A Review On Modeling Approaches For Stochastic Unit Commitment

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Abstract: Due to the incorporation of intermittent renewable resource uncertainty level is increasing in power system which in turn affects overall schedules of a generating unit, results in load shedding, expensive generation schedule in unit commitment. Recent challenge is to provide the model uncertainty level with in power system. As the operational reliability depends on the uncertainty level of intermittent sources, the effective modeling gives effective scheduling. Most of the recent work is based on developing a new model for this stochastic unit commitment approach. Many scenarios generation methods and reduction methods have developed in recent years. This paper gives about the survey of various methodologies to model the stochastic nature of unit commitment and various solution methodologies to solve stochastic optimization problems. This literature may pave a new way for both regulated and deregulated market and also provide a good pathway to develop the effective smart grid technology with greater reliability.

Index Terms: Deregulated market, regulated market, scenario generation methods, scenario reduction methods, smart grid, stochastic unit commitment, unit commitment

1. INTRODUCTION

Unit commitment is scheduling the generating unit in more efficient and economical way to meet time varying demand with various constraints. New challenges arise in the conventional unit commitment problem due to the inclusion of renewable energy resources in conventional power system as wind and photovoltaic energies etc are unpredictable. Because of this, uncertainty level present in electrical networks is rising steadily. This increase in uncertainty may affect the generator scheduling, which results in starting up of the expensive generators or load shedding [1]. The existing power system is not effective to withstand this uncertainty, hence effective modelling is needed to make generation flexible and economic. To maintain reliability and robustness of the energy network their operations should be planned by accurate modelling with correct decision schedules with proper solution methodology.[2],[3]. Researchers have suggested many different modelling approaches for scheduling the generators economically by considering generation as well as load side uncertainty for reliable and efficient operation[8]. Deterministic unit commitment (DUC) is a conventional method in which the uncertainty is modelled by reserve requirements and the units are committed to meet the deterministic forecast. This approach for modelling of uncertainty level gives high risk because it is based on determined forecasted conditions, because the reserve amount changes over a time horizon which is uncertain which makes system inefficient to meet the expected load demands appropriately [9], [10].Many

techniques available to model and to optimize the reserve requirements based on deterministic criteria [4, 7.] Many new models with efficient operation also has been proposed by recent research which focuses on choosing convenient bids for maximizing profit [5], [6]. For efficient operation it is necessary to provide an efficient model which suits for stochastic environment. Miguel A. Ortega-Vazquez, Daniel S. Kirschen, proposed a new technique to find the requirements of the reserve. at every time period over an optimization horizon. It is modest when there is high lost load and in periods of high outages. Similarly, in M.A. Ortega-Vazquez, D.S. Kirschen and D. Pudjianto paper cost of interruptions is considered for scheduling the reserve operating plan. [13], [14].Francisco d. Garland-al proposed a model of scheduling a coupled energy with primary, secondary and tertiary reserves by probabilistic approaches and deterministic approaches [15]. However in some cases reserve requirements could not be determined earlier without considering the optimality [16], [21]. Hence increased penetration of intermittent resources may cause the increased uncertainty level, which makes DUC less effective. The uncertainty may also occur due to unexpected events such as forecast error, unexpected outage [11]. In recent years, most challenging part is to find an effective model for the unit commitment with this uncertainty. This paper gives a survey about with various modelling approaches for incorporating uncertainty in unit commitment and different solution methodology to solve this model.

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2. STOCHASTIC UNIT COMMITMENT (SUC)

Stochastic unit commitment (SUC) is the one of the modelling approaches which deals with uncertainties [22] associated with power generation problems. Depending on different uncertainty modelling stochastic representation of unit commitment may differ. It can be classified into two types [17]

1. Classification based on scenarios
2. Classification based on probability sets
3. Classification based on the uncertain sets
4. Hybrid approaches

2.1 Scenario Based Approach

In this uncertainty modelling the basic idea is to get a large number of scenarios based on uncertain factors. [20] Parallel scenarios are used in two stage stochastic problems, Monte Carlo simulation is one of the technique scenario generation technique which is used to generate parallel scenarios and it is based on probability distribution functions derived from historical data. Also in some cases scenario trees are used and is generated based on scenario generation techniques. Scenario generation is also interrelated with forecasting. Various scenario generation techniques use some temporal effects and spatial effects for modelling the forecasting errors in order to give better input model to the unit commitment. also in such case scenario tree is big and makes more complex problem. To reduce complexity Scenario reduction is used based on incorporating sampling method for the scenario tree rather than probability density function. It is used to limit the number of scenario models [72]. The objective of the scenario based approach is given by:

$$\min \sum_{t\in T}\sum_{i\in I} SC_{i,t} \,.\, x_{i,t} + \sum_{s\in S} \pi_s \,.\, F_i(p_{t,i,s}) + \sum_{t\in T}\sum_{s\in S} \pi_s \,.\, (EENS_{t,s} \,.\, VLL + WS_{t,s} \,.\, VOWS) \quad (1)$$

Where $EENS_{t,s}$ is expected energy not served at interval t under scenarios. VLL value of lost load, $WS_{t,s}$ wind curtailment at interval t under scenario s, VOWS is Value Of Wind Spillage, $SC_{i,t}$ is start up cost of unit i at time t, y_i,t_{is} binary variable :1 for on and 0 for off, $\pi_s$is probability of scenario s, pt,i,s is active power output of unit I at interval t under scenario s, $F_i(p_{t,i,s})$ is running cost function of unit i.

2.1.1 Scenario Generation Techniques

Scenario generation is important in modelling of stochastic unit commitment. A worse scenario generation method will totally collapse the whole optimisation problem. In recent years there is an increasing focus to choose the cost-effective scenario generation methods [18]. The four main scenario generation methods are stated here

1. Statistical approach
2. Sampling
3. Simulation
4. Hybrid methods.

2.1.1.1Statistical Approach:

It is used to determine the particular statistical property for the given data. From that we can determine best fit theoretical distribution for generating the scenarios. Some of the statistical generation procedures are

1. Statistical moment or property matching
2. Principal component analysis
3. Regression and its variants

1. Statistical moment or property matching:

It is generic estimation technique and in this random probability density function is not assumed. Instead the distribution is represented by percentiles. From that we form scenario tree. Hoyll and walleys proposed the following methodology for scenario generation such that it matches uncertain random probability density function instead of minimising error difference between scenario trees and given pdf. They reduce error for which depends on density function moments.

2) Principal Component Analysis:

It is also a generic method of data analysis and can be done by identifying Eigen vectors Eigen values and covariance's vector

3) Regression and its Variants

It is the statistical method of fitting data in mathematical equation which includes quantile regression and reduced rank regression for distribution

2.1.1.2 Sampling:

It takes sample values from probability density function and gives scenario values and its quality is compared by two different indices like sampling stability, and bias testing .some of the different sampling for scenario generation is given below,

1) Monte carlo or random sampling

In this random variable of probability density function P(X) are given based on this we randomly choose numbers (X) and by utilizing P(X) we can generate random scenario values and this scenario generation approximates the pdf using a set of samples as scenarios.

2) Importance sampling

In this centre limit theorem is used, such that random sampling gets a good approximation of the distribution and hence this approximation restricts the random samples to the areas which contribute to the distribution more than the other. Basic idea is to give more importance to sampling few regions more than others.

3) Bootstrap Sampling

It is nothing but taking sampling within a sampling itself.

4) Internal Sampling:

In this sampling is performed at the execution of optimisation algorithm that solves stochastic programming. It has better computational performance. Eg: stochastic decomposition,

5) Conditional Sampling

In this case the choice of next sample is statistical dependent (i.e. conditional) on previous option.

6) Stratified Sampling:

It is based on variation of the importance sampling. In this groupings are formed based on variation in sample values. Such that each group should not belong to the other group and total group should cover entire population. By random sampling in each group sampling error is reduced. In this each group is given weights which can be done on two ways one is based on percentage of elements the whole group holds and other based on standard deviation of group.

7) Markov Chain Monte Carlo Sampling

It is difficult to form probability density function for monte Carlo sampling if distribution is complex. But by markov chain we can construct this complex distribution

2.1.1.3 Simulation:

This method involves the simulation by giving a random number as input into the equation and based on random variable realization scenarios are generated in this case

1) Stochastic process simulation:

It follows a stochastic process and generates random variables. The most common stochastic process is Brownian motion. It can simulate stochastic processes over a time interval by giving random input numbers to Brownian motion

2) Error correction model (ECM)

It is based on modelling economic behaviour. Simulation of ECM is done by fitting the equation to a given set of data and forecasting one period into future by random data path and it help to generate scenario trees and the size can be decreased by grouping method.

3) Vector Auto regressive (VAR)

It first fit the historical data from that fitted value it's easy to get a data path. This process is repeated to provide scenario trees. Also, in this case grouping method is applied to reduce the tree size.

2.1.1.4 Hybrid Methods and Other Methods:
This is to include variety of methods (i.e.) hybrid of sampling with moments matching. This is to give survey of new and uncommon scenario generation methods

1) ANN:
It is an information processing method by training of neurons from the previous given set of data.

2) Clustering:
In this data path is created and then clustered by various method. These clusters form the scenarios. Gulpiner has stated and used this method and this can be performed sequentially or in parallel.

2.1.2 Survey of scenario generation approaches
The previous study gives main focus on representing uncertainty in stochastic model but not on various impacts on forecasting error for validation of scenarios [73]. Each scenario in this case gives the possible uncertainty structure. Nowadays many models are focussed based on modelling of this uncertainty with forecasting errors by normal distributions or Weibull distributions [21] to derive wind output. However directly from wind speed we can find wind output for unit commitment model using discrete distribution [18] [30]. Due to this the performance level increases with increase in scenarios sets, and also the computational burden is increased to extent and this leads to scenario reduction methods. Hence many scenario reduction techniques are used for recent research for incorporating and modelling of uncertainty sets without sacrificing the accuracy. hence it uses probabilistic for modelling SUC where it aggregates all scenarios. K-means algorithm is the one in which it is used to partition the set of scenarios with similar features called clusters. the basic idea is scenario with low probability is eliminated [23].Centre part gives average pattern of all scenario. Original scenario with lower probability distance is used to give cluster. This scenario called medoid of scenario. Dupacova et al also suggested another methodology that can reduces the Kantorovich distance between the original scenario sets and also in reduced set. This is used in forward scenario selection and backward scenario reduction models [23] [25]. Forward approach is adding one scenario from the given set to reduced set until it has desired number of scenarios. Also backward approach eliminates one set from original scenario sets. Heitsch et al implements improved model of forward selection and backward reduction techniques [27]. Morales et al modifies the above approach as modified fast forward scenario selection method which suits more for two stage stochastic approaches [28]. Papavasiliou also proposed an importance sampling that represent the effect of uncertainty on operational cost [29]. A new approach has been proposed [30] in which it combines multiple statistical method which is used to obtain an ensemble of 1000 wind uncertainty sets are generated by different scenario generation algorithm and has less forecasting error compared to single scenario generation method [31]. The following are the statistical algorithm which combines to produce 250 scenarios each: the combination are regularised linear regression, support vector regression, multi-layer perceptron, and random forest. It is well suited for nonlinear wind curves. It generates wind data by non-parametric manner (i.e. from historical data) followed by distribution such as normal, Cauchy, skew Laplace and avoids many assumptions.

S.NO	Category	Principle	Advantages	Disadvantages
1	Sampling	Picking values from a time series or a known underlying distribution	Perfect limit properties, conditional sampling for eg : inter temporal relationships	Complex for multivariate solutions
2	Path based	Generating scenarios by evaluating econometric or time series models	Well known documented and statistically dependent random variables	Representation didn't guarantee
3	Property or moment matching	Match set of statistical properties of uncertain variable	Statistical properties may be defined by the modeler and little information on stochastic variable needed	An increasing number of scenarios does not guarantee reduction, stability or bias
4	Optimal scenario generation based on probability metrics	Minimizing probability metrics between scenario set and original distribution	Smallest possible approximation error for a specific scenario set	Empirical evidence contradicts theoretical performance

Centre forecast scenario model is another model based on historical data and avoids the assumption for making distribution for given wind scenarios. If number of uncertainty sets increased the tractability of stochastic unit commitment (SUC) decreases and hence it is followed by fast forward selection algorithm which reduces scenario sets to 10 from 1000. It gives good balance between cost and computation. Instead of modelling of scenario we can implement the uncertainty range for each wind farms such that IIUC, IUC, RUC formulation are enforcing in this way so that optimal solution is obtained within predetermined area covered by each scenario and hence deviation can be reduced. Lower and upper limit for these models is obtained by empirical probability distribution of the original ensemble of 1000 scenarios. In SUC formulation, to obtain bounds we can use ensemble of 1000 original scenarios instead of reducing the scenario set to 10 and it gives better cost-effective results [32].

2.2 Probabilistic forecasting:
It is another method to model uncertainties in which quantiles, which can be calculated by probability density function (pdf) and cumulative density function (cdf). While cdf is used to predict certain look head time period. Many researches have been done in this probabilistic approach some methods are kernel density estimator [34] time adaptive method [35], quantile regression [33] for wind forecast. In that novel quantile-copula estimator for kernel

density function is studied and find to have better performance compared to traditional approach

2.3 Uncertain set Based Approach

The uncertainty set is based on selecting upper and lower limit and in recent research some developments are made in selecting the limits. This section gives the survey of various strategies applied based on Uncertainty sets in unit commitment.

2.3.1 Robust Unit Commitment (RUC)

In single stage RUC uncertainty [33] is modelled as central forecast and lower and upper range. It performs min max optimisation to protect the system against all uncertainty in the given range. It also reduces worst case cost so that model becomes more conservative and it can be reduced by budget of uncertainty (i.e. allowance of deviation of buses from central forecast in worst case scenario) so that balance is obtained between cost and reliability and also reduces smaller uncertainty level. Mostly RUC characterizes two stage approach where the uncertainty set depends on sources of uncertain levels [37], [38], [39]. Mostly box intervals are used so as to reduce over conservatism but in some cases the polyhedral and ellipsoidal sets are considered by using expectations and covariance in this model [34], [35], [40]. Also non convex discrete, convex and continuous sets are used. [35], [40]. In two stage RUC two uncertainty sets with uncertainty correlations are included among different buses at various time intervals 41. In this uncertainty is represented by polyhedral set rather by probability distribution. RUC models also include single stage model, three stage model, and original two stage can be solved bender decomposition cutting plane dual algorithm and also by bilinear method. For discrete set, MILP is used [36], [40]. Also, column and constraint generation are used to approximate master problem [28] which is given by:

$$\min_{u\in U} c^T u + \max_{vV} F(u,v) \qquad (2)$$

Such that

$$F(u,v) = \min_{P,f} f(q^T p)$$

s.t.AVu+ BvP +Hvf ≥ dv

where u and U represents commitment decisions of traditional units and set of feasible units, vis the uncertainty parameter, and the deterministic uncertainty set. F(u,v) is defined as the optimal objective value of the following minimisation problem. q is objective vector of original quadratic function. dv is uncertain set of right hand vector. Av, Bv, Hv is left side matrix used to model contingency.

2. 3 2. Stochastic Dynamic Programming:

It is a method which is to make systematic decisions in multistage. Similar to multistage stochastic programming, finite horizon with discrete time UC can be formulated. It has less computation burden but it is not feasible for uncertainty model. Various methods like approximate dynamic programming (ADP) value function approximation, policy function approximation and state space approximation are used in which uncertainty is checked while taking decisions, [41],[42], [43] . In policy function approximation [43], [44] the approximations are repeatedly solved by optimal control problem [43]. However, it has two major issues, firstly it gives approximate solution with respect to optimal solution and so solution quality poor. Secondly, electricity pricing under this dynamic market condition is real challenge. The stochastic dynamic programming for unit commitment is given by

$$\inf_{\pi\in\Pi} V_\pi(s_o) = E\sum_{t=0}^{T-1} C_t(s_t, \mu_t(s_t), \xi_t + C_T u_T \qquad (3)$$

where C_t is system cost at time periods at t=0,1,2 V_π is the value function, s_t is state of the system, $u_T$is dispatch time, ξ_t is random variable, $\mu_t(s_t)$is time epoch which maps the system state at t to an action.

2.3.3 Interval Unit Commitment (IUC):

Its objective is to minimize the operating cost of centre forecast by considering all intra hour transitions within the limits of uncertainty sets. It is inferred that solution of IUC within this scenario boundary is feasible. However, it is more expensive than SUC because of intra hour transitions. The formulation is efficient than stochastic because it has three scenarios. It can also be modelled as two stage problem where optimal solution is found in first part and the last part holds for testing the feasibility for the given model [46]. A model based on incorporating wind uncertainty is proposed in. In this forecasting accuracy has greater influence on interval unit commitment. It can also be implemented by bender decomposition method. It provides more conservative solutions [47] compared to SUC but has lesser computation. By comparing with RUC it has no inner min max optimisation and its second stage can be solved easily by linear programming only if binary decisions is constant in first part of problem. In SUC and IUC it has balance between generation and load is incorporated for the scenarios within the limits. But RUC model kept track that this balance is given for predefined scenarios. In this scenario are accurately modelled to capture the wind characteristics accurately rampable capacity of expected wind output should not be larger than maximum up and down ramps observed over all cases or it may lead more high running cost because of high wind volatility.

The objective function of the interval UC is:

$$\min\sum_{t\in T}\sum_{i\in I} SC_{t,i.}.x_{t,i} + F_i(p_{t,i,bc)}] + WS_{t,bc}.VoWS \qquad (4)$$

where $SC_{t,i}$ is start-up cost which is with generator i started at hour t, i.e when binary variable $x_{t,i}$ =1.F($p_{t,i,bc}$) stands for fuel cost of each generator with output $P_{t,i\ ,bc}$, bc is base cost which is assumed as central forecast, $WS_{t,bc}$ is wind spillage at a particular base case at hour t penalised by value of wind spillage (VOWS).

2.3.4 Improved Interval Unit Commitment (IIUC):

Its objective is to improve the reliability. It takes the advantages of both IUC and SUC. But it gives less conservative generation schedules compared to IUC. (i.e. easy computation and more efficient). It is mainly based on wind penetration levels and wind profiles and controllable generator characteristics. It is modelled with five scenarios such as centre forecast, upper ramp limits between odd and even hours, upper ramp limits between even and odd hours, down ramp limits between odd and even hours, down ramp limits between even and odd hours. The SUC is more cost efficient still further if no of scenarios is small its computation time is larger and more complex. But the IIUC model acts as second best option for cost effectiveness compared to IUC and RUC and is much better in computing time.[45]. Its objective equation is given by:

$$\min_{q_{t,i,j} x_{t,i}, y_{t,i}, z_{t,i} c_{t,w,u} g_{t,i,u} g_{t,i,b,u}^{seg} su_{t,i} \theta_{t,s,u}} \sum_{t \epsilon \Omega^{T}} \sum_{i \in \Omega^{I}} su_{t,i} + A_i x_{t,i} + \sum_{b \epsilon \Omega^{B}} K_{i,b} . g_{t,i,b,u_1} \quad (5)$$

Where $q_{t,i}$ is generator start up cost identification matrix (1 if generator is on or 0), $x_{t,i}$ is generator on/off status (1 if on & 0 if off), $y_{t,i}$ is generator start up status (1 if generator is on or 0),$z_{t,i}$ generator shut down status (1 if on & 0 if off),$c_{t,w,u}$ power curtailment of wind farm w under scenario u during hour t (MW),$g_{t,i,u}$ power output of generator i under scenario u during hour t(MW),$g_{t,i,b,u}{}^{seg}$ power output on segment b of generator i under scenario u during hour t(MW),$su_{t,i}$ start up cost of generator I during t($),$\Theta_{t,s,u}$ voltage angle at bus s under scenario u during hour t(rad), Ai is no load cost of generator I ($), $K_{i,b}$ is slope of b^{th} segment in cost curve.

2.4 Hybrid Models:

In recent year many research works focussed on developing hybrid models by combining two models so as to make use of various advantages and to discard the disadvantages as possible. Such as unified stochastic and robust unit commitment and hybrid stochastic / interval unit commitment model [24]

2.4.1 Unified stochastic and robust unit commitment:

This method has been formulated to reduce the conservatism of RUC whereas SUC face computational burden because of many uncertainties sets thus it is more expensive. Hence the hybrid model of this both RUC and SUC yields low expected cost and high robustness. In this SUC and RUC are placed in objective function with different weighing factors and can be evaluated by power system operators. It is two stage problem in which first stage deals with unit commitment schedules for day ahead operation is made. The second stage deals with dispatch for each scenario in SUC and worst-case scenario for RUC. This model uses bender decomposition with optimal cuts to solve the model more efficient. [48].

2.4.2 Hybrid stochastic interval approach

In this proposed model has stochastic formulation at initial hours and taken switched to interval approach for remaining time periods. This basic objective of this model is to minimise the actual operating cost by giving exact balance between both security cost and expected cost of uncertainty associated with day ahead schedule. The switching time influences the model. In first wind forecast are done at more accurate and at second case interval UC is applied to offer more robust solution [49], [24]

The objective function of HUC is given by:

$$\mathrm{Min} \sum_{t \in T} \sum_{i \in I} (SU_{t,i} + SD_{t,i} . y_{t,i}) \sum_{i \in I} \left(\left(\sum_{t \epsilon T^{SUC}} \pi_s \sum_{s \epsilon S} F_i \, p_{t,i,s} \right) + \sum_{t \in T^{SUC}} \sum_{b \in B} \sum_{s \in S} \pi_s . ENS_{t,b,s} . VoLL + \pi_s . WS_{t,b,s} + \sum_{t \epsilon T^{IUC}} \sum_{b \epsilon B} (WS_{t,b,cf} . VoWS_{t,b} \right. \quad (6)$$

Where $SU_{t,i}$ is generator start up cost, $SD_{t,i}$ is shutdown cost, $y_{t,i}$ is binary variable and is non zero, ENS is cost of energy not served, WS is cost of wind spilled, πs is probability of each scenario, VOLL is value of loss load, VOWS is value of wind spillage (penalised if wind spillage is involuntary) the indices I,s, b, t refer to the sets of controllable generators I of scenarios S of bus B at time interval T,

2.4.3 Comparison Of uncertainity set based approach And Scenario Based Approach:

It is observed that SUC has better cost performance than deterministic UC. But there exists sensitivity errors and it has high computation. SUC problem can be solved by two approaches scenario based as well as range based approach, among these the solutions obtained by scenario based method are insensitive to the number of scenarios and has higher computational burden but in case of range based approach this can be overcome and the operating interval are generated automatically so the optimal solution is based on uncertainity interval [20] [47]. In case of IUC. It is less cost but tractable and has better performance than deterministic. Where RUC is less cheap than DUC and shows better computation performance than SUC. But it has no systematic technique to chose uncertainty budget. But the combination of existing UC techniques mitigate disadvantages of that existing one. HUC outperforms SUC in terms of cost and time and remain as reliable as IUC. In case of IUC there is excessive conservatism which can be reduced by IIUC.

Based on number of stages stochastic unit commitment can be classified into

1) Two stage approach
2) Multistage approach

2.3.1 Two stage approach

In two stage approach decisions are classified into two types:

1) Day ahead category
2) Real time decisions

In first stage generation schedules are made. In second stage different scenarios can be generated where various modelling approaches are made based on this scenario generation as discussed earlier, constraint violations are checked and treated independently which tend to give group of optimisation problem. If violations are found bender cuts are generated and add to initial unit commitment formulations. It is more expensive and mostly bender decomposition with cutting planes are employed.[35],[40],[55] and the objective function is:

$$\min_{u \epsilon U} c^{T} u + + E_{\varepsilon} F(u, \varepsilon) \quad (7)$$

And second stage by

$$F(u, s) = \min_{Ps, fs} f(ps) \quad (8)$$

s.t.Asu+ BsPs +Hsfs ≥ ds

2.3.2 Multi stage models:

In multi stage model uncertainty are considered over the time horizon many times and adjust decisions based on those criteria. In these approach scenarios trees are used to represent the uncertainty for formulating the multistage problems. The advantage of this model is scheduling of generators based on uncertainty forecasting is done more accurately. In this number scenarios is increased exponentially and computation burden also increases. And hence it is quite difficult problem compared to two stage problem. [50], [51]

3. SUC - SOLUTION METHODOLOGY –A SURVEY

In stochastic unit commitment approach, uncertainty scenarios are generated based on uncertainty which makes larger problem in case of two stage and multi stage approach. It can be decomposed to smaller problem solved by different optimisation algorithms. It is often chosen to approximate the bounds on possible solution. Some of the conventional and nonconventional methods are proposed to give approximations [52]

3.1 Conventional methodologies:

- Exhaustive enumeration
- Priority listing
- Dynamic programming
- Branch and bound
- Integer programming
- Simulated annealing
- Lagrange relaxation
- Tabu search
- Interior point optimisation
- Bender Decomposition based algorithm

Some of them are explained as follows:

1) Integer L shaped algorithm

The main idea of the Integer L-shape method is to replace the feasibility and optimality cuts points of previous L-shape algorithm by suitable equivalents. In this method optimality cuts represents the value of the integer solutions that have been processed and hence its very weak. Local branching cuts algorithm are added to extend the range of optimality cuts. Usually, one needs to add lower bounding functional derived from partial solutions to obtain good results on larger instances.

2) Exhaustive Enumeration

It schedules generator by different combination and from that least possible combination is chosen as optimal solution. It is not suits for large size system but this method holds accurate result [62], [63]

3) Priority Listing

It schedules the generating unit based on smaller operational price and forms the priority order and UC is solved by this prescribed order. It is also computationally efficient and it is solved in and multi area unit commitment. [64],[65]

4) Dynamic programming:

It is most widely used approach to solve the problem of various sizes and modified to model characteristics of utilities. The disadvantage of this model it yields sub optimal solution. [66]

5) Integer and linear programming

It is modification of branch and bound method. In this mostly the whole unit commitment problem decomposed to sub problems such as nonlinear economic dispatch and a pure integer nonlinear UC by using dantizwolfe method it can be decomposed into linear sub problems and can be solved linear programming or simplex approach. In this by mixed integer programming is solves by reducing solution space [52], [67]

6) Branch and bound:

It is one of the optimization techniques which has all constraints without any priority order of units. It is more flexible and efficient method. It consists of three steps in this first step is based on classification of subsets , second step deals with the constraint handling condition for subset and it is eliminated based on violation. In third step lower and upper bounds are checked based on constraints handling condition. Convergence is attained only when the upper and lower bounds is equal to subset limits.[68]

7) Lagrangian relaxation:

In this optimization approach unit commitment problem deals with three steps. In first step is about cost function. Second step is about the set of constraints, and third step deals with the coupling constraints .its advantage is it can be easily adjusted and modified and its disadvantage it gives suboptimal solution.[52]

8) Interior point method:

It is used for unit commitment scheduling problem based on inner bounds of observation. It is not only feasible to use for both linear and nonlinear programming problem but also combinatorial – non differentiable problems. It has better convergence.[69]

9) Expert System:

It is based on the knowledge extracted from the human expertise to decide and schedule the generator. It is easy solve the problem with more difficult source from the various expertise knowledge in previous case. It is a combination of database management with expert’s system design and with efficient use of man machine interfaces also in further case it is combined with priority list based heuristics rules to find optimal point.

10) Tabu search:

It is one of the optimization procedures that has been applied to combinatorial optimization problems it has disadvantage of having local minima in convergence. It performs the operation based on the iteration by comparing with other methods. It stops the convergence if the solution has no improvement in further iteration. It can be applied to avoid local minima by incorporating flexible memory system. Parallel tabu search and improved methods are also discussed.

11) Simulated annealing

It refers to the process of heating up a solid to a high temperature by slow cooling by decreasing the temperature of environment in steps. The problem of unit commitment problem can be solved into sub problem and it can be classified as combinatorial optimization problem and a nonlinear optimization problem and concluded that it has long CPU time and more complex.[70]

12)Ant colony Search Algorithm

It is an algorithm based on artificial ants cooperate to the solution of a problem by exchanging information based on pheromone level and can be applied to combinatorial problems and can be solved for scheduling of generators in unit commitment.[71]

3.2 Evolutionary algorithms:

In addition to many classical optimization methods, nowadays many evolutionary algorithms are gaining importance because of their common nature to share their information among many search agents [74]. It is developed based on mimicking nature of social behaviour like evolution, swarms searching for food, scientific principles and human activities, etc., Of which it concerns to find the optimal solution. Some of the evolutionary based algorithms are, genetic algorithm [75], differential evolution [76], flower pollination [77] invasive weed optimisation [78] etc., found in literature in which basic steps like selection, mutation reproduction and recombination are used to find the optimal solution. Swarm based algorithm like colonies, swarms etc., are also well developed such as ant colony algorithm[79], particle swarm optimization [80], shuffled frog leaping algorithm [81], cat swarm optimization[82], Elephant herd algorithm [83], cuckoo search algorithm [84], firefly algorithm [85], moth flame optimization [86], grasshopper optimization [87], Grey wolf optimization [88], binary whale optimization [89], Bacterial forging [90], which mimics the social behaviour of searching prey uses velocity, positions, to find optimal solution. In addition to the above technique some of algorithms mimic based on scientific principles like quantum computing [91], multiverse optimization [92], etc., In some cases algorithm also based on human activities like imperialistic competition algorithm [93], teaching learning-based optimization [94]., etc.,

3.3 Hybrid Algorithms

It is mainly based on merging of two or more algorithm and gives a hybrid model. To utilize the benefits of both conventional and evolutionary method, many hybrid algorithms proposed in the literature like Lagrange relaxation genetic algorithm (LRGA) [95], hybrid particle swarm optimization [96], [99], hybrid harmony search random search [97], hybrid particle swarm grey wolf optimization [98] which are developed to obtain more optimal solutions for solving unit commitment problem. Such as fuzzy PSO, hybrid priority ant, hybrid LR, hybrid GA etc [44]

3.4 Survey of various methods used in recent SUC:

Many algorithms are used to solve stochastic optimisation problems. Mostly bender decomposition is made when the equation is linear. If the contingency is obtained and value function is not linear integer L shaped method, disjunctive cuts, or combination of both is used. If the dynamic cuts are larger and it is difficult to convergence hence both regularised and trust region method is used to limit cuts. Lagrange relaxation is another method which split the problem into sub problems by doubling coupling constraints between uncertainty sets [26]. Bundle method is also used in recent papers for solving dual stage problems which has fast convergence which is also used for decoupled single scenario method [53],[54]. In case of multi stage problem augmented LR is chosen over classical LR.in langrage dual cutting method bundle method has more speed for solving multistage problem and it helps to decrease the number of iterations.[55], [56] For two stage SUC, bender decomposition problem is solved and which gives optimal value but has slow convergence. By using accelerated bender decomposition method [57] convergence would be better. LR with bundle method is much good convergence than other method [58]. many new methods are introduced like invasive weed optimisation [12], [23] In case of multistage approach progressive hedging has good performance for MILP problems. Column generation methods is found to be exact approach but has slow convergence but can be improved by combining bundle method. [59], [60].Nested column generation is also used for multilevel problems. In case of contingency based RUC methods primal cuts are shown better performance compared to dual cuts. Value function approximation and policy iteration-based approximation methods are more efficient methods for solving stochastic problems.[61]

4. CONCLUSIONS

Now a days there is increasing research in smart grid and renewable resources. Unit commitment is also paves more important factor in case of stochastic unit commitment. Uncertainty level increased due to intermittent nature of renewable energy sources in conventional power system. It is more difficult to predict the level and duration of these sources more accurately. So in order to maintain the reliability of the system, it is necessary to consider the uncertainty level in day ahead generating schedule. This paper gives the review of many modelling techniques and many computational techniques used for this stochastic optimisation. More advanced model also gives computational challenges to algorithms. Many computational techniques are also discussed in this paper which will help to bring the better model closed to real world techniques. Also multi scale and hybrid provides necessitates the need for more detailed modelling of decisions with many uncertainties. More challenging issue is to overcome the data issue. Many different level of modelling is based on designing the uncertainty level which needs more focus for reliable grid operation. There also needs more focus on market design procedures to include stochastic optimisation techniques. As the forecasting errors affect the stochastic optimisation which in turn affects market design. So, more study has to be done on market design.

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