# Neural Network Approximation of a Hydrodynamic Model in Optimizing Reservoir Operation

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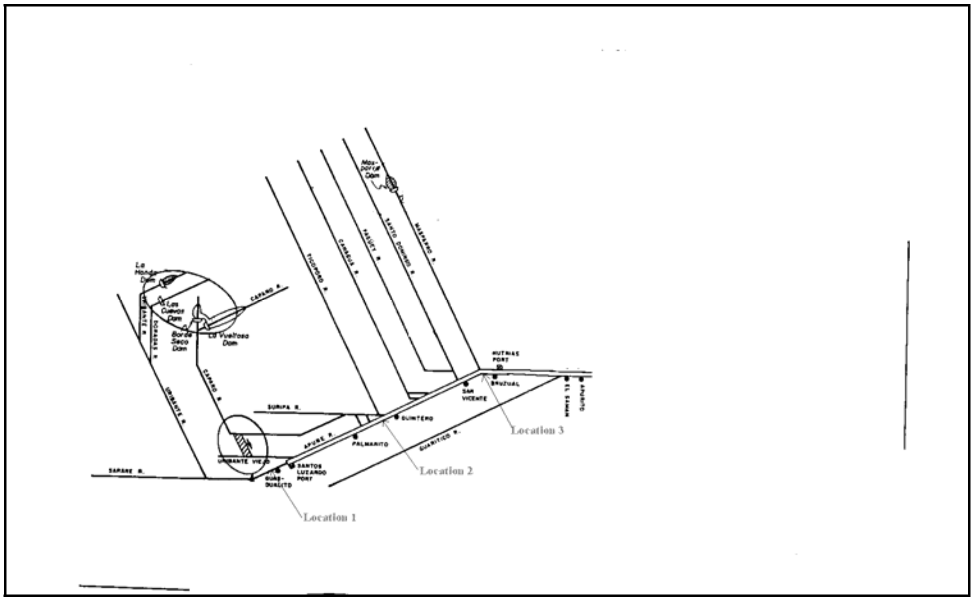
**Presented at the *International Conference on Hydroinformatics. Zьrich, September 1996.***

ABSTRACT: An approach of models approximation, applicable in the model-based optimization of water resources, is described. It was applied to the optimization of a system of the three reservoirs located in the Apure river basin in Venezuela. Its development plan requires to increase the period when the river is navigable along the certain reach. The problem was posed as a multi-criterial decision making (MCDM) problem for which a set of quasi-optimal policies may be found by solving a series of dynamic programming problems with the energy criterion and the navigability constraint. The hydrodynamics and hydrology of the basin was modelled using MIKE-11 modelling package. In order to run it in the optimization loop, the model of the basin was approximated using artificial neural network generator NNN. Such compact and fast representation of the hydrodynamic/hydrologic model, albeit approximate, easily allowed to include the modelling component into the optimization routines. The presented approach to model approximation may be used in various schemes of water resources optimization.

## 1. INTRODUCTION

The present paper describes the way of approximating hydrodynamic and hydrologic models of a river system, with the aim to simplify the optimization of water resources. The approach was applied to the optimization of a system of the three reservoirs located in the Apure river basin, the largest tributary of Orinoco




(Venezuela). The schematization of the river system is presented on Fig. 1. In this basin, one reservoir (*La Honda*) is in operation, one (*Las Cuevas*) is scheduled, and one (*La Vueltosa*) is under construction. In the near future, three reservoirs will be in joint operation, and this is the scenario that was considered.

The multireservoir system located in the Apure River basin was initially developed exclusively for energy production. Currently, the national development plan is aiming at developing this region, and it has been decided to increase the period when the river is navigable along the reach from Orinoco mouth through Bruzual to Guasdualito.

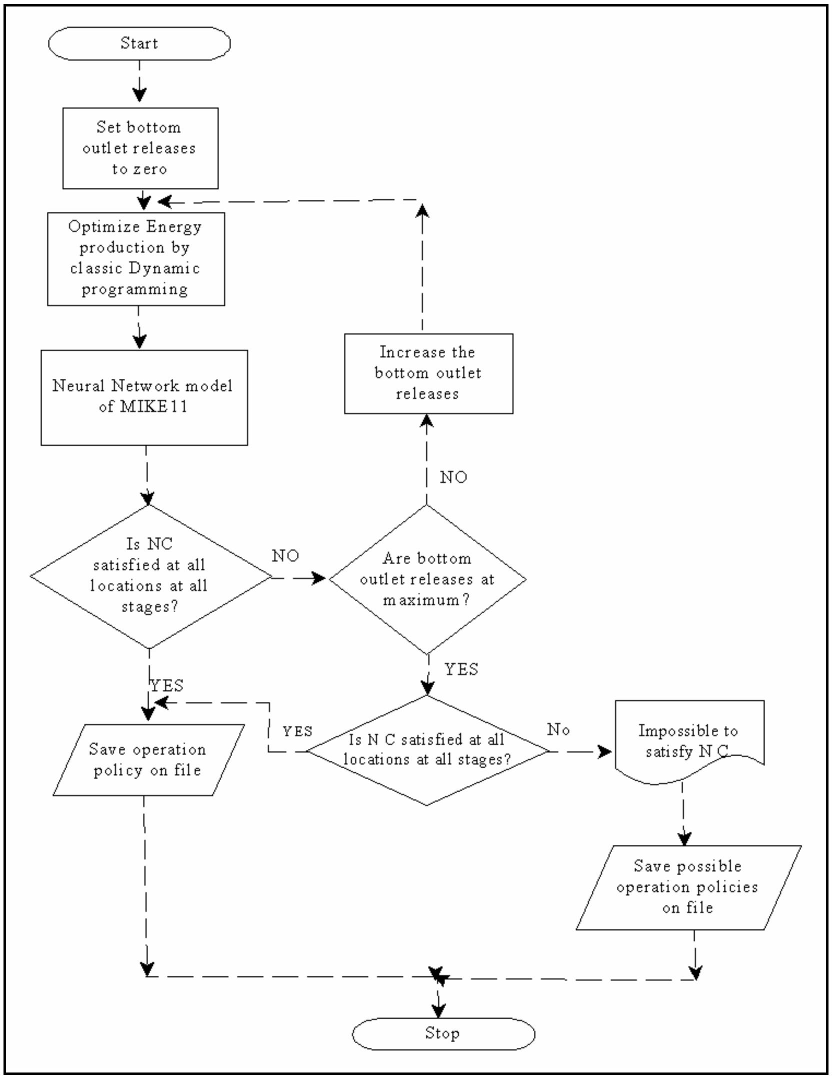
The particular part of the river reach between Bruzual and Guasdualito is the one where navigability is problematic - between locations 1 and 3 on Fig.1. This river reach is 238.88 km long and is currently navigable only 4 months a year. The intention is to investigate the possibilities of making it navigable for up to 7 months a year, by changing the reservoir operation policies so that water is stored in reservoirs during the wet season, and released during the dry season. At the same time, the energy production must be at the high level as well.

## 2. POSING THE OPTIMIZATION PROBLEM

The problem of reservoir optimization is covered extensively in various sources (e.g., one of the latest is Ponnambalam and Adams 1996). In the present paper we do not attempt to provide full analysis of the problem, but rather to show techniques that can be applied in various optimization algorithms of a wide range.

The presented problem is a problem of multi-criterial decision making (MCDM): find the reservoirs' operation policies providing for the high values of the two conflicting criteria: (1) follow the energy production target as close as possible; (2) maximize the period of time when the river is navigable.

Among the various approaches to the multi-criterial problems, the following was chosen: one criterion is considered a "soft" constraint (navigability), and the problem is solved a number of times as a single-criterion problem with respect to the energy criterion. This allows to generate a set of possible alternative operating policies from which the decision maker could then make a choice.




In general formulation, the control variables vector consists of the water releases (*WR*) from the three reservoirs for the specified moments of time (daily, weekly, etc.), which will be called an *operation policy*. The releases are of two types: releases through turbines, or *energy releases (ER)*, and the *bottom outlet releases (BOR)*, or *non-energy releases*, which do not contribute to the energy production.

$$\sum_{i=1}^{N} w_i \sum_{t=1}^{T} POS\,(\ PTAR_t^{(i)} - PGEN_t^{(i)}(WR))\ )^2 \rightarrow \min$$

The single-criterion problem is posed as a dynamic programming problem (DPP) as follows:
where $w_i$ = weighting coefficient of reservoir *i*; *N* = number of reservoirs; $PGEN_t^{(i)}(WR)$ = generated power at time moment *t* at the reservoir *i*; $PTAR_t^{(i)}$ = power target at time moment *t* at the reservoir *i*; reservoir number *i* = 1,2,3; *POS(x)* is 0 for negative *x*, and is *x* for positive *x*), subject to the following constraints (expressed here verbally):

- period of time when water levels $WL_j$ *(WR)*,at the three specified locations *j*=1,2,3 (see Fig.1) are above *h* metres (*h*=1.6...2.0), is longer than *m* months (*m*=5...7) (navigability constraint);
- state transformation constraints linking the reservoir storages at the consecutive time moments;
- upper and lower reservoir storage constraints;
- constraints for minimal reservoir releases *WR* due to the demands for drinking, industrial water, ecological releases, etc.;

Operation policy (water releases *WR*) influences the main criterion (generated power *PGEN(WR)*), as well as the constraints. The most important influence is incorporated in the dependency $WL_j$ *(WR)*, (*j*=1,2,3) of water levels downstream on water releases from the reservoirs; this dependency is modelled by the MIKE-11/NAM modelling system. In order to check the navigability constraint, it is necessary to know the relation between the releases upstream and the water levels downstream - such dependency is provided by the model considered below.

Among various possible ways to approach the full MCDM problem, due to lack of time allocated for the current stage of this research, a simplified approach allowing to obtain a quasi-optimal solution was chosen. The DPP optimization problem (with the energy criterion, over 1 year time horizon) is solved $N$ times with only the energy releases ER as control variables. At first, the solution is found for the case of the zero BOR (bottom outlet, non-energy releases). With every new run of DPP, BOR are subsequently increased in certain time points in such a way, that the water levels along the river reach are pushed up until they are above the level minimally required for navigability.

After every optimization run the data on the two original criteria - (1) deviation in energy production and (2) water levels along the river reach - are stored to file. After that the two-criterial decision problem has to be solved to obtain the overall reservoirs operation policy. One of the considered schemes of obtaining a quasi-optimal solution is presented on Fig.2 (see Solomatine and Tan 1995 as well).

## 3. HYDRODYNAMIC AND HYDROLOGIC MODELLING

In order to model the river basin under study, a MIKE-11 modelling system was used. It includes, among others, the 1-D hydrodynamic module (HD), and the hydrologic rainfall-runoff module (NAM).

### *3.1. Rainfall-runoff modelling*

NAM is a general purpose lumped conceptual modelling tool for simulating rainfall-runoff processes in rural catchments. It accounts for the moisture content in the four different and mutually interrelated storages which represent physical elements of the catchment. In out case study 21 subcatchments of the Apure river basin were selected for the simulation of one year of hydrological data.

The four storages in the model where water is stored are: snow storage (optional), surface storage, lower zone storage and ground water storage. The storages are connected by the equations that simulate the land phase hydrological cycle.

### *3.2. Hydrodynamic modelling*

The hydrodynamic module (HD) is the core of MIKE-11, and forms the basis for other modules, like flood forecasting, advection-dispersion, water quality and non-cohesive transport modules. An implicit finite-difference 6-point Abbott-Ionescu scheme for solving the De Saint-Venant's equations is implemented. HD module receives the runoff hydrographs from NAM module and treats them as boundary conditions for computation of water levels and discharges along the river system. Bed resistances can be described by the Chezy or Manning coefficients.

Main input for the HD component was the following:

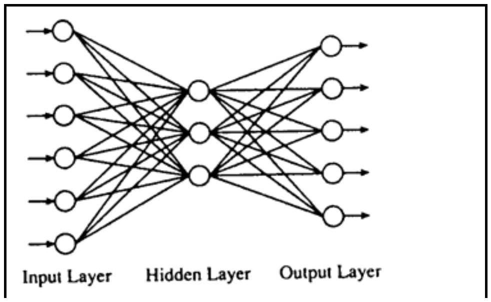
- 15 river cross-sections and bed roughnesses;
- upstream boundary conditions of 'Q type': discharges from each reservoir, and the runoffs from subcatchments supplied by the NAM module;
- downstream boundary condition of 'Q-h type': a rating curve at Bruzual downstream.

For the study of the Apure river basin, not all data necessary for the comprehensive modelling was present, partly because the parameters of the reservoirs under construction are not yet fully known. That is why some data has been artificially generated (several cross-sections, some portions of rainfall and evaporation data, discharges from the reservoirs, area-volume curves of the reservoirs). The MIKE-11 models were calibrated by trial-and-error calibration, due to the certain properties of this package excluding the possibility of the automatic calibration (on automatic calibration of hydrologic models, see Solomatine 1995).

## 4. NEURAL NETWORK APPROXIMATION OF HYDRODYNAMIC/HYDROLOGIC MODEL

In order to include MIKE-11 into an optimization loop, it has been decided not to do it directly but to construct a simplified model of MIKE-11 model, and to use this latter. There were two reasons for that:

- the user communicates with MIKE-11 through the sequence of menus and it is impossible to run only computational modules in an unattended manner, for example activating them from another program;



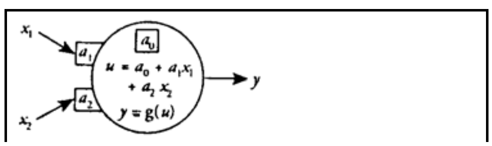

- time of just one HD component run was quite considerable, so the total running time of the full optimization could have been prohibitively long for experiments with it.

In more detail, the architectural aspects of modelling systems are considered by Solomatine 1996a, 1996b. In order to approximate MIKE-11 model (HD and NAM) of the river basin, it was found reasonable to use an artificial neural network (ANN) (see Smith 1993, Zurada 1992). PC-based ANN packages that were available at the time of this study did not allow to generate C or Pascal code representing ANN that could have been compiled into an executable module, so a neural network tool NNN was built. NNN implements a feed forward backpropagation ANN with the steepest descent error minimization, with one hidden layer. ANN is represented on Fig. 3. Inputs to the ANN are distributed between hidden nodes (Fig.4) which transform them into output signals which are sent to all output nodes (Fig.5); which, in turn, are transform them into outputs. Inputs to the

$$x_i\,,\quad i = 1\,,\dots,N_{inp}$$

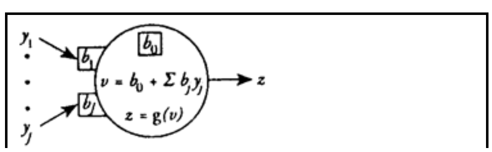
network are:

$$y_j = g\Big(\, a_{0\,j} + \sum_{i=1}^{N_{inp}} a_{i\,j}\, x_i \,\Big)\ ,\quad j = 1,\dots,N_{hid}$$




Outputs of the hidden layer of nodes are:

$$z_k = g\Big(\, b_{0\,k} + \sum_{j=1}^{N_{hid}} b_{j\,k}\, y_j \,\Big)\ ,\quad k = 1,\dots,N_{out}$$




Outputs of the output nodes are:

$$g\,(u) = \frac{1}{1 + e^{-u}}$$

The transfer function $g$ bound between 0 and +1 is

$$(\,N_{inp} + 1)\,N_{hid} + (\,N_{hid} + 1)\,N_{out}$$

In total, there are
parameters (weights $a$ and $b$) to be identified; this is achieved by the so-called *training*, or *calibration* of ANN in such a way that the error in reproducing reality (observed data, or in our case, the MIKE-11 outputs) is minimal.

If observed output is $OBS_i$ and ANN model's output is $MOD_i$ then the mean squared error is

$$E = \frac{1}{Nexamp} \sum_{1}^{Nexamp} ( OBS_i - \mathrm{MOD}_i )^2$$

In order to find the minimum value of E, it is necessary to solve an optimization problem: *find such values of weights a and b that bring E to minimum*

Since function E is known analytically, and it is differentiable, it is possible to use gradient-based methods like steepest descent (Smith 1993), or more efficient conjugate gradients method..

There was a number of experiments using NNN conducted, with the training sets of daily and weekly data, time spans ranging from 1 to 5 years, number of inputs ranging from 25 to 29, number of hidden neurons from 5 to 20, and the number of outputs - from 1 to 3. The limits of this paper do not allow to present all results; Fig. 3 shows the results of ANN training by feeding it with the computed weekly water levels for years 1981-82. Inputs (25 in total) were constituted of runoffs from 21 subcatchments, 3 releases from the reservoirs and the water level at the previous time step. The only ANN output is water level at the certain location. Instead of having one ANN with 3 outputs for the three locations it was found that to have 3 ANNs for each location brings better results.

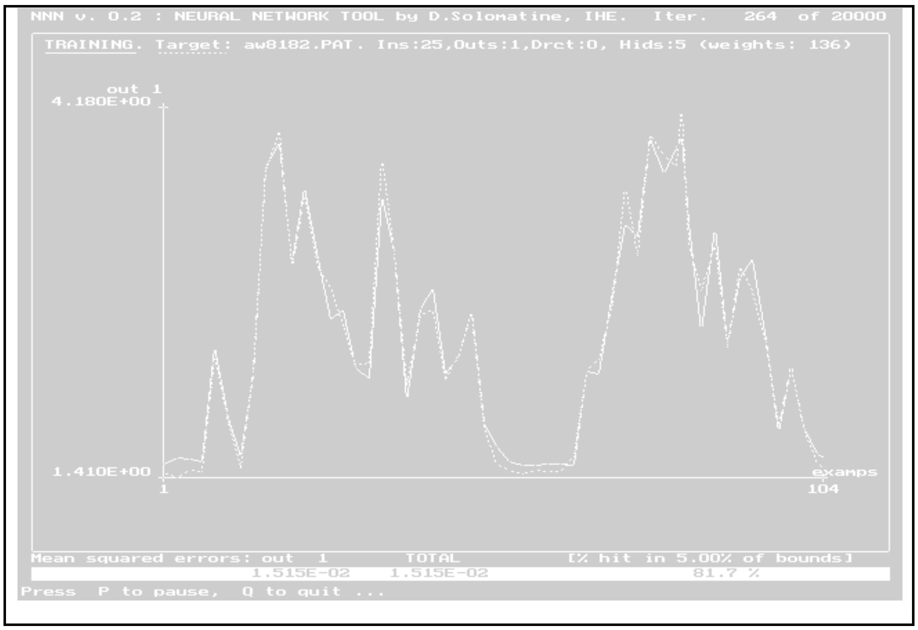
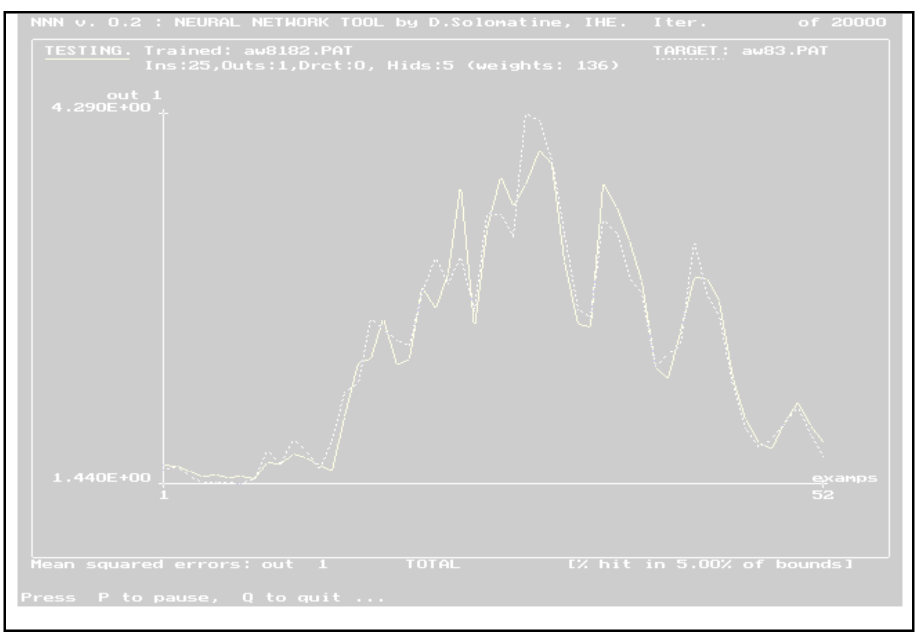
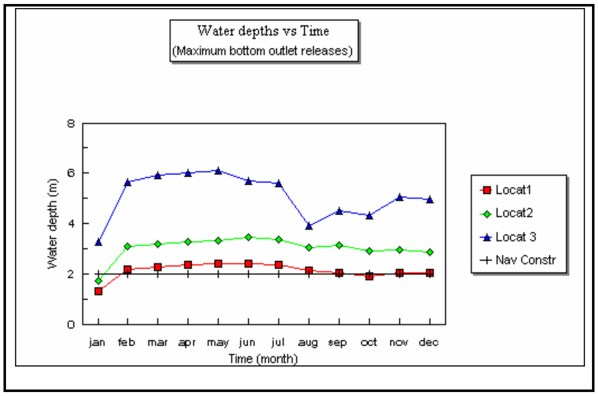



Fig.4 presents the output of the ANN (trained on 1981-82 data) fed by the 1983 input data, which is compared to the actual water levels for 1983 given by MIKE-11. This demonstrates the predicting capabilities of ANN.

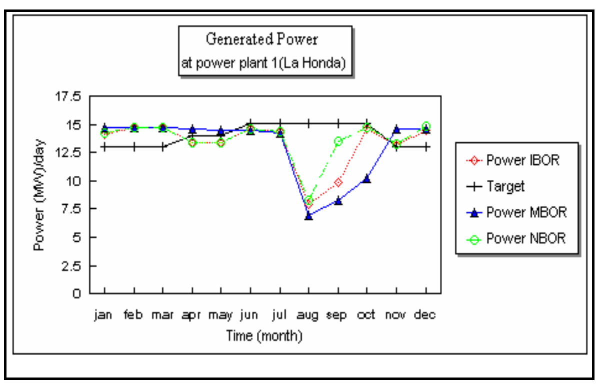


After ANN was trained, the NNN tool generated Pascal code which was then compiled, resulting in the small executable module of 12 Kbytes in size. This module was then included in the optimization loop instead of MIKE-11 system.

## 5. RESULTS OF OPTIMIZATION

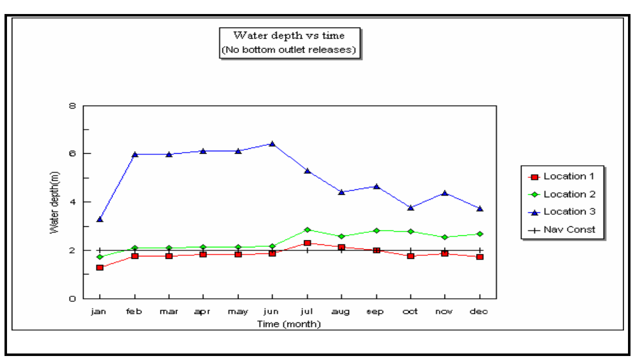



Having the MIKE-11 approximation in the form of an executable generated through the use of NNN neural network tool, it became possible to solve the optimization problem in limited time, and to experiment with the various algorithmic optimization schemes. One of the schemes investigated used was presented on Fig.2. The water depths with no bottom outlet releases (BOR), and with maximum BOR preliminary results are shown on Fig. 8 and 9 respectively. The changes in the generated power and the target curve are shown on Fig.10.




It must be mentioned that because of lack of time and lack of certain data sets, the full optimization was not fully completed. The planned experiments will involve:

- formulation and solving the DPP incorporating the full vector of unknowns *WL*, and possibly using stochastic optimization;
- implementation of the MCDM procedures for choosing alternative policies.



## 6. CONCLUSION

The present paper demonstrates the preliminary results of a multi-model approach to reservoir optimization. In it, the hydrodynamic/hydrologic model (based on HD and NAM components of MIKE-11 modelling system) is placed into an optimization loop, and alternative operation policies are generated by solving a dynamic programming optimization problem a number of times. In order to make experimenting with the optimization codes easier, and to allow running the MIKE-11 model inside the loop, the model was approximated by the artificial neural network, and the corresponding compact and fast code was generated. Such an approach allowed to experiment with various optimization schemes, and may be used in a wide range of water resources optimization problems.

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