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Optimal Reservoir Operation Using MOPSO with Time Variant Inertia and Acceleration Coefficients

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Abstract Recently application of optimization techniques has been suggested to derive reservoir operation policies for multi-objective reservoir systems. Water use involves a large number of stakeholders with different objectives. In reservoir operation some of objectives often are conflicting objectives, hence Optimization techniques are expected to provide balanced their solutions. This paper presents an efficient and reliable swarm intelligence-based approach, namely a novel Particle Swarm Optimization (PSO) approach to Multi-Objective optimization Problems (MOP), called Time Variant Multi-Objective Particle Swarm Optimization (TV-MOPSO) technique, to derive a set of optimal operation policies for a multi-objective reservoir system. Classical optimization methods are often unable to attain a good Pareto front. To overcome this problem for Multi-Objective optimization Problem, this study employs a heuristic algorithm, Time Variant Multi-Objective Particle Swarm Optimization to generate a Pareto optimal set. To show practical utility, TV-MOPSO is then applied to a realistic case study, namely the Doroodzan reservoir system in Iran. The reservoir serves multiple objectives comprise of minimizing domestic supply (industry) deficits, minimizing irrigation deficits and maximizing hydropower production in that order of priority. The results obtained demonstrate that Time Variant Multi-Objective Particle Swarm Optimization is consistently performing better than the standard Particle Swarm Optimization. This study demonstrates the usefulness of Time Variant Multi-Objective Particle Swarm Optimization for water resource management problem.

Keywords Multi-Objective Optimization, Pareto Front, TV-MOPSO, Reservoir Operation

1. Introduction

Reservoirs are most important components of water resources development. Increasing water demands, higher standards of living and excessive water pollution due to agricultural and industrial expansions have caused intense social and political predicaments, and conflicting issues among water consumers [1]. The purpose of a reservoir is to equalize the natural stream flow and to change the temporal and spatial availability of water [2].In the past, various researchers applied different kinds of mathematical programming techniques like linear programming (LP), dynamic programming (DP), nonlinear programming (NLP), etc., to solve such reservoir operation problems. An extensive review of these techniques can be found in Loucks et al (1981) [3], Yakowitz (1982) [4], Yeh (1985) [5], labadi (2004) [6] and simonovich (2010) [7]. But as far as reservoir operation is concerned, no standard algorithm has been developed available, as each problem has its own individual physical and operational characteristics [5, 8]. In the case of multipurpose reservoir operation, the goals are more complex than for single purpose reservoir operation and often involve various problems such as insufficient inflows and larger demands. In order to achieve the best possible performance of such a reservoir system, a model should be formulated as close to reality as possible [8]. Recently many heuristic and meta-heuristic algorithms have been proposed, which though do not always ensure the global optimum solution, however give quite good results in an acceptable computation time. So researchers are persistently looking for newer techniques and their improvements over the years [9]. Some examples of well-known meta-heuristic methods include Simulated annealing (SA), Tabu Search (TS), Genetic Algorithms (GA), Evolutionary Programming (EP), Evolution Strategy (ES), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).

The applications of GA method to solve such reservoir operation problems have been reported recently (Oliveira and Loucks, 1997[11]; Wardlaw and Sharif, 1999[12]; Chang and Chen, 1998[13]; Sharif and Wardlaw, 2000 [14]; Nagesh Kumar *et al.*, 2005) [10]. Particle swarm optimization (PSO) is one of the newest techniques within the family of evolutionary optimization algorithms. The algorithm is based on an analogy with the choreography of flight of a flock of birds. Due to its fast convergence, PSO has been advocated to be especially suitable for multi-objective optimization. A number of multi-objective Particle Swarm Optimization algorithms have extensively been proposed in the literature. Few applications to real-world problems have been reported [15]. Nagesh Kumar and Reddy (2007) using a new strategic mechanism called *elitist mutation* to derive reservoir operation policies for multipurpose reservoir systems [8]. Baltar and Fontane (2008), presents a Multi-Objective Particle Swarm Optimization solver that is used to generate Pareto optimal solutions for two water resources problems with up to four objectives [15]. In this study, formulation and application of a novel strategy of pareto-optimal solution searching in Multi-Objective Particle Swarm Optimization with Time Variant Inertia and Acceleration Coefficients (TV-MOPSO) for continuous domains in water resources management has been studied. To illustrate performance of this method we demonstrate the development and application of Time Variant Multi-Objective Particle Swarm Optimization for optimization of the Doroodzan reservoir operation during 5 years of monthly steps. The reservoir is located in northwest of Shiraz, Iran. To compare the performance of TV-MOPSO, the case study is also solved using standard Particle Swarm Optimization and the results are discussed.

1.1. Multi-Objective Optimization and Pareto Concept

The multi-objective optimization (MO) filed covers many real-life optimization problems. The multi-objective optimization is the problem of simultaneously optimizing a set of two or more objective functions. In multi-objective optimization problems, more than one conflicting objectives will be optimized simultaneously [16]. Pareto optimality is the most important solution concept in Multi-Objective optimization Problem. A Multi-Objective optimization Problem with *K* objectives and *M* constraints can be stated as follows [17]:

$$\text{Minimize } F(x) = \{ f_1 (x), f_2 (x), f_3 (x) \dots f_3 (x)\} \quad (1)$$

$$\text{Subject to } x \in \Psi \quad (2)$$

$$\text{That } \Psi = \{x|\ gj(x) \leq 0, j = 1, 2 \dots M\} \quad (3)$$

Where $X=[x_1, x_2, x_3 \dots x_D]^T$ is a D dimensional vector, functions and constraints can be linear or nonlinear arbitrary functions. An optimum solution in a Multi-Objective optimization Problem (MOP) is different compared to a single-objective, the concept of Pareto dominance is used for the evaluation of the solutions in the MOP. This concept formulated by Vilfredo Pareto is defined as [18]

A vector $u = (u_1, u_2 \dots u_M)$ is said to dominate a vector $v = (v_1, v_2, \dots v_M)$ (denoted by $u \leq v$), for multi-objective minimization problem, if and only if

$$\forall i \in (i,\dots,D),\ u_i \leq v_i \wedge \exists i \in \{1,\dots M\} : u_i < v_i, \quad (4)$$

A solution $u \in U$, where U is global, is called to be Pareto Optimal if and only if exists no other solution $u \in U$, such that u is dominated by v . Such solutions (u) are called non-dominated solutions. The set of all such non-dominated solutions constitutes the Pareto-Optimal Set or non dominated set [19]. Solving a MOP problem is to find the non-dominated solutions in the objective space and its counterparts in the decision space which are called as the efficient solutions [17].

2. Materials and Methods

2.1. Particle Swarm Optimization

Particle Swarm Optimization is a biologically inspired computational search and optimization method that developed in 1995 by Eberhart and Kennedy based on the social behaviors of birds flocking or fish schooling [20].A population moves towards the most promising region of the search space and each particle represents a candidate solution for the search or optimization problems. A swarm in Particle Swarm Optimization is composed of a number of particles. All of the particles iteratively find the solution. Each particle moves to a new position according to the new velocity and the previous positions of the particle. This is compared with the best position generated by previous particles in the objective function, and the best one is kept; so each particle accelerates in the direction of the global best position. If a particle discovers a new probable solution, other particles will move closer to it, to explore the region more completely in the process [21]. In Particle Swarm Optimization, a swarm consists of N particles moving around in a D-dimensional search space. The position of the i-th particle at the t-th iteration is represented by $X^{(t)}_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{iD})$ that are used to evaluate the quality of the particle. They represent candidate solution(s) for the search or optimization problems. During the search process the particle successively adjusts its position toward the global optimum according to the two factors: the best position encountered by itself (pbest) denoted as $pbest_i = (pbest_{i1}, pbest_{i2}, pbest_{i3}. pbest_{iD})$ and the best position encountered by the whole swarm (gbest) denoted as $gbest_i = (gbest_{i1}, gbest_{i2}, gbest_{i3} \dots gbest_{iD})$. Its velocity at the t-th iteration is represented by $V^{(t)}_i = (v_{i1}, v_{i2}, v_{i3}. \ .\ .v_{iD})$ [16].

$$v^i_j[t+1] = wv^i_j[t] + c_1 r_1 (x^{i,pbest}_j[t] - x^i_j[t]) + c_2 r_2 (x^{g,best}_j[t] - x^i_j[t]) \quad (5)$$

$$x^i_j[t+1] = x^i_j[t] + v^i_j[t+1] \quad (6)$$

where j= 1, 2, 3, . . ., n is the dimension of particle; *w* is the inertia weight of the particle, which is employed to control the impact of the previous history of velocities on the current velocity, and it also influences the balance between global and local exploration abilities of the particles (Shi & Eberhart, 1998) [22]; c_1 and c_2 are two positive constants, called cognitive learning rate and social learning rate respectively; r_1 and r_2 are random values in the range [0,1]. In addition, the velocities of the particles are confined within $[v_{min}\ ,\ v_{max}]^D$. [23,24]. PSO is faster in finding quality solutions, compared to other evolutionary computation techniques. It faces some difficulty in obtaining better quality solutions while exploring complex functions. It may face premature convergence and suffer from poor fine-tuning capability of the final solution [8].

2.2. Time Variant Multi-Objective Particle Swarm Optimization (TV-MOPSO)

The simplicity and efficiency of Particle Swarm Optimization to solve Multi-Objective optimization Problems, named multi-objective Particle Swarm Optimization (MOPSO), are the seminal work of Coello-Coello and Lechuga (2002) [25]. They using MOPSO Algorithm with two archives, one for storing the globally non-dominated solutions, while the other for storing the individual best solutions attained by each particle. In recent years, various studies have been applied on multi-objective Particle Swarm Optimization in different field. Most approaches differ basically in two aspects: The way they promote diversity and the way they select the personal and global bests used to update the particles' positions [15]. The difficulty in extending multi-objective Particle Swarm Optimization is how to select a best global particle (*gbest*) for each particle; it's selected from the non-dominated solutions set for each particle of the swarm to attain convergence and diversity solutions [17]. To overcome the problems in standard Particle Swarm Optimization and improved this algorithm to attain better convergence to the Pareto-optimal front, while giving sufficient emphasis to the diversity consideration, suggested the Time Variant Multi-Objective Particle Swarm Optimization. TV-MOPSO is made adaptive in nature by allowing inertia weight and acceleration coefficients to change with iterations [19].

2.2.1. Initialization

To run the TV-MOPSO methodology, the swarm of size Ns is randomly generated. In this phase Na (size of the archive), T (maximum number of iterations), d (the dimensions of the search space) are determinate.

2.2.2. Update

This step is simulation of the flight of the particles. Movement of a particle in the search space is mainly control by the individual particle experience and by the experience of the group, with which it interacts directly. The pseudo code for the TV-MOPSO method is presented in Table 1.

2.2.3. Time-Varying Acceleration Coefficients

In eq.5 there are two stochastic acceleration Component, the cognitive component (c_1) and the social component (c_2). Hence, proper control of these two components is very important to find the optimum solution precisely and efficiently. To incorporate better compromise between the exploration and exploitation of the search space in Particle Swarm Optimization, time variant acceleration coefficients have been introduced in [26]. To promote this concept in Time Variant Multi-Objective Particle Swarm Optimization c_1 is decreased between initial value and final value of it while c_2 is increased between initial value and final value of this parameter. The values of c_{1t} and c_{2t} are calculated with iteration as follows:

$$c_{1t} = \left(c_{1f} - c_{1i}\right)\frac{t}{\max(it)} + c_{1i} \tag{7}$$

$$c_{2t} = \left(c_{2f} - c_{2i}\right)\frac{t}{\max(it)} + c_{2i} \tag{8}$$

Table 1. TV-MOPSO pseudo code

```
Step1:
Determination Ns, Na, T, d
- Initialize population   $x_{i,j}$,   i= {1, 2…, Ns}, j= {1, 2…, d}
- Initialize velocity     $v_{i,j}$,   i= {1, 2…, Ns}, j= {1, 2…, d}
- $Pbest_{i,j} \leftarrow x_{i,j}$           i= {1, 2…, Ns}, j= {1, 2…, d}
- $A_0 \leftarrow$non-dominated solutions in first iteration,
- $A_t \leftarrow$non-dominated solutions in iteration
Step2:
for t=1 to T
  for n=1 to Ns
    for i=1 to d
      (Update swarm and velocity)
      Finding gbest from $A_t$
      Adjust parameters ($w_t$, $c_{1t}$, $c_{2t}$)
      Adjusts the parameters,
      $w_t$: the inertia coefficient,
      $c_{1t}$: the local acceleration coefficient, and
      $c_{2t}$: the global acceleration coefficient
      $v_j^i[t+1] = wv_j^i[t] + c_1 r_1(x_j^{i,pbest}[t] - x_j^i[t]) + c_2 r_2(x_j^{g,best}[t] - x_j^i[t])$
      Update position
      $x_j^i[t+1] = x_j^i[t] + v_j^i[t+1]$
      Updating the archive
      $A_t \leftarrow$ non-dominated solutions
      If $l_A$ >Na shorten archive($l_A$ size of the archive)
      mutate (St) mutating the swarm
final output = $A_t$
```

Where c_{1i} and c_{2i} is initial value of c_1 and c_2 respectively, c_{1f} and c_{2f} is final value of c_1 and c_2 respectively. Max (it) is maximum number of iteration. The values of c_1 and c_2 get updated with iterations in TV-MOPSO in the Step 2 [19].

2.2.4. Time-Varying Inertia Weight

The parameter *inertia weight w* controls the influence of the previous velocity on the present velocity [27]. In the Particle Swarm Optimization (PSO) method in order to better convergence, a strategy for the incorporation of inertia weight *w* is suggested in [28]. If *inertia weight* has high value it will help in the global search to find the optimal solution while lower values help in the local search around the current search space. Time Variant Multi-Objective Particle Swarm Optimization uses a time variant *w* as in [29]. The value of

w_t is decrease linearly with iteration from w_1 to w_2. The value of inertia weight at iteration t, w_t is obtained as

$$w_t = (w_1 - w_2)\frac{\max(it) - it}{\max(it)} + w_2 \tag{9}$$

Where *max (it)* is the maximum number of iterations and *it* is the iteration number.

2.3. Case Study

To illustrate the model application and performance, the operation of the Doroodzan reservoir of Iran is selected as a case study. The Doroodzan dam is located at latitude 30º 12' 27" N and longitude 52 º 25' 5" E and northwest of Shiraz city of Iran. Monthly inflows to the reservoir, along with monthly demands, are presented in Fig.1.The average annual inflow to the reservoir and annual demand, are estimated as 1192 MCM (Million Cubic Meter) and 1267MCM, respectively. The gross storage capacity of the reservoir is 993 MCM and the active storage volume of the reservoir is 860 MCM. The reservoir constructed across the Kor River, satisfies the multiple purposes of water supply including industrial and domestic water uses, irrigation and hydropower generation. This study mainly concentrates on how to arrange water release from the reservoir to best satisfy human demands in the downstream area of the Doroodzan Reservoir. The purpose of this paper is to find the monthly optimum releases for the 5 historical years (1998-2002).

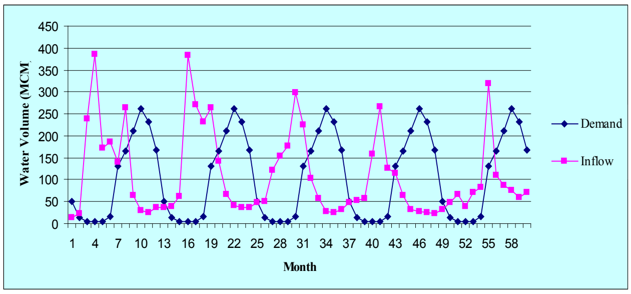

Figure 1. Monthly inflows to the reservoir, along with monthly demands

2.3.1. Mathematical Model Formulation

The objectives of the model are minimizing industrial, domestic and irrigation deficits and maximization of hydropower generation. Minimization of the deficits and maximization of hydropower generation are mutually conflicting objectives, since the one of them tries for minimization of the deficits, requires more water to be released to satisfy demands (industrial, domestic and irrigation) and the other tries to maximize hydropower production, requiring higher level of storage in the reservoir to produce more power. These three competing objectives of the system are expressed as follows:

$$\text{Minimize } f_{1t} = \sum_{t=1}^{12} (D_{1,t} - R_{1,t})\hat{}2 \tag{10}$$

$$\text{Minimize } f_{2t} = \sum_{t=1}^{12} (D_{2,t} - R_{2,t})\hat{}2 \tag{11}$$

$$\text{Maximize } E = \sum p(R_{2,t}H_t) \tag{12}$$

Where f_{1t} is loss function (*Sum of Squared Deviations*) of industrial and domestic, f_{2t} is loss function of irrigation and *E* is the total energy produced in MkWh; t = 1, 2 . . ., 12; D_1 is the industrial and domestic demands and D_2 is irrigation demand; R_1 is releases of industrial and domestic and R_2 is releases of irrigation; *H* is net heads available (m); *p* is power production coefficient.

The optimization is subject to the following constraints:

$$S_{t+1}=S_t+I_t-(R_{1,t}+R_{2,t}+Ev_t+O_t)\ \forall t \tag{13a}$$

$$S_{min} \le St \le S_{max}\ \forall t \tag{13b}$$

Last period is equal to the initial storage of the first period.

$$S1=S61 \tag{14}$$

respectively. Where *S*min and *S*max are the minimum and maximum active storages of the reservoir.

$$pR_{2,t}H_t \le E_{max}\ \forall t \tag{15}$$

Where, E_{max} the maximum amounts of power in MkWh (turbine capacity).

$$D1min,t \le R1,t \le D1max,t\ \forall t \tag{16}$$

$$D_{2min,t} \le R2,t \le D_{2max,t}\ \forall t \tag{17}$$

Where, $D_{1min,t}$ and $D_{1max,t}$ are minimum and maximum of the industrial and domestic demand. $D_{2min,t}$ and $D_{2max,t}$ are minimum and maximum irrigation demand. All of the above formulation involves non-linear optimization. In eq.12 power generated is a non-linear function of release and head causing the flow. In eq.13a evaporation loss is a function of non-linear relation between water spread area and average storage. To bring three the objectives into same units, the hydropower objective is nondimensionalized. So the final fitness function for the model is as follows:

$$\text{Minimize } f_{1t} = \sum_{t=1}^{12}\left(\frac{D_{1,t} - R_{1,t}}{D_{1,t}}\right)^2 \tag{18}$$

$$\text{Minimize } f_{2t} = \sum_{t=1}^{12}\left(\frac{D_{2,t} - R_{2,t}}{D_{2,t}}\right)^2 \tag{19}$$

$$\text{Minimize } E = \sum_{t=1}^{12}\left(\frac{E_{max} - p(R_{2,t}H_t)}{E_{max}}\right) \quad 20)$$

So the final models are to minimize eq.18 to eq.20 duly satisfying the constraints on reservoir continuity, storage bounds, turbine capacity, irrigation demands, mandatory releases, and steady state storage constraint, i.e., Eqs.13-17. In this model, the first priority is given for industrial and domestic demand, and the next priority to meet irrigation demand, and then to hydropower demand. If any excess water is found after meeting these three demands, such water will be spilled out as overflow, for utilization by diversion structures downstream. Releases from the reservoir are considered as decision variables, resulting in reservoir storage as a continuous state variable.

3. Result and discussion

3.1. Test Function

In this study the performance of TV-MOPSO algorithm is compared with some other multi-objective algorithm in the same test function. Coello Coello et al. (2004) compared results of their MOPSO algorithm with those of NSGA-II, MicroGA (microgenetic algorithm) and PAES (Pareto Archived Evolution Strategy) [15]. One of the test functions used by these authors was the multi-objective problem proposed by Kita et al. (1996) [30].

$$\text{Maximize } F = (f_1(x,y),\ f_2(x,y)) \tag{21}$$

Where $f_1(x,y) = - x^2 + y$, $f_2(x,y) = x/2 + y+1$;
subject to $x/6 + y - 6.5\leq 0$, $x/2 + y - 7.5\leq 0$, $5x+y - 30 \leq 0$, $x,y \geq 0$ and $0 \leq x, y \leq 7$,
In order to make a fair comparison with the results by Coello Coello et al. (2004), 30 independent runs of the TV-MOPSO were executed, all of them with the same number of function evaluations (5,000) as used by Coello Coello et al. (2004) [31]. Two performance metrics were calculated. The generational distance (GD) introduced by Van Veldhuizen and Lamont (1998) is used to measure the closeness of the resulting nondominated solutions to the true Pareto front [32], and the spacing metric (SP) proposed by Schott (1995) is used to measure the distribution of the nondominated solutions found so far [33]. These metrics are defined as:

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n} \tag{22}$$

Where n = number of vectors in the set of nondominated solutions and di = Euclidean distance between each of those vectors and the nearest member in the true Pareto front [15], measured in the objective space

$$SP = \sqrt{\frac{\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2}{n-1}} \tag{23}$$

Where $d_i = \min_j\left(\left|f_1^i - f_1^j\right| + \left|f_2^i - f_2^j\right|\right)$, $i, j = 1, \ldots, n$;
$\bar{d}$ = mean of all d_i; and n = number of vectors in the nondominated set. The SP metric measures the distance variance of neighboring vectors in the nondominated set [15]. The results are provided in the Tables 2 and 3, which also present. According to the Tables 2 and 3 the TV-MOPSO results are better on GD and SP in most of algorithms.

Table 2. Generational Distance Results

GD	TV-MOPSO	MOPSO	NSGA-II	microGA	PAES
Best	0.0023	0.0024	0.0039	0.0051	0.0113
Worst	0.0557	0.4768	0.6784	0.9121	0.9192
Average	0.0110	0.0365	0.0842	0.1508	0.1932
Median	0.0062	0.0079	0.0112	0.0898	0.0333
Std. Dev	0.0133	0.1046	0.1652	0.2166	0.2497

Table 3. Spacing Metric Results

GD	TV-MOPSO	MOPSO	NSGA-II	microGA	PAES
Best	0.0352	0.0430	0.0010	0.0656	0.0067
Worst	0.4321	0.5381	1.4887	1.6439	0.4329
Average	0.0967	0.1095	0.0985	0.3150	0.1101
Median	0.0477	0.0675	0.0272	0.1297	0.0810
Std. Dev	0.0622	0.1101	0.3274	0.4217	0.0996

3.2. Multipurpose Reservoir Operation

The TV-MOPSO approach is applied to Doroodzan reservoir system to derive operating policies for the multipurpose reservoir system under multiple objectives. The total number of decision variables of the model is 24 (number of time periods=12 and number of decisions in each period=2), which is equal to the dimension of the problem. The sensitivity of TV-MOPSO algorithm is evaluated by performing a sensitivity analysis which helps to determine the impact of related solution parameters on convergence behavior. Ns=50 (size of the swarm), Na=100 (size of the archive), T=500 maximum number of iterations, *inertia weight* w_1=0.7 and w_2=0.4 c_{1i} = 2.5 and c_{2i} = 0.5 (initial value of c_1 and c_2 respectively), c_{1f} = 0.5 and c_{2f} = 2.5 (final value of c_1 and c_2 respectively). The same reservoir system is also solved using standard PSO technique and the result of TV-MOPSO method is compared with standard Particle Swarm Optimization (PSO). In PSO method, weighted approach has been used to model the objective function. The sensitivity analysis of the Particle Swarm Optimization model is performed with different combinations of each parameter. For this model, the parameters chosen after thorough sensitivity analyses are size of the swarm N=200; inertia weight is varied with iteration, initial w is 0.9 and final is 0.2; Particle Swarm Optimization constant parameters are c_1=c_2=1.5; T=500 (maximum number of iterations). To check the performance of the proposed technique, the models are run for ten random trials. In this reservoir, the first priority is given to industrial & domestic demand and the next priority to meet irrigation demand and then hydropower generation. For this case study industrial& domestic demand is fixed, but the value of Irrigation demand changes in different months thus for some of the months which the Irrigation demand is low the turbine is off (Peak turbine capacity is 10 Mwh), therefore hydropower has been generated for only seven months so energy generation is dependent on irrigation water demand. The average annual of these objectives for this multi objective reservoir system is presented in Table 4. Average annual of Industrial& Domestic, Irrigation and Hydropower production obtained by Time Variant Multi-Objective Particle Swarm Optimization is 64.788 MCM, 955.53 MCM and 50.5 (10^6 kwh) respectively whereas that obtained using Particle Swarm Optimization is only 64.788 MCM, 852.91MCM and 45.45(10^6 kwh) respectively. These models supply 100% of Industrial& Domestic demand because the priority of objective for both of them is Industrial& Domestic demand. Time Variant Multi-Objective Particle Swarm Optimization model supplies 79.42% of Irrigation demand but in PSO only 70.88% of demand is obtained. It can be observed that TV-MOPSO is performing better than PSO method. The other objective of the model is to maximize the hydropower production. Here also it can be noticed that the highest hydropower production is obtained with the TV-MOPSO technique. For Irrigation and Hydropower production objectives, Time Variant Multi-Objective Particle Swarm Optimization performance is better than Particle Swarm Optimization.

Table 4. Values percentages for the Three-Objective Reservoir Operation Problem for TV-MOPSO and PSO methods.

PSO	TV-MOPSO	Objective	Algorithm
100%	100%	f1	Industrial& Domestic(MCM)
70.88%	79.42%	f2	Irrigation (MCM)
87.03%	93.03%	E	hydropower generation

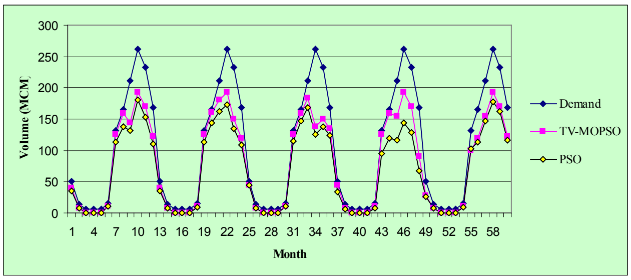

Figure 2. Time series plot of monthly hydropower generated with TV-MOPSO, standard PSO techniques over a period of 5 years

Fig2 shows the time series graph of monthly Industrial& Domestic and Irrigation releases made for both techniques over a period of 5 years. According to Fig2 for most of the month the value of the Time Variant Multi-Objective Particle Swarm Optimization (TV-MOPSO) is better than Particle Swarm Optimization. For some of the months like October, November, December, January and February in which demand is low, both of the algorithms to some extent have the same values, but for some other months that demand is high, the performance of TV-MOPSO is better than Particle Swarm Optimization.

.From these results, the main advantages of Time Variant Multi-Objective Particle Swarm Optimization noticed are, if the number of decision variables and constraints increases in the problem domain, the quality of optimal solution is better than the standard Particle Swarm Optimization. Also, in Multi-Objective optimization Problem like reservoir operation, the result of multi-objective methods like TV-MOPSO is better than single objective methods because in these techniques objectives will be optimized simultaneously. In the overall perspective, it is found that the operating policies obtained by the Time Variant Multi-Objective Particle Swarm Optimization technique are better than the standard Particle Swarm Optimization.

4. Conclusion

Heuristic techniques have great potential in optimizing complex systems. This study proposes Time Variant Multi-Objective Particle Swarm Optimization (TV-MOPSO) for multi-use reservoir management, Doroodzan reservoir that incorporates these objectives, human demand requirements, irrigation requirements and hydropower generation. To have highest yields in Doroodzan reservoir operation in this paper the Time Variant Multi-Objective Particle Swarm Optimization method is demonstrated, it can be effective in this reservoir operation. Conclusively, the operating policies obtained by the TV-MOPSO technique are better than the standard Particle Swarm Optimization techniques, so in Multi-Objective optimization Problem like reservoir operation the result of TV-MOPSO is better than single objective methods because in this technique objectives will be optimized simultaneously. Thus, in this regard the performance of an algorithm like Time Variant Multi-Objective Particle Swarm Optimization is significant.

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