Application of particle swarm optimization to water management: an introduction and overview

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Abstract Particle swarm optimization (PSO) is a stochastic population-based optimization algorithm inspired by the interactions of individuals in a social world. This algorithm is widely applied in different fields of water resources problems. This paper presents a comprehensive overview of the basic PSO algorithm search strategy and PSO's applications and performance analysis in water resources engineering optimization problems. Our literature review revealed 22 different varieties of the PSO algorithm. The characteristics of each PSO variety together with their applications in different fields of water resources engineering (e.g., reservoir operation, rainfall–runoff modeling, water quality modeling, and groundwater modeling) are highlighted. The performances of different PSO variants were compared with other evolutionary algorithms (EAs) and mathematical optimization methods. The review evaluates the capability and comparative performance of PSO variants over conventional EAs (e.g., simulated annealing, differential evolution, genetic algorithm, and shark algorithm) and mathematical methods (e.g., support vector machine and differential dynamic programming) in terms of proper convergence to optimal Pareto fronts, faster convergence rate, and diversity of computed solutions.

Keywords Particle swarm optimization · Water resources · Evolutionary algorithm · State-of-art review

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Introduction

Limited water resources and increased water consumption led to the development of integrated water resource management in many regions (Bozorg-Haddad et al. 2008a; Seifollahi-Aghmiuni et al. 2011; and Jahandideh-Tehrani et al. 2014). Efficient water resources planning and management are required to overcome different aspects of water crisis (e.g., water supply shortage, inefficient water allocation, and drought) (Noory et al. 2012; Jahandideh-Tehrani et al. 2015). Numerous optimization techniques have been proposed and developed to overcome water crisis and achieve efficient water resources management. These optimization techniques can be applied in different fields of water resources, such as reservoir operation (Afshar et al. 2011; Bozorg-Haddad et al. 2008b, c), water distribution network design (Soltanjalili et al. 2010; Fallah-Mehdipour et al. 2011a; Sabbaghpour et al. 2012), hydrology (Cho and Olivera 2012), and the aquifer systems management (Farmer et al. 2015).

Two main types of optimization methodologies are applied in water resources management: (1) mathematical methods and (2) evolutionary and metaheuristic algorithms (EAs). Linear programming (LP), nonlinear programming (NLP), dynamic programming (DP), and stochastic dynamic programming (SDP) are examples of mathematical methods in water resource management. The genetic algorithm (GA), particle swarm optimization (PSO), the harmony search (HS) algorithm, ant colony optimization (ACO), and honey bee mating optimization (HBMO) are classified among the EAs (Bozorg-Haddad et al. 2015).

Metaheuristics are defined as tools applying structure random elements to search and follow empirical guidelines inspired by natural phenomena (Maier et al. 2014). Metaheuristics can be divided into two main categories: (1) population-based algorithms (e.g., GA, PSO, and ACO) and single point-based algorithms (e.g., simulated annealing (SA) and tabu search (TS)) (Maier et al. 2014). EAs are the most well-known family of metaheuristics, belonging to the first stated subcategory (population-based), which are inspired by diverse mechanisms of biological reproduction and evolution such as mutation, crossover, selection, and adaptation (Nicklow et al. 2010). EAs search for acceptable solutions according to randomized operators. These operators simulate mutation and recombination to achieve new individuals that may survive by natural selection, and selection operates based on the fitness of an individual, or fitness function of current solutions of an algorithm (Back et al. 2000). Fogel (2000) concluded that EAs are efficient in solving high-dimensional non-convex, nonlinear, multimodal, and discrete problems without having precise knowledge of the problem's structure. Following this, multiple functions can be optimized simultaneously by EAs (Sarker and Ray 2009). The teacher-learning-based optimization (TLBO) algorithm does not require algorithm-specific parameter tuning (inspired by the impact of teacher influence on learners' output in a class) (Venkata Rao 2016). In contrast, most EAs (PSO, GA, NSGA-II (non-dominated sorting genetic algorithm II), etc.) demand heavy computational burden and require the adjustments of algorithmic parameters; yet, they generally outperform mathematical methods in terms of computational time and faster convergence (Blickle 1997; Venkata Rao 2016). According to Jahandideh-Tehrani et al. (2019), the provision of diverse solution space and efficient objective function by non-animal inspired EAs (e.g.,

GA, SA, and DE (differential evolution)) leads to their good performance, particularly in complex and multi-objective problems, while other optimization methods are beset with large dimensionality (Jahandideh-Tehrani et al. 2019). Reddy and Kumar (2006) indicated that in multi-objective problems, mathematical optimization methods (e.g., LP, NLP, and DP) are generally unable to obtain good Pareto front as these methods are based on point by point search approach, which generates a single optimal solution. The weighted objective function approach is applied in multi-objective problems, but it is unable to consider all objective functions simultaneously in a Pareto sense. Therefore, EAs have been widely developed and used in solving optimization problem in water resources problems.

PSO was introduced by Kennedy and Eberhart (1995). PSO is a population (swarm)-based stochastic search technique derived from the interactions of individuals in a social world (Eberhart et al. 2001). PSO has been applied in a wide range of water resources problems. Gill et al. (2006) applied PSO to parameter estimation in rainfall–runoff modeling. The latter authors calibrated a three-parameter support vector machine model with PSO. Hassan (2020) applied PSO to estimate and calibrate the parameters of a Bartlett-Lewis rectangular pulse (BLRP) model for daily rainfall disaggregation. They indicated that the calibrated model is able to simulate extreme rainfall with satisfactory agreement. Matott et al. (2006) applied PSO approach to groundwater contamination remediation. The PSO was also identified as an effective algorithm in a pump-and-treat optimization problem. Kumar and Reddy (2007) applied PSO approach to reservoir system optimization and derived operating policies for a multi-purpose reservoir system. The PSO was applied to real-time water level prediction in a river by Chau (2007). This algorithm was also applied in a water quality model by Afshar et al. (2011), who calibrated the key parameters of the CE-QUAL-W2 (two-dimensional, hydrodynamic, and water quality model) model in a simulation of water temperature. Regarding the application of PSO in water distribution networks, Suribabu and Neelakantan (2006) designed a water distribution pipeline network with PSO. This approach was tested with two benchmark optimization design problems. Based on previous literature studies, it is concluded that the PSO algorithm was modified and applied in various fields of water resources management,

including reservoir operation, surface water, ground-water, water quality, and water distribution networks.

The purpose of this paper is to assess the-state-of-the-art based on the applications of PSO algorithm and its variants in different fields of water resources management, such as rainfall–runoff modeling, flood routing, groundwater modeling, water quality parameter estimation, flow prediction, basin water transfer, water distribution network design, reservoir operation, and irrigation water allocation. First, the features of the basic PSO algorithm and its search strategy is presented by means of a basic PSO flowchart. Thereafter, the features of the applied PSO variants in surveyed papers, including using single- or multi-objective PSO, comparison between PSO and other EAs, comparison between PSO and other mathematical methods, and benchmark applications are discussed to highlight the potential of PSO algorithm in optimization problems in the realm of water resources engineering. The results of the reviewed papers are also discussed briefly to analyze the performance of different PSO variants in terms of convergence rate, objective function evaluation, Pareto front estimation, and search space evaluation. The remainder of this paper outlines the discussions on the reviewed literature and conclusions of the bibliometric survey.

Particle swarm optimization algorithm

PSO is an evolutionary algorithm proposed by Kennedy and Eberhart in 1995. The particle swarm idea was inspired by simulating a simplified social system of a flock of birds that fly towards their unknown destination (fitness function) in search for the locations of food resources. The PSO algorithm features birds that evolve and coordinate their movement to reach their destination (Shi and Eberhart 1998). The birds (particles) search their destination according to their own experience (personal fitness) and the flock of birds' experience (global fitness). It is seen in Fig. 1 the PSO algorithm is initialized with random particles (birds) with a specific position and velocity for the purpose of computing objective function of an optimization problem. The best personal and global fitness positions are computed over each iteration of running the PSO algorithm. The position and velocity of each bird is updated according to the calculated fitness functions until the optimal solution is obtained (Knight et al. 2015). The position of the ith particle is calculated as follows:

$$X_i(t + 1) = X_i(t) + V_i(t + 1) \tag{1}$$

where $X_i(t + 1)$; $X_i(t)$ denote the positions for the ith particle at $(t + 1)$ and t, respectively; and $V_i(t + 1)$ denotes the new velocity of the ith particle at time $(t + 1)$. The latter term is determined by the following equation:

$$V_i(t + 1) = w \times V_i(t) + C_1 \times r \times \left(X_i^{\text{pbest}} - X_i(t) \right) + C_2 \times r$$
$$\times \left(X_i^{\text{gbest}} - X_i(t) \right) \tag{2}$$

in which $V_i(t)$ denotes the velocity for the ith particle at time t; w denotes the inertia weight; C_1; C_1 denote the weighting coefficients for the personal best and global best positions, respectively; X_i^{gbest} denotes the ith particle's best known position; X_i^{gbest} represents the best position known to the swarm; and r denotes a random number between 0 and 1. C_1 and C_2 should be tuned to obtain optimal solution.

Many varieties of the PSO have been developed since its introduction. Table 1 lists those varieties in chronological order, with the oldest one placed at the top of the list. It is evident from Table 1 that 22 varieties of PSO versions were developed by researchers. The next sections review the main PSOs applied to water resources engineering in chronological order.

Discrete particle swarm optimization

This PSO algorithm was introduced by Kennedy and Eberhart (1997). The PSO searches for optimal solutions by operating on discrete and binary variables. The original particle swarm optimization searches for solutions by manipulating the coordinates of a particle in binary space, where a particle moves through search points (Kennedy and Eberhart 1997). Noory et al. (2012) applied LP, CPSO (continuous particle swarm optimization) and DPSO to optimize an irrigation water allocation and a multi-crop planning problem in central Iran. They demonstrated that both CPSO and DPSO kept the variations in annual net benefit in the range of 2%. DPSO calculated the optimal annual net benefit and standard deviation of 50 independent runs by 167,000 and 0.81, respectively, while CPSO estimated the optimal annual net benefit and standard deviation by 200,000 and 1.09, respectively. Therefore, the latter authors concluded DPSO algorithm obtained more accurate results in shorter time than the CPSO algorithm. Datta and Figueira (2011) introduced an integer DPSO (IDPSO) algorithm. This new algorithm

Fig. 1 Flowchart of basic PSO algorithm
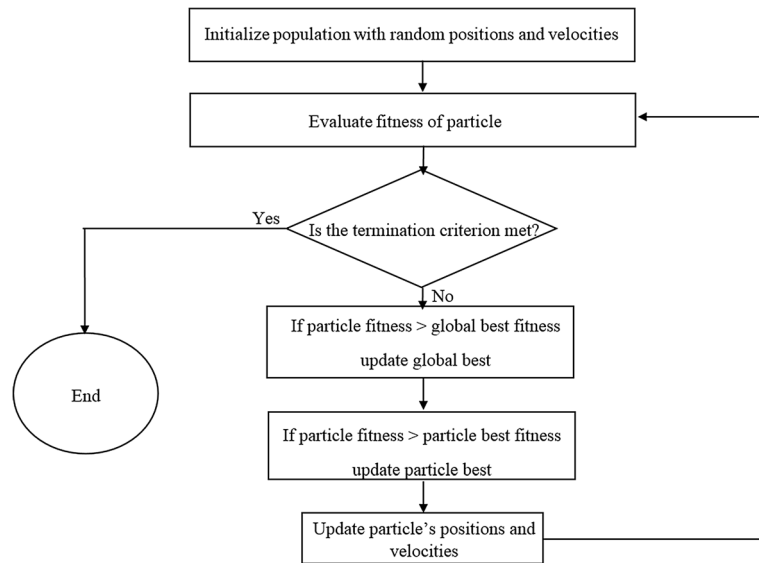
operates with real, integer, and discrete variable. Ezzeldin et al. (2013) applied this algorithm to minimize total design cost of water distribution networks. Their results from a benchmark hypothetical two-reservoir network, IDPSO produced the minimum cost of 1.257×10^8 with 28,036 function evaluations, while compared to the real cost of 1.263×10^8 with 25,200 obtained in a study by Kadu et al. (2008). It was concluded that IDPSO algorithm improved the search process for global optimal solution and saved the computational time through less function evaluations.

Multi-objective particle swarm optimization

Multi-objective PSO (MOPSO) was proposed by Moore and Chapman in 1999, who adopted the PSO for multi-objective optimization by modifying the p-vector (contains the best particle swarm discovered by a particle) to determine all the non-dominated solutions (based on Pareto preference) that a particle could reach. Gill et al. (2006) employed this algorithm and compared their results with NSGA-II, micro-GA, and PAES (Pareto Archive Evolutionary Strategy) to minimize the RMSE (root mean square error) in the process of parameter estimation in a rainfall–runoff model. The latter authors concluded that MOPSO was more efficient than the other three algorithms in determining non-dominated fronts and spanning its search through the parameter space. Fallah-Mehdipour et al. (2011b) applied MOPSO to minimize the sum of square deviations

of reservoir release from demand, storage from target storage, and generated power from installed capacity. The latter authors also applied a new warm-up method (single objective search mechanism) to improve the quality and quantity of Pareto fronts in MOPSO. The latter authors indicated that MOPSO coupled with warm-up method increased flexibility of decisions for reservoir operation under different conditions as premature convergence was prevented. Afshar et al. (2013) applied MOPSO for optimal calibration of water quality model by linking CE-QUAL-W2 to MOPSO which led to proper results. They applied MOPSO to optimize two conflicting CE-QUAL-W2 model calibration objectives, i.e., the minimization of the RMSE for temperature and water surface elevation, and maximization of the model performance in predicting changes in dissolved oxygen. They concluded that given the strong correlation between water quality and hydrodynamic condition of a river-reservoir system MOPSO performed efficiently in generating potential optimal calibration solutions. EL-Ghandour and Elbeltagi (2014) applied MOPSO to maximize pumping rates and minimize pumping costs of a groundwater problem. The latter authors confirmed the capability of MOPSO in solving groundwater management problems. Vonk et al. (2015) employed MOPSO in reservoir operation management. They also compared the performance of MOPSO and NSGA-II in optimizing the shortage index and mean annual energy production of the Xinanjiang–Fuchunjiang Reservoir Cascade. The latter authors

Table 1 Varieties of PSO

Algorithm	Abbreviation	Year of application	Reference
Discrete particle swarm optimization	DPSO	1997	Kennedy and Eberhart
Multi-objective particle swarm optimization	MOPSO	1999	Moore and Chapman
Particle swarm optimization based on artificial neural networks	PSO-ANN	2000	Zhang and Shao
Stretching particle swarm optimization	SPSO	2001	Parsopoulos
Hybrid particle swarm optimization and genetic algorithm	PSO-GA	2002	Robinson et al.
Non-dominated sorting particle swarm optimization	NSPSO	2003	Li
Multi-swarm particle swarm optimization-based optimization	MSPSO	2004	Blackwell and Branke
Hybrid particle swarm optimization and simulated annealing	PSO-SA	2004	Wang and Li
Quantum-behaved particle swarm optimization	QPSO	2004	Sun et al.
Chaotic particle swarm optimization	CPSO	2005	Liu et al.
Comprehensive learning particle swarm optimization	CLPSO	2006	Liang et al.
Adaptive neuro-fuzzy inference system and particle swarm optimization	ANFIS-PSO	2007	Ghomsheh et al.
Elitist-mutated particle swarm optimization	EMPSO	2007	Kumar and Reddy
Particle swarm optimization with mutation similarity	PSOMS	2007	Liu et al.
Particle swarm optimization based on support vector machine	PSO-SVM	2007	Chung-Jui et al.
Adaptive particle swarm optimization	APSO	2007	Li and Tang
Hybrid particle swarm optimization and differential evolution	PSO-DE	2008	Li et al.
Master–slave swarms shuffling evolution algorithm based on particle swarm optimization	MSSE-PSO	2010	Jiang et al.
Catfish effect particle swarm optimization algorithm	CE-PSO	2011	Chuang et al.
Constrained particle swarm optimization	Constrained PSO	2012	Afshar M. H.
Elite guide particle swarm optimization	EGPSO	2013	Zhang et al.
Hybrid bat algorithm and particle swarm optimization	BA-PSO	2018	Ehteram et al.

reported that algorithms performed similarly in obtaining reservoir operating rules, reducing shortage index from 0.36 to 0.06 and increasing the mean annual energy production by 6.4%. Köppen and Yoshida (2007) introduced many objective PSO algorithm, which is based on a so-called set of leaders that generalize the global best particle in standard PSO. Sabzkouhi and Haghighi (2016) applied this algorithm to several objective functions (parameters) in a water supply pipe network. The latter authors coupled this algorithm with a network hydraulic simulation model. The latter author also compared the results of many objective PSO with those obtained by NSGA-II. Their results showed multi-objective PSO slightly outperformed NSGA-II given the number of iteration for convergence (233 for many-objective PSO and 688 for NSGA-II) and the number of EPANET runs. It was concluded that many objective PSO reached solution 4.4 times faster than NSGA-II, while NSGA-II subdivided the problem into eight groups of objective functions, and many-objective PSO optimized the objective function in only one simulation. In the field of inter-basin water transfer, Mousavi et al. (2017) coupled MOPSO with water evaluation and planning (WEAP) simulation module to minimize the project size and maximize the reliability of irrigation water supply. They demonstrated that the irrigation demand was met at an acceptable reliability level (73.2%) achieving 30,000 ha of land development and 237 million cubic meters of water supply. Hojati et al. (2018) applied and compared the applications of MOPSO and NSGA-II to obtain optimal operation of two reservoirs for the objectives of maximizing income

from power production and flood control. Their results indicated that the revenues from power generation and flood control storage were 8.9 million Rial and 10.96 Giga cubic meters for NSGA-II, respectively, while MOPSO obtained 6.9 million Rial and 10.62 Giga cubic meters for power generation income and storage of flood control, respectively. Thus, NSGA-II outperformed MOPSO in terms of better convergence rate and calculation of accurate Pareto front. Yousefi et al. (2018) applied MOPSO to optimize the benefits and negative impacts of using treated wastewater and groundwater for crop irrigation. The latter authors concluded the net benefits of optimizing crop patterns, water supply, and groundwater recharge were increased by 7, 47, and 15%, respectively. In general, MOPSO is one of the most frequently applied multi-objective algorithms in water resources management problems.

Particle swarm optimization based on artificial neural networks

Zhang and Shao (2000) introduced this algorithm. In such hybrid algorithms, one of two modules acts as a simulator while the other is an optimization module. PSO finds optimized calibration model and artificial neural network (ANN) is a simulation model to assess PSO's behavior. Kuok et al. (2010) applied coupled PSO-ANN algorithm to model daily rainfall–runoff process in Sungai Bedup Basin, Sarawak, Malaysia. Their results revealed that estimated coefficient of correlation and the Nash–Sutcliffe coefficient over testing period were 0.90 and 0.81, respectively. Thus, they confirmed the successful use of PSO-ANN in modeling rainfall and runoff. Gaur et al. (2013) and Ch and Mathur (2012) applied PSO-ANN in groundwater management to minimize pumping and piping cost for the installation of new pumping wells and minimize parameter error, respectively. The latter authors both indicated that PSO-ANN performed well in their case studies. Gaur et al. (2013) demonstrated that the coupled PSO-ANN can address the computational burdens and identify the optimal location of well. Ch and Mathur (2012) applied coupled PSO-ANN for the estimation of the storage coefficient and transmissivity. A comparison between PSO and other training algorithms (e.g., gradient descent (GD) backpropagation, gradient descent momentum, and adaptive learning rate (GDX) backpropagation, and one-step secant (OSS) backpropagation) has been conducted, where PSO

featured the lowest error index (13.8%) with faster convergence compared to other methods. Buyukyildiz et al. (2014) employed PSO to estimate monthly water level change of a lake, and compared their results with SVR (support vector regression), MLP (multi-layer artificial neural networks), RBNN (radial basis neural networks) and ANFIS (adaptive network-based fuzzy inference system). However, PSO-ANN showed poor results, while SVR was the most successful method. Kisi et al. (2017) applied PSO-ANN and DE-ANN to model groundwater parameters (SO_4 and sodium adsorption ratio (SAR)). They calculated three goodness-of-fit measures, RMSE, mean absolute error (MAE), and coefficient of determination (R^2), to assess the capability of the groundwater model. It was concluded after comparing the performance of DE-ANN with PSO-ANN that DE-ANN generated more accurate results (closer to the observed SO_4 and SAR) for various numbers of hidden nodes. For instance, over the testing period with 18 hidden nodes, PSO-ANN obtained 3.76, 2.46, and 0.85 for RMSE, MAE, and R^2, respectively, while DE-ANN obtained 2.91, 1.88, and 0.88 for RMSE, MAE, and R^2, respectively for SO_4 modeling. Pandayee et al. (2017) predicted river water level in Thailand using PSO-ANN. PSO has been applied as an optimization toll to tune the ANN parameters (e.g., weights and biases) over training process. According to their results, PSO improved the water level prediction as well as reducing the training process time.

Stretching particle swarm optimization

This algorithm was introduced by Parsopoulos et al. (2001). The latter authors adopted a function "stretching" PSO to tackle the occasional convergence to local minima. This function consists of two-stage objective function transformations that remove the local minima. Mirfenderesgi and Mousavi (2016) applied this algorithm to minimize the capacity of new reservoir construction projects and water shortage. In their study, they linked SPSO with MODSIM model, which required high computation time. Thereafter, to tackle the high computation time, they replaced MODSIM by ANN, support vector machine (SVM), kriging, and polynomial functions, and compared results with those obtained by coupled SPSO-MODSIM, which showed all the four replaced function obtained efficient solutions with less computation time. In the area of climate change predictions, Fereidoon and Koch (2018) studied

the impacts of climate change on agricultural crop pattern. They developed a coupled simulation-optimization tool SWAT[1]-LINGO-MODSIM[2]-PSO (SLMP) to optimize future cultivation crop pattern with focus on economic benefit maximization in the south of the Karkheh River Basin. They successfully applied PSO as an optimization tool to optimize the cultivation areas of different crops. They demonstrated that the annual total benefits are 88.33 and 72.07 (million US$) under Representative Concentration Pathways (RCP) 4.5 and 8.5, respectively. They concluded that PSO application improves the SLMP model in terms of speed and efficiency in maximizing the agricultural benefits.

Hybrid particle swarm optimization and genetic algorithm

Robinson et al. (2002) proposed PSO-GA. The PSO population of solutions is input as the starting population of the GA after fitness evaluation. Wu et al. (2015) and Chang et al. (2013) applied this approach in rainfall prediction and operation of a multi-reservoir system, respectively. Wu et al. (2015) compared their results with conventional GA and NN (neural network) and showed the search efficiency of the PSO-GA and its capacity to avoid premature convergence. Chang et al. (2013) compared their results with PSO and GA and concluded the hybrid method was capable of obtaining optimal solutions and with rapid convergence. Babu and Vijayalakshmi (2013) applied the PSO-GA algorithm to optimize the size of the pipes and compared their results with PSO and GA. The authors confirmed the efficiency of the PSO-GA algorithm compared to PSO. The conventional PSO was unable to identify the historically reported optimal solutions of benchmark water distribution networks, while PSO-GA was able to find the pipe diameter combinations to meet the required minimum nodal hydraulic-head with minimum cost. Gholami et al. (2018) employed coupled PSO-GA in an ANFIS model for back profile shape prediction in a laboratorial stable channel with a sand bed. According to their results and comparison with measured data, the determination coefficient and mean absolute relative error (MARE) calculated by 0.9951 and 0.1575, respectively, which indicated high accurate prediction of stable bank

shape. In general, the hybrid PSO-GA performed much better than PSO and GA in the surveyed papers.

Non-dominated sorting particle swarm optimization

Li (2003) proposed this algorithm. Instead of using a single comparison between a particle's personal best and its offspring, Li (2003) used all particles' personal bests and their offspring to achieve more effective non-domination comparison. Liu (2009) applied this approach to minimize the RMSE of peak flow and low flow. Based on their comparison with NSGA-II, non-dominated sorting PSO (NSPSO) was found to reach superior and diverse solutions. Li et al. (2015a, b) coupled NSPSO with a SWMM (stormwater management model) to minimize the engineering cost and flooding risk of different urban stormwater drainage system designs in China. Their results confirmed the feasibility and validity of their method in solving multi-objective design of detention tanks (cost and flooding risk reduction). The latter authors reported that to address flooding risk, there was a requirement of at least 68 detention tanks with a total cost of 86.07 million RMB (Chinese currency unit).

Guo et al. (2013) implemented an improved NSPSO algorithm to optimize a multi-reservoir system. I-NSPSO maintains the diversity of non-dominated solutions in multi-objective optimization problems. Guo et al. (2013) combined the multi-population mechanism with non-dominated sorting PSO to generate I-NSPSO for minimization of pump station costs and maximization of the lowest water level (for lift delivery reduction) at Guanyinge reservoir. They concluded that I-NSPSO calculated the Pareto optimal set accurately and obtained hedging rules for which the maximum reduced percentage reached 10, 10, and 30% for municipal life, industry, and agricultural supply, respectively, which improved reservoir operation compared to the standard operation policy (SOP) rule.

Multi-swarm particle swarm optimization-based optimization

Blachwell and Branke introduced multi-swarm PSO-based optimization (MSPSO) in 2004. It is an efficient approach to dynamic environments. The latter authors developed a single-population PSO through constructing interactive multi-swarms. Ostadrahimi et al. (2012) applied this approach to a multi-reservoir system in the

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[1] Soil and water assessment tool
[2] Modeling and simulation

USA and four test problems to obtain optimal reservoir operation rules. They also compared their results with the HEC-ResPRM and other stochastic approaches, finding the MSPSO outperformed conventional PSO, FATPSO (fuzzy adaptive turbulence PSO), RegPSO (regrouping PSO), and the GA in terms of positioning near-optimal solutions with fewer function evaluations. Thereafter, they combined MSPSO with the HEC-ResPRM simulation model to obtain real-time operating rules for the three-reservoir system, Columbia River Basin. They determined such coupled model can reduce the average, minimum, and maximum possible penalties (the HEC-ResPRM defined optimal flow and storage through minimization of the total penalties in a system). A multi-swarm comprehensive learning PSO was employed to solve multi-objective operation of the Three Gorges cascaded hydropower system to maximize the hydropower generation and to minimize the difference between estimated outflow and outflow lower target (Yu et al. 2016). The reason for using the multi-swarm comprehensive learning PSO was to distribute multiple non-dominated solutions over the true Pareto front. The latter author compared their results with multi-swarm PSO and revealed that the multi-swarm comprehensive learning PSO optimization framework leads to more efficient convergence rate and solution diversity and extremity. For instance, the mean spacing metric was estimated by 1.19×10^{-2} and 2.70×10^{-2} for the multi-swarm comprehensive learning PSO and multi-swarm PSO, respectively.

Hybrid particle swarm optimization and simulated annealing

Wang and Li (2004) introduced this hybrid algorithm. They applied this hybrid algorithm to increase the diversity of the search particles. The probability of finding the optimal solution is increased. Nikoo et al. (2014) used this approach coupled with SDP (stochastic dynamic programming) to obtain optimized water and waste load allocation rules. PSO was applied to handle the constraints of the problem and SA was used to enforce the upper and lower bounds of constraints.

Quantum-behaved particle swarm optimization

Quantum-behaved PSO (QPSO) was introduced by Sun et al. (2004). It is based on quantum machine and applied for nonlinear and non-convex optimization problems. Wang et al. (2015) applied this approach to obtain rule curves coupled to multiple hedging rules in a multi-reservoir system. The latter authors demonstrated that considering water transfer and water supply of bidirectional inter-basin is efficient. Tian et al. (2011) applied this algorithm to minimize the difference between measured and computed source of contamination in a groundwater problem. The QPSO was found to be efficient and valid in their case study. Chen et al. (2016) used QPSO in a water quality problem that minimizes the sum of squared difference between observed concentration and the computed the mass concentration of the tracer. The latter authors compared the performance of the QPSO with ABC (artificial bee colony) algorithm. The latter authors confirmed that ABC and QPSO performed almost similarly given the convergence rate. Furthermore, a scenario of adding noise (random number) to the known mass concentration was assumed. Under such assumed scenario, ABC reached better solution than QPSO, which calculated 0.2947 as the value of the objective function (minimization of mass concentration) with larger standard deviation (0.066) over 20 independent runs. In terms of combining QPSO with SVM, Zhou et al. (2008) proposed SVM based on QPSO (SVM-QPSO) algorithm. This approach selects the least squares SVM (LS-SVM) hyper-parameters based on the QPSO. Ch et al. (2013a, b) obtained the optimal values of SVM parameter by minimizing the normalized mean square error (NMSE). They confirmed the suitable performance of this algorithm in predicting monthly streamflow with high degree of accuracy and computational efficiency. In Ghorbani et al. (2018), QPSO was coupled with ANN to predict daily evaporation rate. The measured and predicted evaporation were compared, and estimated MAE, RMSE, and Nash–Sutcliff were 0.521, 0.755, and 0.88 mm/day, respectively, which were more efficient compared to those obtained by PSO-ANN model. For the purpose of daily runoff prediction, Niu et al. (2018) combined QPSO with extreme learning machine (ELM) to address the drawbacks of ELM (e.g., trapping in local optimum). The latter authors applied hybrid ELM-QPSO to predict the hydrologic time series of the Xinfengjiang reservoir in China. According to their results, the ELM-QPSO reduce the RMSE and BIAS by 2.6 and 16.1%, respectively, compared to the simple ELM method.

Chaotic particle swarm optimization

Liu et al. (2005) introduced chaotic PSO (CPSO). It is a hybrid algorithm designed to escape from local optima and to keep a dynamic balance between local search and global search. Wang et al. (2012) applied this CPSO to a water-saving planting structure considering four objective functions, water productivity, total net output, total grain yield, and ecological benefits. The latter authors applied this algorithm to improve search performance and prevent trapping in local optimum. According to their results, CPSO indicated a high convergence rate and led to saving 7% irrigated water. He et al. (2014) used CPSO algorithm in a multi-reservoir hydropower system. Furthermore, they compared CPSO's results with those from the GA, DE, and PSO. The latter authors indicated that CPSO generated the best solutions for objective functions (minimum flood peak and minimizing the maximum upstream water level) with the minimum flood peak discharge (49,300 m^3/s) and the maximum peak-clipping rate of 22.85%. Zhong et al. (2017) applied CPSO to obtain optimal operation (power generation maximization) of a cascade reservoir in the Upper Yellow River, China. According to their results, the estimated total power generation has increased by almost 3% compared to the actual power generation.

The adaptive CPSO algorithm was introduced by Chuanwen and Bompard in 2005, which belongs to the sub-category of CPSO algorithms. They proposed this method to increase the convergence rate and resulting precision of PSO. Bai et al. (2014) applied this approach to obtain the optimal combination of the RVR (relevance vector regression) model parameters. They applied three criteria (normalized RMSE (NRMSE), mean absolute percentage error (MAPE), and the R^2) to assess the accuracy of daily forecasts of urban water demand. Using 10 particles, the NRMSE, MAPE, and R^2 equaled 0.0207 m^3, 1.53%, and 0.85 for testing data, respectively. They demonstrated that the proposed coupled ACPSO with RVR captures the chaotic pattern of daily urban water demand.

Comprehensive learning particle swarm optimization

This algorithm was proposed by Liang et al. (2006). The novel learning strategy included all other particles' historical best information to update a particle's velocity. The main advantage of this strategy is the preservation of the swarm diversity to avoid premature convergence.

Piotrowski and Napiorkowski (2011) applied this approach to a hydrologic problem and compared the results with those from DE, DDE (distributed DE), self-adaptive DE, and Levenberg–Marquardt algorithm. The Levenberg–Marquardt algorithm was found to obtain the most efficient performance criteria (mean absolute error and Nash–Sutcliff error) given convergence speed and the median of objective function evaluations over training, validation, and testing periods. Zhang et al. (2016) applied enhanced comprehensive learning PSO (CLPSO) to obtain optimal operation of multi-reservoir hydropower systems. Such enhanced CLPSO outperform conventional CLPSO in terms of exploitation performance. After comparing the enhanced CLPSO results with global and local PSO, the latter authors revealed that enhanced CLPSO, global PSO, and local PSO obtained hydropower generation of 18,378, 18,283, and 28,290 × 10^7 kWh, respectively, which indicates the superior of enhanced CLPSO.

Adaptive neuro-fuzzy inference system and particle swarm optimization

Ghomsheh et al. (2007) introduced this algorithm. PSO is used to train the parameters of ANFIS in this approach. Ch and Mathur (2010) employed ANFIS-PSO to find an optimal solution to a groundwater flow and contaminant transport problem. Their results indicated a reduction of the computation burden of ANFIS-PSO compared to vertex method given two imprecise parameters for one-dimensional solute transport in steady uniform flow. ANFIS-PSO reduced the computational burden by 41%, which also guaranteed less number of simulations for model training. Qasem et al. (2017) applied ANFIS-PSO to optimize sediment transport prediction. They compared the ANFIS-PSO results with those obtained by ANFIS-DE and ANFIS-GA. According to their comparisons, ANFIS-PSO outperformed by obtaining higher performance indices (e.g., $R^2 = 0.98$, RMSE = 0.26, and BIAS = − 0.004).

Elitist-mutated particle swarm optimization

Kumar and Reddy (2007) applied this algorithm to improve PSO. This method replaces the worst particle solutions with the best solution in particle swarms. Therefore, the solution is improved preserving the diversity of the population. This algorithm has been applied to single reservoir hydropower

(Kumar and Reddy 2007; Afshar 2009; and Ghimire and Reddy 2014). A comparison was made between elitist-mutated PSO (EMPSO), GA, PSO, dynamic programming with successive approximation (DPSA) algorithm, discrete differential dynamic programming (DDDP), and folded dynamic programming (FDP). Their results established that EMPSO outperformed PSO and the GA in terms of generating quality solutions with fewer functional evaluations. Afshar (2009) applied EMPSO to find optimal set of reservoir release given the maximization of total power generation. Latter authors concluded EMPSO performed better than PSO through generating better minimum and average cost solutions. Reddy and Kumar (2009b) maximized the total relative crop yields (nine different crops) in a single reservoir problem. EMPSO resolved the shortcomings of the standard PSO with fewer function evaluations and converting to the global optimal solution.

In terms of multi-objective optimization, Reddy and Kumar (2007) proposed elitist-mutated MOPSO (EM-MOPSO) algorithm. They coupled an innovative mechanism named elitist mutation (EM) with the algorithm to explore the search space and keep the diversity of the population. EM is able to develop the performance of PSO using the EM operator which uniformly distributed the non-dominated solutions on the optimal Pareto front. Their case study was a single hydropower reservoir. Reddy and Kumar (2007) indicated that the EM-MOPSO was more efficient than NSGA-II in terms of providing a wide range of solutions with proper convergence to the optimal Pareto front in a multi-objective reservoir operation problem (the Bhadra reservoir system in India). Three competing objective functions have been defined in this research: (i) minimization of the annual irrigation deficit, (ii) maximization of annual hydropower production, and (iii) maximization of acceptable water quality level. After comparing the results, it was concluded that EM-MOPSO generated less standard deviation (37.68) with higher mean spacing metric (258.28) compared to those obtained by NSGA-II (standard deviation of 180.51 and mean spacing metric of 504.32). Reddy and Kumar (2009a) applied EM-MOPSO to minimize the flood risk, maximize the hydropower production, and minimize the irrigation deficit. Similar results were obtained showing the superiority of EM-MOPSO over NSGA-II.

Particle swarm optimization with mutation similarity

Liu et al. (2007) proposed this approach. PSO with mutation similarity (PSOMS) is based on a similarity between the particle and the current global best particle in the particle swarm. Collectivity was applied to mutate the position of the particles randomly. Zarghami and HajyKazemian (2013) applied this algorithm to minimize the cost, maximize water supply, and minimize the environmental hazards of an urban water resources management problem. The latter authors compared the results of PSOMS with PSO and GA, and concluded that PSOMS exhibited more rapid convergence, more suitable results, and improved Pareto frontier relative to the PSO and the GA.

Particle swarm optimization based on support vector machine

Chung-Jui et al. (2007) introduced this algorithm. They applied PSO to implement a feature selection and SVM as a fitness function of PSO for a classification problem. Ch et al. (2013a, b) and García Nieto et al. (2014) applied PSO-SVM in the realm of water quality and reported proper results. Ch et al. (2013a, b) applied PSO-SVM to identify optimal pumping rate and well location to obtain optimal cost in a bioremediation system. The application of PSO-SVM reduced the average number of required simulations by 92, 87, and 92%, compared to GA, SA, and parallel recombinative SA (PRSA), respectively. Similarly, the cost of pumping has declined 9.5, 9.9, and 5.7% compared to GA, SA, and PRSA, respectively. García Nieto et al. (2014) applied PSO-SVM to turbidity prediction and compared results with experimental data. The latter authors demonstrated that the estimated correlation coefficient was 0.90, 0.90, and 0.87 over high, medium, and low waters, respectively. Su et al. (2013) applied GA-SVM and PSO-SVM in optimizing the parameters of the radial basis function (RBF), kernel function, and the penalty parameter of a reservoir operation and management problem. The latter authors indicated that GA-SVM outperformed PSO-SVM in calibration and prediction of monthly reservoir storage. Wang et al. (2013) applied PSO-SVM coupled with ensemble empirical model decomposition (EEMD) in a rainfall-runoff model. They concluded that proposed algorithm (PSO-ANN-EEMD) improved the rainfall–runoff forecasting by 65.99% and reduced the RMSE and the average absolute relative

error (AARE) by 67.7 and 65.38%, respectively. Liu et al. (2019) also employed hybrid PSO-SVM to 15 farms in China to evaluate agricultural water resiliency. According to their results, PSO-SVM obtained more accurate agricultural water resource resilience evaluation compared to TOPSIS and simple SVM models. Overall, PSO-SVM enhances SVM modeling, while one paper confirmed better optimizing efficiency than the GA-SVM.

Adaptive particle swarm optimization

Li and Tang (2012) first applied this approach. This algorithm applies an adaptive dynamic parameter control mechanism for parameter setting. Montalvo et al. (2010) applied self-adaptive PSO to design water supply systems through two benchmark problems, the Hanoi Water Supply System and the New York Tunnel Water Supply System. According to their results, self-adaptive PSO required at least 1459 iterations to obtain optimum solution, while non-self-adaptive PSO needed 1293 as self-adaptive version of this algorithm had search space with higher dimension. The latter authors reported that the proposed self-adaptive version needed no initial feasible particle and complex operators. Zhang et al. (2014a) also applied improved APSO approach to maximize reservoir hydropower generation and compared the results of improved APSO with standard PSO, adaptive PSO, and linearly decreasing PSO. Improved APSO gave results that were more efficient, rapidly convergent, and robust than other algorithms.

Hybrid particle swarm optimization and differential evolution

Li et al. (2008) introduced this algorithm. It is a parallel algorithm that enhances the population of solutions with frequent information sharing. Sedki and Ouazar (2012) applied this approach to minimize the cost design of water distribution systems. In the example of two-loop network, PSO-DE indicated 3080 for the average number of function evaluations, while PSO, GA, SA, shuffled frog leaping algorithm (SFLA), HS, and scatter search (SS) evaluated objective functions by 3120, 65,000, 25,000, 11,323, 5000, and 3215, respectively. Hence, PSO-DE outperformed the standard PSO as the mean fitness values were 419,000 and 422,700 for PSO-DE and PSO, respectively. Overall, it is concluded that PSO-DE calculated better fitness values with fewer function evaluations. Al-Ani and Habibi (2013) applied MOPSO and DE (MOPSO-DE) algorithm. They applied this algorithm to solve constrained optimization problems. PSO is useful when the system is under the risk of converging to premature solutions. To achieve the particles' best positions in the search space, PSO is coupled with DE. Ahmadianfar et al. (2016) employed this approach to obtain the hedging rules for reservoir operation with improved long-term shortage index. The proposed hedging rule improved the maximum modified shortage index (MSI) by at least 34 and 21% for the annual minimum flow and agriculture deficits, respectively.

Master–slave swarms shuffling evolution algorithm based on particle swarm optimization

Jiang et al. (2010) introduced this method by sampling a population of points randomly from the feasible space and then partitioning it into several sub-swarms. The latter authors used this approach to minimize the difference between simulation and observation discharge for hydrological parameters. After comparing the estimated standard deviation of function values and mean CPU time over 20 independent runs, master–slave swarms shuffling evolution algorithm based on PSO (MSSE-PSO) enhanced the accuracy of calibration, reduced the computational time, and improved algorithmic stability compared to conventional PSO. Jiang et al. (2013) used master–slave swarms shuffling evolution algorithm based on self-adaptive PSO (MSSE-SPSO), for parameter estimation of the HIMS hydrological model through water balance error estimation. The latter authors compared the MSSE-SPSO results with simple PSO and MSSE-PSO, where the relative error over the calibration periods estimated by 5.02, 4.33, and 4.29% for PSO, MSSE-PSO, and MSSE-SPSO, respectively. The computed correlation coefficient of PSO, MSSE-PSO, and MSSE-SPSO over the calibration period were 0.72, 0.77, and 0.78, respectively. Therefore, they concluded that the application of the stated algorithm improved parameter estimation process and hydrologic modeling. In another study by Jiang et al. (2015) Master–slave swarms shuffling evolution algorithm based on self-adaptive dynamic PSO (MSSE-SDPSO) algorithm was employed to minimize average values of measured and simulated discharges in a rainfall–runoff modeling. MSSE-SDPSO had faster convergence and

more stable performance in calibrating the parameters of a rainfall–runoff compared with SCE-UA and PSO.

Catfish effect particle swarm optimization algorithm

Chuang et al. (2011) proposed this algorithm. They applied the catfish effect to enhance the performance of the binary PSO through the introduction of new particles in the search space. Peng et al. (2014) applied catfish effect PSO (CE-PSO) algorithm to optimize sediment trapping and flow regulation in a multi-objective optimization. They obtained optimal solutions for flood control and sediment transport through optimizing both downstream and upstream impounding time of Xiluodu–Xiangjiaba Cascade Reservoirs, China. They demonstrated that the impounding time of the downstream reservoir would be advanced from September 21 to September 8 if power generation was increased from 0.47 to 0.67.

Constrained particle swarm optimization

Afshar (2012) proposed this approach. The latter author applied this fully constrained PSO (FCPSO) to maximize water supply and power generation of a large-scale reservoir problem. FCPSO considers the periods of operation in reverse order by defining a new set of bounds for storage volume. FCPSO was found to be superior to the basic PSO and GA in terms of locating near-optimal solutions and convergence characteristics. Afshar (2012) proposed partially CPSO (PCPSO). PCPSO forces the particles of the particles swarm to fly in the feasible area of the search space except for very rare cases. PCPSO was relatively insensitive to the swarm size and the initial swarm in comparison with the original unconstrained PSO and GA. Afshar et al. (2013) proposed partially constrained PSO I (PCPSO1) algorithm to define a new set of bounds for decision variable. The new constraints on the corresponding state variables are satisfied. The latter author employed this algorithm to a hydropower multi-reservoir system and compared the results with FCPSO, unconstrained PSO, and PCPSO2. Constrained algorithms, particularly FCPSO, performed better than UCPSO, DDP (differential dynamic programming), GA, and ACOA. Moeini and Bababaei (2017) applied FCPSO and PCPSO to optimize a large-scale reservoir operation optimization problem in Iran (Dez reservoir). Their results demonstrated that FCPSO and PCPSO

obtained feasible solutions under different operation periods, while constrained PSO could not calculate a feasible solution over the long operation periods (480 months). The FCPSO's search space was smaller than PCPSO's and unconstrained PSO's, which led to the achievement of the best solution cost.

Elite guide particle swarm optimization

Zhang et al. (2013) proposed multi-elite guide PSO (EGPSO) algorithm. This algorithm introduced archival sets into standard PSO while external archival sets that maintain elite solutions over the evolution process are applied to provide multi-elite flying directions for the search particles. The latter authors established MGPSO reduced the energy deficit by 126.21 and 19.9 compared to DE and PSO, respectively. They concluded that MGPSO was robust as after 100 independent runs, the simulation results were raging between 45.75 and 46.15. This algorithm obtained better solutions than standard PSO with lower energy deficit. Zhang et al. (2014b) proposed EGPSO algorithm. It prevents trapping in local optima through an external archival set. Therefore, elite solutions are preserved over the evolutionary search process. The latter authors demonstrated EGPSO is efficient in high-dimensional and complex optimization problems in terms of convergence and computing time.

Hybrid bat algorithm and particle swarm optimization

Ehteram et al. (2018) applied coupled bat algorithm (BA) with PSO to optimize the parameters of a Muskingum model for accurate flood routing in three different case studies in the USA and UK. The aim of coupling two stated algorithms was to improve the convergence rate and obtain optimal absolute response with the purpose of addressing poor performance (e.g., trapping in local optima) of one algorithm. For example, over the Wilson flood, the estimated average solution by BA-PSO was 4.23, while conventional PSO and BA obtained average solution of 5.55 and 5.34, respectively. The BA-PSO model error decreased by 23.71 and 20.70% compared to PSO and BA, respectively. Hence, proposed hybrid algorithm improved flood routing process with less computational time. Zarei et al. (2019) used hybrid BA-PSO to study the operation of a multi-purpose reservoir in Fars, Iran. Total monthly water supplies for agricultural, urban, industrial, and

environmental purposes have been specified using hybrid BA-PSO. Comparison of the results of the proposed BA-PSO with conventional BA and PSO established that the volumetric reliability of supplying urban, environmental, agricultural, and industrial demands were 0.92, 0.89, 0.79, and 0.75, respectively, while less values were obtained for individual BA and PSO. In another study by Yaseen et al. (2019) applied hybrid BA-PSO to optimize power production and irrigation supply of a multi-purpose reservoir system in the state of Karnataka, India. This algorithm reduced the computation time of estimating average monthly irrigation demand by 28, 36, 39, 82, and 88% compared to the shark algorithm, BA, weed algorithm (WA), PSO, and GA, respectively. Given the power generation, hybrid BA-PSO generated 18.08×10^6 kWh, while the shark algorithm, BA, WA, PSO algorithm, and GA produced 17.99, 17.32, 16.96, 16.32, and 15.34 ($\times 10^6$ kWh). The proposed BA-PSO demonstrated its superiority over other stated algorithms.

Discussion

The review presented in the previous sections identified 22 varieties of PSO. It is found that the PSO algorithm and its varieties are applicable and efficient in different fields of water resource engineering, including (i) hydrological modeling (e.g., rainfall–runoff modeling, rainfall prediction, evaporation prediction, and flow prediction), (ii) hydraulic modeling (e.g., water level prediction, pipe network design, water distribution networks, and flow regulation), (iii) reservoir operation (hydropower and non-hydropower operation, reservoir storage design, and hedging rule derive), (iv) groundwater modeling (e.g., well pumping rate design, well positioning, and groundwater parameter calibration), (v) water quality (e.g., water quality model calibration, turbidity prediction, and sediment transport), and (vi) water management (e.g., flood control, flood routing, stormwater, and basin water transfer).

Our comparisons between algorithms and mathematical methods demonstrate the PSO algorithm performed efficiently when coupling with other statistical methods (e.g., SVM, ANN, and ANFIS) and evolutionary algorithms (e.g., SA, GA, BA). Based on the reviewed literature, it is evident that EMPSO and NSPO outperformed NSGA-II with faster convergence, spanned search space, diverse and efficient solution

provision, and higher spacing metric. Moreover, different variants of PSO such as PSO-GA, MSPSO, CPSO, EMPSO, PSOMS, PSO-SVM, APSO, PSO-DE, CPSO, and constrained PSO performed better than GA, primarily in terms of a faster convergence rate. Given the complex evolutionary process of the GA, many iterations are required to reach global optimal solution. As claimed by Banks et al. (2008), the GA generates new population of solutions whose newly generated offspring suffer from lack of knowledge about the group's best positions. It is also concluded that the coupling of the PSO with other evolutionary algorithms such as SA, DE, GA, and shark algorithm leads to proper convergence to optimal Pareto fronts.

Conclusion

Our review demonstrated that PSO has been widely applied in water resources optimization problems. A comprehensive literature review was conducted based on applications of different PSO variants in different fields of water resources engineering. Thirty-three variants of the PSO algorithm were found. The features and performance of the cited algorithms were discussed, and comparisons were made with other EAs and mathematical methods in different fields of water resources engineering. It was found that PSO variants perform efficiently in six main water engineering fields, including hydrological modeling (e.g., rainfall–runoff modeling, rainfall prediction, and flow prediction), hydraulic modeling (e.g., water level prediction, pipe network design, water distribution network design, and flow regulation), reservoir operation (hydropower and non-hydropower operation, single- and multi-objective reservoir, reservoir storage design, reservoir pumping station rate design, and hedging rule derive), groundwater modeling (e.g., well pumping rate design, well positioning, and groundwater parameter calibration), water quality (e.g., water quality model calibration, turbidity prediction, and sediment transport), and water management (e.g., flood control, flood routing, stormwater, and basin water transfer). This paper's review of the surveyed literature revealed that PSO has the potential for hybridization, because it can efficiently be coupled with other statistical methods (e.g., SVM, ANN, and ANFIS) and evolutionary algorithms (e.g., SA, GA, BA, and shark algorithm). Moreover, many multi-objective variants of PSO outperformed NSGA-II due to faster convergence,

diverse search space, and efficient solution provision. Similarly, many variants of single-objective PSO (e.g., PSO-GA, MSPSO, CPSO, EMPSO, PSOMS, PSO-SVM, APSO, PSO-DE, CPSO, and constrained PSO) outperformed conventional GA in terms of fewer required iterations in obtaining the global optimum. Moreover, CPSO outperformed the standard GA, DE, and PSO, because it calculated more accurate results with higher convergence speed.

Surveyed applications of the PSO algorithm in water optimization problems revealed that there is no application of the PSO to hydrodynamic parameter calibration, wave prediction, coastal erosion prediction, flood level prediction, coastal well positioning, and storm surge analysis. Furthermore, combination of PSO with other EAs such as HBMO, ant colony optimization (ACO), firefly algorithm (FA), WCA, and imperialist competitive algorithm (ICA) hold potential in the water resources field as our review determined a gap in applications of such coupled EAs in the water engineering field. It is clear the PSO variants hold substantial potential to solve a wide range of water resources problems.

Compliance with ethical standards

Conflict of interest The authors declare that there are no conflicts of interest.

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