Proceedings of the 17th International Heat Transfer Conference, IHTC-17
14 – 18 August 2023, Cape Town, South Africa

IHTC-17 | ID: XXXX

# Power Booy – AI-based Approach for Determining Optimal Positions

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## ABSTRACT

Hughe amounts of energy are spend for household heating systems. With our new concept for an urban river heat pump concept energy could be saved. The compressor of the heat pump concept could be driven by an underwater river turbine. A power buoy, also known as a free-flow turbine, is a small, floating current power plant that converts the kinetic energy of a free-flowing river into electrical energy. The concept was patented by *Fritz Mondl* in 2005 [1], has been continuously developed since then and is currently being tested at various locations [2]. The advantage of the electricity buoy compared to other systems for the use of renewable energies is obvious: it supplies electricity energy day and night, 8.750 hours a year. The power output is hardly subject to daily or seasonal fluctuations.

Since the *Strom-Boje* or power buoy requires a minimum water depth of three metres and a flow velocity of around two metres per second, it is suitable for use in Europe in medium to large alpine drainages such as the *Danube*, *Inn*, *Rhine*, *Rhone*, *Po* or *Drava* and *Sava*. The question of suitable locations is derived from the boundary conditions of depth and flow velocity. Without reliable flow data as the basis for an economic efficiency calculation, it is difficult to determine a location for the free-flow turbine and consequently no such hydropower plants are built, or at unfavourable locations. A wind map, as for example for wind turbines, does not yet exist for rivers and their local flow profiles. But not only the positioning and efficiency calculation of individual current buoys have to be planned, also aspects of the interaction of current buoys in the field, so-called current buoy clusters, have to be considered. Here, too, exact planning is necessary, as the position of the current buoy can only be changed with a great deal of effort once it is anchored in the riverbed. Good positioning of the buoy with regard to incident flow significantly improves energy generation. The determination of the location (*at which point and how in the cluster*) is therefore an essential aspect that is to be implemented cost-effectively and automatically with the AI-based approach presented here.

**KEYWORDS:** *Urban Heat Pump, Artificial Intelligence, Computational Methods, River, Water Turbine, Renewable Energy*

## 1. INTRODUCTION

The goal of this work is to map riverbed profiles and local flow conditions using Artificial Intelligence to determine the position of small turbine clusters for planning of a heat pump concept. In **Fig. 1** you can see the concept for a new heat pump concept for cities or suburbans near to rivers. A stream buoy is a small, floating stream power plant. It converts the kinetic energy of a free-flowing, undammed river into electrical energy. The concept was patented by *Mondl* and has since been further developed and marketed by *Aqua-Libre GmbH* [1, 2].

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## 1.1 Heat pump concept for cities near rivers

In **Fig. 1** the power buoy is coupled with a compressor unit. Two coupled heat conductors transfer the heat from the river water to the evaporator and further by the second cycle to the consumer household. As refrigerant propane or carbon dioxide could be used.

A picture of such a power buoy is shown in **Fig. 2** on the right side. Without reliable flow data as the basis for an economic efficiency calculation, it is difficult to determine a location for the small turbines and no such hydropower plants are built. Data from riverbed profiles for flow simulation, as they have long been available for landscape profiles (see **Fig. 2** on the left side), are not yet available.

With this new heat transfer concept high amounts of heating energy for households could be saved. Optimal positions for the power buoy cluster must be found in the riverbed (*see:* **Fig. 1**), but also onshore in the cities the position of the consumers and the facilities must be placed in the right location and distance to the river.

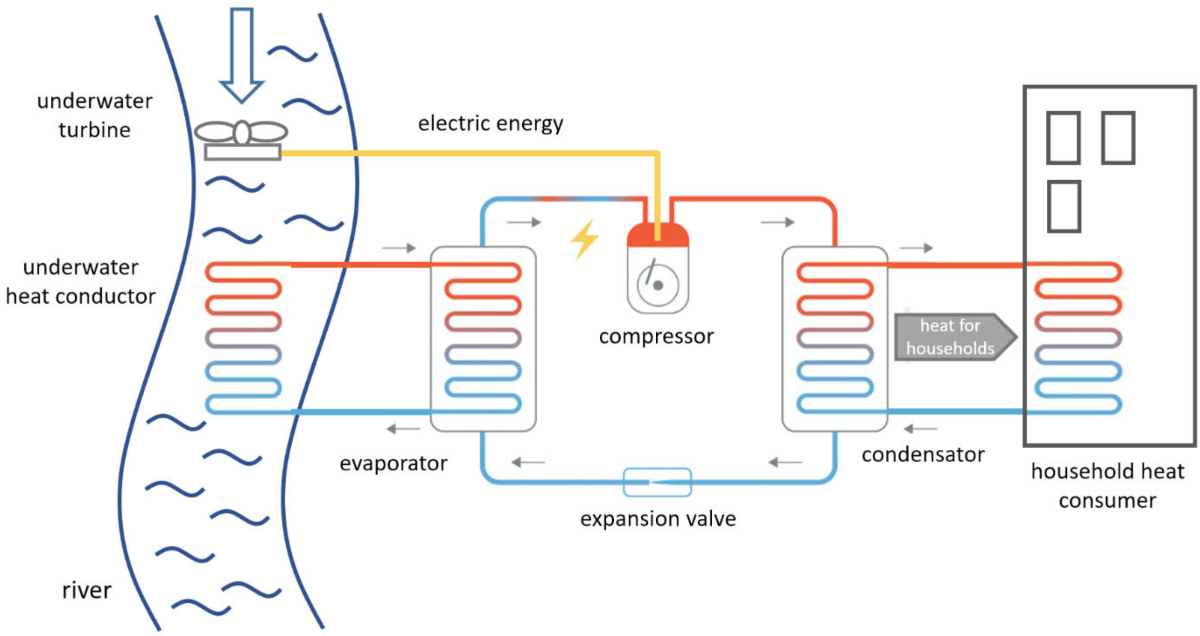



**Fig. 1** New heat pump concept in combination with a smart river turbine clusters for household heat consumer concept for smart cities near river sites

In 2021, electricity production from hydropower in Germany amounted to 19,4 TWh and reached 4 percent of net electricity generation. Accordingly, the use of hydropower is well developed, although there is further potential here using river turbines: "*Technical innovations are relatively common in the field of hydropower plants in flowing waters (hydraulic flow machines)*." [3]

## 1.2 Concept of smart riverbed turbines

The technology of smart riverbed turbines itself is proven and widely mastered [4]. 6,249 small turbines were registered in 2008. [5] Expansion is being sought because, unlike wind and solar power, the usually relatively steady power generation with energy output at a nearly constant rate allows hydroelectric plants to be used as base-load power plants [6]. In 2010, the German Federal Ministry for the Environment presented a comprehensive potential analysis for hydropower. According to this analysis, about 80 percent of the existing potential and 20.9 TWh of standard working capacity is currently being used. The additional potential that can be tapped is about five TWh (4.63 - 5.22 TWh). [7]

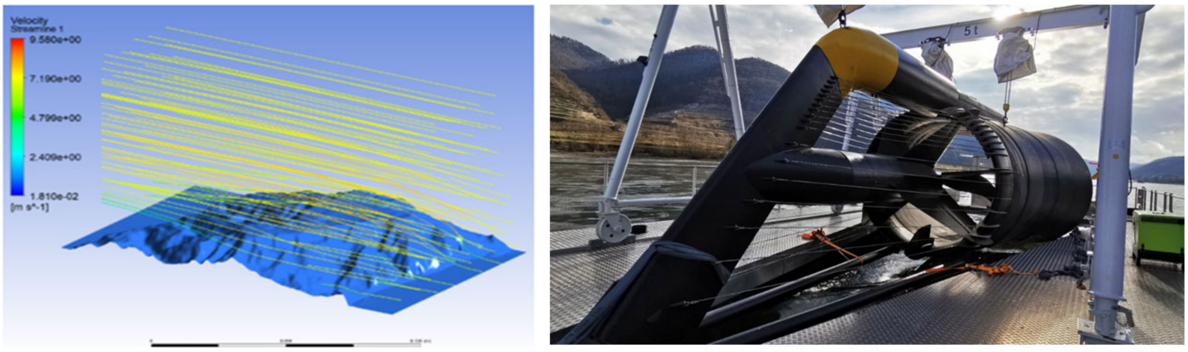



**Fig. 2** Flow simulation of a complex terrain topography (*example:* topology of Madeira) to determine the potential of a wind farm from a previous project (*left*); current buoy of *Aqua Libre GmbH* (*right*)

However, the predictions of possible yields so far (based on estimates of mean flow velocities and other, usually nevertheless very inaccurate assumptions), which can be expected at appropriate sites, are only very limited [3]. The technique of taking overall images of an object underwater exists (*see:* https://www.aqua-nautik.com/de/rov-sonarvermessung), but its use has so far been more common for underwater structures, generally for underwater work [8]. The use of riverbed surveying for simulation-based determination of optimal locations of river turbines is new territory.

## 2. METHODOLOGY AND RENEWABLE ENERGY

Since the power buoy requires a minimum water depth of three meters and a flow velocity of about two meters per second, it is suitable for use in Europe in medium to large alpine drainages such as the Danube, Inn, Rhine, Rhone, Po or Drava and Sava. They can provide up to 100 kW of power around the clock with relatively little intervention in the water body [9]. One power buoy can generate an annual output of 350,000 to 400,000 kWh from hydropower [10]. This corresponds to the annual energy demand of one hundred 4-person households. This form of energy generation is CO2 neutral and renewable. The flow turbines can add to the mix of renewable energy sources as alternatives to wind power and photovoltaics [4, 11].

*This is based on the following problem:* Without reliable flow data as the basis for an economic efficiency calculation, it is difficult to determine a location for the small turbines and no such hydropower plants are built.
A wind map of a complex terrain. e.g., of the topology of island of Madeira (*see:* **Fig. 2** – left side), as for example for wind turbines, does not exist for water flows in the see or in riverbeds. Not only the positioning and efficiency calculation of individual current buoys must be investigated, but also aspects of the interactions of buoys in the field, so-called turbine clusters, are crucial. It is likely that the buoy clusters may also influence each other in the field through their wake vortices. Again, accurate position planning is necessary because once the position is anchored in the riverbed, it is difficult to change. Good positioning of the buoy with respect to incident flow significantly improves energy harvesting.

### 2.1 Mapping fluid flow and topology

Due to the much higher density of water as a medium compared to air in wind turbines, a higher yield is possible with smaller turbines. In addition, the plants provide the energy in continuous operation and thus base-load capable, in contrast to the fluctuating existing systems. In **Fig. 3** on the left side the *Prinzenstein* site near St. Goar in the upper Middle *Rhine River* with planned deployment of 16 stream buoys. To measure the potential of the fluid flow and the depth of the riverbed in this region the research ship LUNA (*acronym:* Research Vessel for Lightweight Design, Environmental Protection, Sustainability and New Analysis Methods) for velocity measurements and riverbed profile survey has been equipped (see **Fig. 3** on the right side). It is known from the field of wind energy that the energy production of these fluid energy machines depends considerably on topography, vegetation, and times of the year and day. Also, topology of the riverbed can change depending on different fluid flow of the river.

**Fig. 3** *Prinzenstein* site near St. Goar in the upper Middle Rhine with planned deployment of 16 stream buoys (*left*); research ship LUNA (*acronym:* Research Vessel for Lightweight Design, Environmental Protection, Sustainability and New Analysis Methods) (*right*)

An analogous problem for the potential analysis of wind turbines has already been worked on in an internal research project. Here, too, seasonal fluctuations are known, and the measurements of the local flow conditions are associated with high effort. A complete coverage of the local river region via grid measurements can only be realized with a very high effort and is only feasible with a coarse measurement grid.
There are the following existing problem-solving approaches. Currently, there is a great need for action in the potential analysis and measurement of the sites. To implement the project, a first important step was the construction of a maintenance catamaran (name: *Current Worker*) [10], which was approved in April 2019 as a so-called floating device, as an inland vessel and can be used throughout Europe. So far, measurement runs have already been carried out.
In addition, there is the possibility on the part of *htw saar* since mid-2021 to use the research vessel LUNA (*acronym:* Research Vessel for Lightweight Design, Environmental Protection, Sustainability and New Analysis Methods). This will be used to measure both the water depth and the local current velocities to have a data basis for the planning of the current buoys.

## 2.2 Objectives for measurement methodology and control (LUNA)

The following measurement methods will be used. The sensor used on the LUNA research vessel will be a vane wheel measurement for current measurement and an ultrasonic Doppler profile current profiler ADCP (*acoustic Doppler current profiler*). This is an active sonar that uses the Doppler frequency shift of the reverberation of stray bodies in the water to determine the local current velocity. In addition, a water depth measurement and riverbed profile survey will be performed using echo sounders. In **Fig.4** on the left side we see the research ship LUNA in action by collecting data on the Saar river. A process computer will be installed on board the LUNA. During the measurement position of the research vessel is mapped by an GPS (*global positioning system*) signal and the depth of the river is mapped by an echelon signal. All data will be provided in Cartesian coordinates. The procedure is shown on the right side of **Fig. 3**. Additionally, water velocities will be measured, too.

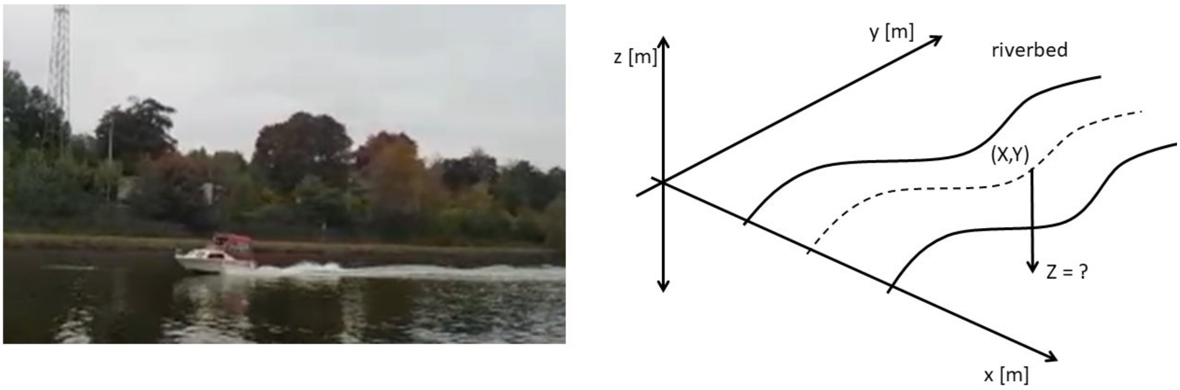



**Fig. 4** Research ship LUNA on the *Saar* river in Germany (*left*) and Cartesian measurement plan and data acquisition with ship position (X, Y) on the river (*right*)

Both the geometric local riverbed profiles and the results of the net measurement of the local flow conditions of the water shall be used as training data with the AI simulation tool Reason on site. The computation times of the *optiflow neural network* (ONN) AI tool is much lower than those of the conventional CFD calculation. Therefore, the learning process can be used directly on the process computer on board the research vessel to train the AI and directly provide the bearing for the next measurement point. The process computer is connected to the sensors via an interface and can perform a new teach-in of the model every minute. In **Fig. 5** on the right side CFD simulation results of the region near St. Goar are simulated to predict the overall fluid velocities and the potential for the buoy.

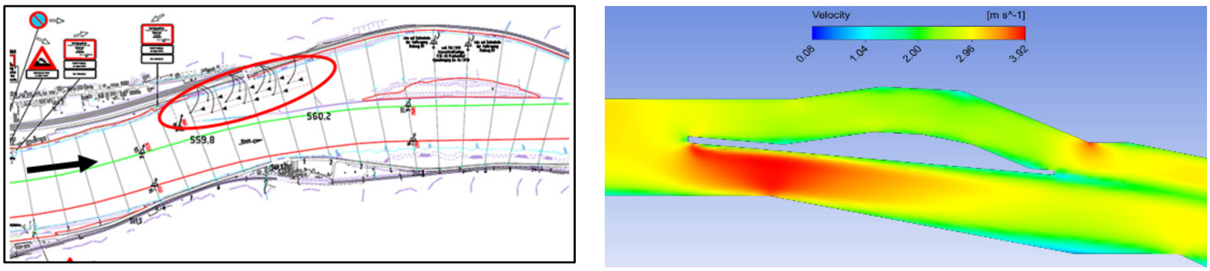



**Fig. 5** Planning of the positioning and potential assessment of the turbine park near St. Goar (*left*); flow simulation for 0.5 m water depth and the surface with ANSYS CFX (*right*)

To explain the GHG mitigation potential, we would like to present an existing example scenario prior to the deployment of the AI solution as shown on the right side of **Fig. 5**. A single buoy has a rated power of 70 kW. The *Prinzenstein Park* near *St. Goar* saves almost 6,000 t of $CO_2$ annually compared to electricity from lignite (2,500 t when applying the Germany-wide Power plant mix), here a cluster of 16 turbines are planned. This corresponds to the annual $CO_2$ emissions of about 650 mid-size cars with an annual mileage of 60,000 km [12]. Due to the very good flow conditions at the site, we expect an annual work of more than 600,000 kWh per buoy. One power buoy can thus supply well over 100 multi-person households with electricity. In contrast to PV systems, this electricity is also available at night.

## 3. ARTIFICIAL INTELLIGENCE

The AI is expected to reduce the number of required network surveys by the research vessel LUNA. In addition, the planning of buoy clusters becomes possible. The placement of buoys outside the vortex street of upstream buoys and the compliance with the other boundary conditions becomes plannable.

The resulting better positioning in areas with higher efficiency will additionally result in more electricity production and thus in higher CO2 savings.

### 3.1 Energy Potential Estimation

Extensive projects for site assessment and potential determination of wind farms are currently already being carried out by the applicants. In the case of river turbines and farms, the influence of small-scale, local river flow is generally largely unknown. Determining the potential or estimating the efficiency of planned turbines is difficult. Public data are only available or usable to a very limited extent. Furthermore, the local topography of the riverbed and the flow velocity of the water is usually unclear. Flow simulations and mathematical methods of AI will be used to supplement the measured data. The efficiency of the turbines depends directly on the local flow velocity. We have performed initial flow simulations for this purpose (*see:* **Fig. 5**). The simulation of the rough geometry at Rhine kilometre 559 already shows differences in the flow velocity at 0.5 m water depth.

### 3.2 Optimising measurement strategies

With the help of an AI, which directly intervenes in the measurement process, the measurement grid of the research vessel is to be optimized during the measurement to have to approach fewer measurement points and to find representative positions on the water. The trained AI models are to be used directly with a process computer on board the research vessel to reduce the number of measurement points and thus the measurement effort and the $CO_2$ emissions during the measurement. In this method, the measurement grid is constantly changed so that positions with higher velocity gradients are measured more accurately and those positions that are irrelevant to the measurement are measured less accurately [13, 14]. This also considers the depth of the riverbed, as well as issues of instability and wake effects of cluster turbines. In **Fig. 6** the systematic measurement of the Cartesian measurement plan is given on the left side. This is compared with an online gradient-based planning of buoy positions and the fluid flow in their surroundings.

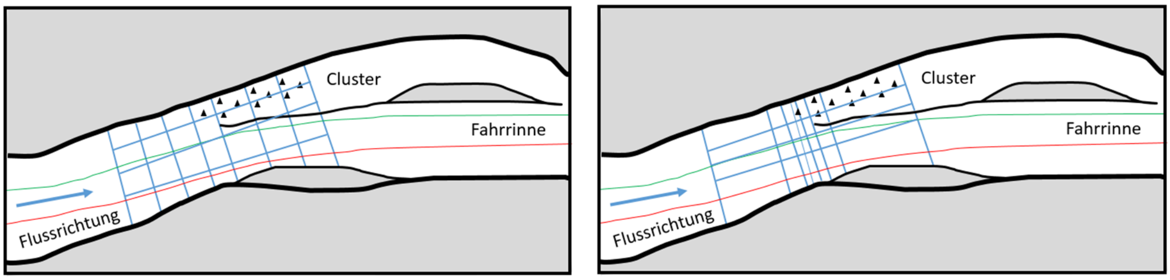



**Fig. 6** Systematic measurement of a Cartesian measurement plan (*left*); gradient-based planning of measurement positions (*right*)

A major problem is that the data must be obtained via a net measurement for the particular location [15]. In addition to this spatial discretization, there is also the problem that the temporal resolution of the data can only be very fragmented. Local weather conditions additionally influence this. Therefore, new mathematical methods must be used to improve both the spatial and temporal resolution of the measured data and to enable prediction for position planning and current yield, e.g., a method of *latine-hypercube-sampling* to collect the data points. Furthermore, dependencies on the level course and changes due to bed load must be considered. With the help of a few spatial data, the AI tool can also partially reconstruct the riverbed surface from the echosounder data.

### 3.3 Objective of artificial intelligence (AI)

The proprietary AI analysis tool ONN was developed at University of Applied Sciences Saarbrücken (*htw saar*) over several years. This software tool has the capability to process large amounts of data, on the one hand to realize data fitting by correlation in n-dimensional space and in combination to use an algorithm that is based on a high-resolution *artificial neural network* (ANN) to map measurement data in time and space [16, 17, 18, 19, 20]. Discretization problems are solved by a third reproduction algorithm. This resulted in mapping and time-dependent potential analysis of future turbine locations [14, 15].

## 4. MODELLING THE RIVER TOPOLOGY

The algorithms of the AI tool *optiflow neural network* (ONN) are already very well developed and optimized in terms of runtime. By transferring the algorithms to a new interface in C++ and Qt, the already learned models can then be used in further test runs with the research vessel LUNA. The ONN tool is based on the *Quickprop* algorithm from *Fahlman* [21].

### 4.1 Measurements and data mapping

To reduce the network of measurement points on the river and improve the quality of the prediction by suggesting targeted measurement points already during the measurement on site (*latine-hypercube method*). This AI can then be used later to determine the optimal positions of the turbines as well as the positioning of the turbines among each other in the cluster. Furthermore, the CFD results already introduced in **Fig. 5** can be used for the training of our AI algorithm. In **Fig. 7** it is shown, how the data is mapped in a Cartesian measurement plan, and in which structure the depth of the riverbed is stored.

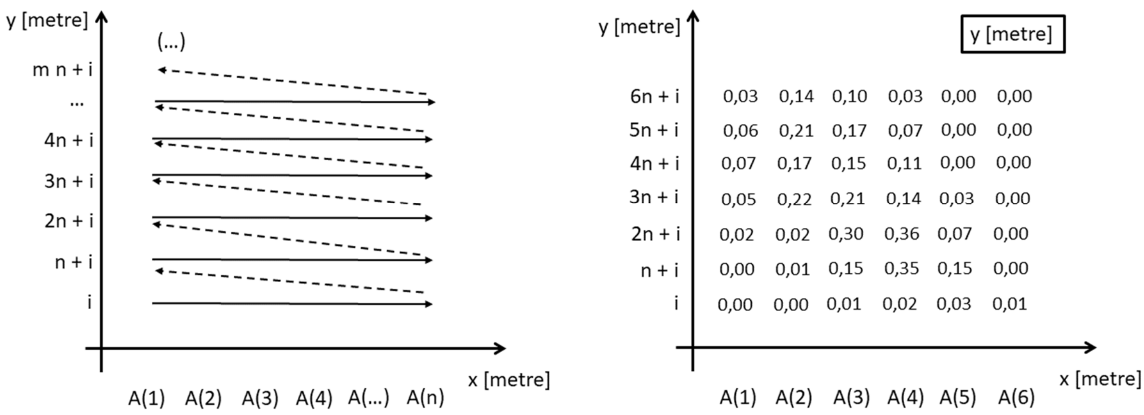
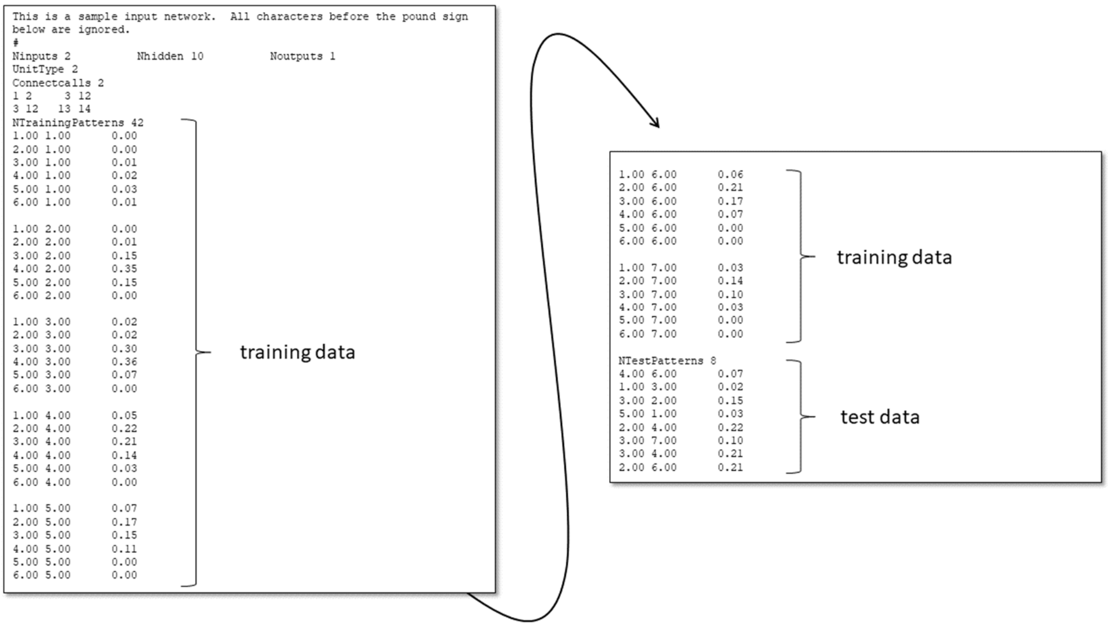



**Fig. 7** Cartesian measurement plan and data acquisition with ship position (X,Y) on the river; data acquisition of measured riverbed data and position in matrix

The so measured data must be stored in a data sheet and has to be defined as training data for the AI. An input file, a so called "**.net*" must be sampled. In the net-file, the structure of the neural network can be defined. Here the number of input nodes (*Ninputs*), the number of hidden nodes (*Nhidden*) and the number of output nodes (*Noutputs*) have to be defined. The format of such a *net-File* is given in **Fig. 8**. In this *net-File* also the connections between the nodes must be defined.



```
This is a sample input network.  All characters before the pound sign
below are ignored.
#
Ninputs 2          Nhidden 10          Noutputs 1
UnitType 2
Connectcalls 2
1 2     3 12
3 12   13 14
NTrainingPatterns 42
1.00 1.00      0.00
2.00 1.00      0.00
3.00 1.00      0.01
4.00 1.00      0.02
5.00 1.00      0.03
6.00 1.00      0.01

1.00 2.00      0.00
2.00 2.00      0.01
3.00 2.00      0.15
4.00 2.00      0.35
5.00 2.00      0.15
6.00 2.00      0.00

1.00 3.00      0.02
2.00 3.00      0.02
3.00 3.00      0.30
4.00 3.00      0.36
5.00 3.00      0.07
6.00 3.00      0.00

1.00 4.00      0.05
2.00 4.00      0.22
3.00 4.00      0.21
4.00 4.00      0.14
5.00 4.00      0.03
6.00 4.00      0.00

1.00 5.00      0.07
2.00 5.00      0.17
3.00 5.00      0.15
4.00 5.00      0.11
5.00 5.00      0.00
6.00 5.00      0.00
```

```
1.00 6.00      0.06
2.00 6.00      0.21
3.00 6.00      0.17
4.00 6.00      0.07
5.00 6.00      0.00
6.00 6.00      0.00

1.00 7.00      0.03
2.00 7.00      0.14
3.00 7.00      0.10
4.00 7.00      0.03
5.00 7.00      0.00
6.00 7.00      0.00

NTestPatterns 8
4.00 6.00      0.07
1.00 3.00      0.02
3.00 2.00      0.15
5.00 1.00      0.03
2.00 4.00      0.22
3.00 7.00      0.10
3.00 4.00      0.21
2.00 6.00      0.21
```



**Fig. 8** Data format for the .net-Files for the *optiflow neural network* (ONN)

Additionally, to the training data for the ONN tool, a block of test data can be defined under the topic (*NTestPatterns*), here also the number of the test data lines have to be given. The format of the test data block must be always in the same format as the block of the training data.

## 4.2 Software Tool for Artificial Neural Network (ONN)

The proprietary AI analysis tool *optiflow neural network (ONN)* was developed at *htw saar* over several years. It is based on *Fahlman's Quickprop* program translated from *Common Lisp* into *C* by *Regier* at the University of California, Berkeley [21]. *Quickprop* is an almost forgotten neural training algorithm also mentioned by *Bonaccorso* [22]. This base version is *Quickprop* was from 1988. An example of network setup data is included at the end of this file. The algorithm and some test results are described in Fahlman [21].

Changes made to the first version of *Quickprop* have been made by *Karunanithi*. Connections can now be specified for multiple ranges of units. For example, if you had 3 layers of hidden units and wanted the third layer to have connections to inputs and the second layer but not the first hidden layer. Additional bug fixes in CONNECT_LAYERS have been inserted by *Dale Romero* inserted into the code in 1991, You may specify hidden and output units as sigmoid functions with ranges of -0.5 to 0.5 (SIGMOIDAL) or from 0.0 to 1.0 (ASYMSIGMOIDAL) in the input file. In 2007 the graphical user interface (GUI) of ONN was implemented in C++ with Qt by *Rückert*. In **Fig. 9** two screenshots of the ONN tool are given on the left side during training scenario. On the left side of the figure, you see the tool while testing. The tool has the capability to process large amounts of data, on the one hand to realize data fitting by correlation in proprietary AI analysis tool was developed at htw saar over several years.

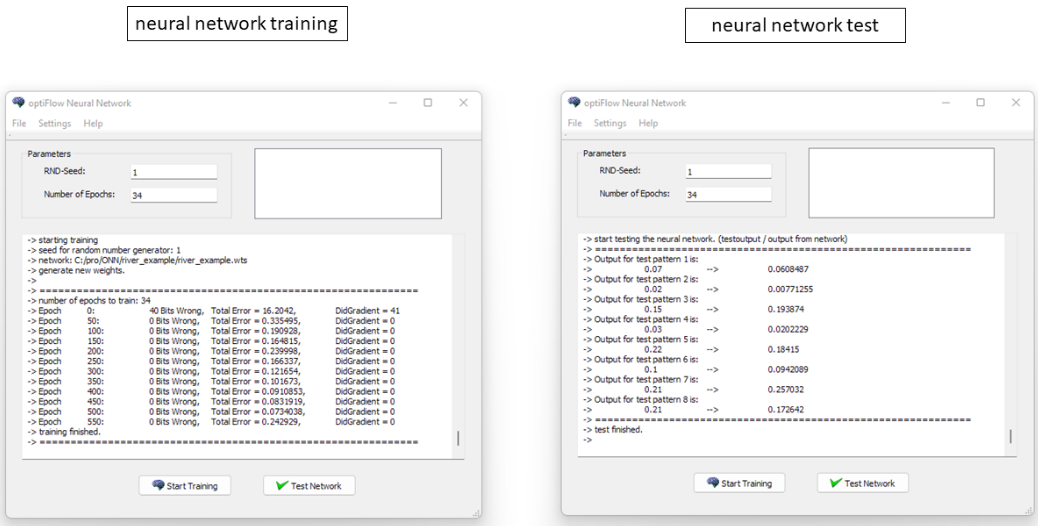



**Fig. 9** Graphical user interface (GUI) of the software tool *optiflow neural network* (ONN)

The opensource software tool ONN and the presented example for the riverbed prediction can be download at our homepage (https://www.optiflow.htwsaar.de/) for all windows systems free of charge [23]You can find the file "*river_example.net*" in the installation folder of ONN. After opening the net-file you should just press the "*Start Training*" button as can be seen in **Fig. 9** on the left side. The number of epochs and the RND-seed can be adapted to change the learning behaviour of the AI.

## 4.3 Results for River Depth Prediction

After the training phase of the neural network is finished, the network can be tested with the test data pattern. This can be simply done by pressing the "*Test Network*", e.g., can be seen on the right side of **Fig. 9**. These example for measurement of data for the riverbed depth and data predication are shown in **Fig. 10**. All simulations are done with *optiflow neural network* (ONN) and the input data for this test cases were given in the net-File shown in **Fig. 7**. The proprietary AI analysis tool predicted the data for the river depth very well.

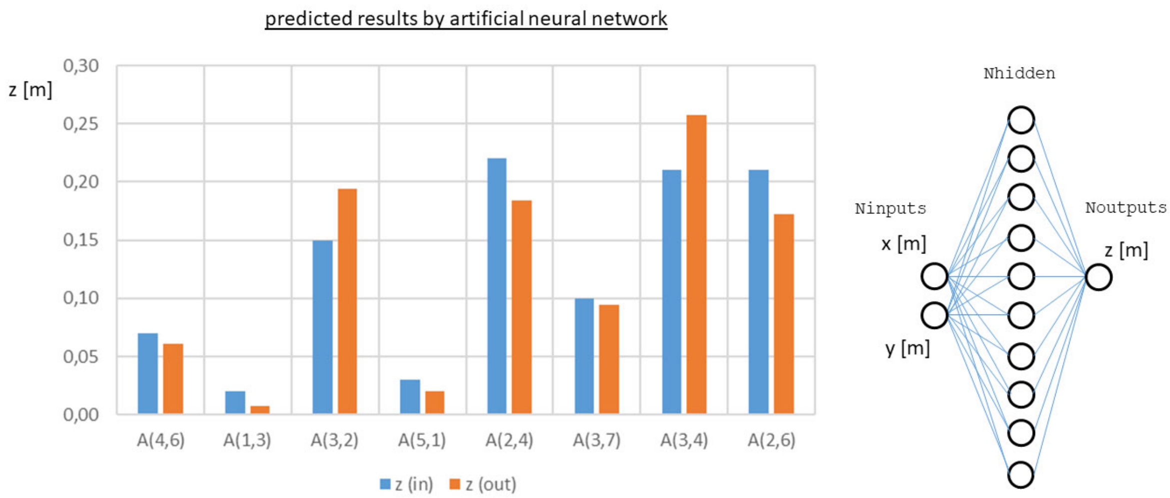



**Fig. 10** Example for measurement of data for the riverbed depth and data predication with *optiflow neural network* (ONN)

On the right side of the **Fig. 10** a picture of the artificial neural network is plotted for better understanding of these structure. The network uses 10 hidden nodes for training, which fits our demand quite well. Different numbers of hidden layer cells can be chosen and tested. Type size of the body of the table depends on the size of the table, adjust type size accordingly. The runtimes of the ONN are fast and should be used in future directly during onboard measurements with LUNA.

## 5. CONCLUSIONS

This paper gave a rough overview of our AI-based research project FluKIT. This is a funding initiative for environmental, climate, nature and resource research as a contribution to the implementation of the German government's AI strategy.

After a short introduction to the technology of the current buoys and a presentation of the problems with, among other things, site planning, the AI-based solution approach was presented. In addition to the theoretical approaches to AI, the practical implementation as well as the execution and evaluation of the measurement results were described (reference is made to the free link to download the developed AI tool).

With the completion of the project, it is expected that a comprehensive overview of potential locations of storm buoys and current buoy clusters in Germany and Central Europe will be available.


## ACKNOWLEDGMENT

Our work is supported by the Germany organization "*Zukunft-Umwelt-Gesellschaft (ZUG) gGmbH*" and the "*Leuchttürme KI*" program. As lighthouses, these projects are intended to set an example for environmentally and climate-friendly digitization [24].


## NOMENCLATURE

All variables are in **SI Units**.

| | | | | | |
|---|---|---|---|---|---|
| *n* | index for coordinates | [ ] | *Y* | coordinate | [m] |
| *X* | coordinate | [m] | *Z* | coordinate | [m] |
| *A* | one dimensional matrix | [ ] | *Ninputs* | number input nodes | [ ] |
| *Noutputs* | number output nodes | [ ] | *Noutputs* | number hidden nodes | [ ] |

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