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# Principles of planning – an application of simulation-optimization approach in choosing of optimal solutions in water resources systems planning

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ABSTRACT

Simulation-optimization approach enables choice of optimal solutions in water resources systems management. Review of machine learning models for solving optimal analysis and optimal synthesis tasks are given in the paper.

## 1 INTRODUCTION

Simulation-optimization approach enables a choice of the optimal solution for given physical conditions and considered hydrological scenario to which water resources systems (WRS) can be exposed. The approach can be used for choosing of optimal management policy of present WRS and optimal design of future WRS. This paper presents a review of simulation and optimization models from the area of machine learning (ML) and their possibilities of usage for both tasks. Possibilities of application for planning related to groundwater management, water allocation, sediment transport, coastal hydrodynamics and structures, water supply and sewage are shown.

Basic classification of hydrological models is on theoretical and empirical models. Theoretical models use mathematical description of governing physical processes generally made by using assumptions of simplified and reduced physical systems. Full mathematical and physical description is very probably impossible to achieve, considering the stochastical nature of hydrological processes and generally all phenomenons in the atmosphere on which hydrological cycle depends. Empirical and statistical models enable bypassing of physical processes description, that is, mathematical tools are used for description of observed data which represent the manifestation of physical process [1]. This is, conditionally speaking, valid partially, because the importance of understanding of hydrological cycle and processes substantial for problem solving cannot be neglected. Through the history of hydrological modelling, hydrologists generally had tendency to physically based models due to the purpose of constant improving of understanding of hydrological cycle, which used to bring more complex models with time [2].

In the last two decades, artificial neural networks (ANN) gained huge popularity. The main advantages are: avoiding the necessity of complete understanding of physical processes, models can be built relatively quickly, it is not necessary to introduce assumptions of linearity and describe relationships between different processes, data usage is flexible [3]. As in the field of machine learning (ML), part of artificial intelligence, the procedure of building models with ANN is generally valid for all the other models, it can be concluded that those advantages are generally valid for ML. General procedure of applying an ML is consisted of model representation choice, search and error estimation [4]. If taken into consideration the number of different ML models and possibilities of approach (different input-output, models and submodels combinations, etc.), mentioned implies that in WRS modelling, the most efficient ML methods are yet to be resolved through future researches. On the other hand, physically based models are of great importance when information about the whole modelling area is needed, while ML is able to function only on those places where data observations exist. Further, while physically based models have defined functioning structure in the sense of input-output relationship, for ML models it is needed to find the input-output structure, often made in the trial-error procedure.

The questions like are ML methods able to replace and to what extent ML methods are able to replace physically based approaches, in the sense of an estimation of the fields of physical quantities, has to be resolved. There is no doubt that ML techniques are of great help in spatial analysis, which can be seen in the examples of the application of self organizing maps in gaining sea wave field patterns (i.g. [5]), principal component analysis for modelling wind field uncertainty (i.g. [6]), support vector machine and random forests for the reconstruction of monthly precipitation over area uncovered with satellite precipitation data [7], support vector machine, random forests and Cubist for sea quality monitoring based on satellite data [8]. By taking into account that ML methods learn from data, the possibilities definitely exist. Also, ML modelling of wider area is possible in the cases when there is enough number of measurements at the whole area. Such example of application on laboratory physical model can be found in [9] and for spatio-temporal simulation of groundwater levels in [10].

### 1.1 *Methodology*

A review is done from the perspective of system theory. Development of cybernetics brought system theory to WRS and gave several advantages in problem solving. It brought understanding that problem solving begins after noticing consequences. Therefore, the question spinning in mind is if there are abilities to improve the prediction of the problem [11]. There are two great groups of tasks in the WRS management: optimal analysis and optimal synthesis task [12]. The first are used for optimization of usage of already built systems, while the second are used for designing of future systems [13]. Optimization is the process of finding the best solution. Simulation is an imitation of the operation of real physical system in hypothetic situations. It does not have an objective function and therefore does not have a built-in optimization problem. It gives an insight into consequencies and effects of individual decision. Therefore, the simulation can be coupled with an optimization problem [14].

## 2 CONCLUSION

Application of ML in WRS is growing field with wide spectrum of possibilities. It is worth to review ML models and relate them to the perspective of systems theory and simulation-optimization approach.

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