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SOLUTION OF HYDROTHERMAL SCHEDULING OF POWER SYSTEMS WITH INCLUSION OF PUMPED-STORAGE HYDROPOWER USING QPSO ALGORITHM

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ABSTRACT

Hydrothermal scheduling is a relevant stage of power system operation planning, whose objective is to minimize the operation cost during the demand horizon. In this paper the hydrothermal scheduling of electric power systems including the modelling of pumped-storage hydropower (PSH) is solved using the quantum-behaved particle swarm optimization (QPSO) algorithm. Simulation results with a test system composed of ten thermal generators and a pumped-storage hydroelectric power plant confirm the applicability of the proposal.

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INTRODUCTION

Hydrothermal scheduling is an operation-planning step where the system operator defines which generators must be in service at each time of the planning horizon. It aims to minimize the total cost of operation in each time slot and meet the restrictions of the electricity grid and generating units. In general terms, the aim is to minimize the total cost of operating thermal plants, which in turn is formed by fuel cost (Kahm*et al*., 2009; Hobbs*et al*., 2002; Zhu, 2015; Uçkun; Botterud; Birge, 2016; Zhang*et al*., 2017; Wood; Wollemberg; Sheblé, 2013; Hasan; El-Hawary, 2016), given by Equation (1).

$$C_{th} = \sum_{t=1}^{T}\sum_{j=1}^{N} F\left(P_j(t)\right) = \sum_{t=1}^{T}\sum_{j=1}^{N}\left[a_j P_j^2 + b_j P_j + c_j\right] \qquad (1)$$

where $C_{th}$is the total hydrothermal scheduling cost of the$N$thermal units in$T$demand periods; $F\left(P_j(t)\right)$is the fuel cost function of unit $j$in period t. Traditional methods for hydrothermal scheduling seek to simplify or even ignore certain restrictions present in real electrical systems, such as generation from renewable sources, and admit that all generators can provide their minimum power limit when activated, that is, they ignore the transient periods between activation and power supply. Furthermore, they can present sub-optimal or local optimal solutions and are computationally expensive. Although they are still used in commercial software, the need to adapt to new forms of generation and the search for efficiency in real-time operation motivated the development of more robust methods (Hobbs*et al*., 2002; Morales-España; Ramírez-Elizondo; Hobbs, 2017; Tejada-Arango, 2020).Artificial Intelligence (AI)techniques were developed not only to meet the new restrictions of electrical systems, but also to be able to model them in the most reliable way possible, that is, that also considers the restrictions that were once simplified by traditional methods. Although they require prior choices of training methodology and the development of a large system even for small/medium sized systems, modern techniques for hydrothermal scheduling solution are continually required due to the capacity to deal with constraints, ability to determine several optimal solutions and the versatility to deal with multi-objective problems. As an example, there are Firefly Algorithm (Rampriya; Mahadevan; Kannan, 2010), Genetic Algorithms (Rudolf; Bayrleithner, 1999), Ant Colony Search (Wu; Chang; Chang, 2017), Binary Grey Wolf Optimizer (Panwar*et al*., 2017) and Particle Swarm Optimization (PSO) (Nivedha; Singh; Ongsakul, 2018). Hybrid methods were also proposed, which explore the best of each modern technique; as an example, there are Hybrid PSO-GA (Marrouchi; Hessine; Chebbi, 2018), Enhanced PSO (Liu; Li, 2010), PSO-Tabu Search (Khatibzadeh, 2011), etc.In this paper, a PSO based on quantum behavior is applied to solve the hydrothermal scheduling problem with the insertion of reversible hydroelectric plants. The algorithm called Quantum Particle Swarm Optimization (QPSO), being able to provide good results to the operator, performs this procedure. To confirm the potential and efficiency of the proposed algorithm, the algorithm is applied to a test system with 10 generators.

This paper is divided as follows

- ***Section I*** –hydrothermal scheduling is presented with the insertion of reversible hydroelectric plants.
- ***Section III***–the proposed method for solving the hydrothermal schedulingincluding pumped storage hydropowerby the QPSO algorithm is presented.
- ***Section IV*** –the results of computer simulations and their analysis are presented.
- ***Section V*** –final considerations are showed.

HYDROTHERMAL SCHEDULING INCLUDING PUMPED-STORAGE HYDROPOWER

Pumped-storage hydropower (PSH): Pumped-storage hydropower is currently the only large-scale energy storage technology (over $100\ MW$) with high commercial application, to the point where there are at least 300 plants installed in the world and a total installed capacity of $95\ GW$. In recent years, there has been an increase in interest in these plants, with projects and new construction in Europe and Japan. Plants can also be found in Australia, Russia, and countries in Asia; however, the largest mills are present in China, Japan and the USA. Although these plants were previously developed to facilitate the integration of large loads, there is currently an interest in connecting them to renewable energy sources such as wind generation (Deane; Gallachoir; McKeogh, 2010; Sigrist*et al*., 2019; Xia*et al*., 2019; Singirankabo; Ijumba; Ntagwirumugara, 2018; Howlader*et al*., 2017). The fundamental principle of reversible hydroelectric plants is to store electrical energy in the form of hydraulic potential energy. Pumping water typically takes place during off-peak periods when electricity demand and prices are low. Generation takes place during peak periods when demand is high. Depending on the choice of the system operator, both pumping and generation can follow a daily, weekly, or seasonal cycle. Unlike traditional hydroelectric plants, reversible plants depend entirely on water that has been pumped into an upper reservoir, a river, or a sea. These plants are also known as closed circuit plants or off-line plants (Deane; Gallachoir; McKeogh, 2010).

PSHs have several advantages already documented in the references. In (Hongwei*et al*., 1998), it is shown that these plants provide generators with shorter start-up and shutdown times, as well as smoothing of peak loads and more attractive turning reserve. In (Liu*et al*., 2019), it is described that the combination of these plants with photovoltaic systems has the potential for high gains in electricity generation, reduction of energy imbalances, increases generation without affecting network reliability and increases the efficiency of hydrothermal scheduling models. When combined with wind generation systems, (Sheng; Sun, 2014) shows that PSH solve the volatility problems of this renewable generation, making the entire generation more efficient.

Hydrothermal scheduling including PSH: The basic procedure for obtaining the hydrothermal scheduling containing reversible plants is to perform both procedures iteratively. An economical dispatch algorithm is used to determine the thermal cost. A general algorithmis described below:

- Run the economic dispatch to get the system thermal cost of each generator, which in turn provides the system thermal cost.
- Determine the PSH configuration that minimizes thermal cost and satisfies system operating constraints.
- Solve hydrothermal scheduling problem where the thermal generation required (that is, the generation supplied by the thermal plants) is the difference between the demand and the power supplied by the PSH; thus, the contribution of the PSH is coupled with the hydrothermal scheduling problem.

The PSH model used in this paper is known as the load model. This is a model where the PSH is seen as a load at off-peak hours, where the energy needed to pump water to the upper reservoir comes from the thermal generators. On the other hand, PSH presents generation behavior at peak times since the stored water is released to the lower reservoir. Thus, as part of the generation comes from PSH, a smaller amount of power is generated by thermal plants, and consequently, there is a reduction in the overall cost of generation. From a modeling point of view, PSH presents positive power values in off-peak hours, and negative in peak hours. It is assumed that PSH always provides fixed power.

Proposed method of solving hydrothermal scheduling including PSH by QPSO: Particle Swarm Optimization is a population-based search algorithm developed in 1995 by Kennedy and Eberhart (Kennedy; Eberhart, 1995). It was developed from the simulation of populations such as schools of fish and groups of birds. It is initialized by a set of potential solutions called particles. Each particle has a position and search speed in solution space to reach its minimum value. Its displacement occurs randomly but is influenced by cognitive and social information obtained from exploration at local and global levels. All particles share their experiences with each other so that the global minimum point is determined. It has few adjustable parameters, and its evolutionary process is flexible and balanced. It has been successful in solving non-linear, combinatorial, and multi-objective problems. More information about this algorithm can be accessed at (Sun *et al*., 2011; Yehescale; Reddy, 2018; Kennedy; Eberhart, 1995; Pattanaik; Basu; Dash, 2019). After the emergence of the PSO algorithm, many improvements were proposed, from the use of different probability functions to changes and insertion of expressive characteristics of other algorithms, such as Genetic Algorithms. Among these performance improvements, there is one that was inspired by the concepts of Quantum Mechanics and observation of the PSO trajectory analysis. More specifically, a strategy based on the δ quantum model was proposed to prepare samples around the best previous points. Shortly thereafter, the calculation of the best average position was introduced into the algorithm. Thus, a new PSO algorithm, called*Quantum-behaved particle swarm optimization* (QPSO). The iterative equation of QPSO is very different from PSO; in addition, it does not need velocity vectors for the particles, as well as having few adjustable parameters, making it easier to implement. This algorithm has been shown to solve many optimization problems(Sun*et al*., 2011).The analysis of particle trajectories in the PSO algorithm shows that convergence can be achieved if each particle converges to the local point$p_i^t = \left[p_{i,j}^t, \dots, p_{i,D}^t\right]$ with coordinates according to (2).

$$p_{i,j}^t = \varphi P_{i,j}^t + (1-\varphi) G_j^t \qquad (2)$$

where φ is a random number.

It is assumed that the PSO is a quantum system, and each particle has a quantum behavior whose state can be formulated by the wave function ψ.$|\psi|^2$is the probability density function of the particle. Inspired by the convergence analysis of the original PSO, it is assumed that in the iteration$t$, particle$i$ move in$D-$dimensional space with apotential δwell-centered in$p_{i,j}^t$in the$j$thposition. Thus, a wave function in$t+1$iteration isshown by Equation (3) (Sun*et al*., 2011):

$$\varphi\left(X_{i,j}^{t+1}\right) = \frac{1}{\sqrt{L_{i,j}^t}} . \exp\left(-\frac{\left|X_{i,j}^t - p_{i,j}^t\right|}{L_{i,j}^t}\right) \qquad (3)$$

where$L_{i,j}^t$is the standard deviation of the double exponential distribution, varying with the number of iterations t. Thus, the probability density function$Q$is a double exponential distribution as followsin (4) (Sun *et al*., 2011):

$$Q\left(X_{i,j}^{t+1}\right) = \left|\varphi\left(X_{i,j}^{t+1}\right)\right|^2 = \frac{1}{L_{i,j}^t} \cdot \exp\left(-2\frac{\left|X_{i,j}^t - p_{i,j}^t\right|}{L_{i,j}^t}\right) \quad (4)$$

and then the probability density function F is

$$F\left(X_{i,j}^{t+1}\right) = 1 - \exp\left(-2\frac{\left|X_{i,j}^t - p_{i,j}^t\right|}{L_{i,j}^t}\right) \quad (5)$$

Using Monte Carlo method, gets the jth position component X_i in the iteration $t + 1$:

$$X_{i,j}^{t+1} = p_{i,j}^t \pm \frac{1}{2} L_{i,j}^t \ln\left(\frac{1}{u_{i,j}^{t+1}}\right) \quad (6)$$

where $u_{i,j}^{t+1}$ is a random number evenly distributed between $(0,1)$. The value of $L_{i,j}^t$ is calculated as

$$L_{i,j}^t = 2\alpha\left|C_j^t - X_{i,j}^t\right| \quad (7)$$

where C^t is known as the best average position of the positions of all particles. This is given by (8).

$$C^t = \left(C_1^t, C_2^t, \ldots, C_D^t\right) =$$

$$= \left(\frac{1}{M}\sum_{i=1}^{M} P_{i,1}^t, \frac{1}{M}\sum_{i=1}^{M} P_{i,2}^t, \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{i,j}^t, \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{i,D}^t\right) \quad (8)$$

where M is the population size and P_i^t is the best position for each particle. Thus, the updated position of these elements is expressed by the Equation (9).

$$X_{i,j}^{t+1} = p_{i,j}^t \pm \alpha\left|C_j^t - X_{i,j}^t\right| \ln\left(\frac{1}{u_{i,j}^{t+1}}\right) \quad (9)$$

where the parameter α is known as the compression-expansion coefficient (CE), which can be used to control the convergence speed of the algorithm. The PSO algorithm that contains Equation (9) is known as *Quantum-behaved particle swarm optimization* (QPSO), where $\alpha < 1.781$ to ensure particle convergence. When used in practical applications, the CE coefficient must be properly regulated. (Sun *et al*., 2011).Broadly speaking, there are two methods of control. One of them claims to fix this parameter during the search process; however, the act of fixing α is sensitive to population size and the maximum number of iterations: if these parameters are changed, the CE coefficient must be different. Another method suggests reducing α_1 coefficient to $\alpha_0 (\alpha_0 < \alpha_1)$, so that the search process is simpler but more efficient. In this approach, the α value is defined by Equation (10) (Sun *et al*., 2011):

$$\alpha = \alpha_0 + (T - t)\frac{\alpha_1 - \alpha_0}{T} \quad (10)$$

where α_1 and α_0 are, respectively, the final and initial values of α. T is the maximum number of iterations, t is the current iteration. References about QPSO advise that, reducing α_0 from 1.0to0.5, it can make this algorithm performance well in general (Sun *et al*., 2011). QPSO contains some features that differentiate it from PSO. Firstly, the exponential distribution of positions makes it globally convergent; secondly, the introduction of the concept of best average position is an innovation in relation to the root algorithm. While in PSO, each particle converges to the best global position independently, QPSO makes each particle unable to converge to the global position without considering the parameters of its peers. Therefore, QPSO never abandons particles that are farthest from the global position. Figure 1 shows the pseudocode for the QPSO implementation. More information about this algorithm can be found at (Sun *et al*., 2011). For the modeling of hydrothermal coordination using QPSO algorithm, it is established that particles are the generators' powers, and the cost-function is the cost of generating the thermal plants. The internal parameters of this optimization algorithm, such as population size, coefficient α, among others, are defined according to the recommendations of the main associated bibliographic references. The PSH is modeled as a load, where the null value of power means being disconnected from the electrical network. On the other hand, during peak load periods, the PSH acts as a negative power load, whose value will be subtracted from the power of the thermal plants, indicating a reduction in the use of this form of generation. During off-peak hours, PSH behaves like a load where the power needed to pump water is supplied by thermal plants (Sun *et al*., 2011). Figure 2 describes the use of the QPSO algorithm to formulate the hydrothermal scheduling with PSH.

Algorithm 1: Pseudocode for QPSO.

```
begin
    Define size population (M), particles' positions and particles' size;
    for t=1 to maximum number of iterations T do
        Calculate the best position according to Equation (8);
        Calculate α according to Equation (10);
        for i=1 to size population M do
            if f (X_i) < f (P_i) then
                P_i = X_i;
            end
            G = arg min (f (P_i));
            for j=1 to D do
                φ = rand (0, 1);
                u = rand (0, 1);
                p_ij = φ · P_ij + (1 − φ) · G_j;
                if rand (0, 1) > 0.5 then
                    X_ij = p_ij + α · abs (C_j − X_ij) · log (1/u);
                end
                else
                    X_ij = p_ij − α · abs (C_j − X_ij) · log (1/u);
                end
            end
        end
    end
end
```

Figure1. Procedure for QPSO implementation

Algorithm 2: Pseudocode for Hydrothermal Scheduling including PSH with QPSO.

```
begin
    Read generators data;
    for i = 1 até N periods do
        Formulate the cost function;
        Insert generators' constraints;
        Call QPSO algorithm described in Section III;
    end
    Calculate the generators' total cost;
    Print results;
end
```

Figure 2. Procedure for implementation of hydrothermal scheduling including PSH with QPSO

The objective-function hydrothermal scheduling is expressed by Equation (11), where a, b e c are cost coefficients, and $\Delta\varepsilon$ is mismatch associatedto power balance, and is defined by Equation (12), where P_i, P_i^D e P_i^{PSH} are, respectively, generators' powers, demand and PSH's power at ith hour. This variable indicates that, in case of deviations between the generated and consumed powers, there will be a penalty in the generation cost. P_{LOSS} are transmission losses, which are expressed as a function of generator powers and B −coefficients. This method uses the fact that under normal operating conditions, the transmission loss is quadratic in the injected real power. The general form of the loss formula using B −coefficients is expressed in Equation (13), where P_i and P_j are the real powers at the ith and jth generators, respectively; B_{ij} are the loss coefficients which are constant under certain assumed conditions; and N_G is the number of generators. Equation (14) is an inequality constraint, and informs that thermal generators have well-defined values of maximum (P_i^{max}) and minimum (P_i^{min}) generation. Equation (15) is an equality constraint defined as power balance, and in it, it is stated that all generated power is used to supply demand (P_i^D), losses (P_{LOSS}) and PSH (P_i^{PSH}), depending on its mode of operation. It is assumed that all generators are available at all problem intervals.

$$C_{th} = \sum_{t=1}^{T} \sum_{j=1}^{N_G} [a_j \cdot P_j^2 + b_j \cdot P_j + c_j] + 10^5 \cdot \Delta\varepsilon \quad (11)$$

$$\Delta\varepsilon = \left| \sum_{i=1}^{N_G} P_i - P_i^D - P_i^{PSH} - P_{LOSS} \right| \quad (12)$$

$$P_{LOSS} = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_i \cdot B_{ij} \cdot P_j \quad (13)$$

$$P_i^{min} \leq P_i \leq P_i^{max} \,; 1 \leq i \leq N_G \quad (14)$$

$$\sum_{i=1}^{T} P_i = \sum_{i=1}^{T} P_i^D + \sum_{i=1}^{T} P_i^{PSH} + P_{LOSS} \quad (15)$$

SIMULATIONS AND RESULTS

This section presents and describes the computational simulations in the MATLAB® computational environment, with the approach of a test system. The parameters used in the QPSO algorithm are shown in Table 1. An Intel® Core i7-5500U microcomputer, 2.40 GHz CPU, 8.00 GB RAM is used.

Table 1. Parameters of QPSO

α_0	0.5
α_1	1.0
Population size	100
Max. number of iterations	300

The test system is formed by 10 thermal generators whose information is shown in Table 2, and it is assumed that they are all available to meet demand in all periods. In addition, a loss matrix whose information is shown in Equation (16) is included; these values are multiplied by a factor of10^{-6}.

$$B_{ij} = \begin{bmatrix} 49 & 14 & 15 & 15 & 16 & 17 & 17 & 18 & 19 & 20 \\ 14 & 45 & 16 & 16 & 17 & 15 & 15 & 16 & 18 & 18 \\ 15 & 16 & 39 & 10 & 12 & 12 & 14 & 14 & 16 & 16 \\ 15 & 16 & 10 & 40 & 14 & 10 & 11 & 12 & 14 & 15 \\ 16 & 17 & 12 & 14 & 35 & 11 & 13 & 13 & 15 & 16 \\ 17 & 15 & 12 & 10 & 11 & 36 & 12 & 12 & 14 & 15 \\ 17 & 15 & 14 & 11 & 13 & 12 & 38 & 16 & 16 & 18 \\ 18 & 16 & 14 & 12 & 13 & 12 & 16 & 40 & 15 & 16 \\ 19 & 18 & 16 & 14 & 15 & 14 & 16 & 15 & 42 & 19 \\ 20 & 18 & 16 & 15 & 16 & 15 & 18 & 16 & 19 & 44 \end{bmatrix} \quad (16)$$

The data from this system is applied to meet a demand formed by 24 periods, whose power values are shown in Table 3. Figure 3 shows the results obtained for the hydrothermal scheduling. The demand is met, and the total cost of generation is$ 674,475.29.We want to connect a PSH to reduce the fuel cost of thermal units and meet demand at critical times. Table 4 shows the PSH power values over the periods. The times formed by the intervals$01{:}00 - 07{:}00$ and $20{:}00 - 24{:}00$are the off-peak hours, where the PSH behaves like load; on the other hand, the interval between$08{:}00 - 19{:}00$is the peak interval.

Table 2. Generator's parameters

P_{smin} (MW)	P_{smax} (MW)	c $(\$)$	b $(\$/MW)$	a $(\$/MW^2)$
150	455	1000	16.19	0.00048
150	455	970	17.26	0.00031
20	130	700	16.60	0.00200
20	130	680	16.50	0.00211
25	162	450	19.70	0.00398
20	80	370	22.26	0.00712
25	85	480	27.74	0.00079
10	55	660	25.92	0.00413
10	55	665	27.27	0.00222
10	55	670	27.79	0.00173

Table 3. System's demandin *MW*

Period (h)	Demand (MW)	Period (h)	Demand (MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

Figure 4 shows the results of the optimization process.

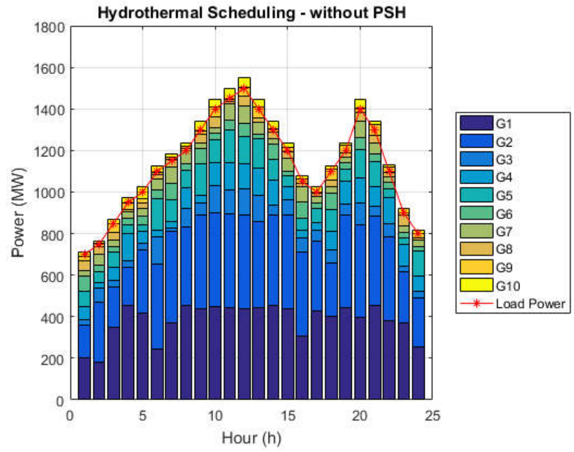

Figure 3. Hydrothermal scheduling results for 10-gen test system, without PSH. Cost: $ $674,475.29$

Table 4. PSH's power values in *MW*

Period (h)	Demand (MW)	Period (h)	Demand (MW)
1	180	13	−180
2	180	14	−180
3	180	15	−180
4	180	16	−180
5	180	17	−180
6	180	18	−180
7	180	19	−180
8	−180	20	180
9	−180	21	180
10	−180	22	180
11	−180	23	180
12	−180	24	180

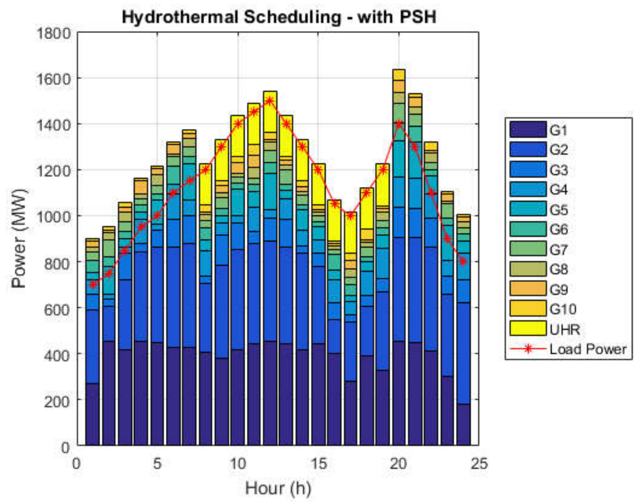

Figure 4. Hydrothermal scheduling results for 10-gen test system, with PSH. Cost: $ $670,0\ 281\ 7$

It is observed that the behavior as a load of the PSH at off-peak hours is offset by the significant reduction of generators at peak hours, so that a reduction of more than$ 4000.00 is obtained in the cost of generation with the use of the PSH.In both cases, the total generation is greater than the load values due to system losses.

CONCLUSION

The implementation of a pumped-storage hydropower in hydrothermal scheduling problem was presented in this paper. A load model was used, where the PSH pumps to the upper reservoirs at off-peak hours and uses the stored water to generate energy and reduce the use of thermal power plants at peak times. The proposed modeling employed the solution method based on the QPSO metaheuristic. Lower cost values were offered in relation to the base case, achieving the objective of reducing the total cost of generation.

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