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Novel Hybrid Framework Based on Deterministic Method and Particle Swarm Optimization for Unit Commitment in Deregulated Era

LOGAVANI K[1], CHRISTY MANO RAJ J.S[2]

[1] *Assistant Professor, Department of EEE, Government College of Engineering, Salem 636011, Tamilnadu India*

[2] *Professor, Department of EEE, Government College of Engineering, Salem 636011, Tamilnadu India*

[1] *Corresponding Author- LOGAVANI K*

ABSTRACT

Power sector is undergoing a global restructuring and decentralization. The vertical integration of the power sector is restructured and the grid is shifting towards horizontal integration to meet the consumer demands at a reduced tariff. The major tasks of the three components remain the same but competition is encouraged in the generation and supply of electricity. Profit based unit commitment is about identifying the optimal commitment schedule by maximizing the profit of the power-producing companies. Optimization of unit commitment schedule is the primary concern in the dispatch of power in a deregulated environment due to the variable spot price. For optimizing the unit commitment schedule many algorithms are proposed in the literature using conventional and intelligent techniques. In this work, a hybrid technique is developed using both the deterministic and intelligent optimization algorithm to satisfy the objective functions. Three stages of deterministic based Modified Dynamic Programming (MDP) is proposed to develop the initial solutions and the Particle Swarm Optimization based Lagrangian Relaxation (PSO-LR) approach produces the optimal global solution. The algorithm is validated for a 10-unit system considering it as a single Generating Company (GENCO). The proposed hybrid algorithm is compared with other approaches stated in literature and it is found that the proposed algorithm reduces the solution search space, yields lower generation cost and high profit. The proposed work is carried out using MATLAB programming.

Keywords: *Deregulation, Economic Dispatch, Lagrangian Relaxation, Modified Dynamic Programming, Particle Swarm Optimization.*

INTRODUCTION

India's National Grid has an installed capacity of 371.054 GW as of June 2020 and the third-largest electricity producer of electricity. The major electricity production is dominated by fossil fuel resource coal that amounts to three-quarters of India's electricity. India is expected to generate 44.7% of the total gross electricity generation by the year 2029-2030 through renewable energy resources. At present renewable energy sources contribute around 35.94% of the total installed capacity of the country. some of the major issues faced by the Indian electricity sector are the lack of timely information on load and demand, unequal electricity distribution, power pricing issues, and lack of adequate coal supply despite the surplus availability. Coal resource is fast depleting and the global availability predicted being another 105 years, the electricity sector expects a tremendous shift towards renewable energy sources to conserve the fossil fuels and to meet the ever-growing demand for electricity. Altogether the electricity demand is not the same throughout the day, week, month, and year respectively. This demands the conservation of coal resources, utilization of small renewable resources in the microgrid level, and operating the available generating units most economically. The above issues of India's electricity sector are realized by using alternate energy resources (like solar, wind, small hydro, biomass, etc), restructured power system components (horizontal integration), and through optimal unit commitment schedule [1-3]. Due to the consistent increase in global demand for electricity, the optimization of generating units is essential to minimize the generation cost as well as to conserve the depleting fossil resource.

Unit commitment (UC) is a significant part of power system operation and control. The UC problem is a mixed-integer, non-linear, combinatorial optimization problem for producing the optimal economic dispatch [4]. The problem of identifying the optimal commitment of units in a deregulated market for maximizing the profit of GENCOs is the Profit Based Unit Commitment (PBUC). Unlike the UC problem in a conventional vertical integrated system, in a deregulated environment the PBUC problem has the objective function of maximizing profit of GENCOs while meeting the required load demand. The main objective of restructuring is to generate competition among the GENCOs and afford the optimal power prices to consumers [5]. Unit commitment in the deregulated market segment is more complex and competitive. Many deterministic and meta-heuristic approaches cannot offer optimal solution, but they might give sub-optimal solution for the UC problem [6-7]. Various classical techniques like the Priority List, Branch and Bound, Bender's Decomposition, Mixed Integer Programming, Dynamic Programming, and Lagrangian Relaxation exists in the literature. These deterministic approaches are fast, simple, and straight forward but suffer from numerical convergence and sub-optimal solution. Moreover, large scale power system problems cannot be solved by these methods easily. As a greater number of constraints have to be solved, these methods have a slow convergence. Global optimum is also not guaranteed in solving the PBUC problem.

Meta-heuristic approaches like Ant Colony Optimization, Genetic Algorithm, Evolutionary Programming, Simulated Annealing, Artificial Neural Networks, Tabu Search, Fuzzy Logic, Reinforced Learning, Shuffled Frog Leaping Algorithm, Artificial Immune System algorithm, Imperialistic Competition algorithm, Firefly algorithm, Bacterial Foraging, Fireworks algorithm, Bat algorithm, Particle Swarm Optimization, etc can yield the local as well as the global optimum solution. As the number of generating units and constraints increases, these approaches also consume large computational time and the solution quality is affected. The complexity of the deregulated power system increases since the competition is encouraged on both the buyer and the seller end. Hence a research work addressing the above mentioned challenges is highly appreciated and it is the core contribution of the proposed work in this paper.

In this work, a hybrid method that combines the Modified Dynamic Programming and Particle Swarm Optimization based Lagrangian Relaxation approach is effectively adopted to solve the objective functions of low generation cost and high profit with optimal economic dispatch. The basic idea of this work is to obtain the initial solution through the Three Stage Modified Dynamic Programming approach and the PSO-based Lagrangian Relaxation algorithm is developed for obtaining the optimal UC schedule and the economic dispatch respectively.

The novelty of the proposed work is explained as follows.

1) Fuel cost parameter λ is optimized using Kuhn-tucker conditions. This is done for all states during each hour.
2) Equality constraint for PBUC is tested for 1\all 10 units. Accordingly, economic dispatch is modified by backtracking the states for each hour. The optimal state is identified.
3) MUT and MDT constraints are applied; the high-cost unit is fixed in ON status. This is done by an exclusive sub-program by trial and error method.
4) The final solution obtained is the best optimal solution and treated as one of the random solutions for the PSO technique. The inertia factor value is tuned to obtain the best possible state. The hybrid technique finally yields the global optimal solution by further reducing the generation cost.

So compared to the conventional Dynamic Programming method, the three stages proposed here optimizes the parameter λ, satisfies equality constraint even in PBUC, identifies the non-availability of optimal states, identifies the high start-up cost unit, and fixes the ON state of the high-cost unit to reduce the overall cost and to improve the profit margin. There is a greater saving in the total cost due to reduced start-up cost as compared to other approaches.

Unit commitment problem formulation and the modifications for the deregulated market are elaborated in section 2. Description of the Modified Dynamic Programming based PSO-LR approach is presented in section 3. The application of the proposed work and the comparison of the results with other approaches like BPSO, PSO-LR, MDP, and DP-LR are discussed in section 4.

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PROBLEM FORMULATION

A. Unit Commitment Problem

Unit Commitment is a non-linear complex optimization problem that determines the ON/OFF status of the generating units to satisfy the forecasted load demand. This facilitates the load dispatch center to cope-up with the uncertainties by satisfying various constraints. 24hr schedule is considered in solving the optimization problem. The objective is to minimize the total fuel cost and maximize the profit while satisfying the demand and other constraints.

OBJECTIVE FUNCTION

$$\text{Min TFC} = \sum_{t=1}^{T}\left[\sum_{i=1}^{n}\left(a_i + b_i Pg_{it}^2\right) + SC_{it}\right] \quad (1)$$

TFC	-	Total Fuel Cost
t	-	Time interval (t=1 to 24hr)
n	-	Number of generating units
a_i, b_i, c_i	-	Cost coefficients
Pg_{it}	-	Power generation of i^{th} unit at time t
SC_{it}	-	Start-up Cost

SUBJECT TO SYSTEM CONSTRAINTS

UNIT STATUS RESTRICTIONS

Must run statuses are given for certain units under all load conditions. In this work, these constraint decreases the start-up cost during the latter part of the demand in solving the UC problem.

POWER BALANCE CONSTRAINT

$$\sum_{i=1}^{n} Pg_{it} = PD_t \quad (2)$$

Where

PD_t is the power demand at time t.

INITIAL CONDITIONS

The first-hour schedule is based on the unit's initial status.

RESERVE CONSTRAINT

$$\sum_{i=1}^{n} Pg_{i\,max} \geq P_L + R_{it} \quad (3)$$

Where

Pg_{imax} - Maximum generation limit in MW of i^{th} unit.

R_{it} – Reserve capacity of unit i at time t.

A percentage of the unit’s maximum generation limit is assumed as the reserve constraint.

SUBJECT TO LOCAL CONSTRAINTS

A. INEQUALITY CONSTRAINTS

$$Pg_{i\,min} \leq Pg_{it} \leq Pg_{i\,max} \quad (4)$$

Where

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Pg_{imin} – Minimum power generation limit of i^{th} unit in MW

MINIMUM UPTIME (MUT)AND MINIMUM DOWNTIME(MDT) CONSTRAINTS

This constraint indicates that the generating unit must remain ON/OFF for a certain duration before it is turned OFF/ON.

$$T_{it}^{ON} \geq T_i^{UP} \tag{5}$$

$$T_{it}^{OFF} \geq T_i^{DOWN} \tag{6}$$

Where

T_{it}^{ON} – ON time of the i^{th} unit in interval t, t = 1 to T

T_{it}^{OFF} – OFF time of the i^{th} unit in interval t, t = 1 to T

T_i^{UP} – Minimum-Up time of i^{th} unit

T_i^{DOWN} – Minimum-Down time of i^{th} unit

START-UP COST (SC)

$$SC_{it} = \begin{cases} \text{hot start-up cost, if downtime} \leq \text{cold start hours} \\ \text{cold start-up cost, otherwise} \end{cases} \tag{7}$$

RAMP RATE LIMITS

This constraint limits the operating range of all committed units and it is validated during every stage of the proposed work. In this work, no penalty factors are considered as the ramp limits are not violated and are stable during every transition stage.

$$P_{gi} - P_{gi}^0 \leq UR_i \tag{8}$$

$$P_{gi}^0 - P_{gi} \leq DR_i \tag{9}$$

Where

P_{gi} - Power generation of i^{th} unit

P_{gi}^0 - Power generation of i^{th} unit during the previous hour.

UR_i - Ramp-up rate limit for unit i at hour t.

DR_i - Ramp-down rate limit for unit i at time t.

B. PROFIT BASED UNIT COMMITMENT PROBLEM

In a deregulated electricity market PBUC determines the optimum generation schedule for maximizing the profit along with the cost minimization as the market is competition based. The objective function is the difference between the revenue generated and the total cost incurred. GENCOs consider the PBUC schedule to obtain a high profit from the forecasted demand and spot prices in the restructured market.

PBUC problem can be formulated as

$$\max PF = RV - TC \tag{10}$$

Where

$$RV = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Pg_{it} . SP_t\right) U_{it} \tag{11}$$

$$TC = \sum_{i=1}^{N} \sum_{t=1}^{T} C_{it}\left(Pg_{it}\right) + SC_{it} \tag{12}$$

SUBJECT TO THE FOLLOWING CONSTRAINTS

DEMAND CONSTRAINT

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$$\sum_{i=1}^{N} Pg_{it} U_{it} \le PD_t \quad \text{for } t = 1 \text{ to } 24\text{hrs} \qquad (13)$$

RESERVE CONSTRAINT

$$\sum_{i=1}^{N} R_{it} U_{it} \le SR_t \quad \text{for } t = 1 \text{ to } 24\text{hrs} \qquad (14)$$

INEQUALITY CONSTRAINTS

$$Pg_{i,min} \le Pg_{i,t} \le Pg_{i,max} \quad \text{for } i = 1 \text{ to } n \qquad (15)$$

PMUT and MDT constraints that allow the units to remain in ON/FF status for a certain period before it can be committed or uncommitted.

Where

PF - Profit of the Generating Companies
RV - Revenue
TC - Total Cost
U_{it} - ON/OFF status of unit i at hour t
SP_t - Spot Price at hour t
$C_{it}(Pg_{it})$ - Cost of power production of unit i at hour t
SR_t - Spinning reserve at time t

All the constraints mentioned above are satisfied in the preliminary stage while the inequality constraints are further enhanced using the three-stage MDP method.

C. MODIFIED DYNAMIC PROGRAMMING BASED PSO-LR APPROACH

Dynamic Programming is a very old yet powerful mathematical method applied to the power system UC problem to find out the most economical optimal schedule [8]. The least-cost state is identified by tracking forward in the DP method and the final solution is obtained by combining all the least-cost states during the 24hour period. In solving using the DP approach, power utilities adopt the lambda-iteration method for economic dispatch due to its simplicity. But the final schedule obtained in the DP approach is not optimally best. To obtain the near-optimal solution with constraint satisfaction, three stages of Modified Dynamic Programming is proposed.

D. LAMBDA OPTIMIZATION USING MODIFIED DYNAMIC PROGRAMMING

In this paper, a three-stage Modified Dynamic Programming is proposed that satisfies Kuhn-Tucker conditions in every stage by optimizing the parameter λ(lambda) and the divergence issues respectively. Besides, the MDP algorithm provides a cost-effective initial solution which is optimally best. In this work, the final optimal PBUC solution is obtained by combining the best schedule obtained from the Modified Dynamic Programming algorithm and the optimized solution from the PSO-LR approach respectively.

UC is a multi-stage complex non-linear optimization process because the fulfillment of one constraint might result in the violation of another constraint. As stated in the literature, a method could be justified that provides a modification of the commitment schedule [9] in order to yield the best optimal solution along with constraint satisfaction. In the conventional DP method, suboptimal solutions are not optimized. So, a three-stage MDP algorithm is implemented in which the fuel cost parameter λ, is optimized in the *first stage*. The feasible states during each hour are checked with the Kuhn-Tucker conditions for its optimality. *The second stage* checks the non-availability of optimal states. Under the “no-state exists” condition, the finest state is identified by modifying the economic dispatch. The optimal solution is obtained in the third stage through a two-step process. In the first step, the MUT and MDT constraints are applied and the expensive units are fixed in continuous commitment status in the second

 https://doi.org/10.37896/pd91.5/9157

step. Through the algorithmic trial and error search method, the start-up cost is calculated for all possible states. This three-stage approach does not violate the constraints and demands the superiority for suboptimal solutions whenever any divergence occurs in the optimization process. In the proposed continuous commitment approach the number of states in each stage is reduced and results in quicker convergence. The MDP algorithm is validated for the 10-unit system. The unit and load data of 10 unit system are shown in Table (1) and (2) respectively.

It is observed that at the end of the first stage, no optimal state exists for the demands 1450MW and 1500MW since λ_{new} reaches infinity in the lambda optimization process. The new lambda value is obtained from equation (16).

$$\lambda_{new} = \frac{\left[\text{New Load} + \left(\text{sum of all nonviolating } \frac{b}{c} \text{ coefficients}\right)\right]}{\left[\text{Sum of nonviolating unit's } \frac{1}{c} \text{ coefficients}\right]} \quad (16)$$

The above-identified problem occurs for the higher demand stage. To resolve the issue, if the demand is fixed for the maximum limit violation, then the equality constraint is not met. So, in the second stage, the states that violated the maximum limits were fixed to their minimum limit and the other states of every hour are adjusted accordingly to produce the optimal solution. This is shown in Table (3).

Other constraints are validated after the minimum limit fixation to check for the feasibility of states once again. The ramp rate limit is taken into consideration without any violation throughout all three stages. In the third stage, the algorithm examines the state with the lowest start-up cost by discarding the expensive units. The final schedule obtained from the novel three stages modified dynamic programming approach is given in Table (4). The final optimal schedule yielded the total fuel cost of $ 5,81,541.95/- for the IEEE 10-unit system. The best solution thus obtained is considered as the initial random solution for the implementation of the meta-heuristic algorithm proposed in this paper.

TABLE I
UNIT DATA FOR 10 UNIT IEEE SYSTEM

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
Pmax (MW)	455	455	130	130	162
Pmin (MW)	150	150	20	20	25
a ($/h)	1000	970	700	680	450
b ($/MWh)	16.19	17.26	16.60	16.50	19.70
c ($/MWh^2)	0.00048	0.00031	0.002	0.00211	0.00398
MUTi (h)	8	8	5	5	6
MDTi (h)	8	8	5	5	6
$Hcost_i$ ($)	4500	5000	550	560	900
$Ccost_i$ ($)	9000	10,000	1100	1120	1800
$Chour_i$ (h)	5	5	4	4	4
Ini State (h)	8	8	-5	-5	-6
	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
Pmax(MW)	80	85	55	55	55
Pmin (MW)	20	25	10	10	10
a ($/h)	370	480	660	665	670
b ($/MWh)	22.26	27.74	25.92	27.27	27.79
c ($/MWh^2)	0.00712	0.00079	0.00413	0.00222	0.00173
MUTi (h)	3	3	1	1	1
MDTi (h)	3	3	1	1	1
$Hcost_i$ ($)	170	260	30	30	30
$Ccost_i$ ($)	340	520	60	60	60
$Chour_i$ (h)	2	2	0	0	0
Ini State (h)	-3	-3	-1	-1	-1

TABLE II
IEEE 10 UNIT DEMAND DATA

Hour [h]	Load [MW]	Hour [h]	Load [MW]
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000

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6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

PARTICLE SWARM OPTIMIZATION BASED LAGRANGIAN RELAXATION (PSO-LR)

Particle Swarm Optimization (PSO) developed by James Kennedy and Russell Eberhart, mimics the collective intelligent behavior of unintelligent creatures. PSO is one of the modern evolutionary and population-based stochastic optimization algorithms such as bird flocking or fish schooling, that is suitable for solving highly nonlinear optimization problems. The individuals known as particles in a PSO have their own position (x) and velocities (v). These individuals are denoted as particles. Each particle remembers its own best positions found so far in the exploration. This position is called a personal best (pbest).

Among these pbests, the particle which has the best fitness value is called as global best (gbest). During the flight, the particles are attracted stochastically towards their own pbest and gbest achieved so far.

TABLE III
INFEASIBLE (PGI<PL) & FEASIBLE STATE (PGI=PL) SCHEDULE OF 1450MW AND 1500MW DEMAND

Load (MW)	Infeasible generation schedule (MW) (At the end of first stage)										P_{gi}(MW)	Total Cost ($)
	1	2	3	4	5	6	7	8	9	10		
1450	455	455	130	0	25	20	25	10	10	0	1130	25,039.66
	455	455	130	130	162	20	25	10	10	10	1407	31,649.26
1500	455	455	130	130	25	20	25	10	0	0	1250	26,962.4
	455	455	130	130	162	0	25	10	10	10	1387	30,831.21
Load (MW)	Feasible generation schedule (MW) (At the end of Second Stage)										P_{gi}(MW)	Total Cost ($)
	1	2	3	4	5	6	7	8	9	10		
1450	455	455	130	130	162	0	53	0	55	10	1450	31,923.69
1500	455	455	130	130	162	0	85	0	55	28	1500	33,316.26

The particles are manipulated according to the following equations

$$V_i^{t+1} = \begin{bmatrix} w * V_i^t + C_1 * \text{rand}(\ ) * w * \left(p_{best} - X_i^t\right) \\ + C_2 * \text{rand}(\ ) * \left(g_{best} - X_i^t\right) \end{bmatrix} \qquad (17)$$

$$X_i^{t+1} = aX_i^t + bV_i^{t+1} \qquad (18)$$

Where

t - Iteration number

w - Inertia weight in the range between (0,1)

C_1 and C_2 - Cognitive and Social parameter

rand - uniformly distributed random number in the range between (0,1)

The PSO algorithm is determined by five-dimensional parameters w, C_1, C_2, a, and b respectively. The exploration properties of the algorithm are controlled by the inertia factor w. The cognitive and social parameters keep the balance between the local and global behavior of particles. The combination of these

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parameters determines the convergence properties of the algorithm. The convergence speed and the parameter setting values are given weightage in this work and this increases the performance of the PSO algorithm. It is observed from the literature study that the parameters (a,b) increase the complexity of the PSO algorithm. Hence it is recommended to fix the values of a and b as 1 in the algorithm.
Therefore, equation (18) is modified as

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{19}$$

The position of each particle is updated on each iteration. This is realized by summing up the velocity vector to the position vector as given in equation (19). Particles update themselves with the internal velocity. Velocity is limited between $-V_{max}$ and $+V_{max}$. In binary PSO, the position X, p_{best} and g_{best} are binary numbers while velocity V_i determines the probability of threshold using the function

$$s(V_i) = \frac{1}{1+\exp(-V_i)} \tag{20}$$

$$\text{if rand} < s(V_i), \text{ then } X_i = 1, \text{ else } X_i = 0 \tag{21}$$

A random number is generated between (0,1) and the value of X is set to 1 if the random number is less than the sigmoidal function value. The state of X_i represents the ON/OFF of the generators in solving the PBUC problem. V_{max} is set with a constant value at the initial phase of the algorithm to limit the range of V_i. A large value of V_{max} results in less chance of bit flipping and vice versa. These limits are set to adjust the value of s(Vi) so that it may not approach too close to 0 or 1.

The weighting function is given in equation (22)

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}}\right) iter \tag{22}$$

$iter_{max}$ - Maximum iteration number
iter - Present iteration number

The iterative process is guaranteed to converge for the parameters w, C1, and C2, only if the conditions are satisfied. The conditions are given in Equation (23) and (24) respectively.

$$-1 < w < 1 \tag{23}$$

$$0 < C_1 + C_2 < 4(1+w) \tag{24}$$

Each particle is estimated using the objective function of the PBUC problem. Each particle's evolution value is compared with its own best position (P_{best}). If the present particle position is better than the old value then this particle position is set as new P_{best}, otherwise, the previous old one is retained. The inertia weight parameter w, regulates the global and local exploration abilities of the particle swarm. A large value of w results in global exploration while a very small value of w aids in local exploration. The number of iterations is reduced to 20 in order to maintain a balance between local and global explorations. To obtain the optimal state, the inertia weight is chosen as 1.2 and decreased thereafter as iteration progresses to aid with the global exploration. In the proposed work the value of C_1 and C_2 is considered between 1 and 3.

Parameter Values

The parameter selection values are given in Table 4. The number of particles considered in the proposed work is 20. Range of particle is set as V_{max} = +25 and V_{mim} = -25.

TABLE IV
PARAMETER SELECTION

Parameters	Values
Number of Particles	20
Particle Size	24(h)*10(units)
Intertia Weight Factor	w_{min} = 0.1 & w_{max} = 1
C_1 and C_2	C_1 = 1.2, C_2 =1.8

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Velocity Limits	V_{max} = +25, V_{mim} = -25
Number of iterations	20

Implementation of PSOLR to PBUC problem

The PBUC problem is solved by Particle Swarm Optimization and Lagrangian Relaxation method. One initial solution is considered from the MDP deterministic approach and the second random solution is assumed representing the on and off states of the units. Since one of the initial solutions obtained is from MDP and since it already satisfies the constraints, the search space for the PSO implementation is reduced. These initial solutions are used to generate more iterations for each hour using PSO. The solution from PSO satisfies various constraints such as equality constraint, MUT, MDT, spinning reserve, ramp rate, and start-up costs respectively. Unit uptime and downtime are considered for the initial solutions. The PSO-LR algorithm is given below

Algorithm

Initialize the generator data and variables.
Generate one initial solution from the MDP algorithm and one random solution with 1s and 0s.
Modify the assumed random solution according to the limits of the generator.
Determine the first iteration value according to (20) and (21).
Update the position and velocity of the particle (unit) using equations (17) and (19).
Apply uptime, downtime, capacity limit constraint, and power balance constraint.
Repeat the previous two for 20 iterations and determine local best and global best solutions
Determine Unit Commitment schedule using the global best solution.
Lagrangian Relaxation – Economic dispatch is carried out and power from each unit is scheduled for a particular hour. Lambda is assigned the p.u value of load. The dispatch for the first iteration is obtained.
The primal value (j) is compared with the optimal value $q(\lambda)$. Relative duality gap = (j*-q*)/q* is calculated from the difference of two values.
Duality gap convergence is validated. If the states converge then stop. Else update lambda.
Unit Commitment schedule is refined to achieve **a** feasible solution.

The position and velocity of particles are updated to obtain the p_{best} and g_{best} values for 20 iterations. Twenty populations are created and the particles are updated in every iteration by inertia weight factor, cognitive and social parameters respectively. A high value of w results in a lower rate of change of particle velocity and thus results in a better fitness value. The parameter sensitivity analysis is performed for various values of w in the range of 0.1 to 1.0. Normally the parameter selection for PSO is for $C_1 = C_2 = C$. The parameter sensitivity analysis for various values of the weighting function for different iterations for $C_1 = C_2 = 2$, $C_1 = 1.2$ and $C_2 = 1.8$, $C_1 = 1$ and $C_2 = 2$, $C_1 = 1.8$ and $C_2 = 1.2$ in terms of total cost are calculated and it is found that the value C_1=1.2 and C_2=1.8 yields the high profit with reduced fuel cost. The global search is enhanced by high values of cognitive and low values of social parameter values. As the search progresses, the increase in cognitive parameter value and a gradual decrease in social parameter value aids in locating the global optimum solution. The final solution is obtained from the local and global best schedule determined for all hours. The Economic dispatch is obtained by the Lagrangian Relaxation method.

Stopping Criterion

The stopping criteria are based on the number of iterations carried out or if the minimum error condition is satisfied. Researchers have proposed about six classes of stopping criteria on a broad structure. They are reference, exhaustion-based, improvement-based, movement-based, distribution-based, and combined criteria respectively. In the proposed work, improvement-based criteria are used which terminates the algorithm run if only small improvements are identified.

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RESULTS AND DISCUSSION

Novel Three Stage Modified Dynamic Programming based Particle Swarm Optimization-Lagrangian Relaxation algorithm was proposed in this work for IEEE 10-unit system considering it as an individual GENCO. The algorithm validated a reduced generation cost and favored profit maximization. It is observed that the results obtained for the 10-unit system are found to be more accurate when compared to other hybrid approaches stated in the literature. The demand equality constraints and must-run constraints are satisfied to obtain the best optimal schedule. The algorithm provided an economic solution compared to other methods stated in the literature. To satisfy some of the constraints the total fuel cost was sacrificed in this MDP algorithm resulting in low profit for certain hours of demand. MDP provides an optimal solution using constraint relaxation although some divergence occurred at higher demand. MDP yields only marginal profit but with the least cost of operation and fast computational time for a 10 unit system. Also, the complexity of the MDP algorithm increases when the number of units is increased. So, considering the overall return for the GENCOs, the method is combined with an optimization technique to produce a globally optimal solution to maximize the profit of GENCOs.

The best optimal solution obtained from the continuous commitment of units using a deterministic approach is fine-tuned by the Particle Swarm Optimization (PSO) intelligence technique in solving the Profit Based Unit Commitment problem. The final global optimal solution is obtained by the hybrid MDP based PSO-LR approach. Economic dispatch is attained from the Lagrangian-Relaxation (LR) method. The spot price data for the 10 unit system is given in Table (5).

The final optimal schedule of the MDP algorithm yielded the total fuel cost of $ 5,81,541.95/- for the 10-unit system is represented in Table (6). The profit realized for the same was Rs 69788.05. Two solutions are considered initially for the PSO-LR optimization technique. One solution from the MDP approach and the other is the random solution that is modified according to the limits of the generator. The iterations are reduced in this MDP-PSO-LR approach as one of the solutions considered for optimization is the near-optimal solution and hence the solution space is small. This makes the computational time fast. The economic schedule is obtained using the Lagrangian Relaxation method.

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TABLE V
SPOT PRICE DATA FOR THE 10-UNIT SYSTEM

Hour (hr)	Forecasted Demand (MW)	Forecasted Reserve (MW)	Forecasted Market Price ($/MWh)	Hour (Hr)	Forecasted Demand (MW)	Forecasted Reserve (MW)	Forecasted Market Price ($/Mwh)
1	700	70	22.15	13	1400	140	24.60
2	750	75	22	14	1300	130	24.50
3	850	85	23.10	15	1200	120	22.50
4	950	95	23.65	16	1050	105	22.30
5	1000	100	22.25	17	1000	100	22.25
6	1100	110	22.95	18	1100	110	22.05
7	1150	115	22.50	19	1200	120	22.20
8	1200	120	22.15	20	1400	140	22.65
9	1300	130	22.80	21	1300	130	23.10
10	1400	140	29.35	22	1100	110	22.95
11	1450	145	30.15	23	900	90	22.75
12	1500	150	31.65	24	800	80	22.55

TABLE VI MDP OPTIMAL BEST NEW SCHEDULE FOR 10-UNIT SYSTEM

Load (MW)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Unit Schedule**	**GC ($)**	**SC ($)**	**TFC ($)**	**Revenue ($)**	**Profit ($)**
700	455	150	95	0	0	0	0	0	0	0	1110000000	14,326.85	550	14,876.85	15505	628.15
750	455	150	62.27	82.73	0	0	0	0	0	0	1111000000	15,832.72	1120	16,952.72	16500	-452.72
850	455	150	115	130	0	0	0	0	0	0	1111000000	17,527.91	0	17,527.91	19635	2107.09
950	455	235	130	130	0	0	0	0	0	0	1111000000	19,261.5	0	19,261.5	22467.5	3206
1000	455	285	130	130	0	0	0	0	0	0	1111000000	20,132.56	0	20,132.56	22250	2117.44
1100	455	375	130	130	0	0	0	10	0	0	1111000100	22,623.99	60	22,683.99	25245	2561.01
1150	455	425	130	130	0	0	0	10	0	0	1111000100	23,499.39	0	23,499.39	25875	2375.61
1200	455	455	130	130	0	0	0	10	10	10	1111000111	25,911.37	120	26,031.37	26580	548.63
1300	455	455	130	130	85	0	25	0	10	10	1111101011	28,319	2320	30,639	29640	-999
1400	455	455	130	130	162	0	25	0	33	10	1111101011	30,541	0	30,541	41090	10549
1450	455	455	130	130	162	0	53	0	55	10	1111101011	31,923.69	0	31,923.69	43717.5	11793.81
1500	455	455	130	130	162	0	85	0	55	28	1111101011	33,316.26	0	33,316.26	47475	14158.74
1400	455	455	130	130	162	0	25	0	33	10	1111101011	30,541	0	30,541	34440	3899
1300	455	455	130	130	85	0	25	0	10	10	1111101011	28,319	0	28,319	31850	3531
1200	455	440	130	130	25	20	0	0	0	0	1111110000	24,605.73	340	24,945.73	27000	2054.27
1050	455	420	0	130	25	20	0	0	0	0	1101110000	21,363.4	0	21,363.4	23415	2051.6
1000	455	370	0	130	25	20	0	0	0	0	1101110000	20,488.16	0	20,488.16	22250	1761.84
1100	455	455	0	130	25	0	25	10	0	0	1101101100	23,252.55	580	23,832.55	24255	422.45
1200	455	455	0	130	115	0	25	10	0	10	1101101101	26,023.74	60	26,083.74	26640	556.26
1400	455	455	0	130	162	0	70.33	55	55	17.67	1101101111	31,825.92	60	31,885.92	31710	-175.92
1300	455	455	130	130	85	0	25	0	10	10	1111101011	28,319	1100	29,419	30030	611
1100	455	375	130	130	0	0	0	10	0	0	1111000100	22,623.99	60	22,683.99	25245	2561.01
900	455	305	130	0	0	0	0	10	0	0	1110000100	18,540.37	0	18,540.37	20475	1934.63
800	455	215	130	0	0	0	0	0	0	0	1110000000	16,052.85	0	16,052.85	18040	1987.15
												575171.95	6370	581541.95	651330	69788.05

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The performance of the proposed hybrid MDP & PSO-LR algorithm is validated in terms of profit and generation cost. The schedule obtained from the PSO algorithm for the PBUC does not consider the demand constraint and it takes only the profit maximization into account. The total cost obtained using MDP based PSO-LR algorithm was $ 551159.44. The total profit realized was $ 100170.56. It is observed that the results obtained from the MDP-based PSO-LR when applied to PBUC problem-solving yield lower production cost, higher profit, and fast computational time compared to other hybrid approaches. The final PBUC schedule, total cost, and profit for the 10-unit system are given in Table (7)

The performance of the proposed algorithm is compared with various approaches like Genetic Algorithm, Binary PSO, Adaptive PSO, Hybrid harmony search algorithm, fireworks algorithm, gravitational search algorithm, etc. The profit obtained is high in MDP based PSO-LR algorithm and the generation cost is minimized compared to other hybrid approaches. Comparison of total fuel cost, revenue, and profit of MDP based PSO-LR with various other approaches are shown in Table (8). The processing time of various approaches is given in Table (9). It is observed that the execution time of MDP based PSO-LR is high than the MDP based approach. But the solution obtained using the proposed algorithm results in a net saving of $ 542.438 thus outweighing the large computational time.

TABLE VII
FINAL PBUC OPTIMAL SCHEDULE FOR THE 10-UNIT SYSTEM, 24HR CASE

Load (MW)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Unit Schedule**	**GC ($)**	**SC ($)**	**TFC ($)**	**Revenue ($)**	**Profit ($)**
700	455	245	0	0	0	0	0	0	0	0	1100000000	13683.12	0	13683.12	15505	1821.88
750	455	295	0	0	0	0	0	0	0	0	1100000000	14554.49	0	14554.49	16500	1945.51
850	455	395	0	0	0	0	0	0	0	0	1100000000	16301.88	0	16301.88	19635	3333.12
950	416	416	119	0	0	0	0	0	0	0	1110000000	18708.58	900	19608.58	22467.5	2858.92
1000	438	438	125	0	0	0	0	0	0	0	1110000000	19561.84	0	19561.84	22250	2688.16
1100	428	428	122	122	0	0	0	0	0	0	1111000000	21910.68	560	22470.68	25245	2774.32
1150	455	455	130	110	0	0	0	0	0	0	1111000000	22765.63	0	22765.63	25875	3109.37
1200	410	410	117	117	146	0	0	0	0	0	1111100000	24537.09	1800	26337.09	26580	242.91
1300	455	455	130	130	130	0	0	0	0	0	1111100000	26184.02	0	26184.02	29640	3455.98
1400	455	455	130	130	162	68	0	0	0	0	1111110000	28768.21	340	29108.21	41090	11981.79
1450	455	455	130	130	162	80	38	0	0	0	1111111000	30592.78	0	30592.78	43717.5	13124.72
1500	448	448	128	128	160	79	0	54	54	0	1111110110	32909.74	0	32909.74	47475	14565.26
1400	451	451	129	129	161	79	0	0	0	0	1111110000	28833.32	0	28833.32	34440	5606.68
1300	455	455	130	130	130	0	0	0	0	0	1111100000	26184.02	0	26184.02	31850	5665.98
1200	455	455	130	130	30	0	0	0	0	0	1111100000	24150.34	0	24150.34	27000	2849.66
1050	408	408	117	117	0	0	0	0	0	0	1111000000	21058.08	0	21058.08	23415	2356.92
1000	389	389	111	111	0	0	0	0	0	0	1111000000	20206.33	0	20206.33	22250	2043.67
1100	428	428	122	122	0	0	0	0	0	0	1111000000	21910.68	0	21910.68	24255	2344.32
1200	455	455	130	130	30	0	0	0	0	0	1111100000	24150.34	900	25050.34	26640	1589.66
1400	478	478	137	137	170	0	0	0	0	0	1111100000	28046.53	0	28046.53	31710	3663.47
1300	444	444	127	127	158	0	0	0	0	0	1111100000	26289.91	0	26289.91	30030	3740.09
1100	455	445	130	40	0	20	0	0	0	0	1111010000	22406.52	340	22746.52	25245	2498.48
900	455	445	0	0	0	0	0	0	0	0	1100000000	17177.90	0	17177.90	20475	3297.1
800	455	345	0	0	0	0	0	0	0	0	1100000000	15427.41	0	15427.41	18040	2612.59
TOTAL												**546319.44**	**4840**	**551159.44**	**651330**	**100170.56**

TABLE VIII
COST AND PROFIT COMPARISON

Methods	**Total Generation Cost ($)**	**Profit ($)**
GA [11]	609023.69	42306.31
GA [12]	591715	59615
MDP [10]	581541.9892	69788.05
Binary coded GA [19]	567367	83963
Binary PSO [13]	565450	85880
IPPD and λ-logic algorithm [22]	564834.4662	86,495.534
GS [15]	563938.0729	87391.9271
HHS [17]	563937.687	87,392.313
Ring cross over GA [21]	563937	87393
Adaptive PSO [13]	561586	89744
WICPSO [23]	559350	91980
Fireworks algorithm [16]	554514	96816

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PSO-LR [18]	551701.878	99628.122
Enhanced Lagrangian Relaxation Method [20]	565508	85822
LR-GA [24]	565825	85505
MDP based PSO-LR (proposed)	**551159.44**	**100170.56**

TABLE IX
EXECUTION TIME COMPARISON

Methods	Execution time
GA [11]	677
Binary coded GA [19]	221
MDP [10]	115
LR-GA[24]	56
PSO-LR [18]	5
IPPD and λ-logic algorithm [22]	0.1298
HHS [17]	16.83
WICPSO [23]	6.94
MDP-PSO-LR (proposed)	**117**

The comparison of total generation cost and profit of the proposed approach with various other approaches are shown in Figure (1)

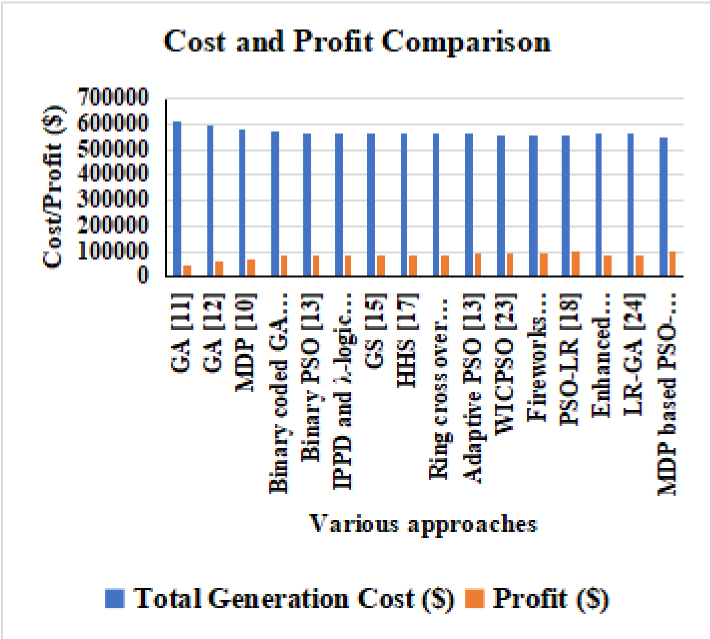

FIGURE 1. **Cost and profit comparison of various approaches**

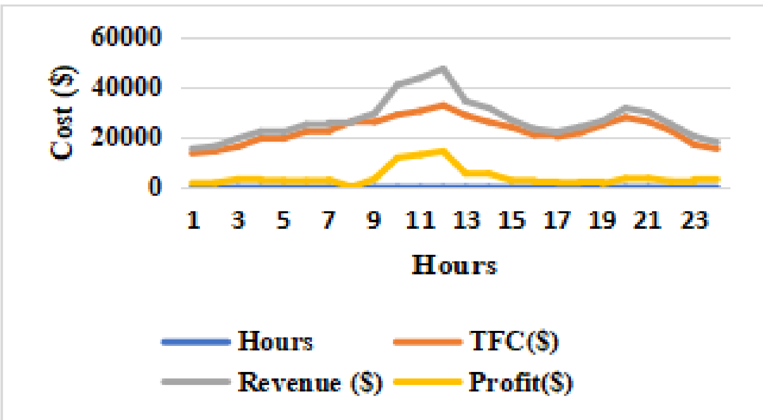

FIGURE 2. **Fuel cost, Revenue and Profit of 10-unit system for 24 Hours by MDP-PSOLR**

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The fuel cost, revenue, and profit of the 10-unit system by MDP-PSO-LR reported for each hour of the day ahead deregulated electricity market is given below in Figure (2).

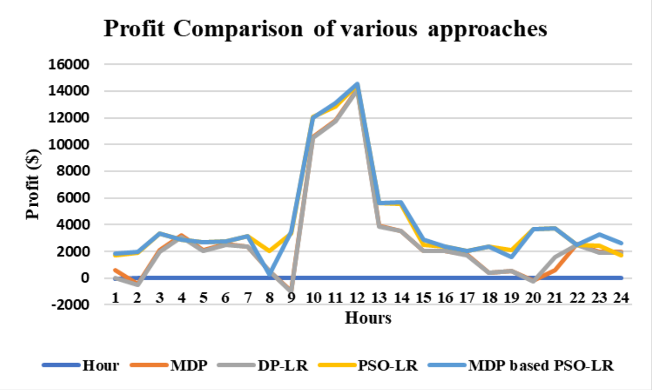

FIGURE 3. **Profit comparison for 24 Hours of MDP-PSOLR with other approaches**

The profit realized in the MDP based PSO-LR is high due to the identification of global maxima in the limited search space. The profit comparison of MDP based PSO-LR with other approaches are shown in Figure (3).

The proposed algorithm MDP-PSOLR results in lower production costs and high profit compared to other methods stated in the literature. The profit obtained is $100170.56 and the generation cost is reduced to $551159.44. There is a net saving of $ 542.438 using the proposed algorithm in terms of profit.

CONCLUSION

In this paper, a novel continuous commitment of units using MDP based PSO-LR approach for solving the profit-based unit commitment was proposed. MDP approach yielded the near-optimal solution through a three-stage optimization process with demand constraint satisfaction. Ramp rate constraint was included in the MDP approach to arrive at the optimal schedule. The divergence was rectified in the second part of the algorithm for the 10-unit system and converged quickly. The near-optimal solution of MDP and the random solution was considered for the PSO optimization process. The lagrangian technique produces the economic dispatch of the units considered. It was observed that the proposed MDP based PSO-LR algorithm produced the best global optimal solution when compared to MDP and PSO-LR approaches individually. Although the execution time of the proposed algorithm is large compared to PSO-LR, the solution obtained is optimal with low generation cost and high profit for the 10-unit system considered as an individual GENCO. Future work is aimed at hybridizing intelligent techniques to obtain a better solution quality and reduced execution time.

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