Introducing a New Long-Lead Hydrologic Forecasting System for Improving Reservoir Operation

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Abstract
Long-lead streamflow forecasting plays an important role in water resources planning and management. In this paper a new forecasting system named FARDA (Forecasting and Related Decision Analysis) is introduced. The results of the application of this system to two great river basins of Iran, namely Karkheh, and Karun are presented, briefly. Three data-driven models including K-Nearest Neighbor Regression (KNN), Artificial Neural Network (ANN), and monthly Rainfall-Runoff (R-R) models are performed within the system as individual forecasting models (IFMs). The fusion of all IFMs best outputs resulted from ordered series of model outputs is applied within the system to report the most reliable forecasts. All the forecasting models are presented in the model base of FARDA. Furthermore, the model base of the system consists of reservoir operation models which get benefit from the outputs of forecasting models to provide the best operating policies for the system of reservoirs. The inputs of those models are supported by the data base of the system which consists of different types of local and global hydro-climatological data as well as dams' data and information. This paper presents some characteristics of the system such as its conceptual model, the framework of its data and model base, and its specific graphical user interface. Some of the results of the application of the system in recent years is also presented.
Keywords: long-lead forecasting, model base, data base, graphical user interface, great Karun river basin, Karkheh river basin.

1. INTRODUCTION

One of the most important issues in long-term management of the surface reservoirs is the awareness of the amount of inflow to the reservoirs for better decision making. Decision making is one of the most significant challenges in the field of water resources and environmental engineering because of either the complexity around a problem or the un-predicted impacts of a decision. This challenge might be a result of multi-disciplinary problems, which may put some contrasting objectives in a competition that no compromising is allowed [1]. To overcome this challenge, new technologies have presented powerful tools to increase efficiency and accuracy of decisions and to accelerate the responses in facing with the real world problems. Decision Support Systems (DSSs) are one of the most efficient tools, with distinctive ability approval in the enormous engineering contexts. This paper presents a DSS namely FARDA which has been developed for long-lead streamflow forecasting, specifically.

A strategy for increasing the accuracy of long-lead forecasting results is to apply data-driven models such as Neural Networks (NN) [2,3], K-Nearest Neighbor regression (KNN) [4], and Support Vector Machines [5,6] which are able to recognize different relations between predictor and predicted variables for forecasting process. Nevertheless, each of those models contains estimation errors that are inevitable, and somehow lead to decline the accuracy of the forecasts.

In order to decrease the forecasting errors resulted from modeling, model fusion technique has been applied in a variety of fields for forecasting process such as cooling-load prediction [7], stock market forecasting [8,9], and wind power forecasting [10].

A forecasting model is developed to help solving a specific problem; however, in cases that we need to frequently face a generic forecasting problem and finding appropriate responses based on the current spatial and temporal state of a system, it is preferred to improve a model to a decision support system. Generally, the decision making procedure includes three main steps namely: data gathering, recognition of alternatives to solve a specific problem, and finally, selection of the best alternative. This procedure may be followed by two different approaches. In the first approach, well known mathematical formulation and decision rules are used algorithmically in different steps of solving a specific problem. Problems that are likely to be solved by this approach are usually called structured problems. These kinds of problems could be possibly solved manually by the use of computer softwares, where no human judgment is needed. In contrast, in some problems, usually called unstructured problems, no decision rules and algorithmic procedure are defined and are dependent considerably to the human judgment to be solved. Decision support systems could be called as the second approach have been developed to be used in solving the latter.

Bonczek et al. [11] has defined DSSs as computer systems including three interactive components of user interface, a knowledge system, and a problem-processing system. Technology developments have changed slightly the definition of such systems in both holistic and detailed manner. Watkins and McKinney [12] have defined a DSS as a computer system which uses analytical models to help decision makers in defining and organizing various alternatives, and analyzing their impacts to choice most appropriate alternatives. In a general definition, the architecture of DSS consists of three components namely data base, model base, and user interface as shown in Figure 1.

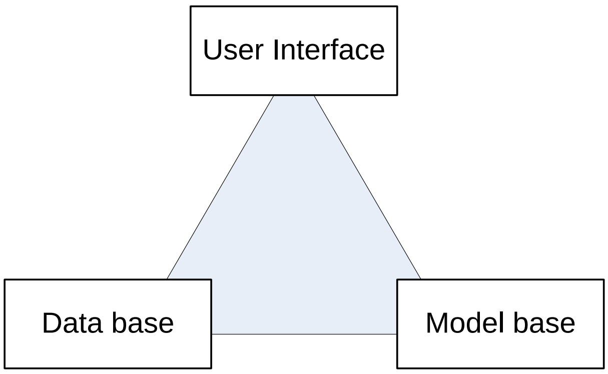


Figure 1. Main components of a decision support systems

DSSs usually are developed for a certain groups of decision makers. This needs a specific design such that decision maker could define new alternatives, and more importantly change an existing alternative to analyze that using the models embedded in the system. Since the delay in responding by the system is considered as an index of inefficiency, an interactive user interface, easy change of input parameters, and quick, understandable and managed output are considered as characteristics of a DSS. Next sections of the paper present the main components of FARDA DSS. The paper ends with the results of applying the system in hydrological forecasting in recent years. However, the system deals with the reservoir operation models either, the emphasis of this paper is on the hydrological forecasting.

2. FARDA: A LONG-LEAD HYDROLOGIC FORECASTING SYSTEM

2.1. CONCEPTUAL MODEL

To get benefit from the forecasting results in a real world system, the system has been developed which enables decision makers to have instant access to data, results of different models, applicable analysis, and saving the reports. As far as the general characteristics of the system is concerned, it is a platform to run different forecasting models, and integrating the forecasting results with reservoir operation models. The system is actually a combination of five following modules:

- Data Base,
- Long-lead forecasting models,
- Reservoir operation models,
- Management dashboard, and
- Report generation.

Figure 1 shows the conceptual model of the system demonstrating the relationship between different modules of the system.

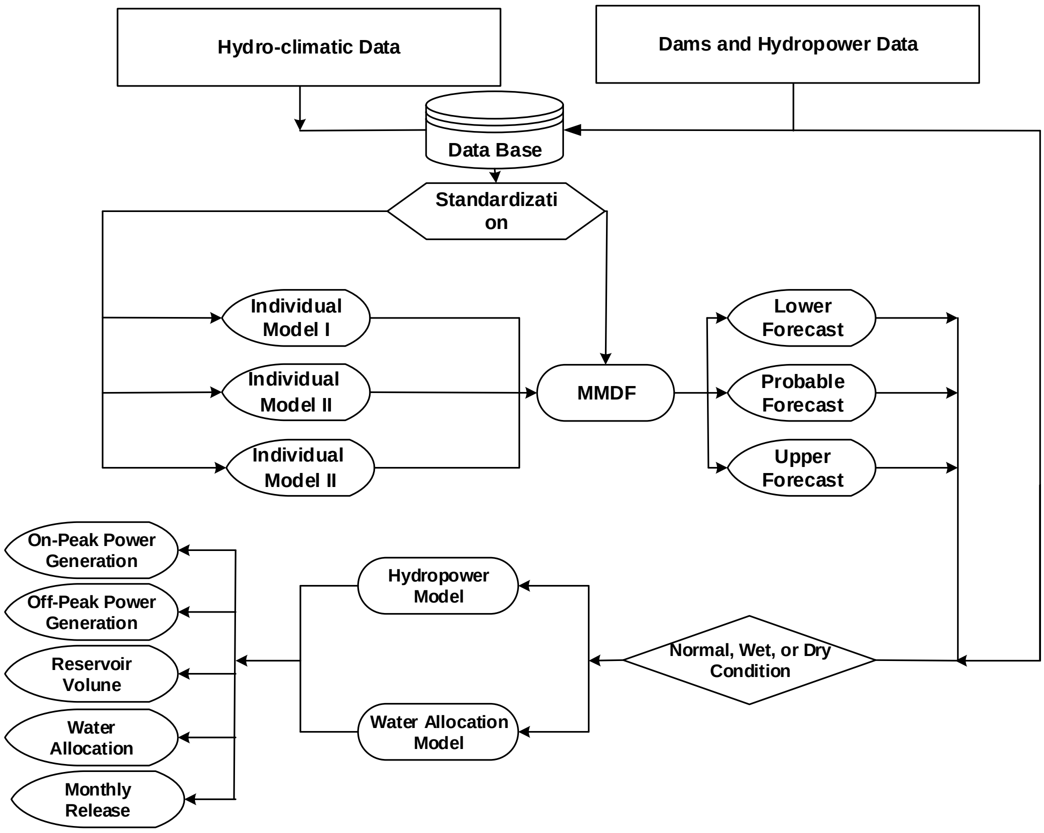


Figure 2. Conceptual model of FARDA system

2.2. DATA BASE AND MODEL BASE

Data base of the system consists of different local and global hydro-climatologic data and reservoir/hydropower data. Hydro-climatologic data of the system include:

- Tele-connection signals including Southern Oscillation Index (SOI), Northern Atlantic Oscillation (NAO), and Pacific Decadal Oscillation (PDO),
- Sea Surface Temperature (SST) data including Persian Gulf and Mediterranean SST,
- Rainfall data,
- Air temperature data,
- Snow cover data, and
- Historical inflow to the reservoirs.

Dam's data include

- Elevation-area-volume curve of dams,
- Hydropower plants parameters, and
- Water demand values at downstream of each dam.

Model base of the system includes forecasting models and reservoir operation models. All forecasting models are employed through the forecasting module of the system. This module is categorized to two interrelated sections: individual models, and the fused model. In addition, all models have been developed in a way to generate, upper bound, lower bond, and most probable forecast values. A list of applied models within the system is presented in Table 1.

Table 1. Different forecasting models of the model base of the system

Category	Models	Name of the Model in the System
Individual Models	Artificial Neural Network	AI
	K-Nearest Neighborhood Regression	K-NN
	Monthly Rainfall-Runoff Model	R-R
Fused Model	Multi-Model Data Fusion Model [1]	MMDF

Due to the effect of available water on the hydropower generation and water allocation of reservoirs, a reservoir operation module has been designed within the system. This module is fed by the results of forecasting module, explicitly. Actually, the inputs to the reservoir operation model comes directly from what has been resulted by the forecasting models (Figure 2).

2.3. GRAPHICAL USER INTERFACE

Different graphical user interfaces in forms of interactive input/output forms, tables, graphs, and management dashboards have been designed and employed through the system. Examples of the graphical user interfaces are presented in this section.

Figure 3, shows the main page of the system. Different modules are presented in this page including:

- Data base,
- Forecasting,
- Reservoir Operation,
- Dashboard,
- System Management, and
- Help

Figure 4, demonstrates the interactive form for hydrologic data base of the system including meteorological data, hydrological data, climatic signals, sea surface e temperature, and reservoir data. Figure 5 shows the user interface designed to report the results of forecasting in a matrix form. By this matrix the user is able to monitor the forecast results for the entire water year in a monthly basis. Furthermore, the observed inflow to the reservoirs from the beginning of each water year to the current time is illustrated in this matrix. Figure 6 shows the management dashboard of the system which demonstrate the forecasting results in forms of informative gauges for months, seasons, half years, and annual basis. Each gauge demonstrate the situation of the forecasts in comparison with the historical experience of inflows to the reservoir. The user explores if the forecast values demonstrate a dry, normal, and wet situation at a glance. Seasonal and annual forecast are also shown in this dashboard. Furthermore, the details in seasonal and annual forecasts are reported in forms of graphs as shown in Figure 7.

Figure 3. Main Page of the System

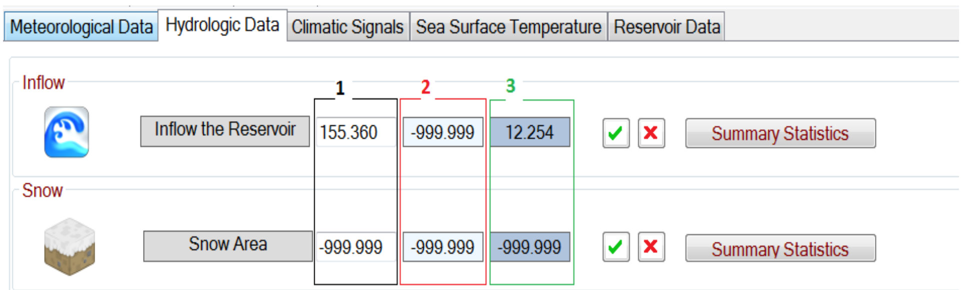
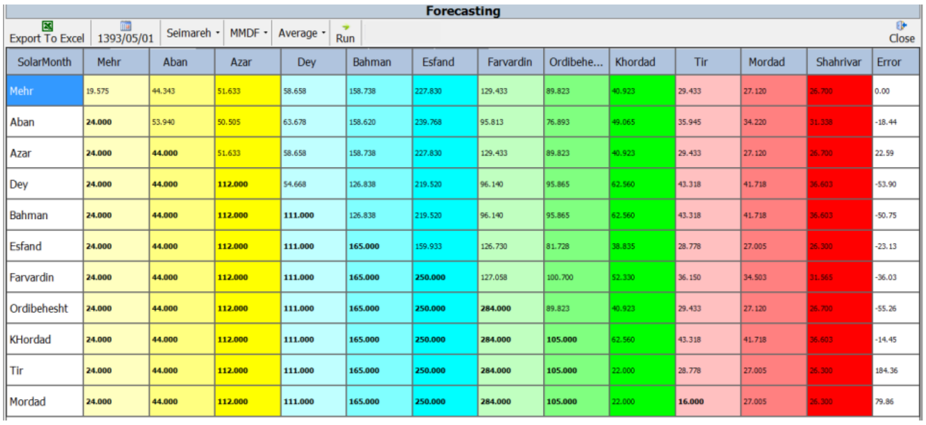


Figure 4. Interactive Form for Hydrologic Data Base of FARDA



Forecasting

Export To Excel | 1393/05/01 | Seimareh | MMDF | Average | Run | Close

SolarMonth	Mehr	Aban	Azar	Dey	Bahman	Esfand	Farvardin	Ordibehe...	Khordad	Tir	Mordad	Shahrivar	Error
Mehr	19.575	44.343	51.633	58.658	158.738	227.830	129.433	89.823	40.923	29.433	27.120	26.700	0.00
Aban	24.000	53.940	50.505	63.678	158.620	239.768	95.813	76.893	49.065	35.945	34.220	31.338	-18.44
Azar	24.000	44.000	51.633	58.658	158.738	227.830	129.433	89.823	40.923	29.433	27.120	26.700	22.59
Dey	24.000	44.000	112.000	54.668	126.838	219.520	96.140	95.865	62.560	43.318	41.718	36.603	-53.90
Bahman	24.000	44.000	112.000	111.000	126.838	219.520	96.140	95.865	62.560	43.318	41.718	36.603	-50.75
Esfand	24.000	44.000	112.000	111.000	165.000	159.933	126.730	81.728	38.835	28.778	27.005	26.300	-23.13
Farvardin	24.000	44.000	112.000	111.000	165.000	250.000	127.058	100.700	52.330	36.150	34.503	31.565	-36.03
Ordibehesht	24.000	44.000	112.000	111.000	165.000	250.000	284.000	89.823	40.923	29.433	27.120	26.700	-55.26
KHordad	24.000	44.000	112.000	111.000	165.000	250.000	284.000	105.000	62.560	43.318	41.718	36.603	-14.45
Tir	24.000	44.000	112.000	111.000	165.000	250.000	284.000	105.000	22.000	28.778	27.005	26.300	184.36
Mordad	24.000	44.000	112.000	111.000	165.000	250.000	284.000	105.000	22.000	16.000	27.005	26.300	79.86

Figure 5. The reporting matrix of monthly/annual forecasts in FARDA

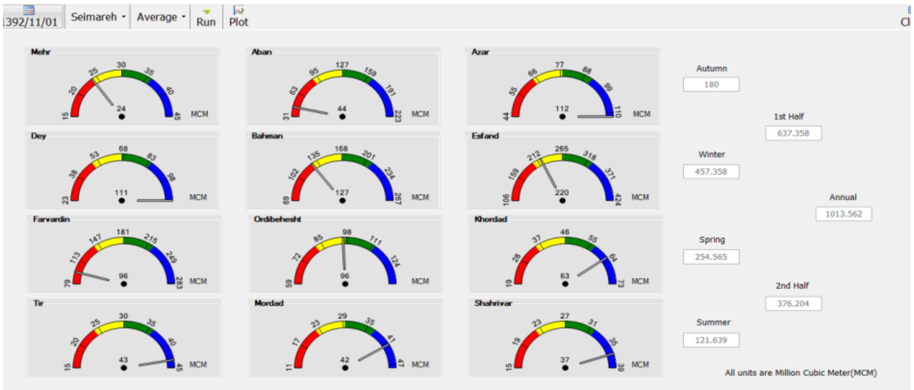


Figure 6. Long-Term forecasting Dashboard of FARDA

Figure 7. The graph of seasonal and annual forecasts in the system

3. CASE STUDY AND RESULTS

Forecasting of monthly to annual inflow to the Seimareh and Karkheh reservoirs in Karkheh river basin, and Karun VI, Karun III, Karun I, Godar, Gotvand and Dez reservoirs in Karun river in southwest of Iran, has been considered in the presented system. Figure 8 illustrates the location of those dams, rivers and their branches in Iran map. At the beginning of each month, a monthly hydrograph of inflow to each reservoir is forecasted by the end of the water year. While the inflow to the upstream reservoirs (Seimareh ,Dez, and Karun VI) are forecasted as natural streamflow of the rivers, the inflow to the downstream series of reservoirs (Karkheh, and the remaining reservoirs on Karun river) are forecasted by the summation of river branches between two dams and the release by the upper dam.

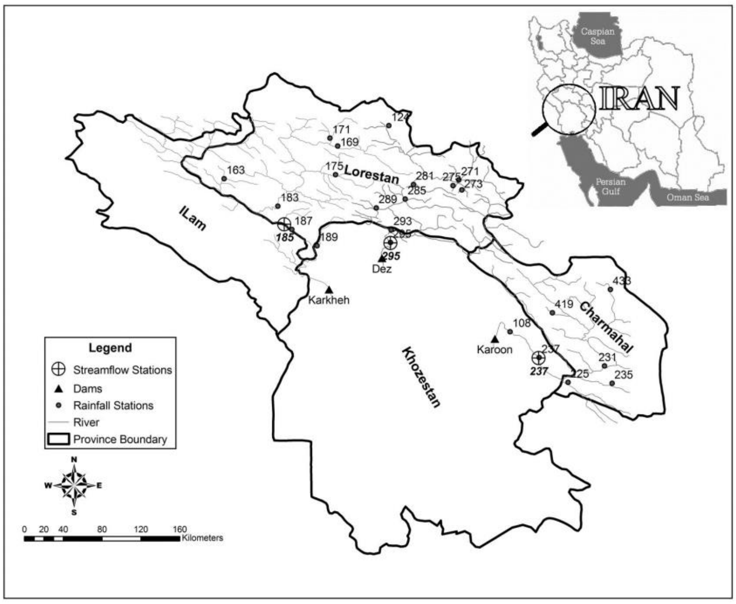


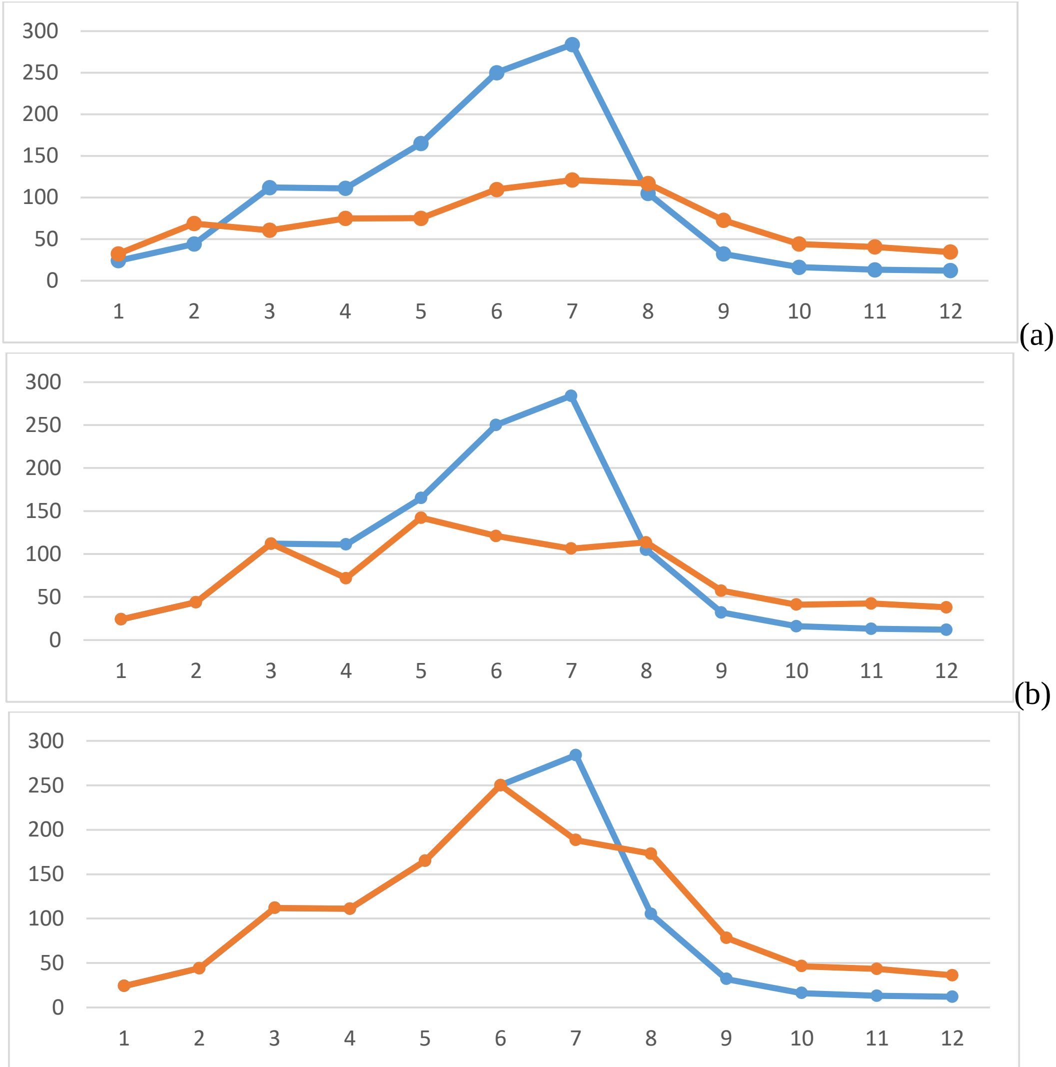
Figure 8. Location of Karkheh, Dez, and Karun I dams

Among the history of forecast values generated by the system, only a few of them is presented here as examples. Table 2 and Figure 9 show the forecast generated by the system for Seimareh dam in water year 2013-14. The forecast error of the system for this dam has been 27 percent as far as the annual forecast generated at the beginning of the water year (October 2013) is concerned. The forecasts became more accurate by the errors of 21 and 9 percent for the forecasts of January, and March 2014, respectively. It demonstrates the precision of forecast by the system as its getting better by receiving new data and establishment of the climate situation. A similar evidence is shown in Figure 10, where the forecast values is illustrated for Karun IV reservoir by the October 2011, and January 2012.

Table 2. Long-lead forecasts for Seimareh dam in water year 2013-14

Seimareh Dam	2013-14
Observed	1156
Forecast of October	850
Forecast of January	914
Forecast of March	1271

As an overall experience of applying the system, an average error of 25 percent is expected at the beginning of each water year, however, the forecast errors became less in recent years where tuning of the models have been applied after real world experience of the system.



(c)

Figure 9. Long-lead forecast of inflow to the Seimareh reservoir generated at October 2013 (a) January 2014 (b), and March 2014 (c) (Red and Blue Lines demonstrate the forecast and observed values, respectively. The unit of the vertical axis is Million Cubic Meter)

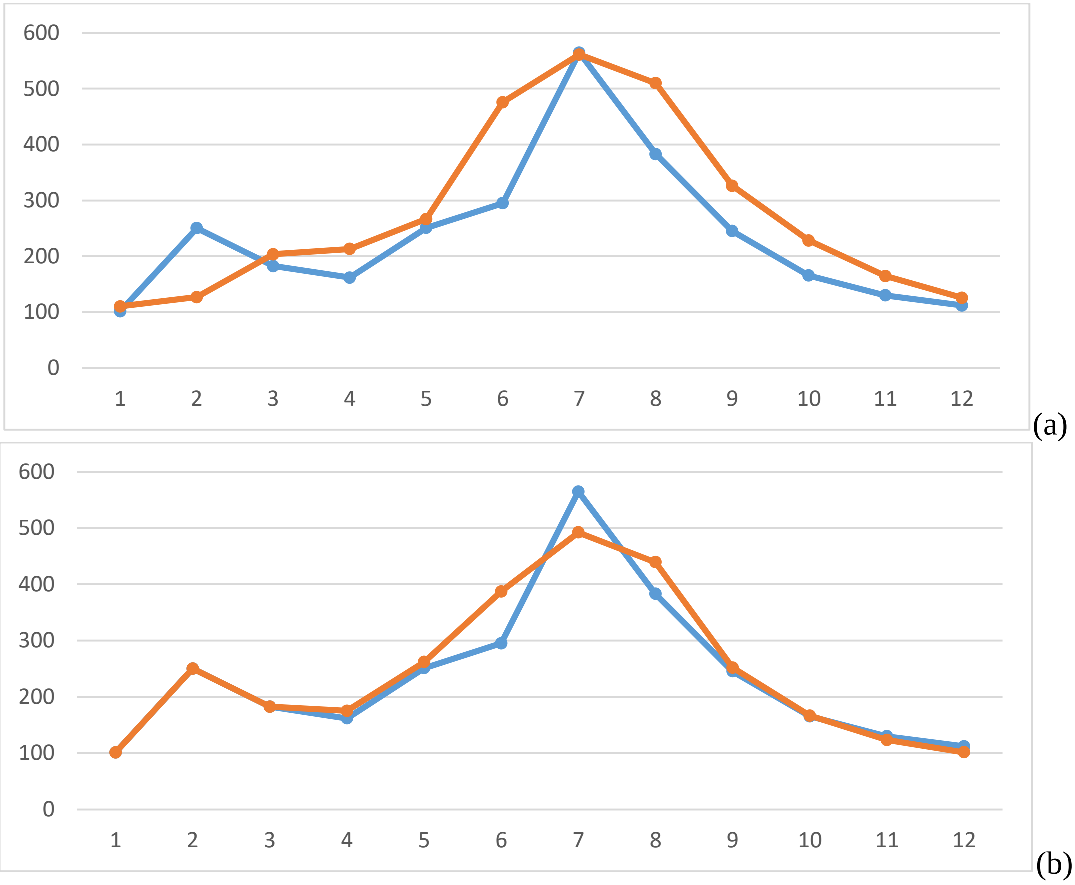


Figure 10. Long-lead forecast of inflow to the Karun IV reservoir generated at October 2011 (a) and January (b) 2012 (Red and Blue Lines demonstrate the forecast and observed values, respectively. The unit of the vertical axis is Million Cubic Meter)

4. CONCLUSIONS

The aim of developing this system was to apply different models which need to be used in a regular basis to forecast the future of hydrologic state of the system for an optimal operation of surface reservoirs. While it was important to develop an efficient system, it was a significant aim to develop a system which is rather user friendly. The system is developed on the basis of a decision support system. Conceptual model of the system was presented in the paper as well as the main framework of its data base and model base and examples of its graphical user interface. While the system deals with both forecasting and reservoir operation models, the focus of the paper was on the forecasting models. The novelty of the forecasting models of the system is the use of multi model fusion strategy which benefits from the skill of different individual forecasting models. The system was applied to the series of operating reservoirs in Karun and Karkheh river basins. The system could be applied to the other systems of reservoirs. The results of applying the system in real world experience demonstrate the efficiency of the system as an applicable tool for long-lead hydrologic forecasting.

5. ACKNOWLEDGEMENT

This study has been supported by a grant from Iran Water and Power Resources Development Company (IWPCo). The technical contributions of the staff of Technical and Research Division of IWPCo is hereby acknowledged.

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