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-RESEARCH ARTICLE-

Artificial Intelligence (AI) Studies in Water Resources

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Abstract
Artificial intelligence has been extensively used in many areas such as computer science, robotics, engineering, medicine, translation, economics, business, and psychology. Various studies in the literature show that the artificial intelligence in modeling approaches give close results to the real data for solution of linear, non-linear, and other systems. In this study, we reviewed the current state-of-the-art and progress on the modelling of artificial intelligence for water variables: rainfall-runoff, evaporation and evapotranspiration, streamflow, sediment, water quality variables, and dam or lake water level changes. Moreover, the study has also identified some future research possibilities and suggestions for modelling of the water variables.

Keywords:
Artificial intelligence methods, modelling, water variables

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Introduction

Water whose chemical denotation is H_2O is a vital substance, and water is signified with a chemical bond that is formed between two hydrogen elements and one oxygen element. Moreover, it exists in three cases: solid, liquid and gas in the nature (Brady & Holum, 1988). It is also said to be among the most important vital resources for all known life forms. Therefore, controlling of water, tracing and conservation should be among the priority work in order to know importance of water and to ensure its sustainability and to leave a world which will have

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the clean water for future generations. Therefore, each country has to do some regulations about water resources and to protect her own natural environment.

Hydrological processes can be regarded as a non-linear process in the nature (Chapra, 2008; Tayfur, 2011; Tayfur, 2017). At this point, it can be said that some variables such as streamflow and precipitation at different places have time-dependence parameter. Therefore, it is required to describe, analyze and interpret these non-linear processes. When algorithms and parameters of AI for modeling are formed appropriately, the created model yields both economic and fast as well as being nearly accurate results. This is one of the most important advantages of AI. Moreover, the accuracy and functionality of a model can be controlled with different recorded data sets. One of the important points is that a person controlling a model needs to be able to identify relationship in the hydrological processes and effects of parameters, and he/she can select or change the model's parameters, functions, iteration numbers and algorithms in case of a change. In this context, the studies carried out by using the AI techniques on the water resources emphasize the importance of this issue. In addition, it can be said that some outcomes which are obtained through all these approaches and models give priority to productivity, utility, sustainability and quality of the environment and living factors (Marquardt, 1963; Zadeh, 1965; Takagi & Sugeno, 1985; Haykin, 1998; Şen et al., 2002; Tayfur, 2011; Hao & Singh, 2016; Tayfur, 2017).

Measurement works of the water variables

Monitoring and continuity of measurements and laboratory works are both difficult and expensive devices to assess quality of the water environments. Moreover, because many of these systems are vulnerable to hazards in the nature. Processes such as maintenance, control, and calibration of them become difficult in some cases. For example, streamflow in a river can be calculated through measuring the flow rates and other variables. Streamflow measurements in a river, the flow rate from certain locations in sections are determined a current meter after identifying the channel cross-sectional area. The level of the river is also determined via a level meter (scales) placed in the stream section. Subsequently, the key curves obtained from the regression analysis are frequently used in practice. In-situ measurements can be reduced thanks to this way. On the other hand, one of the most important difficulties in the data analysis is the measurement intervals acquired with respect to time in terms of measurement practices. Sediment measuring in a river section is also more difficult than the flow measurements. After in-situ measurements, it should be done laboratory works. Like the flow measurements, the key curves obtained from the regression analysis are frequently used in practice. Water level sensors are commonly used in a river to determine the level of river or water level gauges are used. Evaporation/evapotranspiration are measured by using evapotranspirometers (lysimeters). Another measurement is water quality variables. The water quality variables are often observed at non-systematic intervals, and time series are often short. Data sets contain a large number of missing data, and long intervals without measurements. Therefore, water quality data constitutes the most problematic hydrological data and the use of classical hydrological methods is also difficult in their analysis. The quality variables of water can vary depending on using of the water areas such as irrigation, recreation, energy and other specific uses. There are national (Water Pollution and Control Regulation (WPCR)) and international (Environmental Protection Agency (EPA) and World Health Organization (WHO)) regulations for determining the water quality. In these documents, it can be expressed with about 50 variables such as dissolved oxygen, chemical oxygen demand, biological oxygen demand, pH, temperature, nitrate, nitrite calcium, potassium, phosphate, and fecal coliform. In this case, it can be said that there is no such problem in current measurements. For example, a comparison requires that water quality should be defined with many variables even in a single location. Hence, the analysis becomes complex evaluating of many variables when the relationships among water quality variables are looked for even in a single location. If all of the variables are systematically observed at the same frequency, the analysis becomes easier. However, if different variables are observed at different frequencies in the same location, it is too difficult to apply existing methods (Harmancioglu et al., 1999; Şen et al., 2002). On the other hand, AI methods are used as an intermediate control element such as the design of the valve system of the reservoir of the dam, the flow and precipitation forecasts according to the flood analysis, the design of the irrigation systems can be thought of as intermediate parts of the system. At the same time, in many engineering projects, different optimization and modeling schemes coordinated with other branches of science can be considered in order to make many projects more functional and longevity. Hence, AI techniques have been proposed as an alternative option for solving such problems (Harmancioglu et al., 1999; Ward, 2007; Tayfur, 2017). This highlights the need for reliable regionalization models to estimate time series of the water variable in ungauged watershed. For example, there are some studies about approaches based on predicting via AI from the data of hydrologic variables in stations where measurements cannot be obtained (Cibin et al., 2014; Waseem et al., 2015).

As a summary of this section, the application of the AI methods in water resources is an important field, and should be developed by using different approaches. Moreover, meaningful and practical approaches play an important role in the development of these techniques. In addition, advances such as development of computer technology, data management, visualization, and the acceleration of information exchange are even more open to these techniques.

Relevant studies in the literature

As we can see from these valuable studies; several relevant papers, books and projects of established research methods and philosophy of the AI have been discussed for several years. In this context, recently studies performed by using AI methods on rainfall-runoff, evaporation and evapotranspiration, streamflow, sediment, dam or lake water levels and water quality variables are presented in this section.

Many mathematical functions required to use these methods are available in programming languages such as MATLAB, FORTRAN. Among all of AI, the artificial neural network (ANN), fuzzy based models and their hybrids are the most widely utilized for prediction of water variables: rainfall-runoff, evaporation and evapotranspiration, streamflow, sediment, dam or lake water levels and water quality variables. For example, AI methods have been successfully used to predict sediment in width section of a river, evaporation and evapotranspiration, rainfall-runoff, streamflow, water quality variables and modelling of dam or lake water levels as seen in Table 1.

Table 1. Summary table of the recently a number of AI studies according to the variables

Variables	Recent studies
Dam or lake water level	Hipni et al., 2013; Üneş et al., 2015; Li et al., 2016
Evaporation and evapotranspiration	Goyal et al., 2014; Karimi et al., 2016; Güçlü et al., 2017
Rainfall-runoff	Talei et al., 2013; Darras et al., 2015; Londhe et al., 2015; Chithra & Thampi, 2016
Sediment	Demirci and Baltaci, 2013; Güner and Yumuk, 2014; Demirci et al., 2015; Droppo & Krishnappan, 2016; Talebi et al., 2016
Streamflow	Cigizoglu, 2003; Huang et al., 2004; Nourani et al., 2012; Ashrafi et al., 2017
Water quality variables	Ay, 2010; Akkoyunlu et al., 2011; Ay & Kisi, 2011; Ay & Kisi, 2012; Ay & Kisi, 2013a; Ay & Kisi, 2013b; Kisi & Ay, 2013; Ay, 2014; Ay & Kisi, 2014; Chang et al., 2014; Alizadeh & Kavianpour, 2015; Khan & Valeo, 2015; Ay & Kisi, 2017

For instance, the future level values for ANNs (artificial neural networks) method were estimated from the previous level data of river (Li et al., 2016). Using the measured salinity data on the Murray Bridge over the Murray River in the south of Australia, they obtained precise correlation and low error values as a result of modeling through ANN (Maier & Dandy, 1996). In this context, Marsili-Libelli, 2004 has also done algal blooms modeling studies for different aquatic environments. A classification model was proposed by adaptive neuro-fuzzy inference system (ANFIS) using dissolved oxygen (DO), chemical oxygen demand (COD), and ammonium nitrogen. A total of 845 data were collected from 100 monitoring stations in China. The ANFIS method has shown that it gives better results than ANNs (Yan et al., 2010). In addition, many researchers have used ANN modeling techniques in estimating of plankton modeling (Scardi, 2001), algae formation prediction (Wilson and Recknagel, 2001), eutrophication modeling (Kuo et al., 2007), and water coloring and pH (Moatar et al., 1999). The rainfall-runoff relationship which is one of the difficult and complex issues in hydrology is modeled by using ANN method (Lin & Chen, 2004).

Using the AI methods in water resources has been presented as review studies in Table 2 (Maier & Dandy, 1996; Maier & Dandy, 2000; Mi et al., 2004; Chau, 2006; Cherkassy et al., 2006; Maier et al., 2010; Nourani et al., 2014; Yaseen et al., 2015; Afan et al., 2016) in different times.

Table 2. Review studies in the modelling of water variables

Number	Year	Review studies
1	1996	Maier and Dandy, 1996
2	2000	Maier and Dandy, 2000
3	2004	Mi et al., 2004
4	2006	Chau, 2006
5	2006	Cherkassy et al., 2006
6	2010	Maier et al., 2010
7	2014	Nourani et al., 2014
8	2015	Yaseen et al., 2015
9	2016	Afan et al., 2016

Conclusions

Several relevant papers, books and projects and philosophy of the AI have been discussed for several years in water resources. In this review study, we have looked over modelling of water variables. In this context, the conclusion and remarks derived from the based on the existing literature can be in following.

Despite the fact that AI techniques are regarded as black box systems, features such as the output of the models established in the solutions of the nonlinear systems, the stock market efficiency close to the actual system outputs, and the ease of model calibration increase the use of these methods. As it becomes a model for the modeling of a physical phenomenon, studies such as the behavior of the models, the types of functions, and the number of iterations affect one of the weaknesses of the established mathematical models. In this case, to increase accuracy and decrease the error rate, to use different algorithms, to change the functions are proportional to experience of a researcher.

In water resources, modeling of the water variables is an important step for any aquatic environment. The model outputs of the AI methods are also compared with statistical and stochastic approaches. Performance comparisons of the models are usually used the statistical expressions such as mean absolute error (MAE), mean square error (MSE), and correlation coefficient (r), scatter and time series graphs.

As a result, it can be said that the AI techniques generally give better results in the modeling in the water resources than the classical methods. Moreover, these techniques are used with new approaches and are integrated those with different disciplines of science; it may give better predictions. It is seen from the literature studies that preprocessing time series frequency, selecting the most essential input variables, and choosing the most appropriate time scale are the key principles for accurate modeling.

More researches are needed to extend the present frontier of knowledge in AI by integrating principles and philosophies of some traditional disciplines into the existing AI frameworks (Oke, 2008; Tayfur, 2011; Ay, 2014; Tayfur, 2017). The recent advancements may provide a way to bridge the existing gap between the model developers and experts.

References

Afan, H.A., El-shafie, A., Mohtar, W.H.M.W., Yaseen, Z.M. (2016). Past, present and prospect of an Artificial Intelligence (AI) based model for sediment transport prediction. *Journal of Hydrology*, 541, Part B, 902-913.

Akkoyunlu, A., Altun, H. & Cigizoglu, H.K. (2011). Depth integrated estimation of the lake dissolved oxygen (DO). *Journal of Environment Engineering*, 137(10), 961-967.

Alizadeh, M.J. & Kavianpour, M.R. (2015). Development of wavelet-ANN models to predict water quality parameters in Hilo Bay, Pacific Ocean. *Marine Poll Bullet*, 98(1-2), 171-178.

Ashrafi, M., Chua, L.H.C., Quek, C., Qin, X. (2017). A fully-online Neuro-Fuzzy model for flow forecasting in basins with limited data. *Journal of Hydrology*, 545, 424-435.

Ay, M. (2010). Sulama suyu kalitesinin kümelemeye dayalı bulanık sistem ile sınıflandırılması (Classification of irrigation water quality by a clustering based fuzzy system). Yayımlanmış Yüksek Lisans Tezi. Tez no: 269333. 41 sayfa. https://tez.yok.gov.tr/UlusalTezMerkezi/giris.jsp.

Ay, M. (2014). Su kalitesi parametrelerinin yapay zekâ yöntemleri ile değerlendirilmesi (Evaluation of water quality parameters by using artificial intelligence methods). Yayımlanmış Doktora Tezi. Tez no: 360613. 136 sayfa. https://tez.yok.gov.tr/UlusalTezMerkezi/giris.jsp.

Ay, M. & Kisi, O. (2012). Modeling of dissolved oxygen concentration using different neural network techniques in Foundation Creek, El Paso County, Colorado, USA. *Journal of Environmental Engineering*, 138(6), 654-662.

Ay, M. & Kisi, O. (2013a). Modeling dissolved oxygen concentration using neural network and ARMA techniques. 6th International Perpective on Water Resources & the Environment (IPWE-2013). January 07-09. İzmir, Turkey.

Ay, M. & Kisi, O. (2013b). Modelling COD concentration by using different artificial intelligence methods. *Journal of Selçuk University Natural and Applied Science,* Special Issue 2, 477-489, Avaiable at: http://www.josunas.org/login/index.php/josunas/article/view/181/147, JOSUNAS Online, ISSN: 2147-3781.

Ay, M. & Kisi, O. (2014). Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques. *Journal of Hydrology*, 511, 279-289.

Ay, M. & Kisi, O. (2017). Estimation of dissolved oxygen by using neural networks and neuro fuzzy computing techniques. *KSCE Journal of Civil Engineering*, 21(5), 1631-1639.

Ay, M. & Kişi, Ö. (2011). Sulama suyu kalitesini etkileyen $Na^{+}, \left(Ca^{++} + Mg^{++}\right), HCO_3^{-}$, Cl^{-} ve değişkenleri ile tuz konsantrasyonunun modellenmesi. *II. Ulusal Toprak ve Su Kaynakları Kongresi*, Cilt I, Sayfa: 98-105, 22-26 Kasım, Ankara, Türkiye.

Brady, J.E. & Holum, J.R. (1988). *Fundamentals of Chemistry*, ISBN: 978-0471844730, 3rd Edition, 1055pp.

Chang, F.J., Chung, C.H., Chen, P.A., Liu, C.W., Coynel, A., Vachaud, G. (2014). Assessment of arsenic concentration in stream water using neuro fuzzy networks with factor analysis. *Science of the Total Environment*, 494-495, 202-210.

Chapra, S.C. (2008). *Surface Water-Quality Modelling*, 844p. Waveland Pr Inc, ISBN: 978-1577666059.

Chau, K.W. (2006). A review on integration of artificial intelligence into water quality modelling. *Marine Pollution Bulletin*, 52, 726-733.

Cherkassy, V., Krasnopolsky, V., Solomatine, D., Valdes, J. (2006). Computational intelligence in earth sciences and environmental applications: Issue and challenges. *Neural Networks*, 19, 113-121.

Chithra, N.R. & Thampi, S.G. (2016). Downscaling future projections of monthly precipitation in a catchment with varying physiography. *ISH Journal of Hydraulic Engineering*. http://dx.doi.org/10.1080/09715010.2016.1264895.

Cibin, R., Athira, P., Sudheer, K.P. Chaubey, I. (2014). Application of distributed hydrological models for predictions in ungauged basins: a method to quantify predictive uncertainty. *Hydrological Processes*, 28(4), 2033-2045.

Cigizoglu, H.K. (2003). Estimation, forecasting and extrapolation of river flows by artificial neural networks. *Hydrological Sciences Journal*, 48(3), 363-379.

Darras, T., Estupina, V.B., Kong-A-Siou, L., Vayssade, B., Johannet, A., Pistre S. (2015). Identification of spatial and temporal contributions of rainfalls to flash floods using neural network modelling: case study on the Lez basin (southern France). *Hydrology and Earth System Sciences*, 19, 4397-4410.

Demirci, M. & Baltaci, A. (2013). Prediction of suspended sediment in river using fuzzy logic and multilinear regression approaches. *Neural Computing Applications*, 23, 145-151.

Demirci, M., Üneş, F., Saydemir, S. (2015). *Suspended sediment estimation using an artificial intelligence approach. In: Sediment matters.* Eds. P. Heininger, J. Cullmann. Springer International Publishing p. 83-95.

Droppo, I.G., Krishnappan, B.G. (2016). Modeling of hydrophobic cohesive sediment transport in the Ells River Alberta, Canada. *Journal of Soils and Sediments*, 16(12), 2753-2765.

Goyal, M.K., Bharti, B., Quilty, J., Adamowskic, J., Pandey, A. (2014). Modeling of daily pan evaporation in subtropical climates using ANN, LS-SVR, Fuzzy Logic, and ANFIS. *Expert Systems with Applications*, 41(11), 5267-5276.

Güçlü, Y.S., Subyani, A.M. & Şen, Z. (2017). Regional fuzzy chain model for evapotranspiration estimation. *Journal of Hydrology,* 544, 233-241.

Güner, H.A.A. & Yumuk, H.A. (2014). Application of a fuzzy inference system for the prediction of longshore sediment transport. *Applied Ocean Research,* 48, 162-175.

Hao, A. & Singh, V.P. (2016). Review of dependence modeling in hydrology and water resources. *Progress in Physical Geography*, 40(4), 549-578.

Harmancioglu, N.B., Fıstıkoglu, O., Ozkul, S.D., Signh, V.P. & Alpaslan, M.N. (1999). *Water Quality Monitoring Network Design*. Dohrecht, the Netherlands.

Haykin, S. (1998). *Neural Networks- A Comprehensive Foundation (2nd. ed.),* Prentice-Hall, Upper Saddle River, NJ.

Hipni, A., El-shafie, A., Najah, A., Karim, O. A., Hussain, A. & Mukhlisin, M. (2013). Daily forecasting of dam water levels: comparing a support vector machine (SVM) model with adaptive neuro fuzzy inference system. *Water Resources Management*, 27 (10), 3803-3823.

Huang, W., Xu, B. & Hilton, A.C. (2004). Forecasting flows in Apalachicola River using neural networks. *Hydrologic Process*, 18(13), 2545-2564.

Karimi, S., Kisi, O., Kim, S., Nazemi, A.H. & Shiri, J. (2016). Modelling daily reference evapotranspiration in humid locations of South Korea using local and cross-station data management scenarios. *International Journal of Climatology*.

Khan U.T. & Valeo, C. (2015). Dissolved oxygen prediction using a possibility-theory based fuzzy neural network. *Hydrology and Earth System Sciences Discuss*, 12, 12311–12376.

Kisi, O. & Ay, M. (2013). Modeling dissolved oxygen concentration using soft computing techniques. 6th International Perpective on Water Resources & the Environment. January 07-09. İzmir, Turkey.

Kuo, J.T., Hsieh, M.H., Lung, W.S. & She N. (2007). Using artificial neural network for reservoir eutrophication prediction. *Ecological Modelling*, 200, 171-177.

Li, B., Yang, G., Wan, R., Dai, X. & Zhang, Y. (2016). Comparison of random forests and other statistical methods for the prediction of lake water level: a case study of the Poyang Lake in China. *Hydrology Research*, in press.

Lin, G.F. & Chen, L.H. (2004). A non-linear rainfall-runoff model using radial basis function network. *Journal of Hydrology*, 289, 1-8.

Londhe, S., Dixit, P., Shah, S. & Narkhede, S. (2015). Infilling of missing daily rainfall records using artificial neural network, *ISH Journal of Hydraulic Engineering*, 21(3), 255-264.

Maier, H. & Dandy, G. (2000). Neural networks for the prediction and forecasting of water sources variables: a review of a modeling issues and applications. *Environmental Modeling&Software*, 15, 101-124.

Maier, H.R. & Dandy, G.C. (1996). The use of artificial neural network for the prediction of water quality parameters. *Water Resources,* 32(4), 1013-1022.

Maier, H.R., Jain, A., Dandy, G.C. & Sudheer, K.P. (2010). Methods used for development of neural Networks for the prediction of water resource variables in river systems: Current status and future directions. *Environmental Modelling & Software,* 25, 891-909.

Marquardt, D.W. (1963). An algorithm for least squares estimation of non-linear parameters, *Journal of Society Industrial and Applied Mathematics,* 11, 431-441.

Marsili-Libelli, S. (2004). Fuzzy prediction of the algal blooms in the Orbetello lagoon. *Environmental Modelling and Software,* 19 (9), 799-808.

Mi, X., Sivakumar, M. & Hagare, D. (2004). *A general review of applications of artificial neural network to water industry*. In M. Mowlaei, A. Rose&J. Lamborn (Eds.), Environmental Sustainability through Multidisciplinary Integration (pp.234-243). Australia: Environmental Engineering Research Event.

Moatar, F., Fessant, F. & Poirel, A. (1999). pH modelling by neural Networks. Application of control and validation data series in the Middle Loire River. *Ecological Modelling,* 120, 141-156.

Nourani V., Baghana, A.H., Adamowski, J. & Kisi, O. (2014). Applications of hybrid wavelet–Artificial Intelligence models in hydrology: A review. *Journal of Hydrology*, 514, 358-377.

Nourani, V., Baghanam, A.H. & Gebremichael, M. (2012). Investigating the Ability of Artificial Neural Network (ANN) Models to Estimate Missing Rain-gauge Data. *Journal of Environmental Informatics*, 19(1), 38-50.

Oke, S.A. (2008). A Literature Review on Artificial Intelligence. *International Journal of Information and Management Sciences,* 19(4), 535-570.

Scardi, M. (2001). Advances in neural network modelling of phytoplankton primary production. *Ecological Modelling,* 146, 33-45.

Şen, Z., Harmancıoğlu, N., Şorman, Ü. & Bulu, A. (2002). Hidrolojide Veri, İşlem, Yorumlama ve Tasarım Seminer Notları, DSİ Küçük Çamlıca Tesisleri, Su Vakfı Yayınları, 193pp., Editor: Zekai Şen.

Takagi, T. & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics,* 15, 116-32.

Talebi, A., Mahjoobi, J., Dastorani, M.T. & Moosavi, V. (2016). Estimation of suspended sediment load using regression trees and model trees approaches (Case study: Hyderabad drainage basin in Iran).

Talei, A., Chua, L.H.C., Quek, C., Jansson, P.-E. (2013). Runoff forecasting using a Takagi–Sugeno neuro-fuzzy model with online learning. *Journal of Hydrology*, 488, 17-32.

Tayfur, G. (2011). Soft Computing in Water Resources Engineering: Artificial Neural Networks, *Fuzzy Logic and Genetic Algorithms*, WIT Press.

Tayfur, G. (2017). Modern Optimization Methods in Water Resources Planning, Engineering and Management. *Water Resource Management*.

Üneş, F., Demirci, M., Kişi, Ö. (2015). Prediction of millers ferry dam reservoir level in USA using artificial neural network. *Periodica Polytechnica Civil Engineering*, 59(3), 309-318.

Ward, R.C. (2007). Water quality monitoring: Where's the beef?". *Water Resource Bulletin*, 32(4), 673-680.

Waseem, M., Ajmal, M., & Kim, T.W. (2015). Ensemble hydrological prediction of streamflow percentile at ungauged basins in Pakistan. *Journal of Hydrology*, 525, 130-137.

Wilson, H. & Recknagel, F. (2001). Towards a generic artificial neural network model for dynamic predictions of algal abundance in freshwater lakes. *Ecological Modelling*, 147, 69-84.

Yan, H., Zou, Z. & Wang, H. (2010). Adaptive neuro fuzzy inference system for classification of water quality status. *Journal Environmental Sciences*, 22(12), 1891-1896.

Yaseen, Z.M., El-shafie, A., Jaafar, O., Afan, H.A. & Sayl, K.N. (2015). Artificial intelligence based models for stream-flow forecasting: 2000-2015 (Review Paper). *Journal of Hydrology*, 530, 829-844.

Zadeh, L.A. (1965). Fuzzy Sets. *Information and Control*, 8(3), 338-353.