven species into two categories with similar requirements. Two reference species (marked in Table 1) could represent the hydrological spawning conditions for all the species.

2.1 Planned sustainable measures

It was expected that the HPP basin would have an impact on the Krka ecosystem (confirmed with the simulations in Figure 5). Without measures to prevent the damaging of the drainage section of the Krka, there would be negative impacts that would cause degradation of the river ecosystem and the destruction of existing fish habitats in the affected area.

Several main measures are planned to preserve a sustainable regime in the Krka River [27]:

- The Sava riverbed will be deepened, to lower the water surface of the river and to prevent floods in the confluence.
- The bottom of the Krka's riverbed will be widened and raised, to maintain the hydro and morphological river characteristics of the Krka: depth and water velocity.
- A Cascade passage will be constructed at the Krka mouth with a length of 150m, to prevent the spread of fluctuations of the HPP basin into the Krka.

- Four approximately 150m-long pebbled shallows will be implemented in the riverbed of the Krka, arranged as spawning grounds for fish species. The locations of shallows are presented in Figure 2.

The status of the aquatic system and suitability for fish spawning was simulated, considering no sustainable measures applied, implementation of sustainable measures (change of the riverbed geometry), with the hydrological parameters for fish spawning.

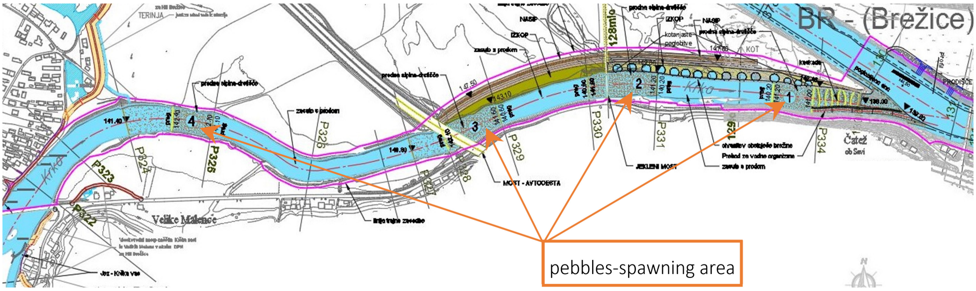


Figure 2 *The part of the Krka River with marked shallows as spawn areas [27]*

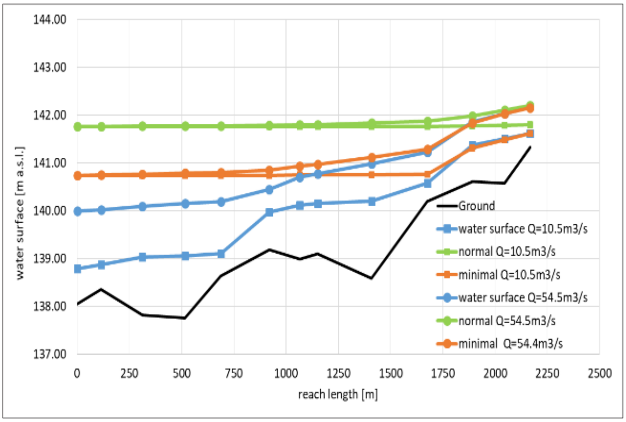
3 RESULTS

The hydraulic component of this study was performed using the HEC-RAS model [19] to construct a one-dimensional hydraulic model simulating water surface levels for the studied stretch, based on the prismatic riverbed elevation values [28, 32]. Since changing flow rates influence the flow velocity and consequently the fish habitat significantly, water depths and velocities were simulated for two different flow values: mean and minimal mean discharge. The HEC-RAS model uses geometric and flow data to calculate steady, gradually varied flow water surface profiles (steady-flow module) from the energy loss computations. A quasi 2D approximation [28] was obtained, by dividing each transect into subsections and distributing the flow along the subsections using simple linear interpolation techniques, and respecting the conservation of energy. The modeling capabilities of HEC-RAS for the water flow rate and calculated velocity values were found to be adequate with the measured values in many publications [e.g., 10, 20, 29].

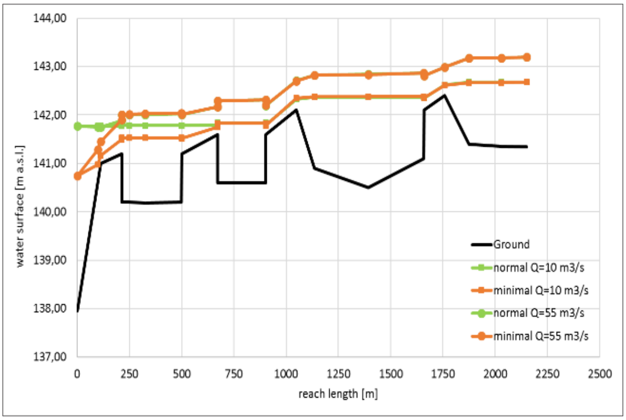
The hydraulic model was calibrated and validated (Manning's values) using the values of the velocity and depth measurements taken during ongoing field investigations by INFRA.

Each cross-section was divided into several longitudinal subsections, defining a grid for every study reach. The water surface levels and flow velocities were simulated for two scenarios: the current situation without an HPP basin, and the new situation after the HPP basin implementation. The results of these simulations could only be calibrated for the first scenario, since the implementation of the HPP basin has not yet been conducted. The study reach was analyzed hydraulically, with hydraulic controls at the downstream end.

In the second scenario, the bed elevation in the Krka River was changed according to sustainable measures. The bed of the Sava River was deepened, and the bed of the Krka River was raised, with spawn areas and deepened buffer intermediate spaces. The change of the Krka riverbed is seen in Figure 3 (Ground), and the results of a water surface analysis in the Krka River are presented for the current situation and planned change of the riverbed for normal and minimal basin levels.



a) Current situation



b) Planned situation

Figure 3: *Results of the water surface level from HEC-RAS for a normal basin level (141.7m a.s.l.) and minimal basin level (140.4m a.s.l.) a) currently, and b) Status after the planned measures*

The results in Figure 4 present the Krka reach. CASiMiR linked the water surface level simulations from HEC-RAS with morphological data, to calculate and interpolate the flow velocity in the river stretch. The depth, flow velocity and dominant substrate values were assigned to each cell of the grid, based on linear interpolation. The simulations were performed for two flows of the Krka River (mean and minimal mean discharge) with the current form of the Krka riverbed. We performed the analysis to simulate the HPP basin impact at normal and minimal basin elevation as hydropeaking disturbances [30,31].

The results presenting water depth and flow velocity showing significant ecological impact of the HPP basin are shown in Figure 4. Even at minimal basin water level, the changes in water depth and velocities are large. The water depth increases severely, and, consequently, the water velocity declines severely, especially in the confluence where the elevation of the basin is higher than the water surface of the Krka River.

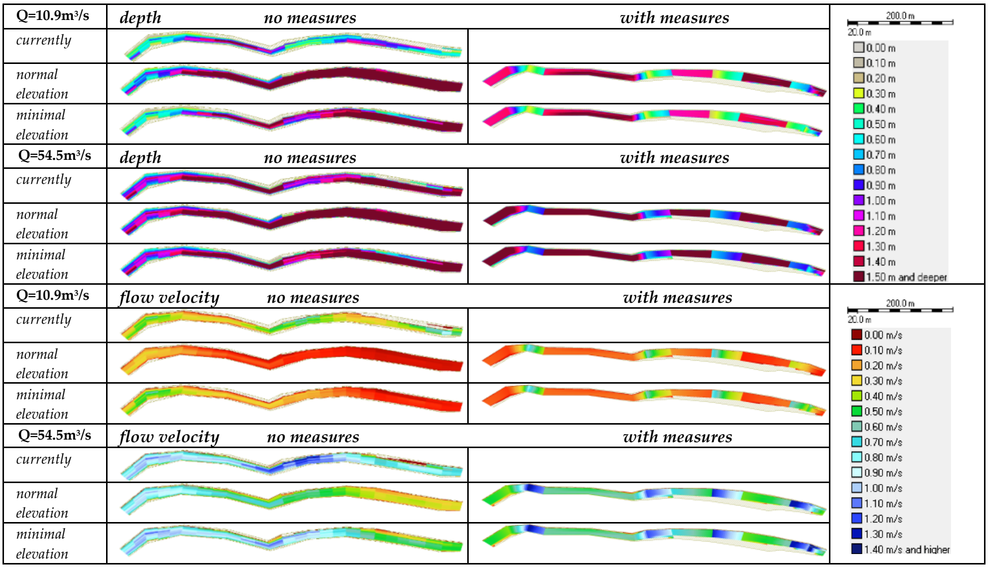


Figure 4: *Results of water depth and flow velocity with CASiMiR for minimal mean discharge nQs=10.9m³/s and mean discharge Qs=54.5m³/s with the current riverbed for HPP Mokrice normal basin level (141.7m a.s.l.) and minimal basin level (140.4m a.s.l.), with and without sustainable measures implemented in the simulation*

The planned sustainable measures were simulated for the same water regime: two flows of Krka minimal mean discharge and mean discharge at normal and minimal basin elevation. The new riverbed geometry was updated with widened banks and elevated bottom of the Krka River; four pebbled shallows were added (spawning area). The results reveal a much more varied picture (Figure 5).

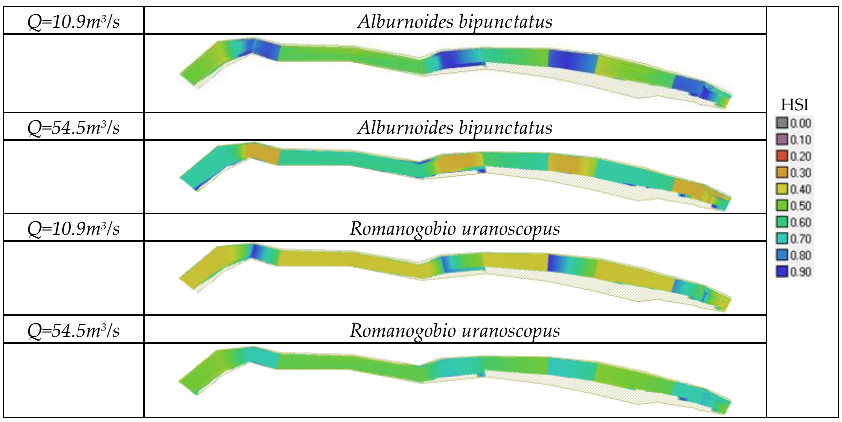


Figure 5: *HSI results from CASiMiR for two fish species for minimal mean discharge nQs=10.9m³/s and mean discharge Qs=54.5m³/s with sustainable measures implemented in the simulation for the minimal basin level (140.4m a.s.l.)*

The depth and water velocities at the shallows are much more suitable for fish spawning. We simulated spawning conditions for two reference fish species with the data from the Fisheries Research Institute of Slovenia presented in Table 1. The results are presented in Figure 5, with the HSI index calculated for two fish species for the mean and minimal mean discharge for normal and minimal basin levels. The results indicate that the hydropeaking (different basin level) has less influence on the HSI index in comparison with the river discharge, which is the primary influence parameter. As can be seen from the results of the simulation, the basin level has less influence on the spawning parameters than expected, much less than the river discharge.

4 CONCLUSIONS

Artificial hydraulic river structures, such as HPPs, introduce discontinuity and disturbances to river natural flows and ecosystems. This paper examines finding a balance between flood management, river regulation, and energy production on the one hand, and the preservation of river ecosystems on the other. The implementation of the chain of HPPs in recent years on the Sava River has consequences. Many modifications of the flow channel due to HHPs and flood control weirs have led to higher depths than under natural conditions and a reduction of the flow rate. The last HPP in the chain on the lower Sava River and its basin influence its upstream Krka tributary significantly.

Non-government organizations and local initiatives in Slovenia [33] argue that the approved project of HPPs leads to the destruction of the flora and fauna of the Sava River, especially because the mouth of the Krka into the Sava River is one of the most important spawning grounds of this species in Slovenia. Eleven fish species (*Barbus balcanicus, Zingel streber, Romanogobio uranoscopus, Romanogobio kesslerii, Cobitis elongatoides, Cobitis elongata, Alburnoides bipunctatus, Rutilus virgo, Hondrostoma nasus, Barbus barbus and Vimba vimba*), protected under the EU Habitats Directive (Directive 92/43 of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora), are endangered by the project. The proposed measures for these species, according to [33], are not conducive, since the basin level intervenes the tributary. According to the study of Schwarz [15] commissioned by Riverwatch and EuroNatur, the dispute about HHP Mokrice is, thus, crucial for the future of the Sava River and for the ecosystem of the Krka River. In contrast to the Sava, the Krka is not a regulated river and is one of few in Slovenia with rich fish habitats, particularly with indigenous fish species.

Within the framework of the projects of HPPs, the level of floods at the Sava and Krka are reduced significantly, with deepening of the three kilometers of the Sava River downstream from the HPP Brežice. The sublimation of the Sava goes a further two kilometers downstream of the Krka outbreak. With additional regulatory measures in the Sava and Krka, the flooding level is reduced by 1.3 m. These measures are strong: they reduce the required range of flood protection of sites that are flooded regularly. In the investigation, the sustainable measures were simulated for two flow rates of the Krka and two basin levels. In the simulations, emphasis was placed on the planned areas for fish spawning for two representative fish species. The results show that the HPP basin has an enormous impact on the hydrological and ecological parameters of the tributary (Figure 5). The depth of the Krka River increases, and the flow velocity decreases; without sustainable measures, the nature of the Krka is different. The changes in the Krka River caused by the basin could be prevented by lifting the bottom of the Krka River in the outflow section, and four pebbled shallows in the riverbed will be created to preserve the hydro morphological river characteristics of the Krka. Taking the planned sustainable measures into account, the hydrological characteristics and HIS (Figures 5 and 6) of the river are more suitable for fish spawning. As can be seen from results, there is no point in presenting weighted usable areas (WUA) or hydraulic habitat suitability (HHS), as only pebbled shallows areas are suitable for spawning. Without measures to prevent the damaging of the drainage section of the Krka, there would be negative impacts that would cause degradation of the river ecosystem and the destruction of existing fish habitats in the affected area. The planned measures need to be renamed from sustainable measures to mitigation measures. More thorough investigations should be carried out for endangered species for spawning, juvenile, and adult fish. The currently planned measures are focused only on spawning and river hydraulics. The uneven bottom along the cross-section of the riverbed could distribute the flow velocity, and an additional winding channel in the riverbed could increase the habitat quality for various fish species at lower flow rates.

The study showed the potential of the modeling approach, and more parameters have been planned to understand the quality and distribution of suitable habitats better very soon.

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A REVIEW OF ARTIFICIAL INTELLIGENCE IN NUCLEAR POWER PLANTS

PREGLED UPORABE UMETNE INTELIGENCE V JEDRSKIH ELEKTRARNAH

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Keywords: Artificial Intelligence, Machine Learning, Supervised Learning, Unsupervised Learning, nuclear power plant, maintenance

Abstract

Nuclear power plants are recognised as complex systems, where maintenance is critical for ensuring safety and operational stability. Time-based preventive maintenance programmes are employed in most nuclear power plants, relying on periodic inspections to prevent equipment failures. However, this method is considered resource-intensive and not always efficient. An alternative is offered by Artificial Intelligence and condition-based maintenance, which allow early fault detection, reduce unnecessary maintenance tasks, and lower operational costs. The potential of Artificial Intelligence in nuclear power plants is vast, ranging from operational improvements to predictive maintenance. Techniques such as Supervised and Unsupervised Learning are highlighted as essential tools for fault detection, pattern recognition, and predictive modelling. In Supervised Learning, known input-output pairs are used to train models, while Unsupervised Learning is employed to identify hidden patterns in unlabelled data, which is particularly useful in the large, unstructured datasets found commonly in nuclear power plants. The challenges in integrating Artificial Intelligence into nuclear power plant operations shall be noted, including the lack of standardised procedures for selecting and applying algorithms. Despite these challenges, AI-driven tools, including Deep Learning and hybrid models, have shown promising results in fault detection and prediction in nuclear power plants. These advancements support the broader goal of improving safety and operational efficiency. In conclusion, although Artificial Intelligence has not yet been adopted fully across all nuclear power plants, it is seen as a promising advancement for the future of nuclear energy operations. Its implementation enhances fault detection, reduces operational risks, and ensures more reliable energy production.

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Povzetek

Jedrske elektrarne so poznane kot kompleksni sistemi, njihovo vzdrževanje pa je ključno za zagotavljanje varnosti in zanesljivega obratovanja. Trenutno se v jedrskih elektrarnah uporablja princip časovno zasnovanega vzdrževanja, ki temelji na periodičnih pregledih za preprečevanje okvar. Pomembno je poudariti, da takšen pristop zahteva veliko porabo sredstev in ni vedno učinkovit. Alternativno lahko uvedemo vzdrževanje na podlagi stanja opreme z uporabo umetne inteligence ob predčasnem zaznavanju okvar, s čimer zmanjšamo stroške vzdrževanja in obratovanja. Potencial umetne inteligence v jedrski industriji je velik, od zagotavljanja zanesljive proizvodnje do vzdrževanja. Tehniki, kot sta nadzorovano in nenadzorovano učenje, sta izpostavljeni v članku, saj sta ključno orodje za zaznavanje napak, vzorcev in razvoja preventivnih modelov. Pri nadzorovanem učenju algoritem učimo z znanimi podatki, ki so klasificirani. Pri nenadzorovanem učenju algoritem učimo z veliko količino neklasificiranih podatkov, iz katerih model izlušči vzorce in zaznava odstopanje. Za integracijo umetne inteligence v jedrske elektrarne pa ostaja še veliko izzivov, med drugim tudi pomanjkanje standardnih pristopov. Ne glede na ponujene izzive pa orodja z uporabo umetne inteligence, globokega učenja in hibridnimi modeli obetajo pozitivne rezultate na področju zaznavanja napak in napovedovanja v jedrskih elektrarnah. Takšni napredki izboljšujejo varnost in omogočajo zanesljivo obratovanje. Čeprav umetna inteligenca še ni bila temeljno vpeljana v jedrsko industrijo, prikazuje pozitivne napredke za njeno prihodnost. Njena implementacija povečuje zaznavanje napak, zmanjšuje obratovalna tveganja ter zagotavlja stabilno in zanesljivo proizvodnjo električne energije.

1 INTRODUCTION

The use of Artificial Intelligence (AI) is on the rise in both the public and private sectors. As interest in this technology grows, the U.S. Nuclear Regulatory Commission has recognised this trend and published several documents addressing these topics. These publications serve as guidelines for the application of AI in nuclear power plants (NPP), and evaluate the current utilisation of these technologies within the industry [1]. Through AI adoption, some licensees aim to meet the requirements set forth in the Code of Federal Regulations. This shift allows for a transition from traditional time-based preventive maintenance (PM) methods to more advanced approaches facilitated by AI and condition-based maintenance (CBM) [2]. The use of AI is also recognised by the International Atomic Energy Agency, which established a working group in mid-2022 to research and implement AI in nuclear power.

It is essential to recognise that NPPs are complex systems composed of various interrelated systems and equipment, including electrical, mechanical, instrumentation and control systems. These components must operate reliably within specified parameters and require some type of maintenance. In most NPPs, PM programmes are implemented, consisting of scheduled activities aimed at ensuring the equipment's proper functioning. These PM programmes involve periodic inspections, and a systematic approach to record-keeping and scheduling maintenance activities. This structured framework helps to maintain equipment integrity and enhance overall operational safety [3].

Time-based preventive maintenance activities could, potentially, be replaced by CBM if faults are detected in advance. However, fault detection presents a complex challenge, particularly in large systems like NPPs. A significant issue arises when the volume of data collected is as extensive as that found in these facilities, making it difficult for manual systems to process and analyse all the available information effectively [2].

It is important to note that the data collected in NPPs are categorised into two main types: process instrumentation and control data, and, periodically, measured maintenance data. The first type, often called online monitoring (OLM), encompasses the plant's critical and non-critical parameters. These data are displayed in the control room, enabling the operators to monitor plant performance and health while being accessible to other personnel. The second type of data consist of measurements taken during outages and periodic equipment check-ups. These periodically gathered data play a vital role in maintaining the reliability and safety of the plant's operations. These data types form the foundation for effective PM strategies and operational decision-making in NPPs [4].

This paper outlines the data-gathering process in NPPs and elaborates on its significance. Chapter 3 discusses the most used advanced computational tools for AI. It is important to note that advancements in this field could potentially lead to significant improvements in the safety and operational reliability of NPPs. These technologies have the potential to decrease the number of faults and reduce operational costs greatly.

Chapter 4 focuses on the application of AI and Machine Learning (ML) in NPPs. The use of these technologies is increasing in various areas, including plant safety and security assessments, degradation modelling, fault diagnosis, prognosis, and overall plant operation and maintenance. By integrating AI and ML, NPPs can enhance their operational efficiency and safety measures, paving the way for a more reliable energy future.

2 DATA GATHERED IN NUCLEAR POWER PLANTS

The data collected in commercially operated NPPs are divided into two categories: process instruments and control data, and periodically measured data from maintenance activities. The OLM data include plant parameters for individual systems and their components, which are crucial for ensuring the plant’s safe and reliable operation [4]. These data are displayed in the control room on various screens and alarm panels, while some can be retrieved by the operating crew from the local panel. Given the enormous volume of data collected, processing them can become challenging, especially during accidents or abnormal operations. In such situations, the operators in the main control room follow established procedures designed to guide the crew through these critical and stressful steps. Their priority is to secure the safety of the reactor core and ensure a safe shutdown, all while minimising the risk of human error [5].

The OLM data are, typically, stored in large databases with limited sampling intervals, often set to one minute, allowing for efficient monitoring of the system`s performance history. These data can then be extracted from the database for further analysis and simulations, enabling the engineers to gain insights into the plant's operational status. In short, the OLM data are used to evaluate the health and reliability of the NPP processes, systems, and equipment [6].

In contrast, the second type of data rely on periodically gathered information from specific PM programmes, which include measurements of component parameters that may indicate the overall health of the components. These measurements can be taken through electrical or mechanical assessments, varying from once per cycle, to more or less frequently, thus providing critical insights into the condition of the components. Such evaluations are essential, as they can reflect the operational integrity of the components directly, potentially signalling a failure, or a state nearing failure [7].

Both types of data are instrumental in detecting deviations from stable and reliable operation within specific components and systems. However, with process instruments and control data, challenges arise from the sheer volume and complexity of the information collected, making manual analysis often inadequate for identifying significant deviations. To address this, alarm and trip values are established for specific measurements, offering a simplified approach to monitoring component states. While effective in alerting operators to faults, this method tends to react only after issues have manifested, necessitating timely intervention. In nuclear power plants, alarm thresholds are set conservatively at lower levels, to ensure that operators are notified promptly, enabling them to take the necessary precautions before situations escalate. On the other hand, periodically gathered data are typically evaluated by field professionals, who conduct thorough assessments of the components based on this information, allowing for informed maintenance decisions, and enhancing the overall safety and reliability of the plant.

A simple dataset collected from a motor-gearbox-pump skid will be examined for easier understanding. Typically, when a medium-voltage motor is involved with a larger pump, a comprehensive set of data is collected to indicate the skid's running parameters. For the electric motor, the temperature of the stator is monitored, often utilising six PT100 sensors or similar devices, with two sensors embedded in each phase at the hottest points. During the 1970s, the standard insulation system used for motors was Class B, which allows for a temperature rise of up to 80°C, as defined by the NEMA MG1 Standards.

In such horizontal machines, sleeve bearings made from Babbitt material with temperature monitoring are employed commonly, permitting operating temperatures to reach 130°C. Vibration monitoring is also implemented frequently, to track the vibrations of the bearings or housing, ensuring they remain within the maximum accepted values. Additionally, the temperatures and vibrations of the gearbox and pump are monitored, with operational values defined clearly. The system operates by transporting fluid at a specific temperature, so the temperatures and pressures at both the discharge and suction sides of the pump are measured typically.

With known operating parameters provided by the original equipment manufacturer and insights gained from operational experience, the limits of the system are established and adhered to throughout its operation. In cases of parameter deviations, or when alarm or trip values are reached, the skid is required to shut down, prompting the initiation of corrective maintenance. Such events can lead to economic consequences and impact the reliability of the plant and its systems. In NPPs each critical system is equipped with backup trains, to ensure that nuclear safety and plant reliability are not compromised by minor defects. However, even simple defects can diminish plant reliability, and introduce transients into the continuous operational cycle. Each transient can have specific effects on the plant, including necessitating shutdowns.

3 ADVANCED COMPUTATIONAL TOOLS

Advanced computational tools such as Artificial Intelligence, Machine Learning, Deep Learning (DL), and others in NPPs are on the rise, especially in health and reliability assessment. This chapter focuses on the advanced computational tools that form the backbone of AI applications in nuclear power plants. These tools, ranging from ML algorithms and neural networks to advanced simulations and probabilistic risk assessment models, offer robust platforms for addressing the unique challenges faced by nuclear energy systems. By leveraging cutting edge computational techniques, nuclear power plants can enhance their operational resilience, reduce human error, and anticipate failures before they occur. while maintaining strict regulatory compliance and safety standards. The chapter will delve into the specific categories of AI driven tools, their architectures, and their implementation strategies in the Nuclear domain.

3.1 Statistics and Computational Tools

Before going further into computational tools, it is essential to understand the core difference between statistics and computational tools. Statistics is a branch of mathematics, whereas computational tools such as AI, ML, and DL are subfields of advanced computing. Statistics focuses primarily on data collection, analysis, interpretation, presentation, and organisation. Its purpose is to uncover patterns, relationships, and trends within the given data, and draw conclusions based on a representative sample. Typically, statistics are applied to smaller datasets, and rely on mathematical methods to interpret and understand the data. By contrast, computational tools like AI and ML often handle vast amounts of data, leveraging algorithms to automate decision-making, predictions and other tasks, without requiring explicit human programming for every scenario. [8].

3.2 Artificial Intelligence and Machine Learning

AI is a field of Computer Science focused on developing advanced software systems designed to perceive their environment and learn to perform actions autonomously. ML, as a subfield of AI, allows machines to be trained using historical data. In ML systems, patterns, rules, or insights are identified from the collected data, which are then applied to make predictions or decisions [9].

A variety of approaches and techniques are encompassed within AI, including rule-based systems, search algorithms, and more advanced methods like Natural Language Processing, Robotics, and Computer Vision. In contrast, as previously mentioned, ML relies on algorithms trained to make predictions

- Supervised Learning,
- Unsupervised Learning,
- Reinforcement Learning,
- Recommender systems.

Deep Learning, a specialised subfield of ML, utilises multiple layers of neural networks to address complex problems. The primary distinction between AI and ML lies in the fact that, while ML focuses specifically on learning from data, AI encompasses a broader range of techniques, including those that do not necessarily involve data-driven learning.

In this context, AI and ML are often used together, but it is important to note their differences and specific areas of application.

3.2.1 Supervised Learning

Supervised Learning is a type of AI learning that involves using training data with known input and output values. The observed data are input into the model along with the expected output values, allowing the model to be trained accurately. Once the training process is completed, the model is expected to predict outputs based on the new inputs with a certain degree of uncertainty. Various algorithms are used widely in Supervised Learning, including [11]:

Artificial Neural Networks (ANNs): These networks are composed of three types of layers, with each layer consisting of nodes, also known as neurons, as illustrated in Figure 1. Typically, a neural network includes an input, output, and multiple hidden layers. The layers are interconnected, and the nodes are associated with weights, representing each connection's significance. These weights are adjusted throughout the learning process. The number of inputs is determined by the dimensions of the input data, while the number of hidden layers and nodes defines the complexity of the model. The more complex the model, the greater its ability to capture intricate patterns in the data [12].

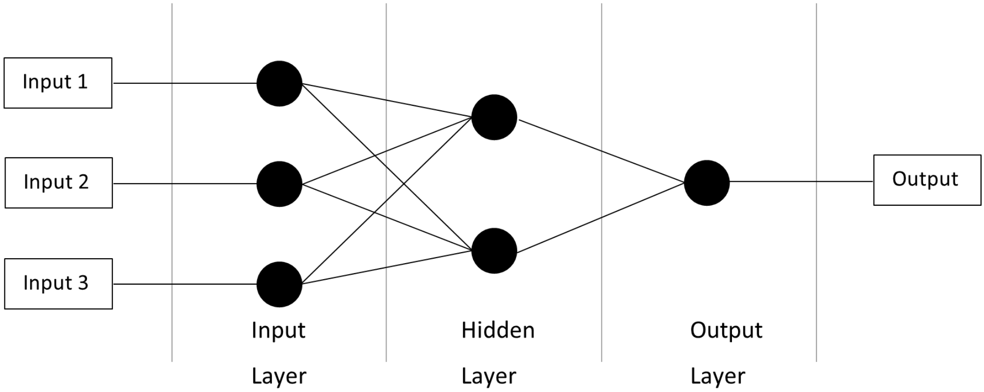

Figure 1: *Simple Artificial Neural Network*

Feedforward Neural Networks (FFNs): FFNs are the simplest type of Artificial Neural Networks. They consist of layers of nodes (neurons) that are connected through weights. In an FFN, the information travels in a single direction, from the input layer to the output layer, without looping back. These networks are used commonly in both regression and classification tasks [13].

Convolutional Neural Networks (CNNs): CNNs are designed specifically for processing grid-like data, such as images. They learn the spatial hierarchies of features automatically by using convolutional layers. These layers apply filters to the input data to capture important features like edges, textures and shapes, making CNNs highly effective for image classification, object detection and similar tasks [14]. CNNs were used in data diagnostics through images created from the data generated from large amounts of data gathered in NPPs [15].

Recurrent Neural Networks (RNNs): RNNs are distinguished by their ability to handle sequential data, as they have connections that form directed cycles. This allows them to retain information from previous inputs, making them suitable for time series analysis, and tasks involving sequential data like Natural Language Processing. RNNs use backpropagation through time, an optimisation algorithm that enables faster learning by adjusting weights efficiently based on errors from previous steps [16].

In addition to the algorithms mentioned, other methods are also used commonly, such as Decision Trees (DTs). These aim to create a tree-like model that predicts the output values based on a series of simple, predefined rules extracted from the features of the data. Random forests were developed to address the limitations of DTs, particularly the issue of overfitting. Overfitting occurs when a model performs exceptionally well on the training data, but fails to generalise

to new, unseen data [17]. Another important algorithm is the Support Vector Machine (SVM), used for classification and regression tasks. SVMs work by constructing a set of hyperplanes that separate different classes of data samples optimally. The goal is to maximise the margin between the classes, to improve the model's prediction accuracy and robustness.3.2.2
Unsupervised Learning

Unlike Supervised Learning, Unsupervised Learning is used to train models on large amounts of data where the label of the data is unknown. Unsupervised Learning is considered a highly promising method in AI, as labelling vast amounts of training data is often difficult. This allows models to be trained without human involvement or supervision. Additionally, one key advantage of these models is that, even in the early stages of their development, insight into the structure of the model can be gained. Similar to Supervised Learning, there are also various algorithms used in Unsupervised Learning:

Clustering analysis: This method enables data to be classified into branches and clusters, ensuring that the data within each cluster are more closely related than data from different clusters. This definition is based on the understanding that some data points exhibit greater similarity than others. Most clustering algorithms operate using numerical attributes, allowing similarity to be described through geometric analogies. There are numerous algorithms available for clustering data, including K-means, Spectral Clustering, Hierarchical Clustering, and more. Each of these algorithms employs distinct methodologies, such as partitional, hierarchical, density-based, grid-based, or model-based. By utilising these various approaches, clustering techniques can organise and analyse data effectively, revealing patterns and relationships that might otherwise go unnoticed [18].

Dimensionality Reduction: These algorithms are used to transform high-dimensional data into low-dimensional data when dealing with big data. It is important to note that this reduction process should not result in the loss of meaningful properties of the original data. In terms of data classification, these methods can be applied in various ways, such as creating superlinear traceable classification schemes, reducing the variance of classifiers, and removing noise. Traditionally, one of the most commonly used linear techniques is Principal Component Analysis (PCA). This method constructs a low-dimensional dataset, that retains as much of the original data's variability as possible by identifying a linear basis for reduced dimensionality. In recent years, more nonlinear techniques have been introduced, including global methods, multidimensional scaling, autoencoders, and Isomap, among others [19].

3.2.3 Reinforcement Learning

Reinforcement Learning is a learning approach involving the interaction of Artificial Intelligence with a dynamic environment. This technique focuses on learning sequential decision-making in complex problems and is inspired by the trial-and-error learning process observed in humans. Unlike Supervised Learning, where models learn from labelled data, Reinforcement Learning operates through feedback in the form of rewards or penalties, which are given based on the actions taken by the agent. This feedback mechanism allows the agent to learn and adapt over time, ultimately improving its performance in decision-making tasks [20].].

4 AN OVERVIEW OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN NUCLEAR POWER PLANTS

The fault detection methods are classified as model-based, signal-based and data-driven-based, and are analysed from on-line data. The method used most commonly is signal-based, and it is used for fault detection based on alarm and trip values. The model-based analysis is also well established, and they use output values from models and compare them with real-time on-line data. The data-based method is the most complex one, as it uses the historical data to learn. Through AI, the models are trained, and are capable of making predictions [21].

Many different types of algorithms can be employed in nuclear power plants, depending on the specific purpose of the task. For instance, models based on classification algorithms should be implemented when AI is utilised to analyse surface images to detect cracks in steel or concrete structures. In cases where large amounts of unstructured data, such as logs from operational experiences and OLM are available, unsupervised learning algorithms could potentially be utilised, particularly those based on clustering techniques.

However, a notable downside of this approach is that there are currently no established procedures for determining and incorporating the most suitable algorithm for each specific task. This lack of systematic guidance may hinder the effectiveness of algorithm selection and application in various scenarios within the nuclear power sector. Further challenges include handling missing data in vast datasets, ensuring sufficient training data quality, and the high cost of implementing AI systems, particularly in a legacy nuclear power plant infrastructure. Additionally, integrating AI technologies into existing NPP systems can pose significant technical and financial hurdles that require careful planning and investment.

4.1 Artificial Intelligence in nuclear power plant operation

The use of AI in operational contexts is welcomed highly, as operators must handle large amounts of data during both normal and abnormal operations. Numerous studies have employed computational data to assist in training predictive models. Given that NPPs typically operate in a stable manner, training models for specific faults and testing their detection capabilities can be challenging. The generated data originate from models of NPPs that are known to have specific faults [22, 23].

Prediction models were utilised to analyse the operations of a small light water reactor facility at Oregon State University, where positive results were reported. Despite the model's complexity, it learned them effectively and applied the reactor's features to make predictions. However, some behaviours remained undetected by the network [24].

Naimi et al. applied Machine Learning techniques to identify faults in NPPs, focusing initially on the detection of various faulty scenarios using neural networks. Subsequently, they employed K-Nearest Neighbours (KNN), SVM, and ensemble-based fault diagnosis methods for comparison. Among all the models tested, the KNN algorithm was identified as the most accurate and cost-efficient, although all the models were able to detect the presented faults [25].

A fault diagnostics method based on a semi-supervised classification approach was described by Ma and Jiang, who utilised data from operational NPPs in conjunction with data from a training simulator [26]. Young-Kuo et al. proposed a hybrid model that integrates PCA, signed directed graphs, and Elman Neural Networks for fault detection, fault isolation and severity estimation. Each component of this hybrid model contributes unique advantages, providing a robust foundation for future research in this area [27].

In recent years, hybrid models have been proposed for the operational analysis of NPPs. This trend can be attributed to the fact that individual models often possess specific strengths, and their integration allows for a more comprehensive approach to fault diagnostics and operational efficiency.

4.2 Artificial Intelligence in nuclear power plant maintenance

As mentioned, three methods of fault detection are used, and data-based methods are the most promising ones for AI applications. Nuclear power plants are critical facilities that need to run safely and within their parameters. Every deviation from normal operation can have an impact on the facility, environment, and economy of the plant. For normal operation, the plant needs to be well maintained; typically, the most successful plant runs on PM with weekly or daily routine check-ups on the equipment, or with periodic works on the components. As PM programmes are well established in NPPs, the only downside of these is their economic impact. The upgrade to PM would be (CBM), which would be viable when a fault detection system would be in place with close to 100% certainty. With CBM in place, unnecessary maintenance operations would not take place, and the cost would be reduced [28].

Data gathered from temperature, vibration and other sensors could be used for Unsupervised Learning with SVM or other algorithms [29]. Seker et al. studied RNNs for analysing a 5HP motor through spectral analysis in a coherent manner and neural networks. It was studied that, through backpropagation of the Elman's RNN, this model brings advantages to the concepts [30]. Qian and Liu studied four deep learning models, Deep-FFN, CNN, GRNN, and CRNN, for fault diagnosis of rotating machines, specifically bearings. After their study, those simple models were not able to extract the fault features accurately [31]. In another study, Qian and Liu developed a deep reinforcement learning that converges more slowly than typical deep learning models that have better stability. They show that, no matter if the data samples are small or large, the model will react and learn better if we interact with the model [32].

5 CONCLUSION

As mentioned throughout the article, the most important property of nuclear power plants is their safe and reliable operation. This can be achieved by following industry regulations and recommendations. It is essential that operational, maintenance and other procedures are established and aligned with the latest Standards and regulations. These procedures should be adhered to by personnel, and human errors must be minimised.

Even when procedures are followed, faults may occur due to human errors or random machine failures. Some machine faults have the potential to be detected beforehand but are often ignored, misinterpreted, or overlooked because of the vast amount of data available. With the help of AI and well-trained models, these faults could be detected in advance and subsequently prevented.

In the nuclear industry, AI is beginning to gain recognition, and some regulations have been established by the U.S. Nuclear Regulatory Commission. However, the use of AI remains an unfamiliar approach for many traditional NPP operators and personnel, as there are significant safety and operational risks involved.

A thorough study of AI and Machine Learning is necessary to train these models to a level of certainty that can earn the trust of the nuclear industry. It is important to note that these methods would not automatically regulate the plant but would instead serve as an alarm system for operators and other personnel, prompting them to respond to various indications. This ensures that human oversight remains central, with AI acting as a decision-support tool to enhance safety and operational reliability. It is also important to note that the use of AI in NPPs requires an interdisciplinary cooperation of computer scientists, nuclear engineers, regulatory subjects, and management for its successful implementation.

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Nomenclature

(Symbols)	(Symbol meaning)
AI	Artificial Intelligence
CNN	Convolutional Neural Networks
DT	Decision Tree
FFN	Feedforward Neural Networks
KNN	K-Nearest Neighbor
ML	Machine Learning
NPP	Nuclear Power Plant
OLM	On-line monitoring
PCA	Principal Component Analysis
RNN	Recurrent Neural Networks
SVM	Support Vector Machines

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FFA FW FLOW INFLUENCE AT NPP KRŠKO

VPLIV FFA NA MERITEV FW PRETOKA V NEK

Robert Kelavić[1ℜ], Jurij Avsec[2]

Keywords: Krško Nuclear Power Plant, heat transfer, film forming amine, feedwater flow measurement, venturi flow element

Abstract

The Krško Nuclear Power Plant (NEK) operates based on a Pressurised Water Reactor (PWR), which utilises three loops for heat transfer: primary, secondary, and tertiary. Heat generation occurs in the primary loop; steam production takes place in the secondary loop; and waste heat is discharged in the tertiary loop. During outages, which occur every 18 months, the secondary systems are exposed to the atmosphere, increasing the risk of corrosion. To prevent this, in 2021, the plant used a chemical solution, Film Forming Amine (FFA), which formed a protective hydrophobic layer on the inner surfaces of the pipelines.

In March 2021, during the first use of FFA, deviations were observed in the main feedwater (FW) flow measurements. This affected the reactor power calculations, leading to a 0.4–0.5 % reduction in plant output (approximately 4 MWe). The main feedwater flow is a critical parameter for secondary calorimetric calculations, and has the largest impact on error in the event of deviations.

The power reduction was confirmed by comparing various process parameters, including changes in the primary loop temperature differences (ΔT), main steam flow (MS), and generator output vs. condenser vacuum. Since the measurement of the main feedwater flow contributes the most to the uncertainty of primary flow and reactor calorimetric calculations, NEK is focused on improving its accuracy.

Developing a numerical model in the computer-based programming environment is proposed

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as part of further research. This model would enable independent calculations of the main feedwater flow, to reduce the impact of the FFA chemicals on the measurement readout and its associated calculations. The model will be based on thermodynamic equations and algorithms for determining the flow with lower uncertainty than the current system. Using this model, correction factors should be obtained to adjust the current venturi meter readings. Ultimately, this approach will ensure better plant management, reduce energy losses, and increase revenues for NEK and its stakeholders.

Povzetek

Nuklearna elektrarna Krško (NEK) deluje na podlagi tlačnovodnega reaktorja (PWR), ki uporablja tri kroge za prenos toplote: primarni, sekundarni in terciarni. V primarnem krogu poteka proizvodnja toplote, v sekundarnem proizvodnja pare in odvajanje odpadne toplote v terciarnem. Med remonti, ki potekajo vsakih 18 mesecev, so sekundarni sistemi izpostavljeni atmosferi, kar povečuje tveganje za korozijo. Da bi to preprečili, je elektrarna leta 2021 uporabila kemično raztopino FFA (Film Forming Amine), ki je na notranjih površinah cevovodov tvorila zaščitni hidrofobni sloj.

Marca 2021, ob prvi uporabi FFA, so se pojavila odstopanja pri meritvah pretoka glavne napajalne vode FW (Feedwater). To je vplivalo na izračun moči reaktorja in povzročilo upad zmogljivosti elektrarne za 0,4–0,5 % (približno 4 MWe). Pretok glavne napajalne vode je ključni parameter za sekundarni kalorimetrični izračun in ima največji vpliv na pogrešek v primeru odstopanja.

Upad moči je bil potrjen s primerjavo različnih procesnih parametrov, kot so spremembe temperaturnih razlik v primarnem krogu (ΔT), s pretokom glavne pare (MS – Main Steam) in meritvijo električne moči na generatorju. Ker meritev pretoka glavne napajalne vode prispeva največ k negotovosti izračuna pretoka primarnega sistema in kalorimetričnega izračuna sredice, smo v NEK osredotočeni na izboljšanje natančnosti te meritve.

V sklopu nadaljnjega raziskovalnega dela se predlaga razvoj numeričnega modela v računalniško podprtem programskem okolju, ki bo omogočil neodvisen izračun pretoka glavne napajalne vode, z namenom zmanjšanja vpliva FFA kemikalije na meritev oziroma s tem povezane izračune moči reaktorja. Model bo temeljil na termodinamičnih enačbah in algoritmih za določanje pretoka z nižjo negotovostjo od sedanje. S pomočjo modela bi morali pridobiti korekcijske faktorje za prilagoditev trenutnih vrednosti venturijevih merilnikov. V končnici bo ta pristop zagotovil boljše upravljanje elektrarne, zmanjšal energetske izgube ter povečal prihodke za NEK in njene lastnike.

1 DESCRIPTION OF THE PROBLEM

Heat transfer in the Krško Nuclear Power Plant (NEK – Nuklearna Elektrarna Krško) occurs in a closed loop, with the primary heat source being a nuclear reactor. The plant features a pressurised water reactor (PWR), the most widely used reactor type worldwide. The facility operates through three largely independent loops [Figure 1].

The primary loop contains the reactor, two steam generators, two reactor pumps, a pressuriser, and primary piping alongside safety system connections. NEK uses two primary loops, circulating coolant water at 155 bar and 323°C. The reactor pumps (22,711 t/h each) circulate the coolant, which transfers the heat to the steam generator without a phase change.

The secondary loop includes steam generators, turbines, reheaters, condensers and a feedwater system. The heat from the primary coolant is transferred to the secondary coolant in the steam generator, where the water is converted to high-pressure steam. The steam drives the turbines, producing mechanical energy to drive the generator. The spent steam then condenses into water in the condenser before returning to the steam generator.

The tertiary loop removes waste heat via the condenser cooling system, which uses Sava River water. The heat is transferred to the river, as the cooling water absorbs energy from the condensing steam, completing the loop.

NEK operates on an 18-month cycle, with maintenance and refuelling occurring every 18 months. The plant runs at full power during operation, following technical specifications limits to ensure safety under normal and accident conditions. The reactor power is a critical parameter that's monitored throughout.

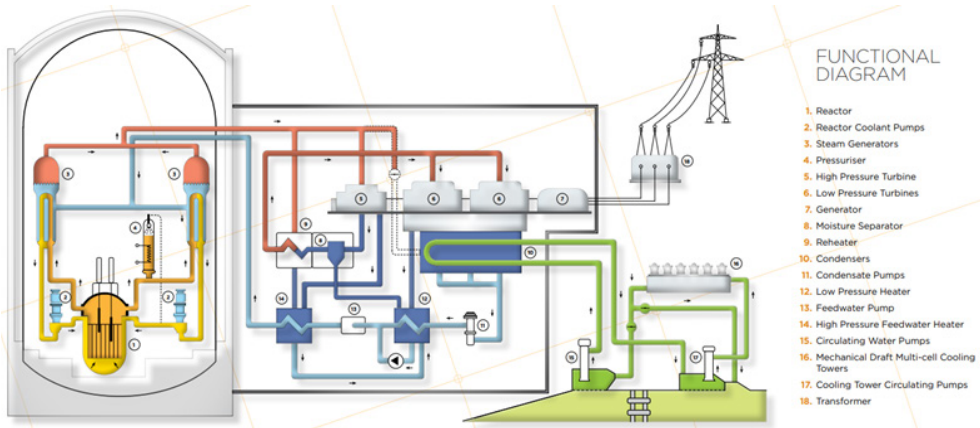

Figure 1: *Functional diagram of NPP Krško; source: www.nek.si*

2 PRIMARY AND SECONDARY SYSTEM INTERACTION

The thermal power of the core can be described by the following equation:

$$\dot{Q}_T = \dot{m}_{prim} \cdot c_p \cdot (T_H - T_C) = \dot{m}_{prim} \cdot c_p \cdot \Delta T \tag{2.1}$$

$\dot{Q}_T$ Reactor thermal power
$\dot{m}_{prim}$ Primary loop mass flow rate
c_p Specific heat capacity of water
T_H Primary loop hot leg temperature
T_C Primary loop cold leg temperature

The temperature difference (ΔT) is a direct indicator of power (assuming that the primary flow rate and specific heat capacity remain unchanged). The losses in the primary loop and additional heat power due to the operation of the primary pumps are not considered in the schematic calculation.

The power on the secondary side is determined through a calorimetric calculation, which is considered the most accurate power measurement, and serves as the basis for safety analyses, as well as monitoring requirements related to reactor power (Rated Thermal Power – RTP = 1994 MW_t).

$$\dot{Q}_{SG} = \dot{Q}_{STM} + \dot{Q}_{BD} \tag{2.2}$$

$\dot{Q}_{SG}$ Steam generator heat flux

$\dot{Q}_{STM}$ Steam heat flux

$\dot{Q}_{BD}$ Blowdown heat flux

According to the NEK procedures, the reactor power is determined based on measurements from ex-core instrumentation, which is calibrated through the determination of secondary calorimetry. The primary parameters used for secondary calorimetry calculations are:

- main feedwater temperature,
- main feedwater flow,
- steam generator pressure,
- blowdown system flow,
- TH average temperature,
- TC average temperature,

The main feedwater flow rate has the greatest impact on the secondary calorimetry measurements, making it a key focus for accuracy. This parameter is associated with the highest uncertainty in reactor power calculations within probabilistic analyses. It is estimated that the deviation of this measurement accounts for 0.66 percentage points of the total 0.81 % calculated uncertainty, within the 2 % limit assumed in the safety analyses.

2.1 Current Secondary Calorimetry Calculation

The calculation of the secondary calorimetry is based on the flow rates of the FW and blowdown (BD) from the steam generators, as well as the enthalpy of the MS at the steam generator outlet, FW and BD system. The thermal power of the steam generators is calculated by subtracting the gains of the reactor coolant pumps (RCP's) and adding the losses of the reactor coolant system (RCS).

The main parameters influencing the calorimetry results include:

- **FW** Flow Rate (Venturi): Measured as Δp and converted to t/h. A 1 % deviation in the Δp measurement (equivalent to 0.72 % in flow) affects power by 0.72 %.
- FW Temperature: A 1 °C deviation impacts the power by 0.249 %.
- MS Pressure: A deviation of 1 bar affects the power by 0.065 %.
- Steam **Moisture Content:** A deviation of 0.1 % impacts the power by 0.084 %.

All the other parameters, and their respective deviations, have a smaller influence on the final result. A complete sensitivity analysis is available in Reference 6.

Table 1: *Uncertainties in the Calorimetric Reactor Power Calculation Based on Secondary Instrumentation (Source: SSR-NEK-3.0 - REVISED THERMAL DESIGN PROCEDURE [ref. 6])*

COMPONENT	INSTRUMENT UNCERTAINTY		POWER UNCERTAINTY (%POWER)
FEEDWATER FLOW			
VENTURI	0.5 % K		0.500
THERMAL EXPANSION COEFFICIENT			
TEMPERATURE	3.5°F	1.96°C	0.007 *
MATERIAL	5.0%		0.060
DENSITY			
TEMPERATURE	3.5°F	1.96°C	0.148 *
PRESSURE	30.0 psi	2.11 kgf/cm²	0.010**
DELTA P	1.13 %Δp		0.81
FEEDWATER ENTHALPY			
TEMPERATURE	3.5°F	1.96°C	0.487 *
PRESSURE	30.0 psi	2.11 kgf/cm²	0.003 **
STEAM ENTHALPY			
PRESSURE	19.3 psi	1.36 kgf/cm²	0.088
MOISTURE	0.10 %moisture		0.084
NET RCS HEAT ADDITION	20.0 %		0.036

$$U_{RTP} = \sqrt{\frac{0.50^2+(0.148+0.487-0.007)^2+0.06^2+(0.010-0.003)^2+0.81^2+0.088^2+0.84^2+0.036^2}{2}} = 0.81\ \% \tag{2.3}$$

U_{RTP} Uncertainty in the RTP (Rated Thermal Power) calculation

3 REASONS FOR FFA INJECTION

The NEK shuts down every 18 months for routine maintenance and refuelling. During these outages the secondary systems are drained and exposed to the atmosphere, leading to corrosion of the systems while the plant is offline. Upon restart, a significant portion of the rust formed during the maintenance period is transported to the steam generators, reducing the heat transfer efficiency and contributing to a degradation mechanism known as "denting."

To prevent the formation of corrosive products, NEK decided to inject a protective amine-based film-forming solution (FFA). This chemical creates a protective film that prevents oxygen from reaching the internal surfaces of the secondary systems during outages when internal structures are exposed to the external atmosphere. The FFAs protect the internal surfaces of the carbon steels from corrosion by forming a temperature-resistant hydrophobic film. This film prevents corrosion during periods when the components are open and empty (during maintenance), and enhances the corrosion resistance of the pipelines during operation by reducing the flow-accelerated corrosion.

During operation, when the systems are filled, the reducing conditions are maintained with a high pH, and with hydrazine, which is added to the secondary system as a corrosion inhibitor (oxygen scavenger). However, during maintenance, the surfaces are exposed to oxygen, creating conditions that lead to corrosion. The resulting corrosive products are transported throughout the secondary system during operation and deposited as sediments in the steam generators.

The injection of the FFA solution must occur while the plant operates at full power. The injection point for the FFA solution is located between heaters 4 and 3, where the secondary water pressure remains low enough, and the temperature is sufficient to ensure the proper solubility of the chemical. The first dosing of the FFA chemical was carried out in March 2021.

3.1 Deviation description

An impact on the power plant's efficiency and the generator's output was observed as a result of the initial dosing of the FFA chemical. It was assumed that a change occurred in:

- the measurement of the main FW flow, measured via a Venturi nozzle and Δp meters,
- or the heat transfer in the steam generators.

Since the measurement of the main feedwater flow is linked closely to the reactor power calculation, any deviation in this measurement is associated directly with an impact on the plant's power output and efficiency. At NEK it was presumed at this point that the indicated FW flow value was higher than the actual value, as a loss of MWe at the threshold was noticeable, ranging from -0.4 % to -0.5 %, or approximately 4 Mwe.

ΔT measurements (in °C) were utilised for a representative assessment of the power drop on the primary side. These measurements represent the average values obtained from all the RTD (Resistance Temperature Detector) NR (Narrow Range) measurements of the primary circuit, and are independent of the calorimetric calculations. ΔT is a measurement between T_H and T_C in the primary loop. For better visualisation, a diagram of the average ΔT values over the entire cycle (510 days) is presented in Figure 2. The downward trend is attributed to the phenomenon of "Hot Leg Streaming," with the slope of the curve representing stable full power and the breakpoint indicating the timing of the FFA dosing.

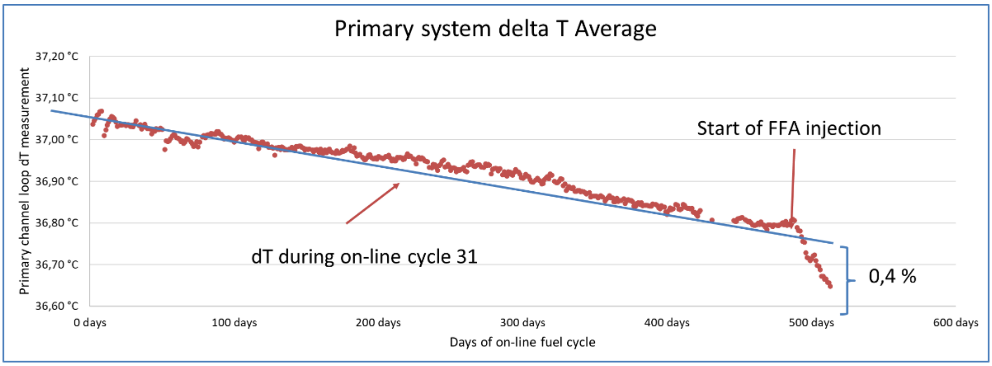

Figure 2: *The drop in calorimetric power based on the ΔT measurement of the primary system*

The next independent assessment was based on the change in MS flow, where the MS calorimetric power is obtained by considering the enthalpies:

$$\dot{Q}_{SG} = \dot{m}_{MS} \cdot \Delta h_{MS} + \dot{m}_{BD} \cdot \Delta h_{BD} \tag{3.1}$$

$\dot{Q}_{SG}$	Steam generator thermal power
$\dot{m}_{MS}$	Main steam mass flow rate
Δh_{MS}	Enthalpy change of water during evaporation
$\dot{m}_{BD}$	Blowdown system mass flow rate
Δh_{BD}	Enthalpy change of water in the blowdown system

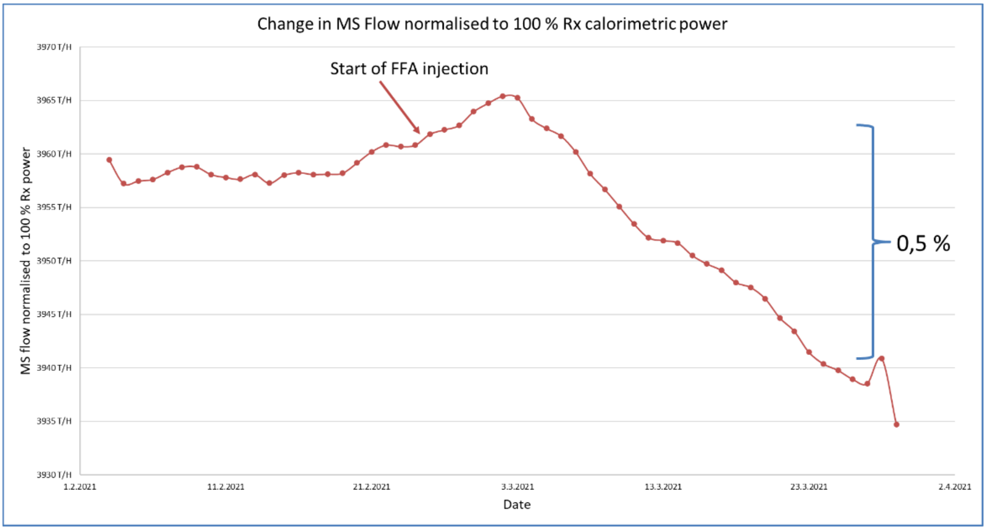

Figure 3: *The reduction in MS flow normalised to 100 % Rx calorimetric power*

The change in power from the MW-power characteristic relative to the vacuum was examined additionally. This characteristic illustrates the gross MWe energy as a function of the vacuum, enabling an assessment of power variation independent of changes in the thermodynamic efficiency (the vacuum in the condenser).

Based on evaluations of the reactor power reduction through independent reviews of the following parameters, it was concluded that:

- The ΔT measurement between the hot and cold legs of the primary circuit indicated a decrease of approximately -0.4 %.
- The change in MS flow indicated a decrease of about -0.5 %, as shown in Figure 3.
- The change in the power characteristic at the generator relative to the vacuum in the condenser suggested a reduction of approximately -4 MWe, or between -0.4 % and -0.5 % of the plant's power, as shown in Figure 4.

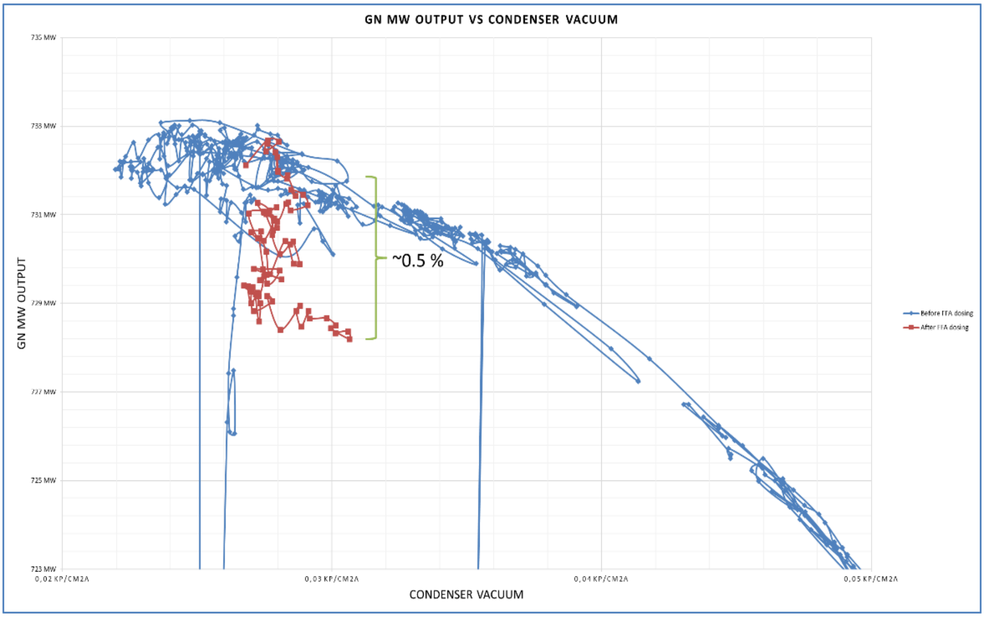

Figure 4: *The MWe characteristic at the generator relative to vacuum during the addition of FFA chemicals*

The operators follow "live" calculations of the plant's calorimetric power, ensuring that the reactor was kept within a two-hour average range of 99.94 % to 99.98 % during March when the FFA chemicals were dosed. However, an issue arose due to suspected inaccuracies in the calorimetric calculation, attributed to the influence of the FFA chemicals on the FW flow measurement, or changes in the heat transfer coefficient in the steam generators.

At NEK, the long-term steam generator maintenance strategy has been set to include FFA chemical dosing before every second outage, starting in September 2025. During this period, accurate FW flow measurements will need to be performed, to correct the current "live" calorimetric calculations and prevent further MWe losses at the generator.

The cost of electricity purchased from NEK by the owners, Gen Energija and HEP, is approximately 40€/MWh. Over an 18-month cycle, this results in a significant loss of revenue for NEK, and, subsequently, for the owners, who market this energy further.

4 PURPOSE AND OBJECTIVES OF FUTURE RESEARCH WORK

The purpose and objective of the future research work is to establish an independent calculation of the calorimetric power of the Krško Nuclear Power Plant. This calculation would enable the determination of "live/real-time" correction factors to be applied in the current calorimetric calculation, ensuring that future injections of FFA chemicals do not result in further power changes caused by their impact on the existing measurements.

To achieve an independent calculation of calorimetric power, a detailed model of the plant is to be developed in a numerically and computationally supported environment. This environment must allow matrix manipulations, function plotting, database/measurement integration, and the implementation of algorithms, to achieve a more precise final calculation of feedwater (FW) flow than the current method, ensuring its suitability for flow correction.

The computationally supported calculation of the main feedwater flow must remain independent of the actual measured FW flow value. Instead, it should rely on the thermodynamic interdependence of other process variables within the system. Additionally, the calculation must meet the accuracy criteria currently set for FW flow measurement. By achieving this, the current measured flow value could be corrected using the mathematically derived value.

If the above equation (2.3) is reformulated to eliminate uncertainties associated with the Venturi flow meter, the theoretical uncertainty of the parameter can be reduced from 0.81 % to 0.69 %.

This reduction highlights the potential of utilising advanced computational modelling to achieve higher accuracy in feedwater flow determination, thereby improving the precision of the overall thermal power calculations.

$$U_{RTPNEW} = \sqrt{\frac{0.487^2+0.010^2+0,003^2+0.088^2+0.84^2+0.036^2}{2}} = 0.69\ \% \tag{4.1}$$

U_{RTPNEW} New computationally derived uncertainty in the RTP calculation

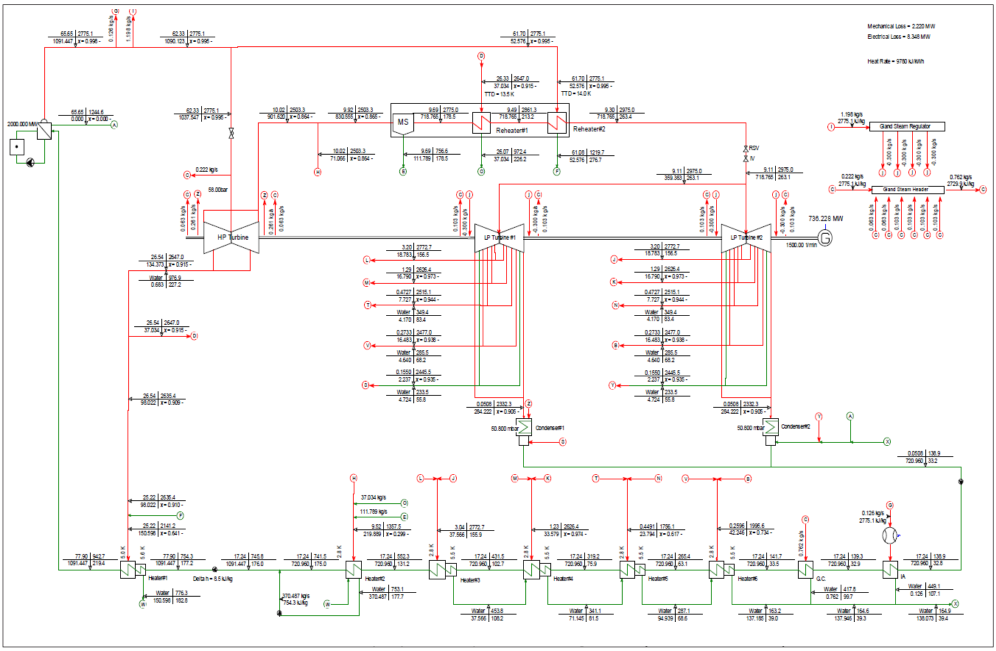

Figure 5: *Heat balance diagram of NEK (Source: NEK*

The required correction factor can be calculated with the newly obtained value of the FW flow. This factor would be applied to the displayed flow value, to calibrate it, and ensure that the actual display reflects the corrected and more accurate flow measurement.

It is assumed that it is possible to model the power plant's secondary system accurately with all the necessary process variables, to the extent that the computer-based model will be capable of performing the FW flow calculation with less uncertainty than is currently included in the NEK safety analyses. The model also assumes that the current measurement of the main feedwater flow will not be required as an input variable in the calculation, but can, instead, be determined/calculated based on other measurable interdependent variables. The NEK model will follow the logic of the current heat balance diagram used at NEK [Figure 5], which will then be supplemented with on-line process data.

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Nomenclature

(Symbols)	(Symbol meaning)
bar	Unit of pressure: 1 bar = 10^5 Pa (Pascal)
BD	Blowdown system
°C	Degrees Celsius
€/MWh	Euro per megawatt hour
°F	Degree Fahrenheit
FFA	Film-Forming Amines
FW	Feedwater system
K	Degree Kelvin
kgf/cm²	Unit of pressure in kilogram-force/square centimetre: 1kgf/cm^2 = 98066,5 Pa
MS	Main Steam system
MWe	Megawatt electric
MWt	Megawatt thermal
NEK	Krško Nuclear Power Plant (Nuklearna Elektrarna Krško)
NPP	Nuclear Power Plant
NR	Narrow Range
Δp	Delta pressure/pressure drop

psi	Unit of pressure in Pounds per Square Inch
PWR	Pressurised Water Reactor
RCP	Reactor Coolant Pumps
RCS	Reactor Coolant System
RTD	Resistance Temperature Detector
RTP	Rated Thermal Power
t/h	Ton per hour
ΔT	The difference in temperature between the hot leg and cold leg of the primary system

Journal of Energy Technology

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[1] Organisation, Department, Address

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Abstract: Abstract should be up to 500 words long, with no pictures, photos, equations, tables, - text only.

Povzetek: - Abstract in Slovenian language.

Main text should be structured logically in chapters, sections and sub-sections. Type of letters is Calibri, 10pt, full justified.

Units and abbreviations: Required are SI units. Abbreviations must be given in text when first mentioned.

Proofreading: The proof will be send by e-mail to the corresponding author in MS Word's Track changes function. Corresponding author is required to make their proof corrections with accepting or rejecting the tracked changes in document and answer all open comments of proof reader. The corresponding author is responsible to introduce corrections of data in the paper. The Editors are not responsible for damage or loss of submitted text. Contributors are advised to keep copies of their texts, illustrations and all other materials.

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Chapter examples:

1 MAIN CHAPTER (Arial bold, 12pt, after paragraph 6pt space)

1.1 Section (Arial bold, 11pt, after paragraph 6pt space)

1.1.1 Sub-section (Arial bold, 10pt, after paragraph 6pt space)

Example of Equation (lined 2 cm from left margin, equation number in normal brackets (section.equation number), lined right margin, paragraph space 6pt before in after line):

Equation (1.1)

Tables should have a legend that includes the title of the table at the top of the table. Each table should be cited in the text.

Table legend example:

Table 1: *Name of the table (centred, on top of the table)*

Figures and images should be labelled sequentially numbered (Arabic numbers) and cited in the text – Fig.1 or Figure 1. The legend should be below the image, picture, photo or drawing.

Figure legend example:

Figure 1: *Name of the figure (centred, on bottom of figure, photo, or drawing)*

References

[1] **N. Surname:** *Title,* Journal Title, Vol., Iss., p.p., Year of Publication

[2] **N. Surname:** *Title,* Publisher, Year of Publication

[3] **N. Surname:** *Title* [online], Publisher or Journal Title, Vol., Iss., p.p., Year of Publication. Available: website (date accessed)

Examples:

[1] **J. Usenik**: *Mathematical model of the power supply system control*, Journal of Energy Technology, Vol. 2, Iss. 3, p.p. 29 – 46, 2009

[2] **J. J. DiStefano, A.R. Stubberud, I. J. Williams**: *Theory and Problems of Feedback and Control Systems*, McGraw-Hill Book Company, 1987

[3] **T. Žagar, L. Kegel**: *Preparation of National programme for SF and RW management taking into account the possible future evolution of ERDO* [online], Journal of Energy Technology, Vol. 9, Iss. 1, p.p. 39 – 50, 2016. Available: http://www.fe.um.si/images/jet/Volume 9_Issue1/03-JET_marec_2016-PREPARATION_OF_NATIONAL.pdf (7. 10. 2016)

Example of reference-1 citation: In text *[1],* text continue.

Nomenclature

(Symbols)	(Symbol meaning)
t	time

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