The State of Art in Particle Swarm Optimization Based Unit Commitment: A Review

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Abstract:

Unit Commitment (UC) requires the optimization of the operation of generation units with varying loads, at every hour, under different technical and environmental constraints. Many solution techniques were developed for the UC problem, and the researchers are still working on improving the efficiency of these techniques. Particle swarm optimization (PSO) is an effective and efficient technique used for solving the UC problems, and it has gotten a considerable amount of attention in recent years. This study provides a state-of-the-art literature review on UC studies utilizing PSO or PSO-variant algorithms, by focusing on research articles published in the last decade. In this study, these algorithms/methods, objectives, constraints are reviewed, with focus on the UC problems that include at least one of the wind and solar technologies, along with thermal unit(s). Although, conventional PSO is one of the most effective techniques used in solving UC problem, other methods were also developed in literature to improve the convergence. In this study, these methods are grouped as extended PSO, modified PSO, and PSO with other techniques. This study shows that PSO with other techniques are utilized more than any other methods. In terms of constraints, it was observed that there are only few studies that considered Transmission Line (TL), Fuel (F), Emission (E), Storage (St) and Crew (Cr) constraints, while Power Balance (PB), Generation limit (GL), Unit minimum Up or Down Time (U/DT), Ramp Up or Ramp Down Time (R-U/DT) and system Spinning Reserve (SR) were the most utilized constraints in UC problems considering wind/solar as a renewable source. In addition, most of the studies are based on a single objective function (cost minimization) and, few of them are multi-objective (cost and emission minimization) based studies.

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Abstract: Unit Commitment (UC) requires the optimization of the operation of generation units with varying loads, at every hour, under different technical and environmental constraints. Many solution techniques were developed for the UC problem, and the researchers are still working on improving the efficiency of these techniques. Particle swarm optimization (PSO) is an effective and efficient technique used for solving the UC problems, and it has gotten a considerable amount of attention in recent years. This study provides a state-of-the-art literature review on UC studies utilizing PSO or PSO-variant algorithms, by focusing on research articles published in the last decade. In this study, these algorithms/methods, objectives, constraints are reviewed, with focus on the UC problems that include at least one of the wind and solar technologies, along with thermal unit(s). Although, conventional PSO is one of the most effective techniques used in solving UC problem, other methods were also developed in literature to improve the convergence. In this study, these methods are grouped as extended PSO, modified PSO, and PSO with other techniques. This study shows that PSO with other techniques are utilized more than any other methods. In terms of constraints, it was observed that there are only few studies that considered Transmission Line (TL), Fuel (F), Emission (E), Storage (St) and Crew (Cr) constraints, while Power Balance (PB), Generation limit (GL), Unit minimum Up or Down Time (U/DT), Ramp Up or Ramp Down Time (R-U/DT) and system Spinning Reserve (SR) were the most utilized constraints in UC problems considering wind/solar as a renewable source. In addition, most of the studies are based on a single objective function (cost minimization) and, few of them are multi-objective (cost and emission minimization) based studies.

Keywords: particle swarm optimization; solar; thermal; unit commitment; wind

1. Introduction

To reduce the impact of climate change, it is vital to mitigate emissions caused by several industries. This can be achieved by utilizing renewable energy (RE). RE sources have gained significance in recent literature due to their positive environmental effect and lower cost of generation [1,2]. Among all types of RE, the deployment of photovoltaic (PV) and wind systems are getting more acceptance in the power generation industry [3]. However, because of the highly uncertain nature of RE, the fossil fuel will continue to be used in thermal plants for some more time. To generate electricity at a reliable and cost-effective manner, UC is used. UC aims to meet the demand and satisfy the reserve requirement in an optimum, and cost-effective way during the period of scheduling. Applying UC ensures that under the prevailing operating conditions, appropriate resources are available to reliably maintain production in that period. Thus, many system operators acknowledge UC as a powerful decision process [4,5].

Several numerical optimization methods [6–8] and meta-heuristic techniques [9–12] have been utilized to achieve near-optimal and efficient solutions for UC problem. Among the optimization techniques mentioned above, PSO has its own reputation. PSO, introduced by Kennedy and Eberhart in

1995 [13], is an evolutionary algorithm. It is inspired by the cognitive and social interaction of animals with one another and with the environment (birds flying and fish schooling). The performance of the algorithm is achieved through iteratively directing its particles toward the optimum using cognitive and social components [14–16]. [17,18], revealed that PSO is robust in solving non-differentiable, nonlinear, high dimensional and multiple-optima problems through a simple procedure with high convergence speed. Thus, these advantages of PSO made it one of the most effective and efficient techniques for solving UC problems. Considering the described research trend, this study aims at reviewing the UC studies that utilized PSO as a solution method. In this context, studies that integrate thermal units with well-known Renewable Energy Sources (RES) (wind and solar) are presented.

To provide a clear presentation of the work done, this study is organized as follows; Section 2 gives the literature review on previous UC related review studies. Section 3 explains the unit commitment principle. Section 4 discusses the methodology including the data collection, objective functions, constraints, technologies and categories of PSO. Section 5 provides a comprehensive review of the studies employing PSO based methods in solving UC problems. Section 6 provides the conclusion of the paper, and suggests future directions.

2. Literature Review

Abujarad et al. [19] reviewed UC in the presence of intermittent RE sources. The study presented UC concepts, objectives and constraints. The authors highlighted some UC optimization methods, such as Heuristic methods (Priority list), classical/mathematical methods (Dynamic Programming, Lagrangian Stochastic, Programming Relaxation), Computational Intelligence known as Meta-Heuristic (Fire Fly, Fuzzy logic) and Hybrid Meta-Heuristic (Different Hybrid Techniques) and discussed their relative disadvantages such as slow convergence, not being able to handle large-scale data and theoretical analysis difficulties. Finally, the authors also discussed energy storage systems and the effect of RE technologies on the UC computational tool as well as the influence associated with UC model, the moment high RES was introduced. Another study conducted by Bhardwaj et al. [20] surveyed various UC problem solution methods such as Dynamic Programming (DP), Priority List (PL), Lagrangian Relaxation (LR), PSO, fuzzy logic and Tabu search. In addition, Saravanan et al. [21] provided a review of the methods used in UC problems for both deterministic and stochastic load. Classical and non-classical techniques that were used in solving a complex UC problem were presented. The study was based on studies that cover 30 years.

As seen above, several review studies have been conducted on UC, however, to the authors' knowledge, none of these studies focused on UC that considers different types of PSO techniques as a whole. Also, the review studies in literature do not cover the most recent studies. The main motivation behind this study, mainly surveying PSO studies, is the advantage it has over other existing methods. PSO algorithms were divided into six categories by Zheng et al. [22] as follows; conventional PSO, extended PSO, modified PSO and hybridization of PSO, theoretical analysis of PSO, and parallel implementation of PSO with other techniques (such as Genetic Algorithm (GA), PL, LR and Time-Varying Acceleration Coefficients (TVAC)). Similarly, in this study, the PSO techniques were grouped into conventional PSO, extended PSO, modified PSO, and PSO with other algorithms. Hence, the main contribution of this study is to focus on the most recent studies that include thermal units incorporated with RES (wind or both wind and solar), and, utilizes PSO as UC solution method.

3. Unit Commitment principle

Unit Commitment is a complex nonlinear optimization problem used to determine the operation schedule of the generating units at every hour under different constraints. Many researchers try to optimally solve that problem in view of:

(a) Scheduling on/off states of all the generating units in the system to meet the total load demand in every hour;

(b) Achieving a certain objective (minimum total cost, minimum emission, . . . etc);

(c) Respecting all system and environmental constraints (power balance, generation limit, fuel, ... etc).

3.1. UC Generalized Formulation

The UC problem can be formulated in general such that minimum total cost and emission can be achieved. The total fuel and emission cost can be described by the following equations [23]:

$$\text{Total fuel cost} = \sum_{t=1}^{T} \sum_{i=1}^{k} [f_i(P_i^t)S_i^t + C_i S_i^t(1 - S_i^{t-1})] \tag{1}$$

$$\text{Total emission cost} = \sum_{t=1}^{T} \sum_{i=1}^{k} S_i^t . EM_i^t(P_i^t) \tag{2}$$

where:

T: The period of short-term dispatch

p_t: The price of electricity in t^{th} period

P_D^t: The load demand in period t including network losses

k: The number of conventional units

$f_i(P_i^t)$: The cost of production function of generator i

P_i^t: The output of generator i in period t

S_i^t: The status of generator i in period t

C_i: The cost of cold start for generator i.

$EM(P_i^t)$: emission cost function of generator i .

The fuel and emission cost functions can be calculated from:

$$f_i(P_i^t) = a_i + b_i.(P_i^t) + c_i.(P_i^t)^2 \tag{3}$$

$$EM(P_i^t) = \alpha_i + \beta_i.(P_i^t) + \gamma_i.(P_i^t)^2 + \mu_i.\exp[\delta_i.(P_i^t)] \tag{4}$$

where:

a_i, b_i, c_i are the fuel cost coefficients of unit i in period t.

α_i, β_i, γ_i, μ_i, δ_i are the emission coefficients of unit i.

3.2. Optimization Methods

Many algorithms have been proposed in order to solve the UC optimization problem. These solution strategies may be classified into two main categories; namely; deterministic and stochastic search methods.

3.2.1. Deterministic (numerical) Optimization Methods

The solution of the UC optimization problem with these conventional analytical techniques can be found through mathematical rules. Some of these methods are: the priority list method, dynamic programming, lagrangian relaxation and the branch and bound methods. These methods may suffer from numerical convergence and the curse of dimensionality. Heuristics-based swarm intelligence can be an efficient alternative.

3.2.2. Stochastic (Intelligent Meta-Heuristic) Optimization Methods

Most of the stochastic techniques are gaining attention for the solution of large-scale optimization problems. The advantages of these methods are that they have the ability to overcome the shortcomings of traditional optimization techniques, and they are less dependent on initial solution. Moreover they have the capability to handle complex nonlinear constraints and the flexibility to obtain high quality

solution. Typical algorithms include simulated annealing, ant colony optimization, tabu search, neural networks, fuzzy logic, genetic algorithms, evolutionary programming, and particle swarm optimization (PSO).

Among of these methods, PSO has attracted many researchers because of its simplicity, easy implementation, derivative free nature, and the requirement of few parameters to tune. They introduced different modifications to improve its convergence speed, deal easily with non-convex objective functions, and to perform a fast search in large scale problems. In this paper, the main focus is on surveying the papers which tried to solve the UC problems using PSO optimization techniques.

4. Methodology

4.1. Data Collection

This paper reviews previous PSO-based UC studies that include thermal units combined with wind or both wind and solar, covering a period of 10 years (2009–2018 inclusive). Hence, several information, such as concepts, objective functions, constraints, adopted technologies, solution methods were collected from the UC, and PSO related papers. The following subsection provides detailed information about each type of data collected, and the comparison categories used in this paper.

4.2. Comparison Framework

This section presents critical information about the adopted comparison structure that includes; objective functions, constraints, technology and categories of PSO used.

4.2.1. Objective Function

The primary objective of any UC problem is to achieve the most economical generation policy that could satisfy a given load. UC problem can be regarded as multi-objective when emission is considered as a second objective function. In this paper, the following UC objectives were considered: minimize emissions (ME), minimize operation cost (MOC), minimize fuel cost (MFC), minimize total cost (MTC) and maximize profit (MP).

4.2.2. Constraints

To optimize the objective function in any UC problem, some constraints need to be satisfied [24]. The constraints may differ from one study to another. Hence, in order to provide a comprehensive review, the constraints observed in different studies are grouped into the following categories:

● *Power Balance (PB) constraints:*

The output power from RES and thermal units should precisely satisfy the load (also considering the network losses) at every hour [3,25].

$$\sum_{i\,=\,1}^{k} P_i^t.S_i^t =\ D^t \tag{5}$$

where D^t is the total load demand including losses at time t, P_i^t is the output of generator i in period t and S_i^t is the status of generator i in period t.

● *Generation Limit (GL) constraints:*

The output power of a unit must not exceed a given limit or range at every hour [3,26].

● *System Spinning Reserve (SR) constraints:*

The spinning reserve requirement (given by the base component and additional fraction to the load demand) must be satisfied at every hour [19,25].

$$\sum_{i\,=\,1}^{k} P_i^t.S_i^t \geq\ D^t +\ SR^t \tag{6}$$

where SR^t is the spinning reserve at time t. It is assumed to be 10% of the total demand D^t.

● *Unit Up/Down Time (U/DT) constraints:*

Due to electrical and/or mechanical limitations, once a unit is committed or de-committed, it should be kept in stable operation for a minimum period of time before transition [25,27].

● *Ramp Up and Down Time (R-U/DT) constraints:*

The rate of change of the generating unit power output should be limited [27–29].

● *Unit Initial Status (UIS) constraints:*

The initial state of each unit has to be considered in the first scheduling hour [30,31].

● *Transmission Line (TL) constraints:*

The transfer capability limitation of transmission systems should be considered; including contingency constraint and thermal rating of the transmission line [19].

● *Fuel (F) constraints:*

The start-up and fuel cost should be limited within a given range for each hour [1].

● *Storage (St) constraints:*

The amount of storage must be between the minimum and the maximum storage capacity of a given system [32,33].

● *Crew (Cr) constraints:*

The number of crew members required for attending to the generating units should not exceed the available number [34].

● *Emission (E) constraints:*

The amount of gas emitted from fossil fuel-based units during generation, at every hour, should be less than a certain limit [1].

4.2.3. Technology

UC involves selecting the most suitable generation units in order to meet the demand at a given time. These generation units can be thermal, or combination of thermal with other RE generation units such as solar, wind, hydro, etc. This study reviews the most recently published articles that consider the UC problem and include thermal units combined with wind and/or solar units. The comparison is made based on the type of adopted RE technology, as thermal unit is common in all of them.

4.2.4. Type of Particle Swarm Optimization

Several studies on UC that utilize PSO as a solution method are reported in the literature. As the different types of PSO algorithms were divided into several categories by Zheng et al. [22], in this study, the authors will use four of these categories, as comparison framework categories. These are; conventional PSO, extended PSO, modified PSO and PSO with other metaheuristic techniques. The advances of PSO in solving UC problem is also presented in this study.

4.2.4.1. Conventional Particle Swarm Optimization

Particle swarm optimization, introduced in 1995 by Kennedy and Eberhart [13], is a stochastic and evolutionary optimization algorithm based on the social behavior of birds. It is initialized with a group of random particles (solutions) and then searches for optimal solution by updating results. The standard form of the PSO can be classified into continuous and discrete (binary) versions. The continuous PSO can be described by the following equations:

$$v_m^{k+1} = w.\,v_m^k + c_1.r_1.\left(pbest_m - x_m^k\right) + c_2.r_2.\left(gbest_m - x_m^k\right) \tag{7}$$

$$x_m^{k+1} = x_m^k + v_m^{k+1} \tag{8}$$

where x_m^k, v_m^k are the position and velocity of the mth particle at the kth iteration. w is the inertia weight factor. c_1, c_2 are the cognitive and social constants (accelerating factors); r_1, r_2 are random numbers, and $pbest_m$, $gbest_m$ are the best and global solutions. The conventional continuous PSO

algorithm consists of three steps; firstly, evaluate fitness (objective function) of each particle. Secondly, update the individual and global best value of each particle. Finally, update velocity and position of each particle. These steps are repeated until some stopping condition is met. When the conventional PSO is used to solve the UC problems, each particle is simulated by a matrix containing the output of all the generators during 24-hour horizon. Typical values for the constants of the PSO equation are: $w = [0.8, 1.2]$, $c_1 = c_2 = 2$, and r_1, $r_2 = \{0, 1\}$.

On the other hand, in the binary PSO, the particle velocity represents the threshold of position which is determined by the sigmoid function. The steps of the binary PSO algorithm are summarized as follows:

(a) Calculate the particle velocity using Equation (7).
(b) Calculate the sigmoid function of the particle velocity from:

$$sig\left(v_m^{k+1}\right) = \frac{1}{1 + \exp(-v_m^{k+1})} \tag{9}$$

(c) Update the particle position by using:

$$x_m^{k+1} = \begin{cases} 1 & if\ r < sig\left(v_m^{k+1}\right) \\ 0 & otherwise \end{cases} \tag{10}$$

where r is a random number generated in the range $\{0, 1\}$.

4.2.4.2. Extended Particle Swarm Optimization

The success of conventional PSO algorithm in solving the UC problem has prompted many researchers to improve the method into multi-objective, binary and discrete optimization [22]. Hence, this category includes; quantum inspired binary PSO (QNPSO), Binary PSO based on a fuzzy logic technique, Multi-objective immune PSO, Reinforcement Learning-based Multi-Objective PSO algorithm (RL-MOPSO) and improved binary PSO.

4.2.4.3. Modified Particle Swarm Optimization

In some studies, in order to solve a complex UC problem, the PSO technique is modified to handle the problem effectively. Some PSO modifications include fuzzy PSO, chaotic PSO, quantum behaved PSO, opposition based PSO, advanced PSO, self-adaptive PSO technique, Improved Inertia Weight PSO (PSO-IIW) and other slight modification methods [22].

4.2.4.4. Particle Swarm Optimization with Other Techniques

Combining metaheuristic techniques with PSO in solving the UC problem has proven to be efficient. Hybridization of PSO with other methods such as GA, PL, LR, and TVAC, etc, can mitigate the disadvantages of conventional PSO and thereby improve the efficiency of the method [22]. Hence, this category includes PSO with hybridization of PL, and PSO_TVAC with PL Method.

5. Comparative Analysis and Discussions

Optimal generation cost and emissions are the main objectives of UC problem, with various constraints that include R-U/DT constraints, GL constraints, PB constraints etc. Table 1 presents the objective function (OF) for the only study [35] that utilizes conventional particle swarm optimization (among the ones considered in this study) and Table 2 describes objective functions related with studies utilizing extended particle swarm optimization. Table 3 shows the objective functions for studies that utilize modified particle swarm optimization while Table 4 presents the objective functions for studies that utilize particle swarm optimization with other techniques.

5.1. Studies that Utilize Conventional Particle Swarm Optimization

Li and Jiang [35] used the conventional PSO to solve the UC power system including thermal and wind units. The authors proposed a method to evaluate the probable risk due to the uncertainty of wind power by considering a penalty factor (related to the wasted energy) for adjusting the wind power prediction. The objective function was chosen to maximize the profit including electricity price and cost of all the conventional generators. To test the applicability of the algorithm, the IEEE 30-bus system, including five thermal generators besides to one wind generator, was used. The result shows the difference between the real and forecasted wind energy and states that the forecasted wind energy selects a lower penalty for the mentioned risk to be averted. Although the traditional PSO has many advantages like simplicity, easy implementation, derivatives-free nature, and few parameters to tune but it may work out of a local optimal solution instead of the global one. In addition, the solution quality falls drastically with large scale power systems. This would deserve the attention of researchers to modify the conventional PSO and overcome these difficulties. Therefore, several methods like as Extended PSO, modified PSO and combined PSO with other techniques were suggested to solve the problem. These methods are discussed in the next subsections.

Table 1. Objective function for the studies that utilize conventional particle swarm optimization.

Ref	OF	Equation	Details
[35]	MP	$F = \max \sum\limits_{t=1}^{T} [p_t P_D^t - \sum\limits_{i=1}^{k} [f_i(P_i^t)S_i^t + C_i S_i^t(1 - S_i^{t-1})]]$	T: The period of short-term dispatch p_t: The price of electricity in t^{th} period P_D^t: The load demand in period t including network losses k: The number of conventional units $f_i(P_i^t)$: The cost of production function of generator i P_i^t: The output of generator i inperiod t S_i^t: The status of generator i in period t C_i: The cost of cold start for generator i.

5.2. Studies that Utilize Extended Particle Swarm Optimization

Several studies used extended PSO as a solution method in solving UC problems. Wu et al. [36] proposed a Quantum-inspired Binary PSO method to solve UC with wind energy plants. The authors combined the concept of quantum theory with the conventional binary PSO (BPSO). In this approach, a quantum bit was selected for the probabilistic representation instead of updating velocity method in the standard PSO. The advantages of this method include robustness, fast convergence, and obtained better solutions, even with a small population. However, the BPSO algorithm has the drawback of premature convergence when handling heavily constrained problems [37]. The proposed technique was tested on 40 units for 24 hours time horizon. The results revealed that emission could be reduced by 8.35% to 22.59% and the generation costs can be reduced by about 8.96%.

Similarly, Chakraborty et al. [38] developed a Binary PSO technique based on fuzzy logic to solve the thermal UC problem combined with the wind-battery system. Fuzzy logic was utilized to solve the intermittency problem while binary PSO was used to break down the solutions into many clusters based on the value of their associated fitness. The fuzzification process includes the unpredicted constraints such as loaddemand, wind speed, spinning reserve, and production cost. This method has the advantage that it permits wider search space using clustering scheme in addition to the advantages listed above. This method is still suffering from premature phenomena.

The proposed method of Chakraborty et al. [38] was compared with other algorithms and simulations results reveal that, the proposed method, integer-coded genetic algorithm (ICGA), lagrangian relaxation and genetic algorithm (LRGA), GA and DP have total generation cost of $563,947, $566,404, $564,800, $565,825 and $565,825 respectively. This proposed method, apart from giving the lowest cost of production also provided useful data that others are not providing.

Similarly, Negi et al. [30] combined the advantages of the improved binary PSO and the dynamic PSO to solve UC problem including thermal and wind power systems. The uncertain nature of the

wind power is modeled by using Weibull probability function. The improved binary PSO involved the priority list approach (to gain its advantages of being simple and fast) in its algorithm to determine the on/off status of generating units by minimizing their operating cost. The dynamic PSO is used to solve the economic dispatch problem. In this case, the inertia weight factor w appearing in Equation (7) is modified to:

$$w = w_{max} - \frac{n\left(w_{max} - w_{min}\right)}{n_{max}} \tag{11}$$

where w_{max}, w_{min} are the initial and final weights, n_{max} is the maximum number of iterations and n is the current iteration. The simulation results showed the total operation cost to be \$715,358 and \$702,654 for a system without and with wind integration, respectively.

Also, Yu and Hu [23] studied a multi-objective thermal-wind UC problem. Multi-objective immune PSO (MOPSO) was used as the solution method to solve the multi-objective wind-thermal unit commitment. The wind forecast error was determined by using Monte-Carlo method. The paper showed that the appropriate confidence level in operating reserve constraints is related to error distributed of by wind forecast. The MOPSO technique is advantageous in improving the searching capability and avoiding local convergence. However, it may be trapped into infeasible solution and requires large computational time.

Finally, Zhou et al. [39] developed a multi-objective problem (cost and emission minimization) under load and wind power uncertainties, utilizing a data-driven UC model. Reinforcement learning-based multi-objective particle swarm optimization algorithm (RL-MOPSO) is proposed to resolve the problem. Kernel density technique (statistical method) was used to estimate the probability density function of the wind power and load. The RL-MOPSO technique has the ability of exploring a set of diverse and high quality non-dominated solutions. However, this technique depends on the trial and error of Reinforcement learning principle which learns to solve a problem by trial-and-error. In addition, it has the disadvantage of its dependency on the statistical information of the individual wind energy conversion systems. The authors proved the effectiveness of their approach through experiments. The findings show that the proposed algorithm captures the correlation between UC and uncertainty representation by tampering with confidence level differences of the value at risk levels.

5.3. Studies that Utilize Modified Particle Swarm Optimization

Many authors used modified PSO as a solution method in solving UC problems. Pappala et al. [40] proposed a stochastic technique for optimal thermal and wind power systems. The RE generation uncertainty was modelled using adaptive PSO algorithm which excludes the unnecessary particles in the global search process. The Artificial Neural Network (ANN) was used to predict the wind power. The obtained results show that the proposed method is efficient to solve the UC problem including large variations in wind power. Also, it was proved that, for power systems planning, the stochastic method is more efficient than the deterministic method. Shayeghi et al. [29] proposed PSO-IIW as an alternative method for UC solutions. In this method, the inertia weight and acceleration constants were modified in order to improve searching ability. Therefore, the particle velocity was updated using the modified equation:

$$v_m^{k+1} = C \left\{ w.\, v_m^k + c_1.r_1.\left(pbest_m - x_m^k\right) + c_2.r_2.\left(gbest_m - x_m^k\right) \right\} \tag{12}$$

where C is the constriction factor which is given by:

$$C = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}} \tag{13}$$

where $4.1 \leq \varphi \leq 4.2$.

Table 2. Objective functions for the studies that utilize extended particle swarm optimization.

Ref.	OF	Equation	Details
[36]	ME & MOC	$F = \min \sum_{j=1}^{T} \sum_{i=1}^{N_g} u_{i,j}[w_c(f(P_{i,j}) + S_{i,j}(1-u_{i,j-1}) + w_e\psi_i g(P_{i,j})]\}$	T: Period N_g: The number of thermal units $u_{i,j}$: The scheduled status of ith thermal unit for j^{th} hour w_c, w_e: The weight factors $f(P_{i,j})$: The fuel cost function $S_{i,j}$: The starting-up cost function ψ_i: The emission penalty factor $g(P_{i,j})$: The emission cost of ith thermal unit at j^{th} hour $P_{i,j}$: The generation of ith thermal unit at j^{th} hour
[38]	MTC	$F = \min \sum_{i=1}^{N} \sum_{t=1}^{T} [F(P_i(t)) + SC_i(1-I_i(t-1))]I_i(t)$	N : The number of generating units T: The total period of scheduling $P_i(t)$: The power generation of ith unit at t^{th} hour SC_i : The starting-up cost for i^{th} unit $I_i(t)$: The off/on states of ith unit
[23]	MFC	$F = \sum_{t=1}^{T} \sum_{i=1}^{N_s} [U_{it}F_i(P_{it}) + U_{it}(1-U_{it-1})S_i]$	T: The number of hours N_s: The number of thermal units U_{it}: The status of ith unit at t^{th} hour P_{it}: The power of ith unit at hour t S_i: The starting-up cost $F_i(P_{it})$: The cost function
[30]	MOC	$F = \sum_{t=1}^{T} (\sum_{i=1}^{n} (C_{i,t}^P + C_{i,t}^e + C_{i,t}^{sudc}) + \sum_{j=1}^{m} (C_{j,t}^c + C_{j,t}^o + C_{i,t}^u))$	n: The number of total thermal units m: The total number of wind units $C_{i,t}^P$: The nonlinear cost function $C_{i,t}^e$: The emission cost $C_{i,t}^{sudc}$: The starting up and shutting down cost of thermal j at t^{th} time $C_{j,t}^c$: The cost of production of the jth wind unit at t^{th} time $C_{j,t}^o$: The cost of overestimation of the jth wind unit at t^{th} time
[39]	MTC	$F = \sum_{t \in T} \sum_{i \in I} [(x_i^t SU_i + y_i^t SD_i) + G(u_i^t, P_i^t) + Q(u_i^t, P_i^t)]$	I: The index of thermal generators t: The index of the time horizons u_i^t: The off/on state of unit i at period t x_i^t, y_i^t: The variables depending on the off/on state of units SD_i and SU_i: The costs of shutting-down and starting-up of generator i $G(u_i^t, P_i^t)$: The cost of generation $Q(u_i^t, P_i^t)$: The cost of emission

The advantages of PSO-IIW algorithm are less computational time, good fitness, fast convergence, and robustness even with the presence of high penetration of wind. However, it requires the selection of optimal acceleration coefficients for the velocity update equation. The simulation results of PSO-IIW were compared with the GA method. The minimum cost and computational time were found to be $ 58,231.87 and 9.134 seconds, and $ 58,232.87 and 47.82 seconds respectively which emphasize the superiority of that method.

Pinto et al. [41] implemented a hybrid technique (DEEPSO) composed of Differential evolution with adaptive properties (DE) and Evolutionary PSO (EPSO). In this technique, the inertia weight was adapted in order to improve the searching mechanism. The mutated weight would become:

$$w' = w + \tau . N(0, 1) \tag{14}$$

where τ is the mutation rate (chosen by the user), and $N(0, 1)$ is a number sampled from the standard Gaussian distribution. Note that the modified weight must lie in the range $0 \leq w' \leq 1$. The particle velocity and position are updated in accordance with the modified weight. This technique has the merits of adjusting the optimum solution to the global direction, and minimizing the computational burden. Nevertheless, the demerits of this method depend on the setting of parameters. The UC problem based on both deterministic and stochastic formulation were analyzed considering PB, GL, and R-U/DT constraints. The simulation results show that the DEEPSO stochastic method is more efficient, robust and have less risk in terms of decision-making.

Similarly, Pinto et al. [42] developed a clustering method and hybrid meta-heuristic DEEPSO to enhance the searching ability in solving stochastic UC problems. Both deterministic and stochastic methods were used to model the UC schedule and compared; the deterministic method used the point forecast while stochastic method depended on several probabilistic wind power scenarios. The study compares the performance between stochastic proposed technique and deterministic UC approach and the results show that the stochastic method is more robust and efficient.

In another study, Zhang et al. [43] developed a modified multi-objective PSO in solving thermal and wind UC problem while considering several constraints such as SR constraints, U/DT constraints, etc. A mutated factor was proposed to update the velocity and position of the particles and thereby, enhance the searching strength. The simulation results reveal that the proposed method results in less operating cost when compared with other methods. The operation cost for Multi-objective Evolutionary Algorithms based on Decomposition (MOEA/D), Non-dominated Sorting Genetic Algorithm NSGA-II, Multi-objective PSO, and the proposed method is $528,257, $527,272, $527,364 and $527,151 respectively.

Similarly, Zhang et al. [44] developed a PSO-oriented dynamic adjustment technique for UC solutions taking the wind and load variation into account. This method improved the convergence performance of the PSO method during the iteration process, which affected positively on the overall solution quality. The simulation was done by considering both, with and without dynamic adjustment cases. The results showed that both methods have similar computational time. However, the operational cost for the method without dynamic adjustment was less, making it a better choice.

Wang et al. [45] implemented PSO with the heuristic search approach to solve the UC problem. The uncertainty of the wind is solved by using the Time Sequence Segment Fitting Method (TSFM), while the modified hybrid PSO method is utilized to solve the dispatch problem. The simulations were done using four case studies that include; overall Un-segmented Fitting Method and Unique Confidence Level (OUFM and UCL) (case 1), OUFM with Time-Varying Confidence Levels (TCL) (case 2), TSFM and UCL (case 3) and TSFM and TCL (case 4). The simulation results show that the total costs of operation for case 1, case 2, case 3 and case 4 are $502,218, $499,781, $496,335 and $492,146 respectively.

Table 3. Objective functions for the studies that utilize modified particle swarm optimization.

Ref.	OF	Equation	Details
[40]	MOC	$$F = \sum_{t=1}^{T}\sum_{i=1}^{I} SC_{i,t}u_{i,t}\left(1 - u_{i,t-1}\right) + \\ \sum_{s=1}^{N_s} \pi_s \sum_{t=1}^{T}\sum_{i=1}^{I} FC_{i,t}^{s}u_{i,t}$$	N_s: The total number of scenarios I: The total number of thermal units T: The planned periods $SC_{i,t}$: The startup cost $u_{i,t}$: The On/Off state of conventional unit i at time t $FC_{i,t}^{s}$: The fuel cost
[29]	MOC	$$F_T = \sum_{t=1}^{T}\sum_{i=1}^{N_T} F_i(P_i(t))$$	F_T: The total cost of operation T: The time intervals in hours N_T: The number of thermal units $P_i(t)$: The thermal unit generation
[41]	MOC	$$F = \sum_{i=1}^{T}\sum_{k=1}^{M} u_{ik} \times PC_k(P_{ik}) + u_{ik} \times (1 - u_{i-1k}) \times \\ SUC_k + LL_i \times M_1 + WS_i \times M_2$$	u_{ik} : The commitment state of conventional generating P_{ik}: The power produced by each conventional unit PC_k and SUC_k: The production and start-up cost of generating unit respectively WS_i and LL_i: The wind spilled and load curtailment of ith period respectively M_1 and M_2: Constants
[44]	MTC	$$F = \sum_{s=1}^{N_s} P_r(s) \times f(s,u) = \\ \sum_{s=1}^{N_s} P_r(s) \sum_{t=1}^{T}\sum_{g=1}^{N_g} \{F(PG_{g,t}^{s})U_{g,t} + \\ SC_{g,t}^{s}U_{g,t}(1 - U_{g,t-1})\}$$	$f(s,u)$: The cost of generation $P_r(s)$: The scenario's probability of occurrence $PG_{g,t}^{s}$: The conventional unit power output $U_{g,t}$: The state of g at t T: The cycle of unit commitment N_g: The number of conventional units $F(PG_{g,t}^{s})$: The cost of operating g under s $SC_{g,t}^{s}$: The starting-up cost
[42]	MTC	$$F = \min \sum_{k=1}^{N_{WSC}} P_k \sum_{j=1}^{N_T}\sum_{i=1}^{N_G} [\sum u_{ij} \times \mu_i \times P_{ijk} + u_{ij} \times \\ (1 - \mu_{i,j-1}) \times SUC_i + M_1 \sum_{m=1}^{N_B} LL_{jkm} + \\ M_2 \sum_{l=1}^{N_{wF}} WS_{jkl} + M_3 \times SRNS_{jk}]$$	u_{ij}: The states of the generation unit P_{ijk}: The power generated by wind unit i in time j P_k: The scenario k of wind power probability μ_i and SUC_i: The production and starting-up cost and cost of generation unit i LL_{jk}, $SRNS_{jk}$ and WS_{jk}: The total load loss, spinning reserve not supplied and the total wind power spilled in period j respectively N_{WSC}, N_B, N_{wF}, N_T, N_G: The the number of generators, buses, wind farms, wind scenarios, and look-ahead periods. M_1, M_2, M_3: Constants
[43]	MTC	$$F = \sum_{s=1}^{S} Pr(S)f_{cost}^{s} = \\ \sum_{s=1}^{S} Pr(S)\{ \sum_{j=1}^{T}\sum_{i=1}^{N} [SC_i(1 - u_{i,j-1})u_{i,j} + u_{i,j}f_i(P_{i,j}^{s})]\}$$	i: The index of thermal unit j: The time interval s: The wind power reduced scenario N : The thermal units number S: The wind power reduced scenario number T: The time intervals $Pr(S)$: The scenario s probability of occurrence SC_i: The starting-up cost of ith unit $u_{i,j}$: The off/on states of ith unit $P_{i,j}^{s}$: The power generated by unit i at hour j $f_i(P_{i,j}^{s})$: The fuel cost
[45]	MTC	$$F = \min_{P_i^t, u_i^t, \alpha_k^t, \beta_k^t} (F(p_i^t, u_i^t) + S(x_i^t, u_i^t) + \\ V(\alpha_k^t, \beta_k^t) + E(\alpha_k^t, \beta_k^t)$$	$F(p_i^t, u_i^t)$: The fuel cost $S(x_i^t, u_i^t)$: The starting-up cost $V(\alpha_k^t, \beta_k^t)$: The risk cost of LLCW and TR $E(\alpha_k^t, \beta_k^t)$: The costs of ER ER: The extra reserve. TR: The conventional fixed reserve LLCW: The wind loss of load curtailment p_i^t: The unit i generation during time t period u_i^t: The status of unit i at time t x_i^t: The on/off time intervals of unit i α_k^t, β_k^t: The confidence interval parameter

5.4. Studies that Utilize Particle Swarm Optimization with Other Methods

Several studies used PSO with other techniques as a solution method in solving UC problems. Chakraborty et al. [1] proposed an optimal thermal unit combined with RES. The UC problem was solved by using an improved GA-operated binary PSO method, while the optimum solution was reached by refining the number of generations. To achieve fast convergence, the authors proposed a method for dynamic adjusting of PSO Parameters. Thus, the particle velocity was updated using:

$$v_m^{k+1} \ = \ w. \, v_m^k + \ c_1.r. \left(pbest_m - \ x_m^k\right) + \ c_2.r. \left(popbest_m - \ x_m^k\right) + \ c_3.r. \left(gbest_m - \ x_m^k\right) \tag{15}$$

where $r = \{0, 1\}$ is a uniform random number and c_1, c_2, c_3 are acceleration factors. The $popbest_m$ is introduced for refined process on each population individual. The dynamic adjustment of parameters $c_{1,2,3}$ is such that $c_1 = $ rand (1.5, 2), $c_2 = $ rand (1, 1.4), and $c_3 \ = \ 4 - c_1 - c_2$.

To show the effectiveness of such approach, the authors compared the total cost with other algorithms. The simulation results depicted that the total cost for GA, DP, LR and the proposed method is \$565,825, \$565,825, \$568,825 and \$475,815.22 respectively.

Similarly, Chakraborty et al. [46] proposed security constrained UC for thermal plants combined with wind system. In this proposal the UC problem was solved by using PSO while LR method was used to relax the objective functions and constraints. The method divided the load hours into homogeneous groups and obtained solutions for each group. In order to validate this approach, simulation results were taken from 66-bus Indian utility system and compared with GA method. The total cost was recorded as Rs 4883886.99 for GA method in contrast to Rs 4875,983.08 for the proposed method.

This technique has the advantages of offering faster solution but it may encounter numerical convergence problems.

Wan et al. [47] developed a model to solve UC problem of thermal plants and wind power systems. The developed model considers three models of optimization, namely "discarded wind power option", "unit operational cost option", and "system risks option". These three models of optimization were solved by using fuzzy multi-objective model and Quantum-behaved PSO algorithm. The results reveal that the total cost of operation of model 1, model 2 and model 3 were 25.568 million Yuan, 24.419 million Yuan, and 25.901 million Yuan, respectively.

He et al. [32] proposed a chance-constrained UC model with Superconducting Magnetic Energy (SME) storage and wind. The method used PSO and branch/bound method to solve the non-convex problem and, the authors compared the performance of the system using three different scenarios. In first scenario the wind output equals to the forecast, while in scenario two, the wind output is at maximum and minimum in the third scenario. The simulation results revealed that the proposed method could provide better autonomy to balance the system dispatch cost and reliability. The disadvantage of this method is that the computational time increases exponentially with the increment of the dimension of the UC problem as a result of using the branch/bound technique.

Jiang et al. [48] developed an application of forecast error on UC with the integration of RE. To decrease the quantity of uncertain variables, the algorithm classified the errors as uncertain error, certain error, and system's total forecast error. The study depicted that using PSO, based on Monte-Carlo method, could reduce the cost of operation and computational time.

Similarly, Alam et al. [34] proposed a hybrid PL-PSO algorithm to solve thermal and RE (wind and solar) power plant problems. The Economic Load Dispatch (ELD) was handled by the PSO while PL algorithm solved the on/off decision of thermal plants. The simulation results indicated that an improvement in terms of computation time when compared with the obtained results by that of PL-GA as 9.43 seconds and 373 seconds respectively.

Also, Ji and Wang [33] proposed a revised binary PSO to solve the problem of thermal UC with wind power integration. A Revised Lambda Iteration Method (RLIM) is utilized to solve the dispatch problem while revised binary PSO is used to decide the on/off status of the units. The simulation

results (total operation cost) were found to be \$563,074, \$563,938 and \$563,977 for the developed model, ES-Elite PSO and quantum-inspired binary PSO respectively.

Tiwari et al. [31] presented optimized generation planning of RE system with storage incorporated with conventional generators. Hybridization of PSO_TVAC with PL Method technique was applied to resolve the deterministic UC Problem of a thermal generation system comprising of ten units operating over a day. Simulation results compared the case when the load was carried by thermal units only with the case when the system was integrated with batteries and wind energy to carry the same load. The results revealed that the cost of generation could be reduced by about 12%.

Table 4. Objective functions for the studies that utilize other method with particle swarm optimization.

Ref.	OF	Equation	Details
[1]	MTC	$F = \sum_{I=1}^{N} \sum_{t=1}^{T} [F(P_i(t)) \, SC_i(1 - I_i(t-1))] I_i(t)$	N: The number of generating units i: Number of the unit T: The scheduling total period. t: The hour $F(P_i)$: The fuel cost function SC_i: The starting-up cost for i^{th} unit $I_i(t)$: The off/on state of ith unit
[46]	MTC	$F = \sum_{i=1}^{UN} \sum_{t=1}^{HN} [F(P_i(t)) + SC_i(1 - I_i(t-1))] I_i(t)$	UN: The number of generating units HN: The scheduling hours numbers $P_i(t)$: The power loss of the system at t hour SC_i: The starting-up cost for i^{th} unit
[47]	MOC	$F = \min \sum_{t=0}^{T_d} \sum_{k=1}^{NG} \left(\begin{array}{c} u_{k,t} \cdot m \cdot F_{k,t}^{coal}(P_{gk,t}) + \\ u_{k,t}(1 - u_{k,t-1}) S_{k,t}^{coal} \end{array} \right)$	$u_{k,t}$: The on/off status of kth unit in t time $P_{gk,t}$: The output of kth unit in t time m: The consumption price of a unit coal $F_{k,t}^{coal}(P_{gk,t})$: The coal power generating consumption of kth unit $S_{k,t}^{coal}$: The starting-stopping consumption of coal unit NG: The units total number T_d: The number of time period
[32]	MOC	$F = \{ \sum_{i=1}^{N_G} U_{Gi,t} \left[C_{Gi}^{E}(P_{Gi,t}) + C_{Gi}^{Spin}(R_{Gi,t}^{Spin}) + C_{Gi}^{UR}(R_{Gi,t}^{UR}) \right.$ $\left. + C_{Gi}^{DR}(R_{Gi,t}^{DR}) \right] \min \sum_{t=1}^{T} [-U_{Gi,t-1}) U_{Gi,t} C_{Gi}^{ST}(P_{Gi,t})$ $+ U_{Gi,t-1}(1 - U_{Gi,t}) C_{Gi}^{SD}(P_{Gi,t})]$ $+ \sum_{i=1}^{N_M} U_{SMESi,t} [C_{SMESi}^{UR}(R_{SMESi,t}^{UR}) + C_{SMESi}^{DR}(R_{SMESi,t}^{DR})]$	$P_{Gi,t}$: The thermal generation unit schedule $C_{Gi}^{ST}(P_{Gi,t})$ and $C_{Gi}^{SD}(P_{Gi,t})$: The costs of starting-up and shutting-down respectively $R_{Gi,t}^{Spin}, R_{Gi,t}^{DR}, R_{Gi,t}^{UR}$: The output committed, up and down regulation, spinning reserve, thermal regulation of ith unit respectively $R_{SMESi,t}^{UR}$ and $R_{SMESi,t}^{DR}$: The regulation up and down of ith SMES respectively $U_{SMESi,t}$: The binary variables of SMES N_M and N_G: The number SMESs and of thermal units respectively
[48]	MOC	$F = \sum_{t=1}^{T} \sum_{i=1}^{N_g} [I_{i,t} f(P_{Gi,t}) + I_{i,t}(1 - I_{i,(t-1)}) S_{i,t}]$	$I_{i,t}$: The binary variable $S_{i,t}$: The starting up cost and shutting down cost of conventional i^{th} unit in t period (\$/h) $P_{Gi,t}$: The conventional unit output in t period (MW)
[34]	MFC	$F = \sum_{j=1}^{24} \sum_{i=1}^{N} U_{ij} F_i(P_{ij}) + U_{ij}(1 - U_{ij-1}) S_i$	U_{ij}: The off/on states of ith unit P_{ij}: The generated power by unit i in hour j N: The number of units S_i: The starting-up cost of ith unit
[33]	MTC	$F = \min \sum_{w=1}^{k} p(w). C_M(w) =$ $\sum_{w=1}^{k} p(w).[\sum_{i=1}^{T} \sum_{i=1}^{N} u_i^t(1 - u_i^{t-1}) S_{ONi}^t(w) +$ $\sum_{i=1}^{T} \sum_{i=1}^{N} u_i^t H(P_{Gi}^t(w)) + \mu_w \sum_{i=1}^{T} L_{wind}^t(w) +$ $\mu_l \sum_{i=1}^{T} L_{load}^t(w)$	k: The scenarios w: The scenarios from 1 to k $C_M(w)$: Each scenario cost of operation S_{ONi}^t: The startup cost $H(P_{Gi}^t(w))$: The cost of fuel consumption $L_{load}^t(w)$: The penalty term for shedding load p(w): Each scenario probability u_i^t: The start/stop status of ith unit at time t μ_l and μ_w: load shedding and penalty coefficient of the loss of wind curtailment respectively
[31]	MOC	$F = \sum_{h=1}^{H} \sum_{i=1}^{N} [FC_i(P_{ih}) + SC_i(1 - U_{i(h-1)})] U_{ih}$	U_{ih}: The off/on states of the ith unit $FC_i(P_{ih})$: The fuel cost (P_{ih}) power output at hour h FC: The fuel cost function

5.5. Comparison of Constraints and Technologies of All Algorithms

Table 5 presents the details about the constraints and technologies used by the respective articles for quick and easy reference. Also, the table shows that PB, GL, U/D T, R-U/D and SR are the most utilized constraints, while there are few studies that considered TL, F, E, St and Cr constraints. As seen in the table below, the first five constraints are present in all types of PSO. Moreover, one can see that the PSO category that can handle the most constraints, and can adapt to the two technologies, is the PSO with other methods. Therefore, according to the table, the optimal PSO can be stated as the PSO combined with other methods, due to the fact that such algorithms can be used to solve more complex problems including many constraints. From the table it can also be noticed that the most of the time, the studies focus on only one technology (wind) rather than considering hybrid case.

Table 5. Constraints and technologies.

Type of PSO	Ref.	Constraints											Technology	
		PB	GL	SR	U/DT	R-U/D	UIS	TL	F	St	Cr	E	Wind	Solar
Conventional PSO	[35]	●	●	●	●	●							●	
Extended PSO	[36]	●	●	●	●	●							●	
	[23]	●	●	●		●							●	
	[38]	●	●	●	●	●							●	
	[30]	●	●	●	●		●						●	
	[39]	●	●	●	●		●						●	
Modified PSO	[40]	●	●	●	●	●	●						●	
	[29]	●	●	●	●	●							●	
	[41]	●	●	●	●	●							●	
	[44]	●	●	●	●	●							●	
	[42]	●	●	●	●	●			●				●	
	[43]	●	●	●	●	●							●	
	[45]	●	●	●	●	●							●	
PSO with other methods	[1]	●	●	●	●	●		●	●			●	●	●
	[46]	●	●	●	●	●		●	●				●	
	[47]	●	●	●	●	●							●	
	[32]	●	●	●		●				●			●	
	[48]	●	●	●	●	●							●	●
	[34]	●	●	●	●						●		●	●
	[33]	●	●	●	●	●					●		●	
	[31]	●	●	●	●		●						●	

6. Conclusions

This paper presents a state of the art review on UC studies based on PSO algorithms, by covering the research articles published in the last decade. Several studies that used PSO or its variants as a solution method in solving the UC problem were reviewed. This is done by categorizing the considered studies into extended PSO, modified PSO, conventional PSO, and PSO with other techniques. As seen in this study, that PSO is one of the most effective and efficient techniques used in solving the UC problem. A critical review that highlights PSO methods utilized in solving the UC problem was presented. This study considered UC models that include thermal, wind and solar plants. The study shows that PSO with other techniques are utilized more than the other PSO based methods in solving the UC problem. Moreover, the PSO with other methods has proven to be the most effective in dealing with several constraints. It is also found that, PB, GL, U/DT, R-U/D and SR are the most utilized constraints in the studies considered in this review. This study may serve as a reference for researchers in need to have a quick search on UC models based on PSO technique.

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