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REVIEW ARTICLE

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A solution to the unit commitment problem—a review

Abstract Unit commitment (UC) is an optimization problem used to determine the operation schedule of the generating units at every hour interval with varying loads under different constraints and environments. Many algorithms have been invented in the past five decades for optimization of the UC problem, but still researchers are working in this field to find new hybrid algorithms to make the problem more realistic. The importance of UC is increasing with the constantly varying demands. Therefore, there is an urgent need in the power sector to keep track of the latest methodologies to further optimize the working criterions of the generating units. This paper focuses on providing a clear review of the latest techniques employed in optimizing UC problems for both stochastic and deterministic loads, which has been acquired from many peer reviewed published papers. It has been divided into many sections which include various constraints based on profit, security, emission and time. It emphasizes not only on deregulated and regulated environments but also on renewable energy and distributed generating systems. In terms of contributions, the detailed analysis of all the UC algorithms has been discussed for the benefit of new researchers interested in working in this field.

Keywords unit commitment (UC), optimization, deterministic load, stochastic load, evolutionary programming (EP), hybrid

1 Introduction

The unit commitment (UC) problem deals with the optimum amount of time for which a generating unit must be operated at a per hour basis in order to meet the load requirements effectively. With the help of this optimization, it is possible to supply power with least possible losses and minimum fuel consumption, in order to maximize the profit. Besides achieving minimum total production cost, a generation schedule needs to satisfy a number of operating constraints. These constraints reduce freedom in the choice of starting-up and shutting-down of generating units. The constraints to be satisfied are usually the status restriction of individual generating units, minimum up time, minimum down time, capacity limits, generation limit for the first and last hour, limited ramp rate, group constraint, power balance constraint, spinning reserve constraint, etc. The high dimensionality and combinatorial nature of the UC problem curtails the attempts to develop any rigorous mathematical optimization method capable of solving the whole problem for any real-size system. Nevertheless, in the literature, many methods using some sort of approximation and simplification have been proposed. This paper provides a detailed summary of all the latest optimization techniques for UC under different constraints for both stochastic and deterministic loads.

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2 General background about UC

The off-peak and on-peak demands of electricity may vary for different purposes. If the units consumed are properly monitored, it may be possible to save some units when the demand is less, for instance the load is lesser at night compared to the day time. Thus, the main objective of this paper is to plan the operating time of different generating units such that it satisfies constraints. The UC problem is applied for both deterministic and stochastic loads [1]. The deterministic approach provides the definite and unique conclusions. However, the results obtained for stochastic loads may not be exact. For the deterministic loads data envelopment analysis (DEA), the principal component analysis (PCA) approach is employed. DEA is a non-parametric method, in which first the input and output variables are defined. In the PCA, the numbers of variables used are reduced to the minimum. However, in stochastic models, the constraints are changed into determinate constraints and then the formulation can be solved by any of the usual algorithms. The various kinds of objective functions for various environments are as follows.

2.1 Conventional fuel based environment [2]

In Eq. (1), there are three costs to minimize. The first one is $P(i, t)$ which is generation of unit i at time t, and $C(P(i, t))$ is fuel cost of unit i at time t. The second one is the start-up cost and the third, shutdown cost.

$$\min\sum_{t=1}^{N_t}\sum_{i=1}^{N_0}[C_i(P(i,t))I(i,t)+SU(i,t)+SD(i,t)]. \tag{1}$$

2.2 Stochastic environment [3]

Stochastic environment is one in which randomness is included either in the objective function or to the constraints. In Eq. (2), the second part creates randomness due to the addition of wind generation. Nowadays, uncertainty occurs in power systems due to the large scale integration of renewable resources like solar, wind, etc. Hence, the demand and supply may also differ for the successful and reliable operation of the system within an uncertain environment which is also called a stochastic environment.

$$\min\sum_{t=1}^{N}\left[\sum_{t=1}^{T}(C_iP_{i,t}+C_{i,t,U}+C_{i,t,D})\right] +M\sum_{k=1}^{N}\sum_{t=1}^{T}\left(\hat{w}_{k,t}-w_{k,t}\right), \tag{2}$$

s.t.

$$\sum_{i=1}^{N}P_{i,t}+\sum_{k=1}^{N_w}W_{k,t}=D_t\ (t=1,2,...,T), \tag{3}$$

$$P_{l,\min}\leqslant\sum_{i=1}^{N}G_{l-1}P_{i,t}+\sum_{k=1}^{N_w}G_{l-k}w_{k,t}-\sum_{i=1}^{K}G_{l-i}D_{i,t}\leqslant P_{l,\max}, \tag{4}$$

$$g_{\mathrm{I}}(I_{i,t})\leqslant 0, \tag{5}$$

$$g_{\mathrm{r}}(P_{i,t},I_{i,t})\leqslant 0, \tag{6}$$

$$g_{\mathrm{c}}(C_{i,t,U},C_{i,t,D},I_{i,t})\leqslant 0, \tag{7}$$

$$0\leqslant w_{k,t}\leqslant\hat{w}_{k,t}, \tag{8}$$

$$I_{i,t}P_{i,\min}\leqslant P_{i,t}\leqslant I_{i,t}P_{i,\max}. \tag{9}$$

Objective function (2) consists of operation and start-up/shutdown (STSD) costs of thermal generators, as well as the expected wind power spillage; Equation (3) corresponds to system power balance constraints; Equation (4) corresponds to DC transmission constraints; the g in Eq. (5) denotes the constraints only associated with integer variables, like minimum online/ offline time limits; the g_{r} in Eq. (6) denotes ramping-up and ramping-down constraints; the g_{c} in Eq. (7) denotes constraints for STSD cost ; Equations (8) and (9) denote the upper and lower limits of the real power output of wind and thermal generators.

2.3 Profit based environment [4]

The profit based environment is one in which the main objective is to maximise the profit of an individual generation company. The UC schedule has an indirect effect on the price and a direct effect on the average cost, thus it is an important part of any bidding strategy. Also there is flexibility in the UC schedule. Objective function (10) can be defined by maximising $F(i,t)$ which is the profit of the GENCO.

$$\max\sum_{i}\sum_{t}F(i,t), \tag{10}$$

where $F(i, t)$ = Revenue – Cost.

For unit i and at tth hour, it is as follows

$$\begin{aligned}F(i,t)&=\{\rho_{\mathrm{gm}}(t)P(i,t)+\rho_{\mathrm{rm}}(t)R(i,t)+\rho_{\mathrm{nm}}(t)N(i,t)\\&\quad-C_i(P(i,t)+R(i,t)+N(i,t))-S(i,t)\}\\&=I(i,t)+\{\rho_{\mathrm{nm}}(t)N(i,t)-C_i(N(i,t))\}(1-I(i,t)),\end{aligned} \tag{11}$$

where $F(i,t)$ is the profit of unit i at tth hour; $\rho_{\mathrm{gm}}(t)$ is the forecasted market price for energy at tth hour; $\rho_{\mathrm{rm}}(t)$ is the forecasted market price for spinning reserve at tth hour; $\rho_{\mathrm{nm}}(t)$ is the forecasted market price for non-spinning reserve at tth hour; $C_i(\cdot)$ is the cost function of unit i; $S(i,t)$ is the start-up cost of unit i at tth hour; and $I(i,t)$ is the commitment state of unit i at tth hour.

The various constraints involved in UC are as follows.

2.3.1 Time based constraint for UC

Under this constraint, the main challenge is to minimize the time taken to obtain the optimal architecture. The time constrained UC (TCUC) problem comprises of non-linear constraints such as the minimum up and down time for each unit [5]. Once the unit is running, it should not be turned off immediately, and when it is turned off, there is a minimum time before which it cannot be turned back on. Thus to meet this constraint, the operation scheduling should be done according to the up-time and down-time of the generating units. Here the stopping criterion, Total CPU time greater than or equal to Allowed time is added to stop the algorithm exactly at a moment where the total CPU time taken exceeds the allowed time [6].

$$\left(T_{\mathrm{on}}(i,t-1)-T_{\mathrm{up}}(i)\right)\ \left(I(i,t-1)-I(i,t)\right)\ \geqslant 0, \tag{12}$$

$$\left(T_{\mathrm{off}}(i,t-1)-T_{\mathrm{down}}(i)\right)\ \left(I(i,t-1)-I(i,t)\right)\ \geqslant 0, \tag{13}$$

where $T_{\mathrm{on}}(i,t)$ is the continuous on-time of unit i at time t, T_{off} means off time; and $T_{\mathrm{up}}(i)$ is the minimum up-time of unit i, T_{down} means down time.

2.3.2 Emission based constraint for UC

More than 50 percent of the emission comes from the fossil fuel based power systems [7]. Hence it can be concluded that the maximization of the profit of GENCOs and the minimization of the emissions are two conflicting objectives. Therefore, a multi-objective approach can be followed to achieve sub-optimal solutions if not optimal solutions [1]. If both the cases are considered, it will lead to a small saving of cost which will bring down the fuel consumption and hence the emission rate.

$$\sum_{t=1}^{T}\sum_{i=1}^{N} C_{\mathrm{e}}(P(i,t)I(i,t)) + S_{\mathrm{e}}(i,t) \leqslant E^{\max}, \tag{14}$$

where C_{e} is the emission function of unit i; $S_{\mathrm{e}}(i,t)$ is the start-up emission of unit i at time t; $E^{\max}$ is the maximum allowance of total emission; $P(i,t)$ is the generation of unit i at time t; and $I(i,t)$ is the on/off status of unit i at time t (on = 1 and off = 0).

2.3.3 Fuel based constraint for UC

The present scenario requires efficient power generation by utilizing the resources properly. The cost of fuel is also a major economic concern. During off-peak load conditions, if the generating units can be managed, then fuel requirements will be able to be reduced.

$$F^{\min}(i) \leqslant \sum_{t} C_{\mathrm{f}}(P(i,t)I(i,t)) + S_{\mathrm{f}}(i,t) \leqslant F^{\max}(i), \tag{15}$$

where $F^{\min}(i)$ and $F^{\max}(i)$ is the minimum and maximum fuel consumption for unit i; C_{f} is the fuel consumption function; and S_{f} is the start-up fuel of unit i at time t.

2.4 Ramp based constraint

The ramp based constraint determines the maximum range, by which the power generated can be increased in a particular duration of time.

$$P(i,t) - P(i,t-1) \leqslant \mathrm{UR}(i), \tag{16}$$

$$P(i,t-1) - P(i,t) \leqslant \mathrm{DR}(i), \tag{17}$$

where $\mathrm{UR}(i)$ and $\mathrm{DR}(i)$ are the maximum ramp-up and ramp-down rates of unit i.

2.5 Transmission constraint

With the UC schedule, GENCOs have to satisfy customer load demands and maintain transmission flows and bus voltages within permissible limits. It is not possible to satisfy all these constraints using a single optimization technique, therefore a hybrid algorithm approach can be used to achieve it.

$$-P_{k\mathrm{m}}^{\min} \leqslant P_{k\mathrm{m}}(t) \leqslant P_{k\mathrm{m}}^{\max}. \tag{18}$$

2.6 Spinning reserve

The spinning reserve is the unused capacity, which can be activated on decision of the system operator and which is provided by devices that are synchronized to the network and able to affect the active power.

$$\sum_{i=1}^{N} I(i,t) r_{\mathrm{s}}(i,t) \geqslant R_{\mathrm{s}}(i,t), \tag{19}$$

where $R_{\mathrm{s}}(i,t)$ is the spinning reserve requirement at time t.

2.7 System operating system requirements

The system operating reserve requirement (R_0) gives the time required for the quick start capability of a particular unit from the off state. During the on time, it will consider the spinning reserve capacity.

$$\sum_{i=1}^{N} I(i,t) r_0(i,t) \geqslant R_0(i,t). \tag{20}$$

3 UC problem solving techniques

UC is the problem of determining the schedule of generating units within a power system subject to device and operating constraints. Several optimization techniques have been applied to find the solution to the thermal UC problem. The solutions available are classified into conventional techniques, non-conventional techniques and hybrid algorithm.

3.1 Conventional techniques

Conventional techniques include exhaustive enumeration, priority listing, dynamic programming, branch and bound, integer programming, simulated annealing, Lagrangian relaxation, tabu search, and interior point optimization.

The exhaustive enumeration method is the simplest of the combinatorial optimization techniques. The principle of this method is to evaluate all combinations of the discrete variables. It assures the global optimum of the objective function, but the computational time is very huge [8]. Branch and bound (BB or B&B) is a general algorithm for finding optimal solutions of various optimization problems, especially in discrete and combinatorial optimization. This method was first proposed by Land and Doig [9]. Dynamic programming is a methodical procedure, which systematically evaluates a large number of possible decisions in a multi-step problem. When the existing conventional dynamic programming method is utilized, although its solution is correct and has the optimal value, it takes a lot of memory and takes a lot of time in getting an optimal solution [10]. Mixed Integer Linear Programming (MILP) helps reduce the solution significantly and also the nonlinear constraints can be easily linearised. The MILP UC function developed by Chang et al. [11] can be used for very large systems which also supports bidding strategies in the power market.

The stimulated annealing (SA) method facilitates in searching the work space rapidly, but it does not work properly in the case of wide temperature variation. In the original SA method, a large share of the computation time was spent in randomly generating and evaluating solutions that turned out to be infeasible [12]. In order to improve the performance, a hybrid of SA and local search was developed in 2003 by Purushothama et al. [13] and the results were verified using C++. This simple modification makes it possible to reduce the number of iterations required at each temperature, and it generates solutions with lower cost than that obtained by using previous algorithms. Lagrangian relaxation was first applied to UC in 1977 by Muckstadt et al. [14]. The problem is formulated in terms of a cost function, that is the sum of terms each involving a single unit, a set of constraints involving a single unit, a set of coupling constraints (the generation and reserve requirements), one for each hour in the study period, involving all units. When the Lagrangian relaxation based methods are applied to solve power system UC, the identical solutions to the sub problems associated with identical units may cause the dual solution to be far away from the optimal solution [15]. Tabu search is based on the hill climbing method that iteratively evaluates a best solution each time the neighborhood is updated and it stops if the solution is not improved to minimise the cost function. The major drawbacks are that it gets stuck in the local minima. To overcome the problems above, the parallel tabu search (PTS) is developed [16,17]. The idea makes it possible to find out the better solution from different directions [18].

3.2 Non conventional (Non classical) techniques

In Expert systems, for a particular load pattern, a priority list based heuristic model in the form of interface rules has been proposed by Ouyang et al. [19]. An expert system consisting of dynamic load pattern matching interface and a commitment schedule database has been designed by Ouyang et al. [20]. In Fuzzy system, the use of fuzzy logic in the UC problem was demonstrated by Saneifard et al. [21]. Using this, the characteristics of the system and the response can be found out without any mathematical calculations. Unexpected load variation leads to insufficient commitment capacity, therefore Zhai et al. [22] has demonstrated a technique for examining the effect of load variation on UC. The Hopfield neural network was used by Sasaki et al. [23] to solve UC problems and it obtained satisfying results, but the accuracy was a major concern. An extension of the mean field annealing neural network approach was demonstrated by Liang and Kang [24]. Walsh and Mallry [25] designed a new way of interconnecting neurons to produce an energy equation involving both discrete and continuous terms. Kurban and Filik [26] proposed a method to reduce the production cost by combining load forecasting with UC problem using artificial neural network (ANN) model with auto regression (AR) in 2008. The Ant system was developed by Salam et al. [15] and is based on the idea that a colony of ants is able to succeed in a task to find the shortest path between the nest and food source. This path is reinforced and many ants follow the trail to achieve the shortest path.

The genetic algorithm (GA) is a general purpose, simple and robust, stochastic and parallel search method based on the mechanics of natural selection and natural genetics. The GA works with a population of chromosomes. A chromosome is a string of bits 0 and 1. Ma et al. [27] suggested an improved GA method using C++ compilation in 2011. This method was tested using C++ on a 6 unit system over a scheduling period of 6 hours. Abookazemi and Mustafa [28] developed a parallel structure to handle the infeasibility problem in a structured and improved GA which provides an effective search and therefore greater economy in 2009. This method was developed and tested by using C# program. Tests have been performed on 10 and 20 units systems over a scheduling period of 24 hours. Atashpaz-Gargari et al. [29] first introduced the imperialistic competition algorithm (ICA) in 2007. In the ICA, the initial population individuals (countries) are in two types: imperialists and colonies that all together form some empires. The imperialistic competitions among these empires converge to a state, in which there exists only one empire.

3.3 Hybrid algorithms developed (employing both classical and non classical methods)

3.3.1 Hybrid priority list ant

Withironprasert et al. [30] devised a new method hybrid ant system priority list (HASP), in which there are many units with different paths that can be selected at hour *t*. At this stage, *m*th ant probabilistically selects unit *i* and commits it as '1' status for satisfying the UC constraints. AS search space for priority list method, considering size of UC search space, the maximum number of paths to be selected by *m*th ant at hour *t* of the proposed approach is *N*, which is equal to the number of units, while the maximum number of paths to be selected by using AS algorithm without the priority list method [31] is $2N-1$ combinations. It is clear that the search space of *N* is much smaller than $2N-1$ combinations, so that the UC search space based on the proposed approach is significantly reduced. This method has greater flexibility and achieves greater economic saving whereby saving computational time. Sum-im T and Ongsakul tested their algorithm with 10 unit system and got their total operating cost as $564324 for 24 hours. Also they validate their results by comparing them with LR ($565825), GA ($565825), evolutionary programming (EP) ($564551) and ICGA ($566404).

3.3.2 Hybrid ant colony optimization

Yu et al. [32] suggested a hybrid method of ant colony optimization (ACO) and lambda iteration method for the UC problem in 2010. The ACO algorithm is used to optimize the on/off status planning of units in the upper level, and the lambda iteration method is used to optimize economic load dispatch in the lower level. To verify the effectiveness of the method proposed, it is applied to a test system [33] that consists of 10 units. For the systems of 20, 40 and 60 units, the basic 10 unit system is duplicated. The proposed method provides better results than the GA, EP and PL. For a 10 unit system the total operating cost was $562989 as compared to $564950 (PL), $565825 (GA) and $564551 (EP).

3.3.3 Hybrid Lagrangian relaxation

The hybrid Lagrangian relaxation method (LR) was devised by Zhang et al [34]. The advantages of LR in dealing with large-scale power systems and GA in making up the shortage of Dynamic Programming are used. By using Lagrangian multipliers to relax system-wide demand and reserve constraints, the UC problem is decomposed and converted into a two-level optimization problem. The optimal commitment of a single unit is solved by using GA in the low-level problem. Crossover and mutation are very important operations on which the convergence of the GA depends. It has good convergent rate and was faster, and provides high quality solution. The developed algorithm was tested with 10 unit system and the total operating cost was $557726.4, which was comparatively less when compared to $565825 (LR), $565825 (GA) and $564551 (EP).

3.3.4 Hopfield neural network

Kumar and Palanisamy devised a method that employs a linear input-output model for neurons, which is extremely different from all Hopfield methods previously reported as the previous methods apply the iterative procedures requiring a large quantity of computation to converge to accurate solutions. However, based on the formulations developed, the proposed method computes its solutions analytically, and no iteration is needed in the solving process. Consequently, computational efforts are greatly reduced which was demonstrated by its use in the 10- and 20-unit systems. Although it works on a neural network, it does not require any training. It requires 32 times less CPU time than the LR [35]. Therefore, for a 10-unit system, the total operating cost was $564959 as compared to $565508 (ALR), $565825 (GA) and $565475 (LR).

3.3.5 Hybrid EP and particle swarm optimization (PSO)

This hybrid intelligence technique proposed by Lal raja Singh and Christober Asir Rajan [36] in June 2001 for UCP utilizes PSO algorithm and EP. PSO is used to determine the units and their optimum generation schedule for a particular demand with minimum cost. Evolutionary programming (EP) assisted by PSO is used to determine the UC that minimizes the cost for different possible demands. Therefore, for a 7-unit NTPS, the total operating cost (in p.u.) is 0.7516 as compared to 0.93690 (PSO), 0.97483 (LR) and 0.93461 (EP).

3.3.6 Hybrid GA

Chang and Luo [37] used the binary-coded genetic algorithm incorporating a priority list ordering scheme to solve the "unit scheduled" decision. The genetic algorithm incorporates the solution produced by the priority list unit scheduled as part of its initial population; this injects domain knowledge into its search space. Since the merit order unit scheduled forms part of the initial population, the hybrid genetic algorithm is guaranteed to provide a global solution. The feasibility of the proposed method was demonstrated for a 10-unit system, and the result is a hybrid GA (HGA) that produced better results than those obtained by the simple GA (SGA), PSO and BPSO. Therefore for a 10-unit system, the total operating cost is

\$556760 as compared to \$565804 (BPSO), \$581450 (PSO) and \$609023 (SGA).

3.3.7 Hybrid PSO

Alshareef devised an advanced PSO, in which some parts of PSO are modified (e.g., includes bacterial foraging operations) to converge the system in 2011. Besides, a repair method is applied for the fast convergence of the system. The hybrid PSO was tested on a 135-unit system for a scheduling period of 24 hours. The execution time is growing rapidly considering the size of the problem [38].

3.3.8 Hybrid fuzzy logic

The hybrid fuzzy logic was developed by Mantawy and Abdel-Magid [39] in 2002, in which the UCP is formulated in a FL (fuzzy logic) frame to deal with the uncertainties in the load demand. The SA algorithm is used to solve the combinatorial optimization of the UCP. This hybrid fuzzy logic was tested with a 10-unit system and a total operating cost of \$536260 was obtained which validated the result with \$536622 (SA).

3.3.9 Hybrid ACO Lagrange

The hybrid ACO Lagrange methodology proposed by Nascimento et al. [40] in 2011 was proven to be competitive in relation to the optimization techniques biologically inspired in the behavior of the ant colony found in literature, conciliating quality solutions and a reduced colony; the use of Lagrange multipliers associated with discrete variables of the Thermal UC problem act as a source of information for the ant colony algorithm. However, the computational simulation time increases considerably, making this alternative unfeasible, mainly in medium-to-large sized systems and/or with large programming periods. The hybrid ACO Lagrange methodology was proven to be competitive in relation to the optimization techniques biologically inspired in the behavior of the ant colony found in literature, conciliating quality solutions and a reduced colony. It was tested with a 10-unit system and the total operating cost is \$563937 and this cost is less when compared to \$564049 (ACSA), \$563977 (DACO) and \$563977 (RACO).

3.3.10 Shuffled frog leaping algorithm

The shuffled frog leaping algorithm (SFLA) was developed by Ebrahimi et al. [41] in 2011. The SFLA is a metaheuristic optimization method which is based on observing, imitating, and modeling the behavior of a group of frogs when searching for the location that has the maximum amount of available food. The SFLA has been applied to ten up to 100 generating units, considering one-day and seven-day scheduling periods. The most important merit of the SFLA is its high convergence speed. The simulation results of the SFLA have been compared with the results of the algorithms, such as Lagrangian relaxation, genetic algorithm, particle swarm optimization, and bacterial foraging [14]. Therefore, for a 10-unit system, the total operating cost is \$564769 as compared to \$566404 (ICGA), \$564842 (BF) and \$565475 (LR).

3.3.11 Fuzzy tuned PSO (FTPSO)

PSO is the mathematical modeling and simulation of the food searching activities of a flock of birds. Each particle moves with a different velocity towards the optimal point. The velocity of a particle is calculated by three components: inertia, cognitive, and social. The particles move around the multidimensional search space until they find the optimal solution. A fuzzy system is utilized to tune the inertia weight and learning factors with the best fitness (BF). This FTPSO has been applied to a 10- and 20-bus system in MATLAB and is proven to increase the reliability of the system. It is faster than ACO and BP and is capable of solving both small scale and large scale problems [42]. Therefore for a 10-unit system, the total operating cost is \$557952 as compared to \$565825 (GA), \$564551(EP) and \$ 565475 (LR).

3.3.12 Memetic algorithm

A memetic algorithm (MA) is a hybrid computational model of two sources. The first source is modeled by a GA that mimics biological or Darwinian evolution and the second source is modeled by a local search algorithm that mimics cultural evolution or the evolution of ideas. The unit of information in a GA is termed as a gene whereas in a MA it is termed as a meme. Genes are improved by crossover and mutation operators that are part of a GA and memes are improved by a local search operator. This method is useful for the price based UC [43]. The method has been implemented on test systems of up to 110 units and the results show that in every case examined the MA converges to higher profit price based UC (PBUC) schedules than the genetic algorithm, the simulated annealing, and the Lagrangian relaxation method. Therefore for a 10-unit system, the average profit was \$1899.39 as compared to \$1898.85 (SA) and \$1899.21 (GA).

3.3.13 Binary/Real coded PSO

The PSO can produce higher quality solution within a short interval of time and stable convergence characteristic than other stochastic optimization methods. The PSO model consists of a swarm of particles moving in a D-dimensional real-valued space of possible problem solutions [44]. In this particular algorithm, the tanh function is implemented to enhance the particle searching performance of binary PSO. The binary/real coded PSO methodology is tested and validated on a 3-, 17-, 26- and 38-generating unit system for 24 hour scheduling and hence it is concluded that it can be implemented for a large scale power system. The algorithm was tested for a 38 unit system and the total operating cost (in million Dollars) is 196.10 as compared to 196.73 (FAPSO), 207.8 (SA) and 209 (LR).

4 Environments for UC

4.1 Price based UC

In PBUC, satisfying hourly loads is no longer a restriction and the objective is to maximize the payoff. Thus in the price based approach, the deciding parameter resulting in the on/off state of a generating unit would be the price including the fuel purchase price, energy sale price and so on. Li and Shahidehpour [45] suggested the use of mixed integer programming as compared to Lagrangian method for the PBUC problem. In the present context, it is more advisable to go for individual UC separately based on the market forecasted price and then combine these individual schedules to optimize the scheduling of the whole group of generators [46].

4.2 Profit based UC

In today's competitive scenario, GENCOs are no longer bound to serve the given demand in the open electricity market. The problems under a deregulated environment are more complex and competitive than traditional problems. GENCOs solve economic dispatch and UC not to minimize the total production cost as before, but for maximizing their own profit. Many evolutionary programming models were developed in the literature for profit based UC [47].GENCOs can now consider a schedule that produces less than the predicted load demand but creates a maximum profit.

4.3 Security based UC

Under this constraint the main objective is not only to minimize the generation production cost but also to meet the other constraints for the overall operating period [48]. The security based UC planning involves determining whether a generating unit is functioning efficiently, accordingly the decision has to be taken, that it should be turned on or off at a particular time. Despite market related pressures, system security should always be the foremost priority. While formulating the solution, power flow constraints and generator maintenance constraints should be taken into consideration.

5 UC in deregulated environment

In the present scenario of deregulated markets, it is required from the GENCOs to submit their power bids separately. Each bid consists of a cost function and a set of parameters that define the operative limits of the generating unit [49]. Cost suboptimal solutions that result in lower prices may exist and therefore the applicability of cost minimization UC models for power pool auctions is questioned [46]. In Aug. 2001, Madrigal and Quintana [50] investigated the existence, determination and effects of competitive market equilibrium on UC power pool auctions to avoid the conflict of interest and revenue deficiency. A new formulation to the UC problems suitable for an electric power producer in a deregulated market has been provided by Valenzuela and Mazumdar [51] and Lasen et al. [52] in 2001.

6 Conclusions

This paper presents a review on concept of the UC problem and methodologies proposed for solving it. In solution methodologies, more details about the newly evolved hybrid models has been given, which is the combination of both classical and non-classical methods, and can handle the present day complex UC problem commonly seen in the world. This paper is based on many research articles published in the last 30 years [53,54] and periodic bibliographic updates on this topic will be useful for upcoming researchers in the field of UC. Also in Table A1, additional UC paper for the past decade is tabulated by classifying the kind of algorithm used by the authors of this paper, objective function, constraints, test problem, etc. It is hoped that the readily available table in the Appendix is highly useful for quick references.

Appendix

In the appendix, a table was attached which gives the details about the type of UC problems, constraints, test system, objective of the algorithm, software used to do the simulation and type of algorithm used by the respective author(s) for easy and quick reference.

Table A1 UC paper review for the past one decade (From 2004 to till date)

Ref. No.	Type of problem	Constraints used in the problem	Test system used	Objective function	Real time	Software used	Algorithm used
[31]	Deterministic	Load demand Generation limits Minimum up down time Ramp rate limits Spinning reserve Operating reserve	10 unit system	Minimize fuel cost	None	MATLAB	Ant system Priority listing
[33]	Deterministic	Load demand Generation limits Minimum up down time Ramp rate limits Spinning reserve	10 unit system	Minimize fuel cost	None	C++	Ant system Lambda iteration
[34]	Deterministic	Power balance Generation limits Minimum up down time Ramp rate limits Spinning reserve	10 unit system	Minimize fuel cost	None	VC++	Lagrangian relaxation Genetic algorithm
[35]	Deterministic	Power balance Generation limits Minimum up down time Spinning reserve Start up cost	10 unit system 20 unit system	Minimize fuel cost	None	MATLAB	Dynamic programming Hopfield neural network
[37]	Deterministic	Power balance Generation limits Minimum up down time Spinning reserve Ramp rate limits	10 unit system	Minimize fuel cost	None	MATLAB	Genetic algorithm Priority listing
[38]	Deterministic	Power balance Generation limits Minimum up down time Spinning reserve Ramp rate limits	135 units	Minimize fuel cost	Applied to load Demand of Jeddah, Saudi Arabia	VC++	Modified particle swarm
[40]	Deterministic	Power balance Generation limits Minimum up down time Spinning reserve	10 unit system 20 unit system 40 unit syatem	Minimize fuel cost	None	MATLAB	Ant system Lagrangian multipliers

(*Continued*)

Ref. No.	Type of problem	Constraints used in the problem	Test system used	Objective function	Real time	Software used	Algorithm used
		Start up cost					
[41]	Deterministic	Power balance	10-100 unit system	Minimize fuel cost	None	MATLAB	Shuffled frog leaping algorithm
		Generation limits					
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[42]	Deterministic	Power balance	10 unit system	Minimize fuel cost	None	MATLAB	Fuzzy tuned particle swarm optimization
		Generation limits	20 unit system				
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[43]	Deterministic	Power balance	110 unit system	Minimize fuel cost	None	MATLAB	Memetic algorithm
		Generation limits					
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[44]	Deterministic	Power balance	3 unit system	Minimize fuel cost	None	MATLAB	Binary coded particle swarm optimization
		Generation limits	17 unit system				
		Ramp rate limits	26 unit system				
		Spinning reserve	38 unit system				
		Minimum up down time					
[55]	Stochastic	Minimum up/down time	Revised 118 bus system	Minimize fuel cost	None	C++	Sample average approximation
		Spinning reserve					
		Start up cost					
		Ramp rate limits					
		Generation limits					
[56]	Combined cycle	Generation limits	1 CCP unit system	Minimize fuel cost	None	FORTRAN	Dual programming
	Plants (CCP)	Minimum up down time					Dynamic programming
[57]	Security	Power balance	6 bus system	Minimize fuel cost	None	MATLAB	Benders decomposition
	Constrained	Generation limits	Modified 118 bus system				
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[58]	Deterministic	Power balance	100 unit system	Minimize fuel cost	Taipower 40 unit	MATLAB	Expert system
		Generation limits			168 hr system		Elite PSO

(*Continued*)

Ref. No.	Type of problem	Constraints used in the problem	Test system used	Objective function	Real time	Software used	Algorithm used
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[59]	Deterministic	Power balance	10-100 unit system	Minimize fuel cost	None	MATLAB	Imperialistic competition
		Generation limits					Algorithm
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[60]	Stochastic	Power balance	IEEE 30 bus system	Minimize fuel cost	None	MATLAB	Interval number optimization
		Generation limits					Benders decomposition
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[61]	Contingency	Power balance	10-100 unit system	Minimize fuel cost	None	Xpress MP7.0	Robust optimisation approach
	Constrained	Generation limits					
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[62]	Deterministic	Power balance	10 unit system	Minimize fuel cost	Applied to Chile	MATLAB	Particle swarm optimization
		Generation limits			Large Northern		
		Minimum up down time			Interconnected		
		Ramp rate limits			System		
		Spinning reserve					
[63]	Deterministic	Power balance	100 unit system	Minimize fuel cost	None	MATLAB	Quantum inspired evolutionary
		Generation limits					Programming
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					
[64]	Security	Power balance	Modified IEEE-118 bus system	Maximize system	None	CPLEX 11.0	Hourly demand response
	Constrained	Generation limits		Social welfare			Intertemporal demand
		Minimum up down time					
		Ramp rate limits					
		Spinning reserve					

(*Continued*)

Ref. No.	Type of problem	Constraints used in the problem	Test system used	Objective function	Real time	Software used	Algorithm used
[65]	Security	Power balance	IEEE 31 bus system	Minimize fuel cost	None	CPLEX 11.0	Lagrangian relaxation
	Constrained	Generation limits	IEEE 24 bus system				
		Transmission line limits	IEEE 118 bus system				
		Spinning reserve					
		Ramp rate limits					
[66]	Security	Power balance	IEEE 8 bus system	Minimize fuel cost	None	CPLEX	Using compressed air storage system (CAES)
	Constrained	Generation limits	IEEE 118 bus system				
		Transmission line limits					Benders decomposition
		Spinning reserve					
		Ramp rate limits					
[67]	Stochastic	Power balance	10 unit system	Minimize fuel cost	None		Binary PSO Integer PSO
		Generation limits					
		Transmission line limits					
		Spinning reserve					
		Ramp rate limits					
[68]	Stochastic	Power balance	IEEE 6 bus system	Minimize fuel cost	None	CPLEX 12.1.0	Interval optimization approach
		Generation limits	IEEE 118 bus system				
		Transmission line limits					
		Minimum up down time					
		Spinning reserve					
		Ramp rate limits					
[69]	Deterministic	Power balance	10 unit system	Minimize fuel cost	None	CPLEX	Tighter Mixed Integer Linear Programming
		Generation limits					
		Minimum up down time					
		Spinning reserve					
		Ramp rate limits					
[70]	Deterministic	Power balance	2 unit system	Minimize fuel cost	None		Tighter Mixed Integer Linear Programming
		Generation limits					
		Minimum up down time					
		Spinning reserve					
		Ramp rate limits					
[71]	Deterministic	Power balance	IEEE reliability test system (1996)	Minimize fuel cost	None	CPLEX 10.2 GAMS 22.5	Mixed Integer Linear Programming
		Generation limits					
		Transmission line limits					
		Spinning reserve					
		Ramp rate limits					

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