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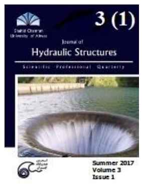

Developing Self-adaptive Melody Search Algorithm for Optimal Operation of Multi-reservoir Systems

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Abstract

Operation of multi-reservoir systems is known as complicated and often large-scale optimization problems. The problems, because of broad search space, nonlinear relationships, correlation of several variables, as well as problem uncertainty, are difficult requiring powerful algorithms with specific capabilities to be solved. In the present study a Self-adaptive version of Melody Search algorithm is presented and applied to obtain Operating Rule Curves for multi-reservoir systems. The self-adaptive mechanism is implemented to satisfy problems constraints and perform algorithm parameters evolution going through different iterations. The research initially evaluates capability of extended algorithm using eight benchmark problems comparing other well-known metaheuristic algorithms, and verifies its effectiveness. Then, the algorithm is adopted for optimal operation of a four-reservoir system located in Karkheh river basin to properly meet agricultural requirements and to decrease the probability of major failures; and finally, the results are provided.

Keywords: Multi-reservoir operation; Melody Search Algorithm; Self-adaptive method; Operating rule curve; Demand deficit.

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1. Introduction

Due to large number of decision variables, several multiple purposes, and uncertainty and risk ruling over multi-reservoir systems, these problems are considered as complex difficult problems of planning and decision-making area [1]. Since problems' coordinated operation policies are hardly found due to the problem high dimensions, they are often termed as large

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scale problems [2]. Effective coordinated management of operating such systems implies a policy implementation leading to maximum benefits and or minimum costs for the whole system through controlling storage values and reservoir releases [3]. To attain the purpose, system operators and managers often prefer using operation rule curves based on system extant conditions. The operating rule curves are often hybrid simulation-optimization model outputs utilizing efficient search algorithms. In this case, the simulator model simulates system reaction using a particular operating rule curve; while, optimization algorithm tries to find optimal operation policy from all existing alternatives.

According to complex nature of multi-reservoir systems and regarding technical difficulties of the system management, search algorithms used in the models must be highly capable so that system simplicity assumptions are less used as much as possible and the considered system can be analyzed in much real conditions. Therefore, researchers have been always trying to find more capable efficient optimization approaches. In recent decades, different artificial intelligence-based approaches including evolutionary computation, metaheuristic algorithms, artificial neural networks, as well as fuzzy theory computation have substituted classic methods such as linear programing and dynamic programing in solving multi-reservoir management problems [4]. However, despite high-speed solution and great coordination of linear and dynamic programing approaches, respectively, in multi-reservoir operation problems; applying these approaches, due to functional constraints and computational difficulties, is neither possible nor cost-effective for any problem.

Although, using metaheuristic algorithms may never ensure attaining global optimal solutions; in practice, the algorithms have largely been succeeded in finding optimal solutions to unsolved problems through classic methods [5]. Of various metaheuristic algorithms, in the past years, genetic algorithms were widely used for reservoir optimization problem solving. Oliveira and Loucks, [1], presented an approach using a real-coded genetic algorithm to define reservoirs' optimal operation curves. Wardlaw and Sharif, [6], employed and recommended genetic algorithm for definitive optimization of reservoir system operation as an effective approach. Sharif and Wardlaw [7], also, developed GA model for multi-reservoir system optimal operation and compared the results with policies of various DP-based models. Moreover, genetic algorithm was also used in a simulation-optimization model to determine a single-reservoir minimum and maximum operating optimal curves [8]. Dariane and Momtahen, [9], benefited a typical genetic algorithm model to specify operating rule curve parameters from a single purpose multi-reservoir system. The results were compared to the results obtained from popular optimization models such as SDP and DPR.

Wang et al., [2], introduced MIGA model for optimization of Shihmen reservoir operating problem in Taiwan. Jalali et al., [10], planned monthly operation of a single purpose reservoir through using three different Ant-based algorithm formulations. Then, Kumar and Reddy [11], provided an ACO model for operation problem of a multi-purpose reservoir and investigated its capability. The model objective was to maximize hydropower generation in addition to meeting regional agricultural demands considering flood control and environmental requirements as system constraints. Besides, they proposed the so-called EMPSO modified algorithm to identify reservoirs' operation curves, too. The proposed algorithm was utilized in a single reservoir operation system in India and the obtained results were compared with results of PSO and GA standard algorithms [12]. To acquire optimal operation policy leading to maximum energy production in successive reservoirs, Fu et al., [13], introduced a hybrid metaheuristic algorithm called IA-PSO and applied it for Qingjiang River basin system planning. Ostadrahimi et al., [14], presented a hybrid method determining optimal operation system parameters for a three-reservoir system through using a multi-swarm optimization algorithm, MSPSO, and the popular simulator model HEC-ResPRM.

Fang et al., [15], proposed joint operating rules including; water diversion rule, hedging rule, and storage allocation rule to optimal operate of a multi-reservoir system. The predefined rules determined the amount of diverted water in a current period, the total release from the system, and the reservoirs' releases, respectively. A modified version of Particle Swarm Optimization (PSO) algorithm implemented within a simulation-optimization approach to optimize the key points of the water diversion curves, the hedging rule curves, and the target storage curves. Ashrafi, [16], applied an Efficient Adaptive version of Melody Search (EAMS) algorithm to find optimal operation policy of multi-reservoir systems. EAMS was adopted within a simulation-optimization framework to derive optimal operating rule curves for a multi-reservoir system in Iran. The obtained results showed the superiority of the developed approach in comparison with other conventional methods. A combined water and hydropower operating rule was introduced by Zhou et al., [17], to enhance the efficiency of multi-reservoir system operation. Three modules formed the main framework. A deterministic module derived the optimal reservoir storage policy a fitting module determined the optimal releases of the reservoirs and finally, a testing module was utilized to test the derived operating rules with observed inflows. Ashrafi and Dariane, [18], proposed Coupled Operating Rules (COR) to optimally operate multi-reservoir systems with distributed local demands. They defined some decision points within the considered system and suggested application of two types of linear rules to determine total releases and local water allocations in decision points. The main objective of the study was reducing the intensity of the local demand shortages throughout the system. The proposed algorithm was more effective in achieving precise solutions over a long-term period, compared to other conventional algorithms. Ak et al., [19], developed a non-linear programming model to obtain optimal operating policies for hydropower plants in single-reservoir systems. Maximization of the average annual energy generation was assumed as the main objective of the study where the short term electricity price variations were considered and be incorporated into the long-term plan.

Bozorg-Haddad et al., [20], applied conflict resolution methods to extract compromise solutions for water resources management problems. The Genetic Programing approach was utilized to calculate monthly, real-time, water allocation rule curves regarding the urban-industrial, agricultural, and environmental water uses downstream of the Zarrineh-roud River basin. Despite many studies conducted on the area of multi-reservoir systems operation optimization, scholars are still determined to come across algorithms and solutions leading to better solutions with cost-effective computational expenses. The present paper has attempted to extract an optimal operation policy from a four-reservoir system with scattered requirements through establishing a new powerful Self-adaptive Melody Search (SaMeS) optimization algorithm. The problem purpose is to properly supply agricultural demands in the whole system and to enhance reliability and decrease system failures.

Melody Search (MeS) algorithm was initially introduced by Ashrafi and Dariane, [21], and applied as a modified version of Harmony Search (HS) algorithm for a multipurpose single reservoir system operation optimization [22], where its efficiency was verified comparing other conventional methods. The proposed metaheuristic algorithm was expanded more effectively to solve continuous numerical and real-word optimization problems [23]. Although the MeS algorithm was proposed as a novel effective version of HS, the computational structure of the algorithms differed substantially. The basic HS performs weakly in exploitation process, especially in broad solution space [24] while, MeS algorithm could improve the weakness.

Generally, MeS is more powerful in solving continuous problems with broad search space and high dimensions than other variants of HS. The algorithm was later explained in more details by scholars and more extensive experiments were carried out through introducing an adaptive version of MeS [25]. Most recently, the MeS algorithm was adopted in different researches as a powerful optimization algorithm to prove the capabilities of innovative metaheuristic methods (e.g. [26]; [27]; [28]). Moreover, some novel hybrid optimization algorithms were introduced based on the MeS algorithm to solve different real-word engineering problems efficiently (e.g. [29]; [30]).

2. Multi-reservoir system operation

The research objective is achieving an optimal operation policy of a four-reservoir system located in Karkheh River basin for a long-term period (47 years). Karkheh River, situated in southwest, carries the third volume of water in Iran and is critical respecting surface water resources. Understudied system includes four reservoirs of Sazbon, Tang mashoureh, Pa Alam and Karkheh (which are schematically shown in Figure 1 as Reservoir 1 to 4, respectively), and four agricultural areas. Figure 1 schematically shows the system. System main purposes are agricultural land development, region flood control, as well as supplying environmental requirements. The modelled agricultural demands at Karkheh reservoir downstream is considered as total agricultural needs of Dasht-e Abbas, Avan, Dousalgh, Arayez, Bagheh, and lower Karkheh area.

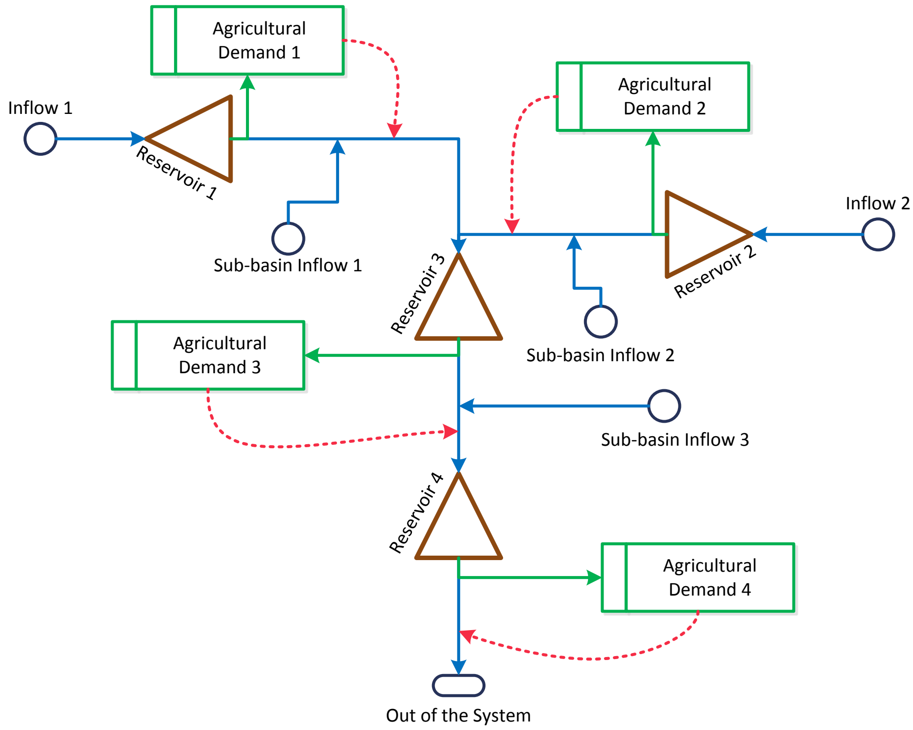

Figure 1. Schematic illustration of considered multi-reservoir system

Modeling regarded four points, in system, for controlling minimum environmental flow of the river at various periods. System agricultural Demands and reservoirs' characteristics are summarized in Table 1.

Table 1. Characteristics of reservoirs and agricultural demands

Reservoir:	1	2	3	4
Total Storage Capacity (mcm)	1608	950	3127	7600
Dead Storage Capacity (mcm)	957	352	1842	433
Active Storage Capacity (mcm)	650	598	1285	7167
Average Annual Net Evaporation (mm)	1334	1252	1580	2079
Annual agricultural demand				
Agricultural area:	1	2	3	4
Annual Demand (mcm)	400	300	307	3700

Distributed multiple demand areas and how they are localized in the system have made a complicated problem, optimization of which requires using a capable and adaptable optimization method.

3. Optimization problem

Meeting environmental requirements and agricultural demands were considered as system main objectives for modeling. In this context, environmental requirements at different river tributaries were modeled as the model constraints and meeting agricultural demands as problem objective function. As a result, the problem objective function to minimize shortage values of agricultural areas in a long-term period is assumed as follows.

$$Min\ OF = \sum_{t=1}^{T}\sum_{j=1}^{n_D}\left(\frac{TD_{t,j} - RD_{t,j}}{TD_{t,j}}\right)^2 \quad (1)$$

Where, $TD_{t,j}$ and $RD_{t,j}$ stand for demand and release to j^{th} agricultural area in t^{th} time period, respectively. The n_D indicates total number of agricultural areas and T is the last period of time horizon. The advantage of applying this particular form of objective function is that it tries to equally distribute system deficiencies, as much as possible, depending on the amount of defined demand in different regions and at different periods. Model constraints including mass continuity equation in reservoirs, reservoir storage limits, flow rate limits for meeting agricultural demands, limits of minimum flows at river various tributaries and final storage constraints are defined as follows:

$$S_{t+1,j} = S_{t,j} + Inflow_{t,j} - RR_{t,j} - RD_{t,j} - Eva_{t,j} - Spill_{t,j} \qquad for: \begin{cases} t = 1,2,...,T \\ j = 1,2,...,n_R \end{cases} \quad (2)$$

$$S\min_j \le S_{t,j} \le S\max_j \qquad for: \begin{cases} t = 1,2,...,T \\ j = 1,2,...,n_R \end{cases} \quad (3)$$

$$0 \le RD_{t,j} \le TD_{t,j} \qquad for: \begin{cases} t = 1,2,...,T \\ j = 1,2,...,n_D \end{cases} \quad (4)$$

$$RR_{t,j} \ge MFR_{t,j} \quad (5)$$

$$S_{1,j} = S_{T+1,j} \quad (6)$$

Where, $S_{t,j}$ is the beginning storage of ith reservoir in month t, $RR_{t,j}$ is the water release from jth reservoir in month t, to downstream area, $RD_{t,j}$ indecates the amount of released water from *j*th reservoir in month *t*, for satisfying local agriculture demand. $Inflow_{t,j}$, $Eva_{t,j}$, $Spill_{t,j}$ are the amount of total inflows, net evaporation loss and amount of spilled water for j^{th} reservoir during t^{th} time period, respectively. $Smin_j$ and $Smax_j$ are minimum and maximum storage volumes for the j^{th} reservoir, respectively, and $MFR_{t,j}$ is the minimum flow requirement in month *t* downstream j^{th} reservoir.

4. The proposed optimization algorithm

In the present study a modified version of Melody Search algorithm is proposed to find optimal operating rule curves of multi-reservoir systems. In order to enhance the MeS algorithm ability in a long-term multi-reservoir system optimization, a Self-adaptive adjusted scheme is implemented requiring no predetermined algorithm parameter values. Despite the obvious superiority of MeS algorithm to HS and other its variants, the algorithm suffers from large numbers of parameters. Number of algorithm parameters is decreased in the new released versions of MeS and the accuracy is intensified [25]. To increase algorithm efficiency, three parallel linear equations are applied in Player Memory Consideration (PMC) operator of the proposed algorithm (SaMeS). These equations determine the variables value for new melody improvisation in each memory, as follows:

$$X^{k}_{i,new} = X^{k}_{i,L} \pm rand\,() \times bw(k) \quad where\ L \in U(1,\ \ldots,\ PMS) \tag{7}$$

$$X^{k}_{i,new} = X^{h}_{i,L} \pm rand\,() \times bw(k) \quad where\ L \in U(1,\ \ldots,\ PMS)\ and\ h \in U(1,\ \ldots,\ D) \tag{8}$$

$$X^{k}_{i,new} = X^{k}_{g,best} \quad where\ g \in U(1,\ \ldots,\ PMN)\ and\ best{:}\ the\ best\ melody\ form\ the\ specified\ PM \tag{9}$$

To obtain the current variable value, for the first equation, a linear relationship is set with one of corresponding variables selected from the player memory. Respecting the second equation, the linear relationship is established with a non-corresponding variable randomly selected from the extant melody variables in memory. Value of the considered variable, in the third equation, equals corresponding variables in the best existing melody in one of the memories. Aforementioned relationships are utilized relying on how well they succeeded in producing top melodies through using success rate parameter (SP_{α}). At onset, success rate value is assumed equal for all three relationships; then, it is measured and upgraded following a series of given iterations (*Lp*) based upon produced top melodies.

Algorithm 1. Determining the possible variable ranges

For *each* $k \in [1, \ldots, D]$ ***do***

$LB_k = min\,(x^{k}_{i,\,best},\ i=1,\ldots,PMN) - [max\,(x^{k}_{i,\,best},\ i=1,\ldots,PMN) - x^{k}_{Group\text{-}Best}]$

$UB_k = max\,(x^{k}_{i,\,best},\ i=1,\ldots,PMN) + [x^{k}_{Group\text{-}Best} - min\,(x^{k}_{i,\,best},\ i=1,\ldots,PMN)]$

Done

Parameter values of Player Memory Consideration Rate (*PMCR*), Pitch Adjusting Rate (*PAR*), and Bandwidth Distance (*bw*) for each top melody successfully entered memory are stored; and mean values, at a given number of iteration, are recognized as the relevant parameter values for further iterations.

The calculation of random possible variable ranges in the proposed algorithm are demonstrated in Algorithm 1 where, *best* subscript indicates the best found solution in each melody memory, $x^{k}_{i,best}$ is the k^{th} variable of the best solution stored in i^{th} memory, *Group-Best* subscript stands for the best found solution throughout all memories, and $x^{k}_{Group\text{-}Best}$ is the kth variable of the Global-Best solution. Hence, the permissible search space for randomization is symmetrically determined around the Global-Best solution of Melody Memory (MM) in each iteration. Figure 2 represents the flowchart of the proposed algorithm for solving constrained multi-reservoir optimization problem.

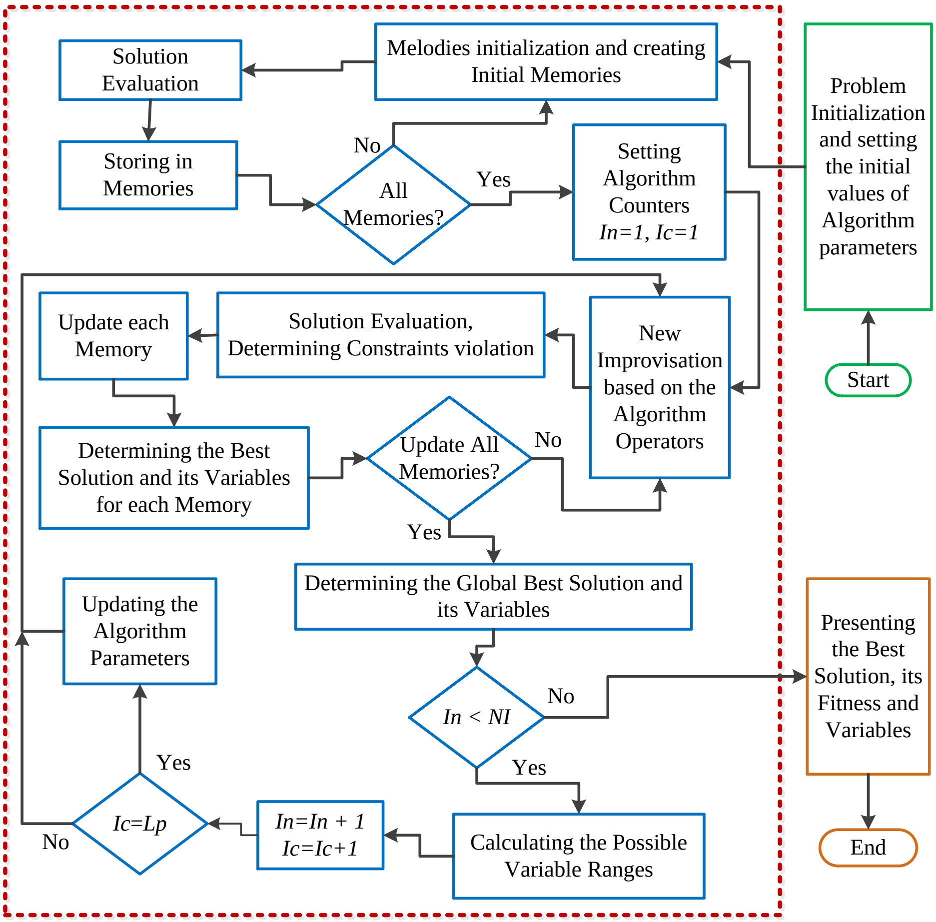

Figure 2. Flowchart of the proposed SaMeS algorithm

The values of the algorithm parameters (e.g. *PMCR*, *PAR*, *bw*) are randomly determined at the initial iteration of the algorithm. The values of parameters are improved going through different iterations based on a predefined adaptive mechanism. For more details about the parameter estimation, [25] is referred. The self-adaptive mechanism implemented in SaMeS, identifies better solutions according to the problem constraints violation. Consequently, infeasible solutions would be omitted from the memories going through different iterations. To specify the proposed algorithm capability, algorithm performance is investigated solving eight benchmark problems in continuous space compared to the performance of three popular optimization algorithms and basic-HS and basic version of MeS algorithms. The results are reported in Table 2. According to the obtained results, each algorithm statistical parameters of 30 independent executions are shown.

Table 2. Results for problems with 50 dimensions (*D*=50) and *NoFE*=50,000

		SaDE	ABC/best	GA-PSO	basic HS	basic MeS	SaMeS
Mean	Sphere	5.94E-13	2.46E-05	3.53E-10	5.31E+02	7.26E-16	**0.00E+00**
Std.		4.02E-13	6.78E-06	2.63E-10	1.23E+02	2.07E-16	**0.00E+00**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Worst		1.53E-12	1.67E-03	7.28E-10	8.47E+02	1.11E-15	0.00E+00
Best		8.22E-14	9.78E-06	5.19E-15	2.95E+02	3.09E-16	0.00E+00
Mean	Step	6.09E-13	1.39E-11	2.20E-12	5.25E+02	1.99E-02	**0.00E+00**
Std.		3.62E-13	6.13E-12	1.44E-12	8.87E+01	8.92E-02	**0.00E+00**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
Worst		1.53E-12	2.35E-11	4.55E-12	6.59E+02	3.99E-01	0.00E+00
Best		8.07E-14	1.79E-13	8.44E-14	3.56E+02	9.75E-09	0.00E+00
Mean	Shifted Sphere	8.89E-12	5.63E+00	5.16E+01	5.68E+02	1.63E+04	**6.55E-28**
Std.		9.07E-12	2.07E+00	2.01E+01	1.29E+02	1.95E+03	**9.99E-27**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	15.00%
Worst		3.99E-11	9.28E+00	8.67E+01	8.15E+02	1.96E+04	2.75E-21
Best		1.34E-12	2.39E+00	2.22E+01	3.20E+02	1.24E+04	0.00E+00
Mean	Shifted Rosenbrock	1.75E+02	1.65E+03	4.68E+02	2.38E+06	1.37E+09	**1.26E+02**
Std.		**1.36E+02**	3.20E+02	8.90E+01	1.13E+06	2.89E+08	2.52E+02
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Worst		6.46E+02	9.88E+03	9.83E+03	6.07E+06	1.88E+09	5.83E+02
Best		4.73E+01	3.55E+02	3.57E+01	1.17E+06	8.11E+08	2.00E+01
Mean	Shifted Ackley	1.26E-01	6.13E+00	1.29E+02	5.44E+00	1.50E+01	**6.15E-16**
Std.		3.31E-01	2.61E+00	4.62E+02	3.29E-01	5.17E-01	**1.42E-17**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Worst		1.16E+00	1.02E+01	2.27E+03	6.01E+00	1.63E+01	5.92E-11
Best		2.18E-07	3.26E-01	1.06E-06	4.92E+00	1.44E+01	4.90E-20
Mean	Shifted Griewank	1.64E-03	6.92E-01	1.27E+01	6.01E+00	1.41E+02	**1.11E-19**
Std.		3.39E-03	4.19E-01	1.41E+01	1.26E+00	2.64E+01	**3.42E-19**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	90.00%
Worst		9.86E-03	1.32E+00	4.15E+01	7.78E+00	1.95E+02	1.11E-17
Best		2.25E-12	8.11E-04	1.14E+00	3.62E+00	8.95E+01	0.00E+00
Mean	Shifted Rotated Rastrigin	3.28E+02	9.20E+03	4.10E+03	4.71E+02	5.99E+02	**1.85E+02**
Std.		**1.83E+01**	9.00E+02	7.32E+02	4.23E+01	3.88E+01	4.45E+01
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Worst		3.60E+02	1.77E+04	1.64E+04	5.38E+02	6.66E+02	5.97E+02
Best		2.91E+02	5.10E+02	1.32E+02	3.53E+02	5.24E+02	4.34E+01
Mean	Shifted Rotated Griewank	8.99E-01	1.25E+00	2.82E+02	4.07E+01	5.14E+02	**3.84E-02**
Std.		2.56E-01	5.48E-01	3.11E+02	1.21E+01	6.78E+01	**2.89E-02**
Success Rate		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Worst		1.28E+00	1.90E+00	8.17E+02	7.71E+01	6.38E+02	9.45E-02
Best		2.17E-01	1.28E-01	1.21E+01	2.56E+01	3.42E+02	9.06E-04

Table 2 compares results of the proposed algorithm with the results of Basic-HS [31], Basic-MeS [21], SaDE algorithm [32], AB/best algorithm [33], and GA-PSO hybrid algorithm [34]. Basis functions were specified with 50 decision variables. In order to perform a firm comparison, total number of fitness evaluations (*NoFE*) is assumed as 50,000 for all algorithms, thus, the total iteration number (*NI*) is calculated for each algorithm based on its structure. As seen, the proposed algorithm attained the best solutions and outperformed other algorithms in statistical comparisons indicating algorithm capability in solving multimodal problems in high dimensioned broad continuous search space.

5. Results

As earlier explained, a metaheuristic simulation-optimization model is developed to determine the best operation policy of a four-reservoir water resources system. Reservoirs' monthly releases are estimated according to reservoir monthly mean storage volume and predefined operating rule curves. The simulator, models system details per optimization algorithm solution and computes objective function value and problem constraints violation. Decision variables considered in optimization model determine specified reservoirs' rule curves. To eliminate non-feasible solutions, dominance feasible solutions method was applied using values of constraints violation.

Two operation rule curves are defined for each reservoir including, Upper and Lower rules. The predefined rules determine the wet, normal and dry conditions for reservoir operators. In a case that reservoir storage per given month is higher than the upper operation curve level, discharge would be equal to total local agricultural demand of the reservoir plus reservoir storage difference to the upper operation curve level. This additional volume supplies downstream reservoirs and other regional needs, when the reservoir monthly storage indicates wet condition. If reservoir storage volume is between two operation curves, reservoir release would just equal to local demands (normal condition). When reservoir storage volume is less than the lower curve, only 70% of local agricultural demand, which is not smaller than minimum environmental flow would be released (dry condition). Figure 3 illustrates mean monthly inflows and monthly demands defined in the system. As illustrated in Figure 1, return flows of agricultural areas supply downstream local demands and reservoirs, even in dry condition.

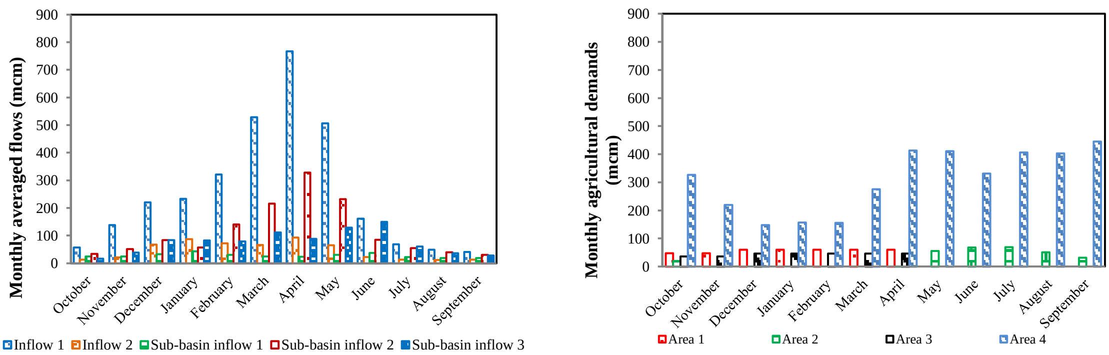

Figure 3. Averaged monthly inflows and agricultural demands

According to inflow statistics and system requirements in a long-term 47-year period, reservoirs operation rule curves are determined in a way that the lowest distributed deficiency in the whole system is obtained. To solve the considered problem, SaMeS algorithm with 5 player memories and 5 melodies in each memory was provided. Maximum iteration number for optimal solution was set 50,000. Respecting 30 independent executions, mean solutions obtained 91.04 for objective function at standard deviation 90.23. Of these, the best and worst solutions were 25.7 and 324.87, respectively for objective function revealing that the algorithm is well converged to the problem optimum solution.

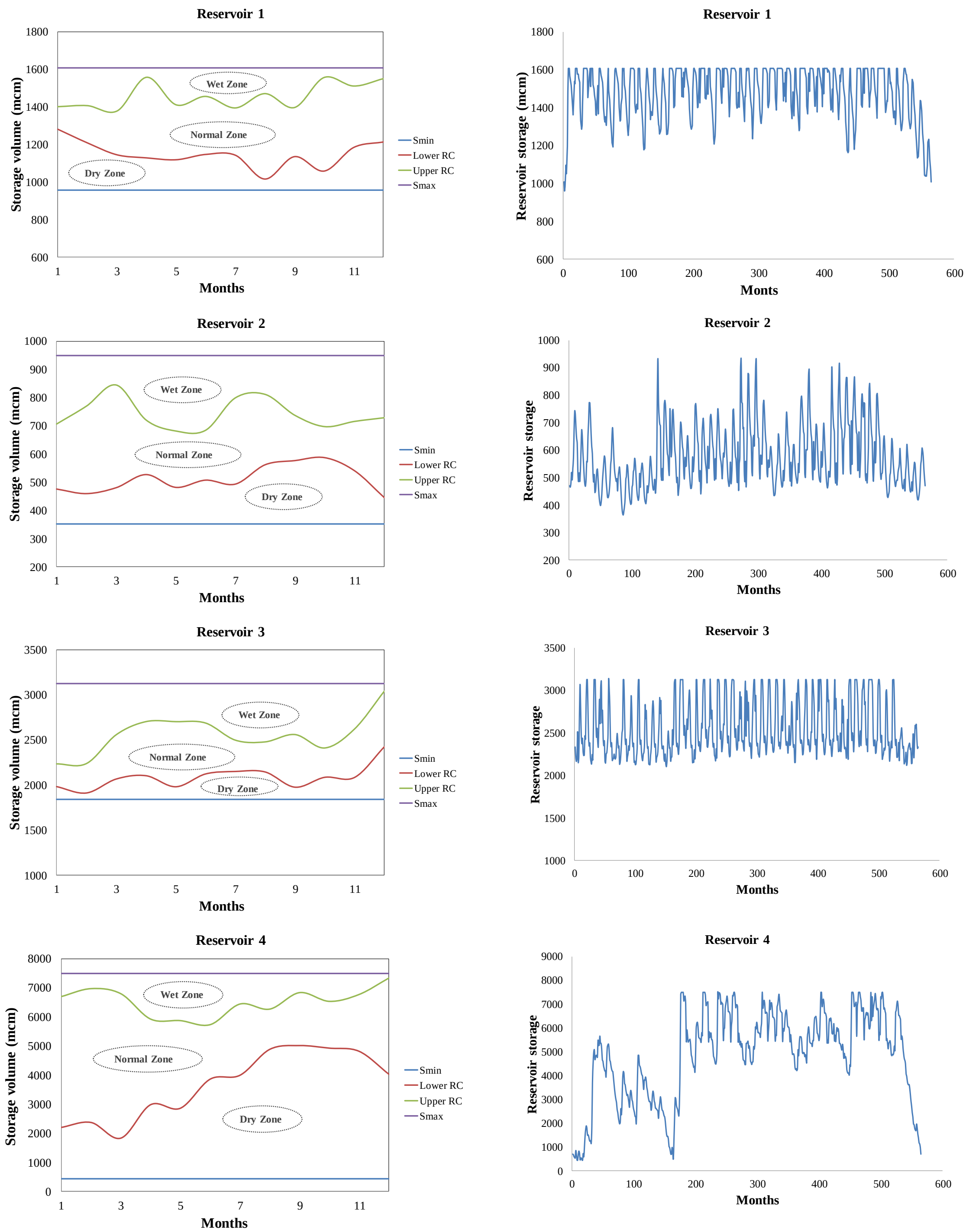

Figure 4. Operation rule curves and simulated storage variation of reservoirs

The algorithm enjoys the ability of rapid recognition of the problem feasible space to search for optimal solution. Figure 4 represents reservoirs rule curves and simulated reservoirs' storages resulted from the best obtained solution. As observed, Reservoir 2 operation curves are obtained such that downstream released flow would be maximized in most months due to low local agricultural demands.

Moreover, Reservoir 3, which contributes as additional storage supplying downstream requirements, has rule curves tending to release flow and supply Reservoir 4. Optimal operating rule curves of Reservoir 2 and Reservoir 4 are set such that the maximum possible values of reservoirs volume are attributed to supply their local requirements. The results are consistent with systemic optimization concepts demonstrating optimization of operation process. Table 3 summarizes simulated results of all four reservoirs through using optimum systemic operation curves for a long-term 47-year period.

According to the achieved results related to the best solution, all demands showed approximately close quantitative reliability, which was the purpose sought for in the model objective function definition. Thus, the model tries to distribute the deficits for different periods respecting basin requirements and to prevent great failures; while, demands time reliability was different. Moreover, it is observed that Reservoir 3 plays the supportive role for Reservoir 4; further, it was full overflowing during the long-term period supplying downstream demands. The reservoir empty percentage is zero.

Table 3. Results of system simulation using the best obtained rules

	Reservoirs			
Parameters	1	2	3	4
Annual Evaporation (mcm)	37.8	30.3	28.3	136.3
Annual Spill (mcm)	1830	260	3482	104.0
Time percent of Emptiness	31.5%	78.0%	82.0%	13.7%
Time percent of being full	0.5%	1.8%	0.0%	53.2%
	Agricultural Demands			
Agricultural Area	Reliability		Quantitative Reliability	
1	57.4%		70.2%	
2	61.3%		78.3%	
3	62.5%		75.6%	
4	42.3%		75.9%	

On the other side, time percentage of being full for Reservoir 4, and consequently, the spill were less than other reservoirs since the reservoir spill values were inaccessible in understudied system regarded as system waste. In other word, optimization model tries to reduce wastes as much as possible to better meet system demands. Figure 5 shows the long term average monthly demand deficits and reservoir spills. It clearly shows that in the optimum solution found by the proposed SaMeS algorithm there is the lowest possible spill from Reservoir 4, the last one in the system. An optimal operating strategy must control and decrease the system losses such as spill and net evaporation. In Reservoir 2, spills mainly occur during high flow periods of February to June. Meanwhile, spills from Reservoir 2 and 3 are considered as losses but they can be used to satisfy lower demands, help the Reservoir 3 and 4 to supply their local demands and supply environmental minimum flow requirements.

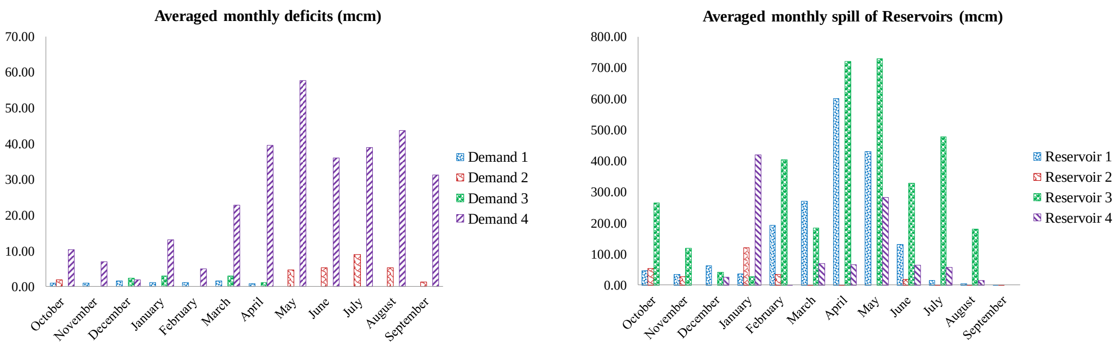

Figure 5. Averaged monthly demands' deficits and reservoirs' spills

6. Conclusion

The present research attempted to determine a four-reservoir system operation, located in Karkheh River, through developing a capable optimization-simulation model. The optimization algorithm was an improved Self-adaptive Melody Search algorithm. According to research findings, it may be concluded that the proposed algorithm is highly competent and efficient for solving complicated continuous problems in comparison to the well-known optimization algorithms. The proposed algorithm outperformed other well-known algorithms in statistical comparisons and attained the best solution. The proposed SaMeS algorithm benefits from the multi-memories structure and utilizing a self-adaptive mechanism. The cooperative rule curves for a multi-reservoir system achieved by the proposed simulation-optimization approach is able to manage the diversity of demand deficits in a long-term period. The Quantitative Reliability of different local demands are determined as close as possible where the optimal rule curves reduce the total losses of reservoirs such as spill and net evaporation. In general, each agricultural area encounters the least failure probability. This is the best policy to deal with systemic water resources problems, which would never be achieved in individual reservoir analysis.

7. References

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