



Physics Based Intelligent Approach for Clean and Economic Operation of Distribution Systems Involving Adaptive Load Shifting Policy

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Abstract:- Apart from minimizing generation cost, modern-day power systems are equally concerned about minimizing the pollutants released to the environment in the form of hazardous chemicals. Large incorporation of renewable energy sources have undoubtedly helped in this regard to a great extent. Still, we can achieve better cost and emission reduction if we can perform proper demand-side management. This paper aims to demonstrate the effectiveness of load shifting based demand side management approach as well as a novel approach of demand side management combined with unit commitment in reducing the generation cost in microgrid systems. Microgrids can operate in both islanded as well as grid connected mode. In grid-connected mode, both active and passive participation by the grid takes place. Two test systems are studied, where one microgrid is operating in islanded mode, and the other operates in grid-connected mode. For islanded microgrid, the complex dynamic economic emission dispatch based on the fractional programming method, as well as environment-constrained economic dispatch is considered. For the grid-connected microgrid, economic load dispatch is considered. A very recently reported physics-based evolutionary algorithm based on rime – ice (RIME) is considered as the optimization technique for this study. Numerical results are conclusive of the fact that proper demand side management combined with unit commitment is able to significantly reduce the cost of generation when compared to all other scenarios, establishing the effectiveness of the proposed method.

Keywords: Artificial intelligence, combined economic emission dispatch, demand side management, economic load dispatch, emission dispatch, environment constrained economic load dispatch, unit commitment.

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1. Introduction

Modern Economic Load Dispatch (ELD) leverages energy from renewable sources. In ELD, every connected unit contributes to generation cost for each unit of power, implying varying



costs for production. The total load demand needs to be satisfied by the collective energy output from the generators [1]. ELD is divided into static ELD (SELD) and dynamic ELD (DELD) based on load demand: SELD deals with specified daily loads, while DELD adapts to varying load demands. SELD, having fewer constraints like forbidden operation zones and ramp rates, is less complex [2]. Researchers in [3] addressed stochastic economic emission load dispatch (EELD) considering uncertainties in load demand and power production costs. DELD poses a more challenging optimization task due to constraints like distributed energy resources (DER), time limitations, and other factors, including SELD constraints [4]. Start-up times and turn off of DERs, as well as energy storage techniques during charging and discharging, are key challenges in solving the DELD problem.

Several researches in the literature focus on the optimal distribution of RES. The primary aim is to seamlessly integrate these decentralized RES into the existing economic framework. Given the escalating costs of petroleum and related concerns, saving the environment and integrating RES have become paramount for governmental agendas. To address optimal placement of distributed generating units and shunt capacitors in distribution networks, a probabilistic approach was proposed in [5]. This method aimed to reduce costs of generating power, emissions, and losses in the network, improve the voltage profiles, and avert line overloads simultaneously. Evolutionary programming, tailored to varying dimensions and complexities of ELD problems, employing experimental learning levels was explored in a study presented in [6] that was otherwise not traceable by methods based conventional gradient. Utilizing Particle Swarm Optimization (PSO), authors in another study [7] tackled power production cost reduction across four distinct test scenarios. In a study presented in [8], a multi-objective ELD problem with combined cooling, heating, & power microgrid (MG) was addressed using renewable sources, energy storage, and incentive based demand response mechanisms. The study transformed the original nonlinear optimization model into a Mixed Integer Linear Programming issue using linearization techniques. The utilization of Biogeography-Based Optimization (BBO) to tackle traditional unit economic dispatch challenges, both convex and non-convex, was introduced in [9]. Another study [10] proposed a hybrid metaheuristic approach for managing clean and economical energy in MG systems connected to grid. Investigating non-dispatchable DERs like solar and wind energy in a rural MG, the authors in [11] devised a stochastic framework for effective day-ahead electrical energy management. Proposing a smart energy management technique using a genetic algorithm based optimization technique, [12] addressed day-ahead MG optimization considering probabilistic photovoltaic (PV) output, power forecasting, and energy storage systems (ESS). Cuckoo search strategy was employed to tackle MG power dispatch challenges in [13], providing an efficient algorithmic solution. In [14], the authors designed a virtual power plant and managed its economic and operational aspects with an economical algorithm Kasaei. Researchers in [15] explored a new approach investigating ELD, ED, and combined economic



emission dispatch (CEED) on a PV and wind based three-unit islanded MG using the Internal Search Algorithm (ISA). Focusing on dynamic control of a distributed network with dynamic components like plug-in hybrid electric vehicles, smart transformers, and soft open points, authors in [16] conducted a survey involving residential energy customers and a utility company. [17] proposed a novel solution addressing Multi-Objective Dynamic Economic and Emission Dispatch (MODEED) problem using Demand Side Management (DSM) and Multi-Objective Particle Swarm Optimization (MOPSO) approach. [18] outlined various aspects describing an ideal energy purchasing technique in a DC MG with storage systems, renewable energy sources (RES), and demand responsive elastic loads. [19] Provided insights into the optimal operation of combined heat and power (CHP) units in a MG, utilizing heat boilers. Considering both internal and external markets for effective energy trading in MGs, [20] proposed a flexible price elasticity-based demand response program with grid participation. A distinctive challenge in MG energy management is presented in [21], incorporating an incentive-driven demand response program (DRP) based on flexible price for analyzing node voltage differences and power losses of the reconstructed distribution networks: IEEE-33 bus and IEEE-38 bus. Proposing an efficient MG energy management system (EMS) having price-dependent DRPs, [22] aimed to improve synchronization between suppliers and users of energy to minimize operating cost. [23] Emphasized peak load reduction and operational cost improvement with day-ahead scheduling of MGs in presence of diesel generators (DG). Employing a game theory based DSM approach, and a multi-objective dynamic optimum power flow (MODOPF) model, [24] focused on energy consumers and providers. [25] Introduced a technical approach towards implementing Crow Search Algorithm (CSA) for optimal MG operation. Discussing an energy hub optimization strategy incorporating DRPs, risk factors, and chaos theory based algorithm, [26] highlighted substantial decrease in operational and emission costs. The review paper [27] discusses decentralized control strategies for MGs corresponding to growing use of renewable energy. It outlines the benefits of MGs, robust and adaptive control strategies, and centralized and decentralized architectures, summarizing recent research approaches and findings while proposing future research directions. The model outlined in [28] integrates constraints on capacity and supply-demand balance, and coproduction ratio. It ensures plant privacy and offers seamless plug-and-play operation. It is effective in reducing costs for the network as suggested by the numerical results. [29] Proposes a perspective for transforming a multiobjective problem into single objective using a distributed algorithm that does not depend on the initialization process. Simulation results validate that supply-demand constraints as well as capacity inequalities are met in every time slot by the optimal solution. The study in [30] discusses a dual-stage optimization technique for electric vehicle charging. For preventing grid from overload condition, it employs particle swarm optimization and elastic demand response. [31] Introduces an enhanced two-archive multi objective evolutionary algorithm that considers costs, probability of power



supply loss, emission of pollutants, and power balance as the objective functions. This algorithm utilizes two archives with different strategies of selection and incorporates a decision-making approach based on fuzzy logic to maintain equilibrium between diversity and convergence within the high dimensional and complex objective space. [32] Explored carbon-constrained economic dispatch (CCED) in a MG system under different grid pricing schemes, considering uncertainty. [33] Investigated optimal scheduling of DSM-based grid participating MG systems using a hybrid optimization, for varying wind profiles. [34] Addressed environment-constrained economic dispatch (ECED) for a MG system with changing electricity market pricing strategies, using DSM. In [35], the authors studied MG system energy management with a demand response program for a cleaner and economic operation. [36] Proposed DSM integrated evolutionary algorithms for dynamic economic emission dispatch of distribution systems. [38] Investigated the effect of changing grid price and grid participation for cost-efficient operation of MG systems. [39] Demonstrated the importance of DSM in rural and residential MG systems for economic operation. [40]-[41] studied the design and application of newer metaheuristic algorithms to solve cleaner economic energy management of MG systems.

Demand side management is a widely used practice by researchers, utilities, and electricity firms to reduce peak load demand, improve load factor, and enhance the economic operation of distribution systems. Recent studies in DSM, up to 2024, have primarily focused on environment-constrained economic dispatch, highlighting its significant benefits in MG systems. Among the various DSM strategies, the load shifting policy emerges as one of the most effective. This policy aims to reduce peak load demand and optimize generation costs by shifting electricity consumption to off-peak hours when prices are lower. However, researchers often overlook the potential reduction in the need for certain generators during these off-peak periods when implementing load shifting policies.

Unit commitment plays a crucial role in addressing this oversight. Integrating unit commitment and DSM becomes essential to minimize generation costs effectively, provide sufficient standby time for operating systems, and extend the longevity of generators by allowing them time for maintenance and correlation. By combining these approaches, the proposed methodology aims to optimize the economic operation of distribution systems while ensuring their reliability and sustainability. This integrated approach not only minimizes costs but also enhances the overall efficiency of the system, contributing to a more sustainable energy future.

The paper is organized into the following sections: Section 2 presents mathematical formulation of the different objective functions studied; Section 3 presents a brief overview of the proposed RIME algorithm applied to solve the present problem;



2. Mathematical Formulation of Objective Function

The following section presents a description of the objective functions and the associated constraints:

2.1. Objective Functions

2.1.1. MG Cost for Real Power Generation

The cost function of a grid connected MG with n number of DG units is formulated [25] as under:

$$ECD = \sum_{t=1}^{24} \left[\sum_{m=1}^n \left\{ (a_m P_{m,t}^2 + b_m P_{m,t} + c_m) + \left| d_m \times \sin \left(e_m \times (P^{min} - P_{m,t}) \right) \right| \right\} + C_{g,t} \times P_{g,t} \right] \quad (1)$$

where,

a, b, c, d, e = cost coefficients

n = number of DG units

$P_{m,t}$ = power output of m^{th} DG unit at t^{th} hour.

$P_{g,t}$ = grid power at t^{th} hour.

$C_{g,t}$ = dynamic grid price (variable with respect to time)

2.1.2. MG Emission from DGs

The harmful emissions to the atmosphere caused by fossil fuelled machines can be formulated as under:

$$EMD = \sum_{t=1}^{24} \left[\sum_{m=1}^n (\alpha_m P_{m,t}^2 + \beta_m P_{m,t} + \gamma_m) + \xi_m \times \exp(\lambda_m \times P_{m,t}) + E_{g,t} \times P_{g,t} \right] \quad (2)$$

EMD = total value of emissions

$\alpha, \beta, \gamma, \xi, \lambda$ = emission coefficients

$E_{g,t}$ = emission coefficient for grid

2.1.3. Combined Economic Emission Dispatch (CEED)

This objective function is designed to minimize the ratio of EMD to ECD [34] with the hope of achieving better results and is formulated as under:

$$CEED = \frac{EMD}{ECD} \quad (3)$$



2.1.4. Environment Constrained Economic Dispatch (ECED)

This objective function is designed to achieve the best compromising solution between (1) and (2) and is described as under:

$$ECED = w \times \left[\frac{ECD - ECD_{min}}{ECD_{max} - ECD_{min}} \right] + (1 - w) \times \left[\frac{EMD - EMD_{min}}{EMD_{max} - EMD_{min}} \right] \quad (4)$$

where, w = weight factor and is between 0 and 1.

ECD_{min} = best cost value obtained on minimizing (1)

EMD_{max} = worst emission value obtained on minimizing (1)

EMD_{min} = best emission value obtained on minimizing (2)

ECD_{max} = worst cost value obtained on minimizing (2)

2.2. Constraints of the Problem

The operating constraints of the problem are given below (5) – (8):

$$\sum_{t=1}^{24} \sum_{m=1}^n P_m = Demand_t \quad (5)$$

$$\sum_{m=1}^n P_{m,t} + P_{REN,t} = Demand_t \quad (6)$$

$$P_{m, min} < P_m < P_{m, max} \quad (7)$$

$$P_{g, min} < P_g < P_{g, max} \quad (8)$$

$Demand_t$ = demand at t^{th} hour

$P_{REN,t}$ = RES generation at t^{th} hour

2.3. Modelling Uncertain Generation for RES

As generation from RES are unpredictable and governed by nature, it is mandatory to consider the uncertainty in mathematical formulation as follows: [25].

2.3.1. Uncertain Solar Generation

$$SPV_{un,t} = SDev_{PV,un} \times n_1 + SPV_{fc,t}$$

$$SDev_{PV,un} = 0.7 \times \sqrt{SPV_{fc,t}} \quad (9)$$

where,

$SPV_{un,t}$ = uncertain generation from solar PV at t^{th} hour.



$SPV_{fc,t}$ = day ahead forecasted value of SPV.

$SDev_{PV,un}$ = standard deviation of uncertain PV output.

2.3.2. Uncertain Wind Generation

$$W_{un,t} = SDev_{W,un} \times n_2 + W_{fc,t} \quad (10)$$

$$SDev_{W,un} = 0.7 \times \sqrt{W_{fc,t}} \quad (11)$$

where,

$W_{un,t}$ = uncertain wind generation at t^{th} hour.

$W_{fc,t}$ = Day ahead forecasted value of wind generator.

$SDev_{W,un}$ = standard deviation of output from solar PV.

n_1, n_2 = random distribution functions with 0 standard deviation and mean =1.

The mathematical formulation of power generated from wind can be represented as follows [25]:

$$WP_m = \begin{cases} P_{rated} \times \left(\frac{v_t - v_{m,in}}{v_r - v_{m,in}} \right) & \text{when } v_{m,in} < v_t < v_r \\ P_{rated,m} & \text{when } v_{m,in} \leq v_t \leq v_{m,out} \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

where,

WP_m = wind power output from m^{th} wind farm.

$P_{rated,m}$ = rated wind power of m^{th} wind farm.

v_t = dynamic wind speed

v_r = rated speed

$v_{m,in}$ = cut -in speed of m^{th} wind farm.

$v_{m,out}$ = cut- out speed of m^{th} wind farm.

2.4. Demand Side Management

The DSM method [25] identifies flexible loads and optimizes their placement on the load curve to minimize the utility electricity bill. This practice brings down the peak demand, thereby increasing the utility load factor, although the total load demand (TLD) remains the same after



completion of a scheduling period (typically a day). Utilities are capable of reducing the system's peak load demand and improve monetary savings by employing dynamic DSM strategy.

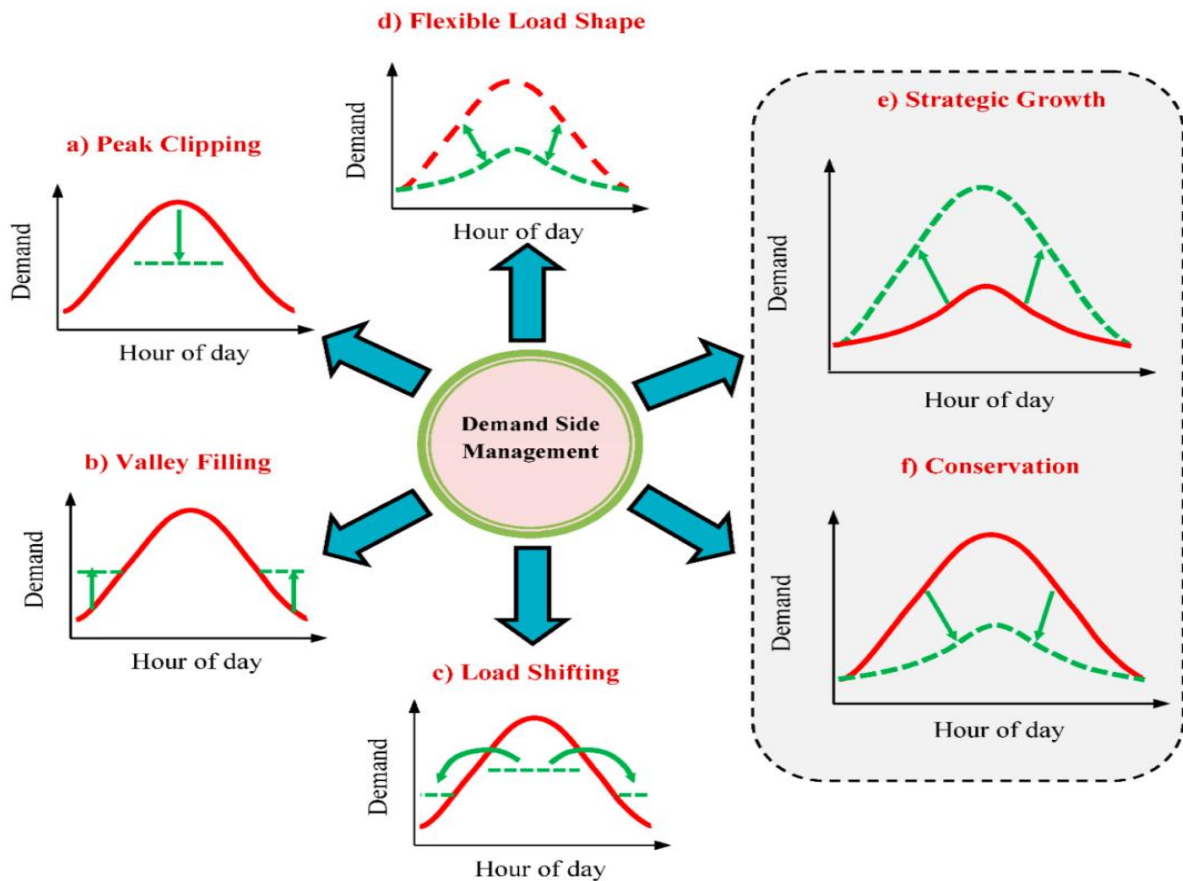


Figure 1. Different DSM techniques [42].

Customers are often incentivized by the utilities to participate in DSM. Tactical load management, which includes variable load shaping and planned load conservation, is a method for controlling TLD by proper management and system design. Load shifting, peak clipping, and valley filling, are three commonly applied load control strategies that are used to adjust controllable loads to improve the load-demand curve. Other strategies involve load shifting, flexible load shaping, strategic conversion, strategic expansion, and valley filling. The most popular among all load management strategies is the load shifting approach that combines peak clipping and valley filling. This helps to shift controlled loads from peak hours to off-peak hours without changing energy utilization. The controlled/elastic loads are entered as a percentage of the hourly load demand on the basis of percentage of DSM participation, in case they are not explicitly mentioned. The rest part of the load is the inelastic load.



The different DSM methods are depicted in Figure 1. The peak, minimum and total inelastic loads are calculated and the following equation is optimized:

$$\text{minimize } [C_{g,t} \times (Demand_{inelastic,t} + Demand_{elastic,t})] \quad (13)$$

where, $C_{g,t}$ = time of use (TOU) based electricity price at time t .

$Demand_{inelastic,t}$ = inelastic demand at time t .

$Demand_{elastic,t}$ = elastic demand at time t .

Equation (13) is optimized subject to the following constraint:

$$0 \leq Demand_{elastic,t} \leq \max (Demand_{elastic}) \quad (14)$$

The updated load model is the sum of the total of inelastic load over 24 hours and the total of optimized elastic load as under:

$$Demand_{total} = \sum_{T=1}^{24} (Demand_{inelastic,t} + Demand_{elastic,t}) \quad (15)$$

The steps involved in obtaining an updated load model after DSM is better understood from the flowchart given in Figure 2 below:

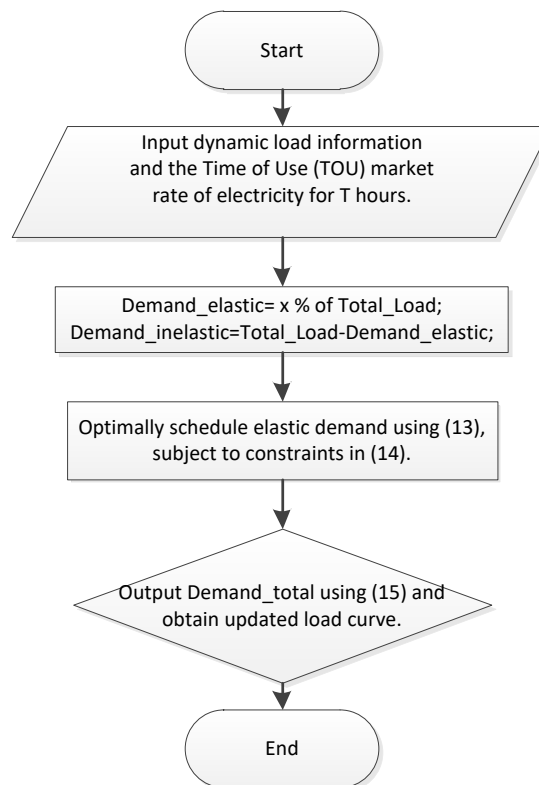


Figure 2: Steps involved in DSM using load shifting technique.



3. Mathematical Model of RIME Algorithm Applied to the Problem

This section presents a brief overview of the optimization technique used. The RIME optimization algorithm presented in [37] mimics the formation and growth of rime ice. Rime ice forms when airborne water vapor accumulates and freezes on objects like tree branches at low temperatures, creating a distinctive landscape. Certain regions, characterized by their unique climate and topography, consistently experience the formation of rime ice annually. Simulating the growth process of rime strips involve analysis of the impacts wind speed, cross-sectional area of the material attached, freezing coefficient, and growth time. The four stages of this algorithm are depicted in Figure 3:



Figure 3. Stages of RIME algorithm.

3.1.1. Initialization

The RIME population P is initialized for N rime agents and D rime particles as follows:

$$R = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{iD} \end{bmatrix} \quad (16)$$

3.1.2. Soft RIME Search Technique

In the second stage, particles condense into soft rimes following five motion characteristics [38] which are mathematically formulated as under:

$$P_{ij}^{new} = P_{best,j} + r_1 \times \cos \theta \times \beta_{en} \times (h_{ad} \times (Ub_{ij} - Lb_{ij}) + Lb_{ij}), r_2 < E; \quad (17)$$

where, $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, D$

$$\theta = \pi \times \frac{iter}{10 \times maxiter} \quad (18)$$

$$\beta_{en} = 1 - round\left(\frac{w \times iter}{maxiter}\right) / w \quad (19)$$

$$E = \sqrt{\frac{iter}{maxiter}} \quad (20)$$

P_{ij}^{new} = new position of the updated particle,

$P_{best,j}$ = j^{th} particle of best agent in P .



r_1 = a random number in $[-1,1]$

β_{en} = environmental factor

h_{ad} =degree of adhesion, a random number in $[0,1]$

$iter$ = present iteration

$maxiter$ =maximum iterations

E = coefficient of attachment

$w=5$, a factor that controls the number of segments in β_{en} .

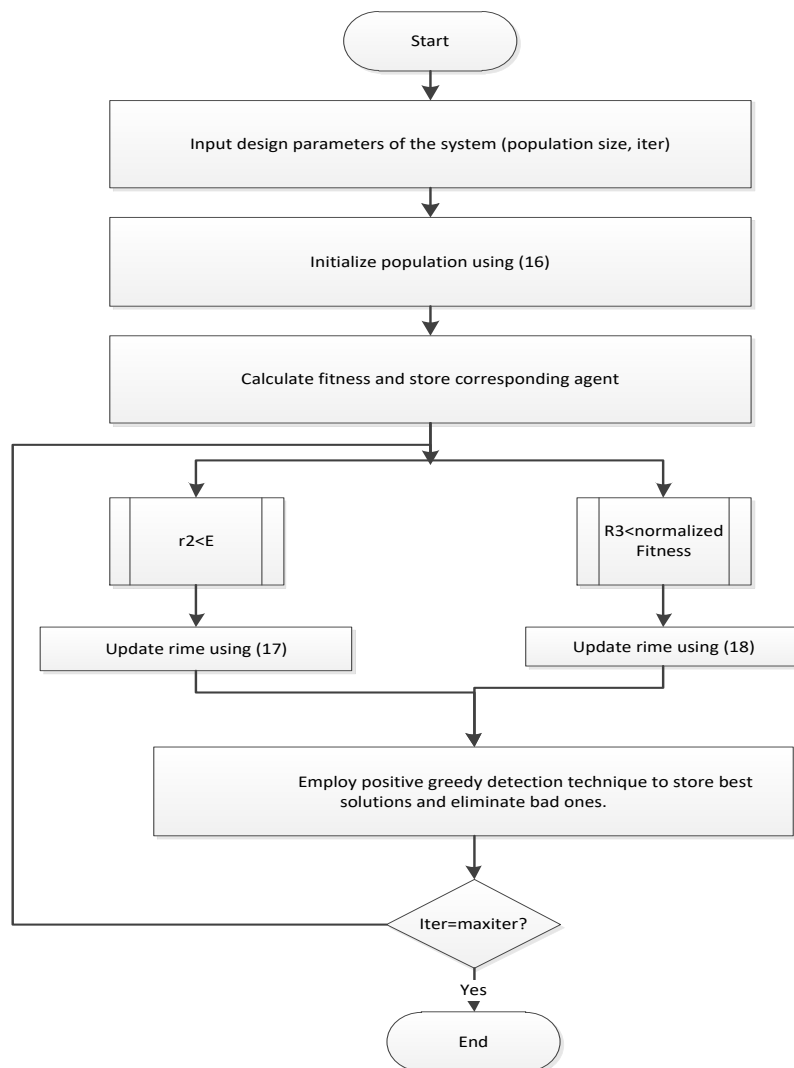


Figure 4: Flowchart for RIME algorithm.



3.1.3 Hard RIME Puncture Technique

Condensation of soft RIME into hard RIME is expressed as follows:

$$P_{ij}^{new} = P_{best,j}, r_3 < Fit^{normr}(X_i) \quad (21)$$

where, $Fit^{normr}(P_i)$ = normalized fitness value of present agent X_i .

3.1.4. Greedy Selection Technique

After every update, greedy selection technique replaces the best fitness value and stores the corresponding best agent. In this algorithm, the updated fitness value of an agent is compared with fitness value of an agent prior to the update, and if the updated fitness value is superior to the value prior to the update, it is replaced.

3.1.5. RIME Applied to Energy Management of Distribution System

The application of RIME algorithm for the energy management of distribution systems is depicted using a flowchart above in Figure 4.

4. Description of test systems and cases studied

Two test systems with multiple DERs have been studied to prove the significant advantages of the mathematical formulations done in Section 3. All the codes for the present study were developed in MATLAB R2022b, and ran on a laptop with 4GB RAM, Intel(R) Core(TM) i5 CPU clocked @ 2.50GHz. All the studies were carried out for a population size of 100 and a maximum iteration count of 500.

4.1. MG Test System 1 (MGTS 1)

MGTS 1 comprises of 40 fossil fuelled generators. DER parameters, load demand and DER cost coefficients have been obtained from [46]. Electricity prices used for DSM are mentioned in [47].

For this test system, the MG is operated in islanded mode with and without DSM load, and ECD, EMD, CEED and ECED are performed on the system with valve point loading conditions. The peak load on the system is considered as 10500 kW.

Cost and emission coefficients for this test system are provided in Table 1 below for reference:

Table 1: MG DER cost coefficients [46]

DER	Gmin	Gmax	a (\$/kW ²)	b (\$/kW)	c (\$)	d	e	α (kg/kW ²)	β (kg/kW)	γ (kg)	ξ	λ
G1	36	114	0.0069	6.73	94.705	100	0.084	4.8	-222	6,000	1.31	0.0569
G2	36	114	0.0069	6.73	94.705	100	0.084	4.8	-222	6,000	1.31	0.0569
G3	60	120	0.02028	7.07	309.54	100	0.084	7.62	-236	10,000	1.31	0.0569
G4	80	190	0.00942	8.18	369.03	150	0.063	5.4	-314	12,000	0.9142	0.0454



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G5	47	97	0.0114	5.35	148.89	120	0.077	8.5	-189	5,000	0.9936	0.0406
G6	68	140	0.01142	8.05	222.33	100	0.084	8.54	-308	8,000	1.31	0.0569
G7	110	300	0.00357	8.03	287.71	200	0.042	2.42	-306	10,000	0.655	0.02846
G8	135	300	0.00492	6.99	391.98	200	0.042	3.1	-232	13,000	0.655	0.02846
G9	135	300	0.00573	6.6	455.76	200	0.042	3.35	-211	15,000	0.655	0.02846
G10	130	300	0.00605	12.9	722.82	200	0.042	42.5	-434	28,000	0.655	0.02846
G11	94	375	0.00515	12.9	635.2	200	0.042	3.22	-434	22,000	0.655	0.02846
G12	94	375	0.00569	12.8	654.69	200	0.042	3.38	-428	22,500	0.655	0.02846
G13	125	500	0.00421	12.5	913.4	300	0.035	2.96	-418	30,000	0.5035	0.02075
G14	125	500	0.00752	8.84	1760.4	300	0.035	5.12	-334	52,000	0.5035	0.02075
G15	125	500	0.00708	9.15	1728.3	300	0.035	4.96	-355	51,000	0.5035	0.02075
G16	125	500	0.00708	9.15	1728.3	300	0.035	4.96	-355	51,000	0.5035	0.02075
G17	220	500	0.00313	7.97	647.85	300	0.035	1.51	-268	22,000	0.5035	0.02075
G18	220	500	0.00313	7.95	649.69	300	0.035	1.51	-266	22,200	0.5035	0.02075
G19	242	550	0.00313	7.97	647.83	300	0.035	1.51	-268	22,000	0.5035	0.02075
G20	242	550	0.00313	7.97	647.81	300	0.035	1.51	-268	22,000	0.5035	0.02075
G21	254	550	0.00298	6.63	785.96	300	0.035	1.45	-222	29,000	0.5035	0.02075
G22	254	550	0.00298	6.63	785.96	300	0.035	1.45	-222	28,500	0.5035	0.02075
G23	254	550	0.00284	6.66	794.53	300	0.035	1.38	-226	29,500	0.5035	0.02075
G24	254	550	0.00284	6.66	794.53	300	0.035	1.38	-226	29,500	0.5035	0.02075
G25	254	550	0.00277	7.1	801.32	300	0.035	1.32	-242	31,000	0.5035	0.02075
G26	254	550	0.00277	7.1	801.32	300	0.035	1.32	-242	31,000	0.5035	0.02075
G27	10	150	0.52124	3.33	1055.1	120	0.077	184.2	-111	36,000	0.9936	0.0406
G28	10	150	0.52124	3.33	1055.1	120	0.077	184.2	-111	36,000	0.9936	0.0406
G29	10	150	0.52124	3.33	1055.1	120	0.077	184.2	-111	36,000	0.9936	0.0406
G30	47	97	0.0114	5.35	148.89	120	0.077	8.5	-189	5,000	0.9936	0.0406
G31	60	190	0.0016	6.43	222.92	150	0.063	1.21	-208	8,000	0.9142	0.0454
G32	60	190	0.0016	6.43	222.92	150	0.063	1.21	-208	8,000	0.9142	0.0454
G33	60	190	0.0016	6.43	222.92	150	0.063	1.21	-208	8,000	0.9142	0.0454
G34	90	200	0.0001	8.95	107.87	200	0.042	0.12	-348	6,500	0.655	0.02846
G35	90	200	0.0001	8.62	116.58	200	0.042	0.12	-324	7,000	0.655	0.02846
G36	90	200	0.0001	8.62	116.58	200	0.042	0.12	-324	7,000	0.655	0.02846
G37	25	110	0.0161	5.88	307.45	80	0.098	9.5	-198	10,000	1.42	0.0677
G38	25	110	0.0161	5.88	307.45	80	0.098	9.5	-198	10,000	1.42	0.0677
G39	25	110	0.0161	5.88	307.45	80	0.098	9.5	-198	10,000	1.42	0.0677
G40	242	550	0.00313	7.97	647.83	300	0.035	1.51	-268	22,000	0.5035	0.02075

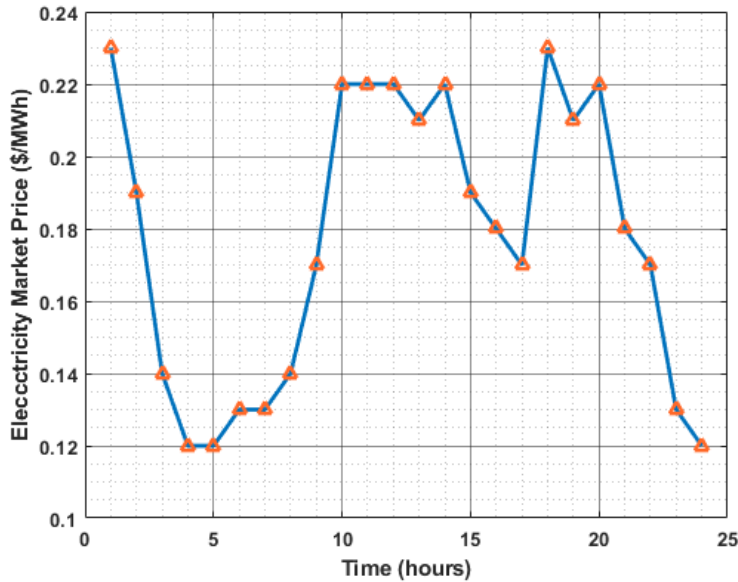


Figure 6: Dynamic market price of electricity [43].

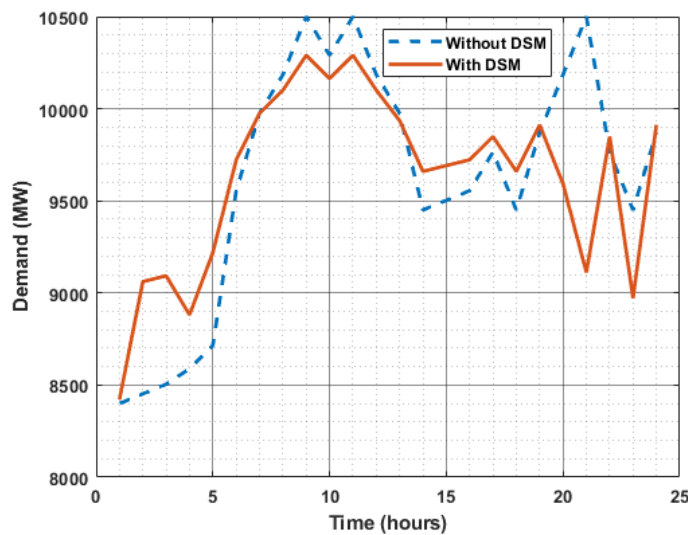


Figure 7: Load demand over a day.

Figure 6 represents the dynamic grid price and Figure 7 represents the load demand over 24 hours with and without DSM.

Case 1 MG Operation in Islanded Mode with and without DSM Load

For this test system, MG is considered to be operating in islanded mode where; the MG operates without grid support and is only dependent on DERs. ECD, EMD, CEED and ECED values are obtained using RIME algorithm and compared with results in the literature. The operations



were performed with and without DSM to show the impact of DSM in cost reduction. The results obtained show a significant reduction in cost when load shifting based DSM is applied to the MG system.

Table 2: Results obtained for MGTS1 using RIME.

Operation	Without DSM			Operation	With DSM		
	Cost (\$)	Emission (Kg)	CEED		Cost (\$)	Emission (Kg)	CEED
ECD	2659646	7766300	-	ECD	2656500	7804000	-
EED	2863300	2805400	-	EED	2858018	2720322	-
CEED	2895200	2821700	0.9602	CEEDFP	2895200	2737900	0.9382
ECED ($\mu = 0.5$)	2732200	3532700	-	ECED ($\mu = 0.5$)	2727200	3358600	-

It can be observed from Table 2 that, DSM was able to reduce the cost for ECD by **3146 \$** when compared to the cost obtained without using DSM. For EED, the emission was reduced by **85078 Kg** while using DSM based load. CEED and ECED provide a trade-off between cost and emission. DSM based CEED was less by **2.34%** as compared to load model without DSM. As established in [32], ECED provides better trade-off between cost and emission. DSM based ECED reduced the cost by **5000 \$** and emission by **174100 Kg** as compared to ECED without DSM.

A comparative study of the results obtained using RIME algorithm with those reported in recent literature was done and is presented below in Table 3:

Table 3: Comparative analysis for MGTS 1.

Algorithms	ECD (\$)		CEED	
	Without DSM	With DSM	Without DSM	With DSM
DE [46]	28,50,316		-	-
PSO [46]	27,31,322		-	-
CSA [46]	27,42,666		-	-
JAYA [46]	27,18,006		-	-
TLBO [46]	27,11,517		-	-
SCA [46]	27,70,733		-	-
CSASCA [46]	27,47,405		-	-
CSAJAYA [46]	26,61,260	-	0.9602	-
RIME	2659645.9	2656500	0.9602	0.9382



It is observed from Table 3 that RIME algorithm superseded other algorithms in minimizing the generation cost obtained using numerous other algorithms in the literature. It was able to reduce the cost of generation by **1614.1 \$** without DSM and **4760 \$** with DSM when compared to the last best reported CSAJAYA algorithm. It obtained the best cost for both ECD and CEED. The comparative convergence characteristics for ELD, EED and CEED with and without DSM using RIME algorithm are presented in Figure 8, Figure 9 and Figure 10 respectively.

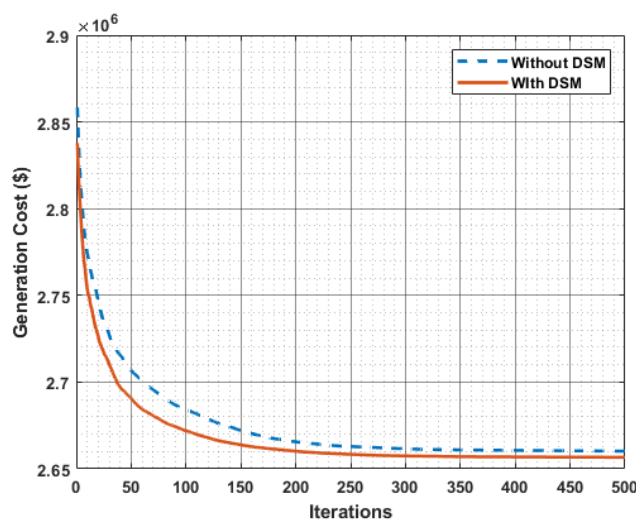


Figure 8: Convergence curve of ELD with and without DSM.

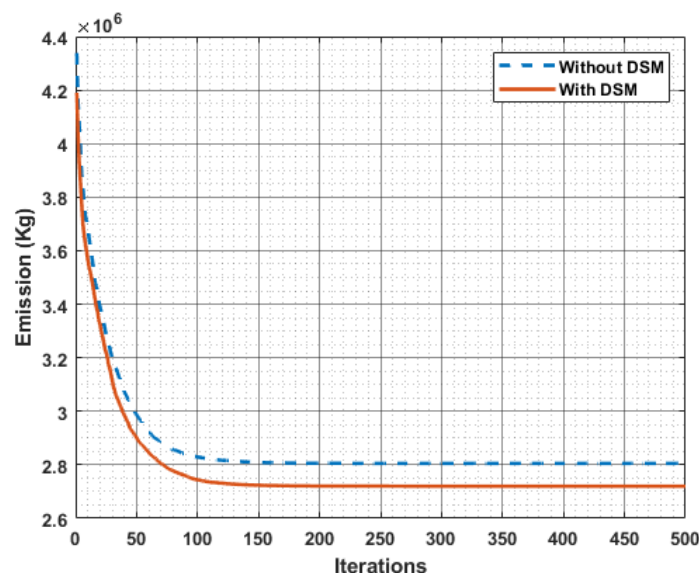


Figure 9: Convergence curve for EMD with and without DSM.

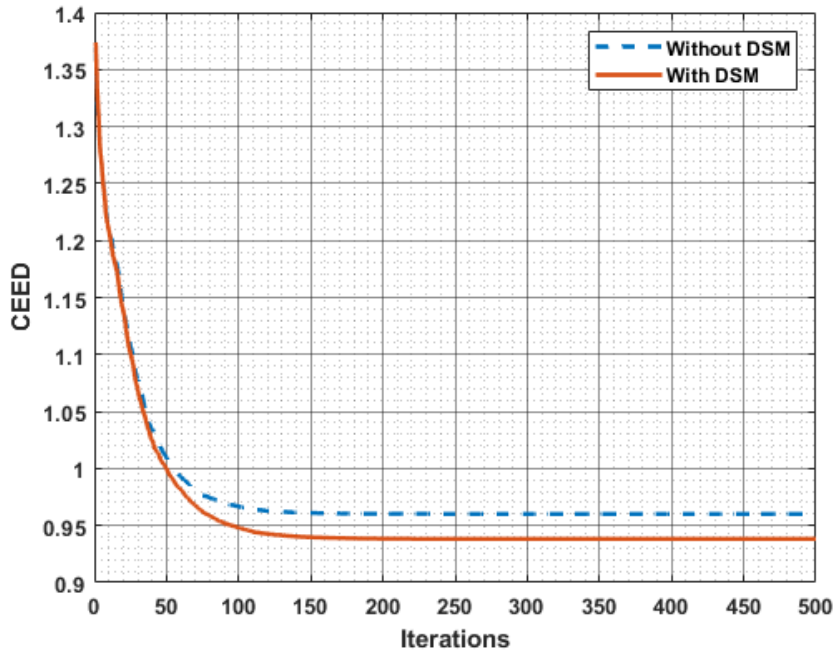


Figure 10: Convergence curve of CEEDD with and without DSM.

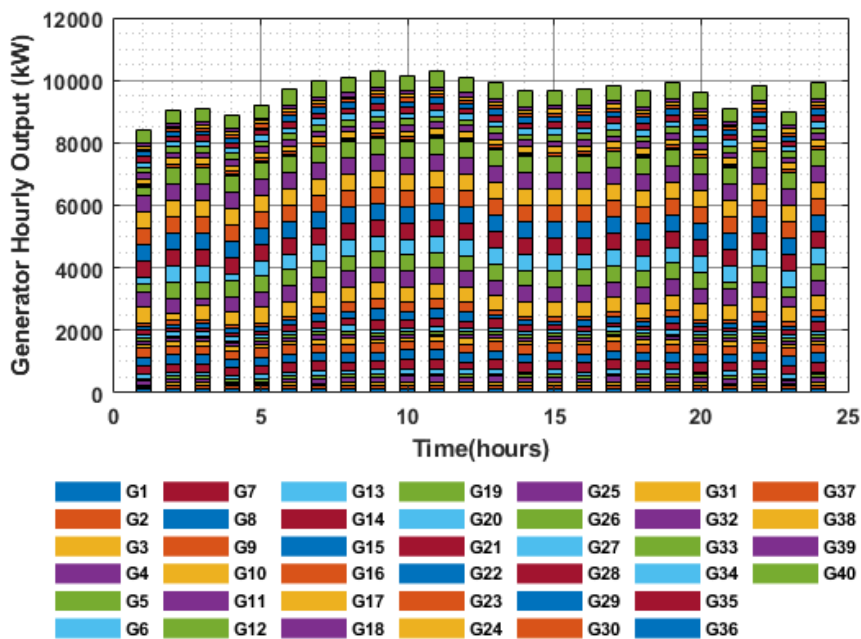


Figure 11: Hourly contributions of units with DSM for ELD operation using RIME.

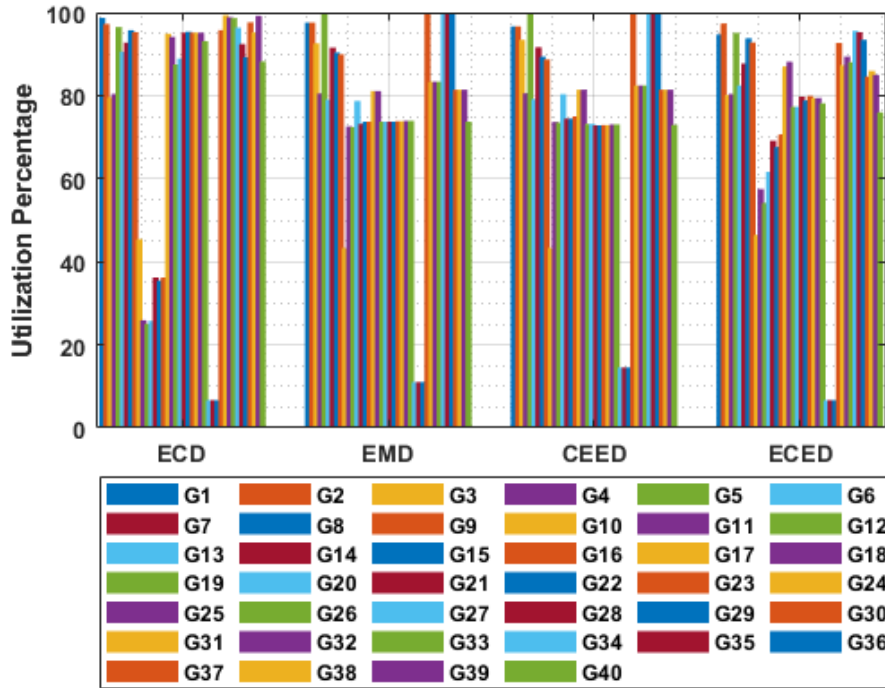


Figure 12: Utilization percentage of the units for ECD, EMD, CEED and ECED operations utilizing DSM.

Figure 11 shows the optimal contribution by the units and Figure 12 shows the utilization percentage of the units for DSM based load for islanded MG operation. From Figure 12, we can infer that, the units having higher generation for ECD as compared to EMD are low cost generators. However, they contribute towards polluting the environment more. Similarly, the generators having higher utilization percentage for EMD are high cost generators with low emission.

4.2. MG Test System 2 (MGTS 2)

MGTS 2 is a grid-supported IEEE 69 bus system shown in Figure 13, comprising of 7 DERs namely: 2 CHP, 1 DG, 1 fuel cell (FC), 1 micro turbine (M-T), 1 gas turbine (G-T) and PV and WT as the renewables [44].

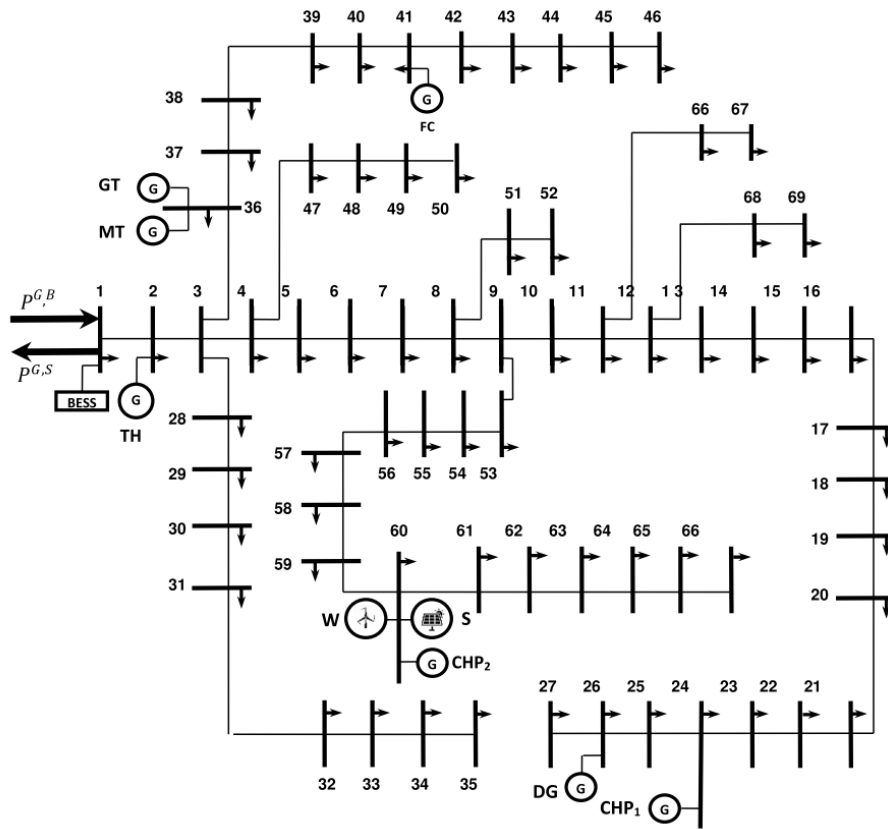


Figure 13: Illustration of IEEE 69 bus test system for MG [44].

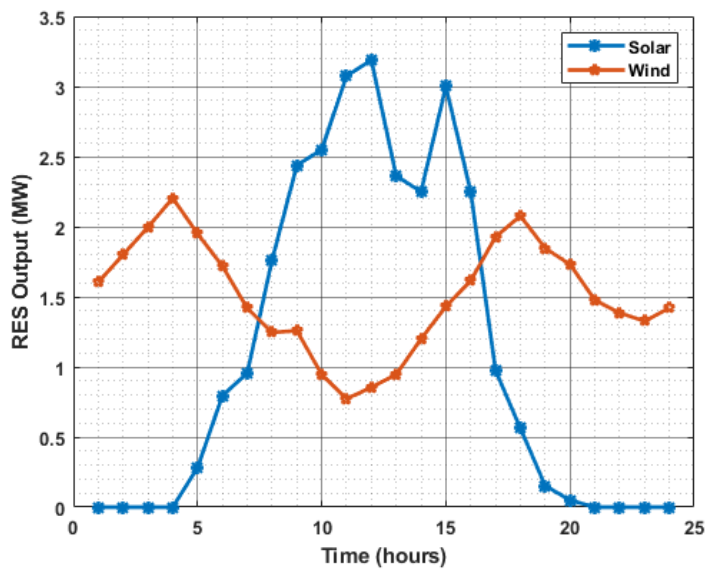


Figure 14: Solar and wind farm output [44].

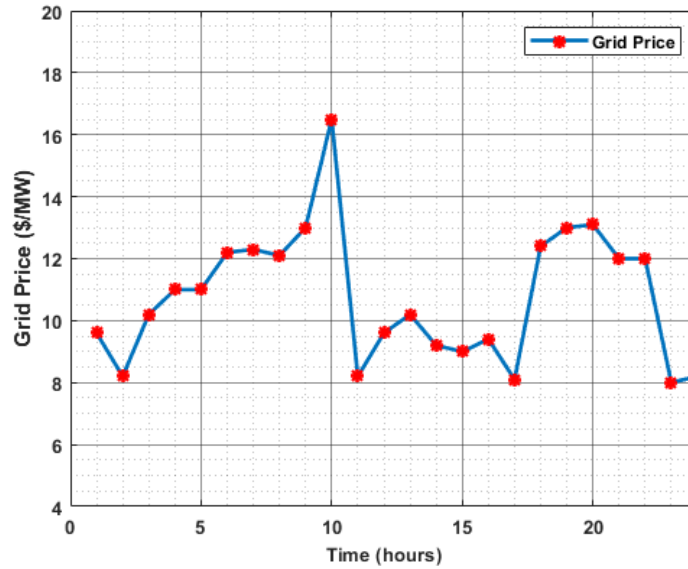


Figure 15: Dynamic market price of electricity [45].

Figure 14 represents the hourly output from the RESs and Figure 15 represent the hourly dynamic grid price. For this test system, the grid actively buys from and sells power to the MG. Passive grid participation was also considered, where the grid only supplies power to the MG. The DER generation limits and cost coefficient data are provided below in Table 4:

Table 4: MGTS 2 DER coefficients [44].

SI NO	DER	Limits (MW)		Cost coefficients		
		Minimum	Maximum	a (\$/MW ²)	b (\$/MW)	c (\$/h)
1	MT	0.3	1.00		0.1188	
2	GT	0.2	1.0	0.0001987	0.0116	0.4969
3	DG	0.2	2.0	0.038	2.0109	95
4	FC	0.6	3		0.0848	
5	CHP1	1.0	6.0	0.0345	14.5	265
6	CHP2	3.5	4.5	0.0435	36.0	125
7	Grid	-5	5		Figure 15	

For this test system, different case scenarios are considered as given below:

- Case 1: Base case where the grid is actively participating at ± 5 MW levels, and the load is shared by the RESs. No DSM and no UC are considered here.
- Case 2: This is the case with active grid participation at ± 5 MW levels, and the system is operating without RESs.



- Case3: Consider active grid participation with static/fixed grid price without DSM and UC in presence of RESs.
- Case 4: Passive grid participation without DSM and without UC in presence of RESs.
- Case 5: This case considers UC, active grid participation at ± 5 MW levels in presence of RESs and feeds DSM based load. CHP2 having the highest cost coefficient is considered for UC.
- Case 6: For this case, demand is increased by 10%, DSM is done, and UC is considered. Active participation of grid in presence of RESs is considered.

Table 5: Generation cost obtained for different MG scenarios.

Case No.	Description	Cost Obtained (\$)
case 1	Base case: Grid +/-5 MW, no DSM, no UC, only renewables	15339.69
case 2	No DSM, no renewables , no UC	16036.63
case 3	Fixed grid, without DSM, UC and with renewables	15366.4080
case 4	Passive grid, without DSM, UC and with renewables	15439.48
case 5	Grid +/-5 MW, with DSM and renewables and Unit commitment	14553.71
case 6	Increase load demand by 10% and perform case 5	14947.4

For case 1, TOU price for grid is considered, which varies during different hours of the day. The grid is actively transacting power with the MG throughout the day and the price is dynamic. It can be observed from Table 5 that the cost is high for case 1 when the system is working only with RESs and DERs and no DSM or UC is performed. If RESs are removed, the cost increases further by **4.54%** as seen in case 2. When we consider fixed grid price throughout the day, and the grid is actively transacting power with the MG, the price is increased by **0.17%** as compared to dynamic grid pricing in case 1. Now for the third case, when passive grid participation is considered, i.e., when the grid is only selling power to the MG, the cost increases further by 0.65% as compared to when the grid is actively selling and buying from the MG as in case 1. The MG cost would be lesser if it was able to sell its surplus power to the grid. Cases 1-4 did not consider DSM or UC. To reduce the cost further, application of DSM and UC is proposed and presented in case 5. Only DSM is sufficient to reduce the cost significantly. But, since, during different hours of day, not all the units need to generate power to meet the demand, UC is added. For this, we shut down the CHP2, with the highest cost coefficient during hours 17-24. As expected, the cost of generation significantly reduced by



5.4% using our proposed approach as compared to case 1 and 10.19% as compared to case 2 which is devoid of RESs. To justify this approach, the demand was increased by 10% and the DSM and UC were applied in the next case. We can clearly see that the cost still remained lower by 2.62% as compared to the base case.

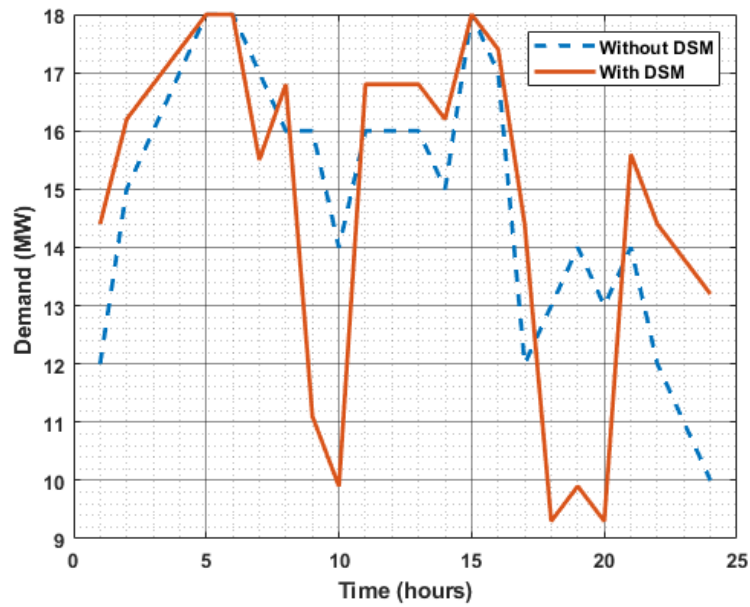


Figure 16: Load demand over 24 hours [44].

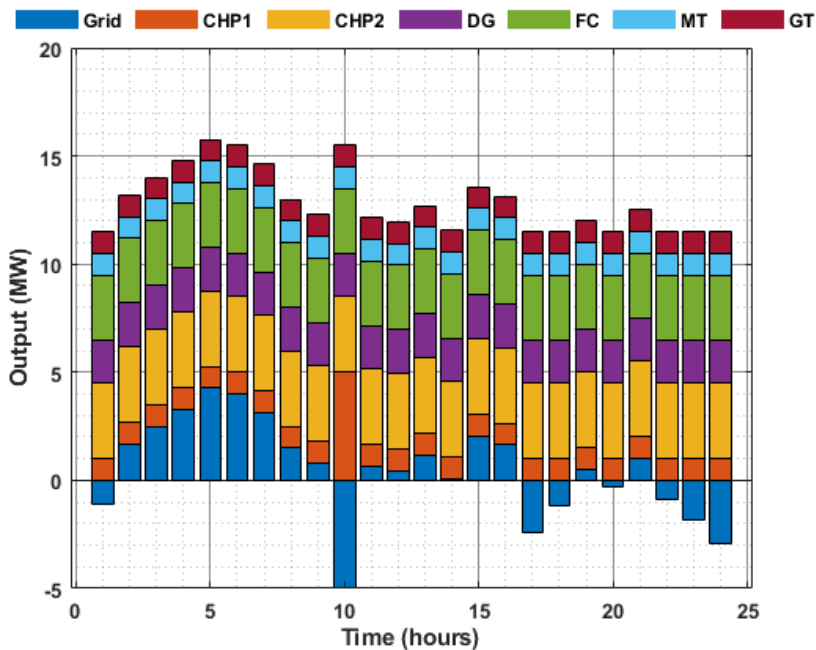


Figure 17: Hourly output for active grid participation in Case1.

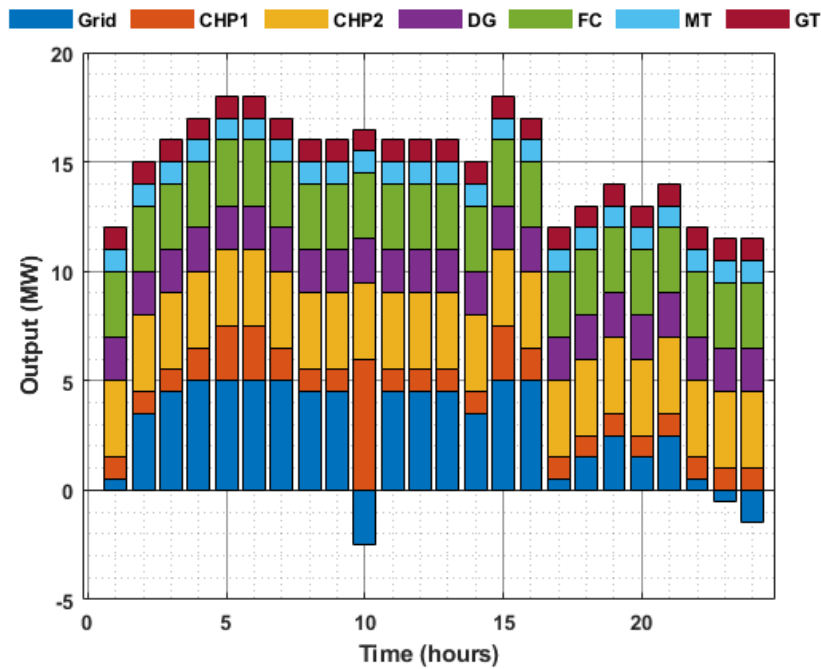


Figure 18: Hourly output for active grid participation in Case2.

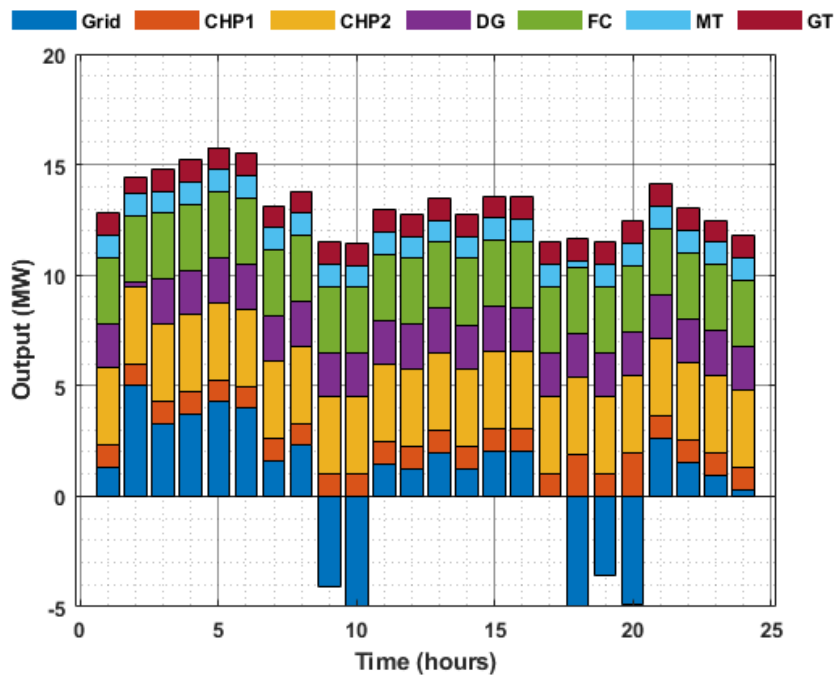


Figure 19: Hourly output for fixed price grid participation in case 3.

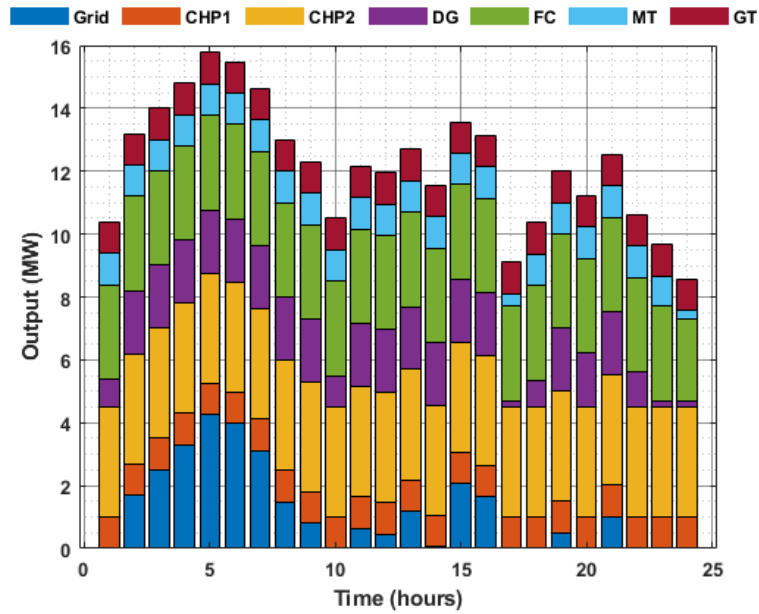


Figure 20: Hourly output for passive grid participation in case 4.

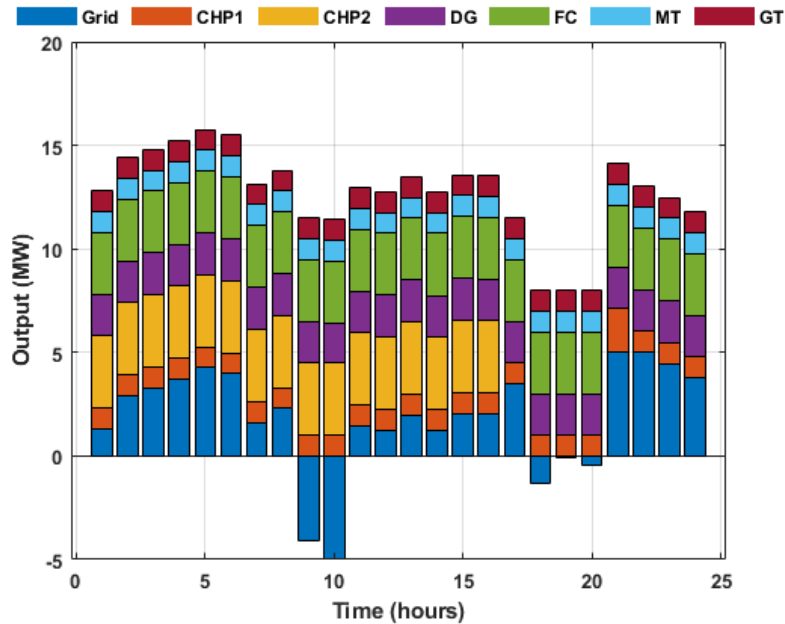


Figure 21: Hourly output for active grid participation with DSM and UC in case 5.

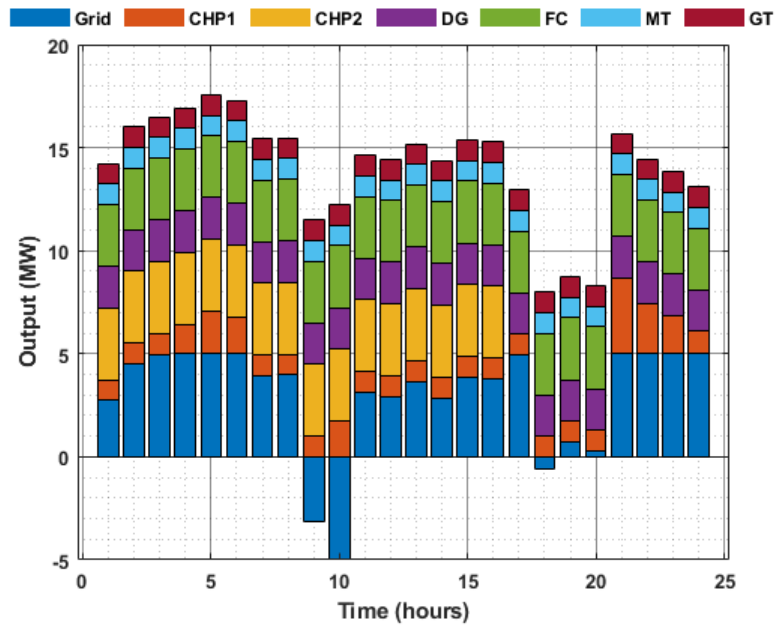


Figure 22: Hourly output for active grid participation in case 6.

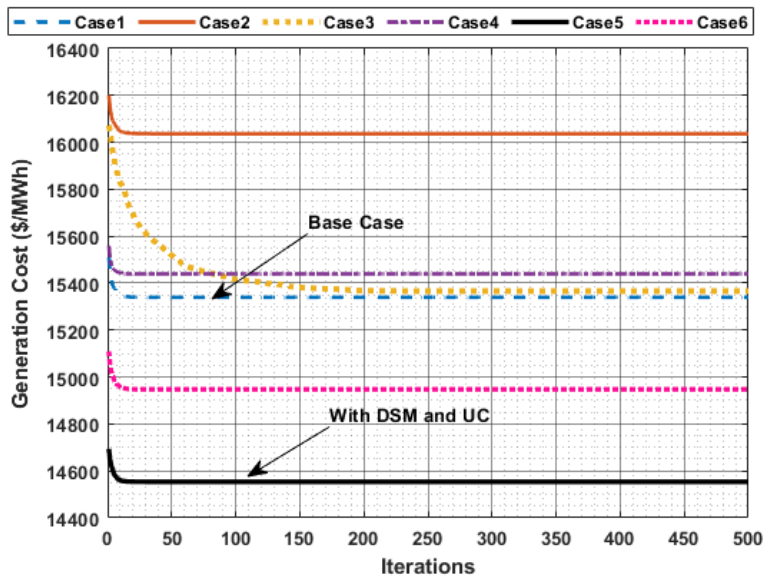


Figure 23: Convergence curve for all the cases of MGTS2 using RIME algorithm.

Figure 16 shows the load profile for the system over a day with and without DSM. Figure 17-22 shows the generation contribution of the DERs and grid and Figure 23 shows the convergence characteristics of all the cases obtained using RIME algorithm. It can be observed that for case 1-3, and case 5-6, the contribution of grid is the highest as it has the least price, leading to an overall reduction in the generation cost of MG. Only if the grid has passive



participation, the benefit is reduced as the MG cannot sell its surplus power to the grid. The least cost is obtained for case 5, when DSM and UC are considered. This technique helps to spread the load by shifting maximum load to off peak hours and schedule the output of DERs in such a way that high cost coefficient DER does not contribute to generation till other DERs are able to meet the demand, thereby reducing the cost significantly. From the convergence characteristics, we observe that RIME was able to quickly attain the desired solution within 50 iterations for 5 out of 6 cases. For case 2, it attained convergence after 100 iterations. This proves the superior exploitation capability of RIME over other algorithms, that need much more number of iterations to converge.

The cost obtained for this system using RIME is compared with Hybrid CSAJAYA reported in [45] below:

Table 6: Comparative study for MGTS2.

Grid support = ± 5 MW	Hybrid CSAJAYA [45] (Without DSM)	RIME	
		Without DSM	With DSM and UC
Active Grid	15906 \$	15339.69 \$	14553.71 \$
Passive Grid	16368 \$	15439.48 \$	NA

It can be observed from Table 6 that RIME was able to obtain better result than recently reported Hybrid CSAJAYA algorithm for both active and passive grid cases. Without DSM, RIME was able to reduce the cost for active grid by **3.69%** and for passive grid by **6.01 %** as compared to Hybrid CSAJAYA. After incorporating DSM and UC, the cost reduced by **9.29 %** as compared to Hybrid CSAJAYA algorithm for active grid participation at 5 MW levels.

Conclusion

This paper presented a novel application of DSM and DSM combined with UC for minimizing generation cost of the system. Two test systems were studied: the first one was studied for ECD, EMD, CEED and ECED while for the second test system, only ECD was performed. For the first test system, when DSM was applied, it resulted in significant reduction of the generation cost and emission as compared to cases without DSM. For the second test system, both DSM and UC were applied which resulted in a greater reduction of generation cost as compared to the other cases. The proposed RIME algorithm showed better performance than all other algorithms it was compared to. Comparative studies with recent literature demonstrate the superiority of the proposed technique in reducing the generation cost by reducing the burden on the system during peak hours.

Declaration

The authors declare no conflict of interest for the work reported in this paper.



Data Availability

Data will be made available on request.

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