Methodological Approaches to Building the Scenarios of Inflows into Reservoirs When Modeling Long-Term Regimes of Hydroelectric Power Plants

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1 Introduction

In energy and water management systems, the planning (regulation) of reservoir operation is usually limited to a period of 1–3 months. Such a planning horizon for the hydroelectric power plant is associated with the extreme complexity of long-term forecasting of water inflows into reservoirs and low reliability of forecasts even for an indicated period. Currently, the Hydrometeorological Center of Russia gives a probable (interval) inflow forecast for the coming month—at the end of the previous month and for 3 months—once a quarter. There are no forecasts for a more distant period. However, planning and forecasting in the electric power industry are made for the time horizon of up to one year or more. This is due to the need to plan long-term operating conditions and forecast the balance of electricity and capacity in the power system. This issue is especially relevant for power systems with a large share of hydroelectric power plants. Such power systems include the interconnected power system of Siberia, in which hydroelectric power plants account for about 50% of the total electricity generation.

The main feature of energy systems with a high share of hydroelectric power plants is the considerable dependence of electricity generation on a natural factor, i.e., natural fluctuations in water inflows into reservoirs. For example, the deviation in the power output of the Angara–Yenisei HPPs cascade from the long-term average values can reach up to 30% in some water years [1, 2]. This circumstance highly complicates the planning of electricity and heat output at thermal power plants

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(TPPs), the creation of fuel reserves, the planning of repairs of power equipment and electrical networks, and the solving of other problems. In addition, when regulating the regimes of HPPs many water management restrictions and environmental conditions are often required, for example, level regime regulation in Lake Baikal, which is the reservoir of the first stage of the Angara cascade (Irkutsk HPP) [3, 4].

In the absence of forecast indices of water inflows into reservoirs for more than three months, the long-term planning of operation and prospective energy balances, as a rule, relies on past period statistical data in the form of average long-term and monthly average indices. Such planning and forecasting provide acceptable results under normal conditions (close to the long-term average) but are not appropriate in other contexts, especially during extreme water periods [5–7].

Recent years have seen significant changes in global and regional climate and changes in the previously established trends, which makes it ineffective to use the average long-term and monthly average indices for forecasting [8–12]. It is therefore advisable to use new approaches to plan the long-term energy balances and operating conditions of power plants. In particular, one can use prognostic scenarios of water inflows into reservoirs for a period of up to 1 year and more, based on the data from global climate models and multivariate neural networks.

2 Materials and Methods

2.1 Global Climatic Models

Over the past two decades, significant progress has been made in the creation and use of global climate models for long-term forecasting of natural processes. They can also be used to make long-term assessments of water inflows into reservoirs for one year. One of the best-known models is the global climate model CFSv2 (Climate Forecast System version 2), developed by the international organization NCEP (National Centers for Environmental Prediction) [13–16]. This model is employed daily to update the prognostic ensembles of the state of the atmosphere and the ocean with a time interval from several hours to 9 months for the entire globe. The ensemble forecasting method used in global climate models allows making probabilistic estimates of the atmospheric state in the long term.

To increase the reliability of long-term projected estimates of water conditions and temperatures under current conditions, the Energy Systems Institute SB RAS has developed a long-term forecasting system GeoGIPSAR, which is used in energy and water management studies [17, 18]. The system includes various methods designed to analyze spatially distributed climatic data (Reanalyses, GPCC), which can serve as a basis for quickly calculating long-term estimates of precipitation, temperature, pressure, geopotential, and other indices on the territory of the river basins, and for periodically updating them (in a week, a decade, a month, a quarter, a season). To refine the prognostic estimates, one can also use the data from meteorological and gauging stations, various geo- and heliographic indices, such as solar activity, lunar cycles, and others.

The estimates of the indices of individual predictive ensembles obtained from different sources can vary within wide limits, which complicates their direct use in practice. The method developed in the GeoGIPSAR system for processing a set of individual forecast ensembles makes it possible to form, through their aggregation (with different weights), the most probable spatial distributions of meteo-hydrological indices for given periods. For example, we can create climatic maps of absolute and relative indices for each month that show the boundaries of river catchment areas. For specific points and individual territories, there are tools developed to process the data on dynamics of changes in studied indices. The data obtained from the ensemble projections based on the global climate model and monitoring the data from global centers are used to determine the most probable characteristics of meteorological indices in the region under consideration and build the scenarios of inflows into the reservoirs of hydroelectric power plants in the form of ranges of probability distributions.

Figure 1 shows a schematic diagram of building long-term scenarios of water inflows into reservoirs of hydroelectric power plants and temperature conditions. Scenarios are based on the synthesis of two approaches (1) based on the projected estimates obtained by approximate and probabilistic methods, including neural network; (2) based on prognostic maps of meteo-hydrological indices, created through the processing of individual sets of prognostic ensembles, for example, averaged statistical indices over a selected time interval.

By regularly monitoring the ensembles of predictive data on the state of the atmosphere, converting, accumulating, and subsequently processing them, we create the most probable maps of the distribution of a selected index (surface temperatures,

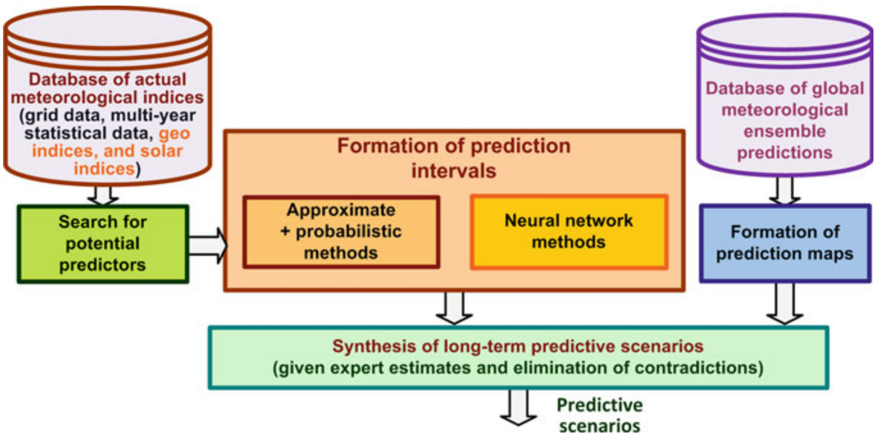

Fig. 1 Scheme of building long-term prognostic scenarios of water inflows into reservoirs of hydroelectric power plants and temperature conditions

precipitation rates, pressure, geopotential, etc.) with the assignment of various weight coefficients of their significance.

2.2 Multivariate Neural Network

In the GeoGIPSAR system, there is a multivariate neural network developed, first of all, to make the interval estimates of the index under study, for example, the net inflow of water into reservoirs for individual months or the temperature for specific points or a selected region. The use of the interval estimation method is associated with the inaccuracy of measurements of the actual inflow indices.

Figure 2 shows a neural network with an input layer (x_i), output layer (y_s), and with two hidden layers. The neurons of each layer include signal adders with different weighting coefficients ($w_{i,j}^{m;n}$) and sigmoid functions ($\varphi_x^m(p)$) with varied parameter p. The coefficients are determined by the back-propagation method. For interval estimates according to a given algorithm, the interval of admissible values of the studied process is divided into k intervals. Then, instead of the value of the time series index, the number of the interval to which this value belongs is substituted.

Figure 3 shows a methodology for building interval projected estimates of the process under study. A set of potential predictors (Ω) affecting the projected estimates is determined from the global GeoGIPSAR database. Sets of internal parameters (Λ) and predictors are determined through the block for minimizing the error of deviations in prognostic and actual indices for a given verification sample. It is worth noting that once any parameter has changed complete training and verification cycle is performed.

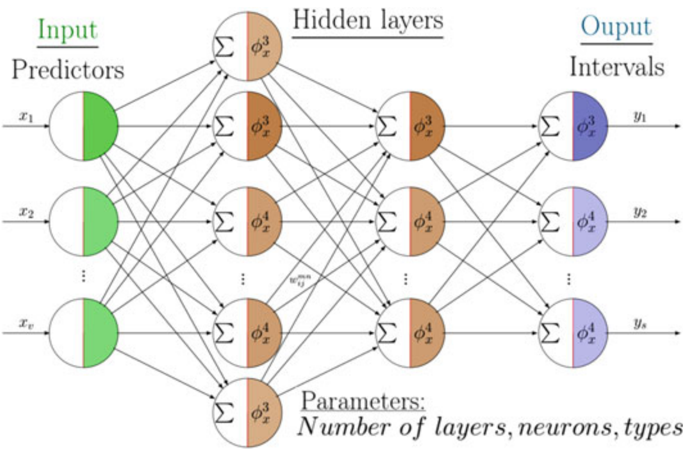

Fig. 2 An example of a core of a 2-layer multivariate neural network

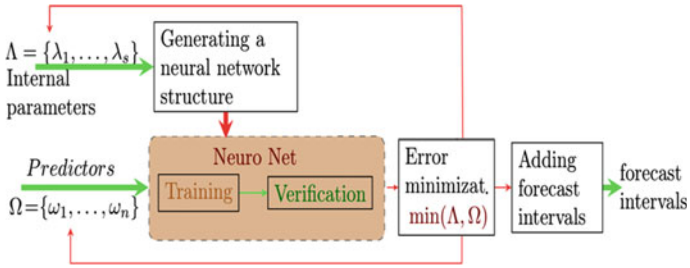

Fig. 3 Methodology for calculating interval projected estimates

Since the verification usually generates a significantly larger error compared to the training sample, the parameters of a multivariate neural network (MNN) are selected to satisfy the criterion of minimum verification error (for example, a deviation of no more than one interval from actual indices), and are then recorded in special storage. The developed MNN with the interval estimate method allows large-scale studies for various indices: water inflows into reservoirs of hydroelectric power plants, temperature conditions, and other stochastic natural processes.

3 Results and Discussion

A methodological approach that employs the data of global climate models and multivariate neural networks was used to build predictive scenarios of water inflows into Lake Baikal and reservoirs of the Angara–Yenisei cascade HPPs for the period from January 2021 to April 2022.

As an example, Fig. 4 shows the distributions of average temperatures in July and average daily deviations of precipitation rates in the catchment basins of Lake Baikal and the reservoirs of the Angara–Yenisei cascade HPPs in months 6–9 of 2021.

Temperature conditions are expected to be close to normal, while the increased precipitation is likely in the basin of the Selenga River, especially in its eastern tributaries (the Chikoi, Khilok, and Uda). Naturally, these are probabilistic indices as of the beginning of February 2021. In the case of significant disturbances (changes) in the atmosphere, the prognostic indices may also change, given the processing of new ensembles of the global CFSv2 model. The generated most probable predictive distributions of meteorological indices are used to determine the closest analogous years based on which (according to the available statistics of inflows) the predictive scenarios are synthesized for the future of up to 2 years with a time resolution of a month or a decade. For the period of over nine months, only neural networks and approximate long-term forecasting methods are employed.

Generally, the most probable scenario for the period under consideration is an increased water level in the Baikal and Angara basins and an average and low water level in the Yenisei basin.

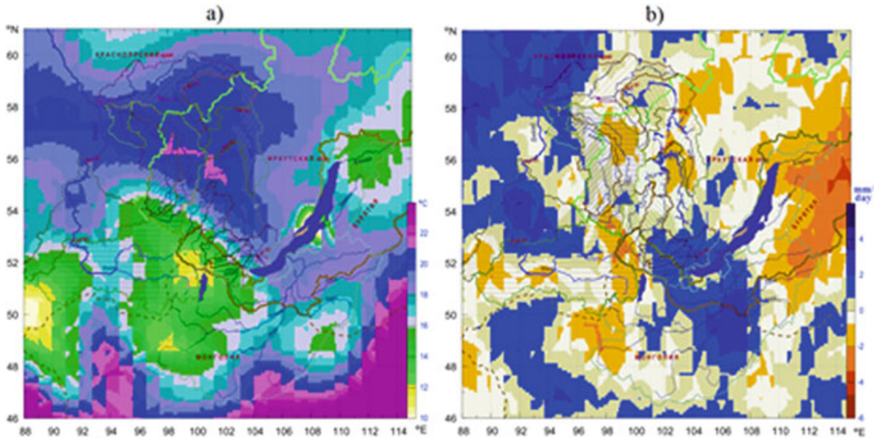

Fig. 4 An example of the distribution of predicted indices in the Lake Baikal, Angara River, and Yenisei River basins in the summer of 2021: **a** temperatures for July; **b** average daily precipitation rate deviations from the norm for months 6–9

Based on the predictive scenarios of water inflows into Lake Baikal and the reservoirs of the Angara–Yenisei cascade HPPs, and using the system of HPP control models developed by a research team of ESI SB RAS [19, 20], we obtained the estimates of projected electricity generation by individual hydroelectric power plants for the minimum, maximum and most probable inflow scenarios (Table 1).

The results of modeling the operation of the Angara–Yenisei cascade HPPs for 2021–2022 show that the electricity generation index can change significantly, depending on the inflow scenario. The range of fluctuations over the summer period can reach 11 200 million kWh, and in winter—9200 million kWh, which is comparable to the operation of one large HPP of the cascade. In the summer, there is also a risk of idle discharges in the Angara cascade under the maximum inflow scenario because the Bratsk reservoir is full, and there are large snow reserves accumulated in the basin during the winter. Therefore, planning the HPP operation should factor in the long-term most probable forecast scenarios of water availability.

4 Conclusion

A long-term forecasting system GeoGIPSAR was developed to increase the reliability of long-term projected estimates of water availability and temperatures to model long-term operating conditions of a cascade of HPPs. This system employs the data from various sources of information, including global climate models and multivariate neural networks. These tools help quickly obtain long-term estimates of precipitation, temperature, pressure, geopotential, and other indices on the territory

Table 1 Estimates of electricity generation by HPP of the Angara–Yenisei cascade (million kWh) for the minimum, maximum, and most probable inflow scenarios for the period from January 2021 to April 2022

HPP period	Irkutsk	Bratsk	Ust-Ilimsk	Boguchany	Sayano-Shushensk	Mainskaya	Krasnoyarsk	Angara–Yenisei cascade
January–April 2021	1402*	6695	6374	5297	6058	458	5463	31 745
	1479*	7079	6712	5578	6812	513	5644	33 814
	1428*	**6826**	**6504**	**5395**	**6556**	**494**	**5474**	**32 677**
Summer 2021 (May–October)	2134	11 572	10 707	9055	14 837	1033	11 955	61 292
	2261	13 922	12 662	10 615	17 991	1144	13 913	72 510
	2196	**12 953**	**11 847**	**9970**	**16 314**	**1094**	**12 692**	**67 065**
Winter 2021 (November–April 2022)	1983	11 791	10 853	9118	9412	695	8326	52 179
	2399	13 858	12 624	10 542	10 841	796	10 309	61 368
	2176	**12 758**	**11 681**	**9737**	**10 177**	**750**	**9870**	**57 149**
Total in 2021	4364	22 835	21 036	17 528	24 250	1725	20 303	112 039
	4613	26 161	23 837	19 764	28 176	1891	22 860	127 302
	4453	**24 582**	**22 505**	**18 694**	**26 229**	**1822**	**21 435**	**119 720**
Total over the period	5519	30 058	27 934	23 470	30 307	2186	25 744	145 216
	6139	34 859	31 998	26 735	35 644	2453	29 866	167 692
	5800	**32 537**	**30 032**	**25 102**	**33 047**	**2338**	**28 036**	**156 891**

*The first value in the column is calculated according to the minimum inflow scenario, the second—according to the maximum inflow, the third—according to the most probable inflow (highlighted in bold) of the considered basins, and refine them periodically (in a week, decade, month, quarter, season).

Processing the data of predictive ensembles obtained by global climate models, other data and forecasting methods, as well as a multivariate neural network, enables us to build the scenarios of average monthly net inflows and dynamics of changes in operating conditions. It also allows us to estimate the amount of electricity generation by individual HPPs and the Angara–Yenisei cascade as a whole for up to one year or more.

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