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Research Paper

Sensitivity Analysis Based Multi-Objective Economic Emission Dispatch in Microgrid

Naveen Kumar [1], *Surender Dahiya* [2, *], *and K.P.Singh Parmar* [3]

[1] *Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Haryana, India.*
[2] *Department of Electrical Engineering, Deenbandhu Chhotu Ram University of Science and Technology, Murthal.*
[3] *Deputy Director, National Power Training Institute, Faridabad, Haryana, India.*

Abstract— *The microgrid (μG) is an integration of distributed generation and local loads with energy storage system. Cost minimization is one of the main objectives in modern power systems.Economic dispatch(ED) is a fundamental problem related to μG and the conventional grid. Economic dispatch(ED) provides the optimal output of generators in order to reduce the total operating cost. Emission dispatch (EMD) is one of the other major problems associated with CG. The emission dispatch (EMD) solution provides the optimal generator operation to reduce harmful pollutants for a specific load demand. Multi-objective economic emission dispatch (MEED) provides a compromise between ED and EMD. In this paper, two test systems have been proposed. Test system one consists of Six CG. Static ED, EMD, and MOEED analysis has been provided for test system one. Test system two consists of four CG, One wind turbine generator (WTG), and one photovoltaic module (PVM).This paper intends to provide sensitivity analysis and uncertainty regarding the curtailment cost of RES. CPLEX solver in GAMS has been proposed to optimize the three fundamental problems. Comparative study and sensitivity analysis show optimal results, and the GAMS solver provides a more comprehensive framework. Reduction in cost due to uncertainty in ED is 9.58% as compared to 9.7% for test system two. The cost has been reduced in MEED by 9.33% as compared to 9.46%. MEED comparison shows the increment in cost of 2.66 %, but the emission is reduced by 18.98 % for test system two.*

Keywords—Economic Dispatch, Emission Dispatch, General Algebraic Modeling System, Micro-grid, Multi-Objective Economic Emission Dispatch.

NOMENCLATURE

AI	Artificial Intelligence
$B_j(X_i)$	Membership function
B_j^{max}	Maximum value of objective function
B_j^{min}	Minimum value of objective function
BESS	Battery energy storage system
CG	Cost function
CG	Conventional generators
CHP	Combined heat and power
CO	Carbon oxide
DED	Dynamic economic dispatch
DEG	Distributed energy generator
DES	Distributed energy sources
ED	Economic dispatch
EMD	Emission dispatch
ESS	Energy storage system
GA	Genetic algorithm
$GAMS$	General Algebraic modeling system
LD_t	Electricity load demand at time t (MW)
μG	Micro-grid
m_i	Coefficient of cost
MEED	Multi-objective Economic emission dispatch
MILP	Mixed integer linear programming
MPC	Model predictive control
n_i	Coefficient of cost
NLP	Non-linear programming
NO_X	Oxides of nitrogen
o_i	Coefficient of cost
$P_{i,min}$	Minimum power(MW)
$P_{i,max}$	Maximum power(MW)
$P_{i,t}$	Power output of generator i at time t (MW)
PCC	Point of common coupling
PVM	Photovoltaic module
PSO	Particle swarm optimization
q_i	Coefficient of emission
r_i	Coefficient of emission
RD_i	Ramp down limit of generator i(MW)
RU_i	Ramp up limit of generator i(MW)
RES	Renewable energy sources
s_i	Coefficient of emission
SED	Static economic dispatch
SO_X	Oxides of sulphur
TC	Total cost
TV	Total variable
VPC	Value of Photovoltaic power curtailment
VWC	Wind turbine generator power curtailment

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*Corresponding author:
E-mail: 16001902005naveen@dcrustm.org (N. Kumar)
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WOA	Whale optimization algorithm
WTG	Wind turbine generator
η	Variable between minimum and maximum emission

1. Introduction

1.1. Research Motivation

Economic load dispatch(ED) is one of the basic problems that need to be addressed in power systems [1]. ED allocates the power of generating units so that the fuel/operating cost is reduced while satisfying all the constraints. Emission is one of the key issues with CG. RES such as WTG and PVM reduce these harmful pollutants and the cost. RES has several advantages such as reduction in the cost, emission, and improvement in reliability, etc. Uncertainty is one of the main issues associated with RES. RES output may be reduced due to uncertainty and randomness in power production. ED with RES curtailment is a complex issue in the modern power system. Uncertainty in terms of RES curtailment value in microgrids is a challenging issue [2].

ED may be classified as a static and dynamic problem. Static ED is the cost minimization problem in a single time snapshot under different constraints. Dynamic ED problem is the optimal generation of each conventional generator so that operating costs may be reduced for different times of the day. Dynamic ED considers different time horizons with an interval of some time (one hour, 15 minutes, or 5 minutes) and follow-up ramp limits. The day ahead and real-time dispatch are the two different scheduling strategies [3]. The schedule of generators and demand is maintained before a day in the day ahead ED. In real-time ED, the schedule is maintained in real-time according to generation and demand. ED may be classified as cost-based and market-based. Cost-based ED does not consider any forecasted price. According to bidding in market, the forecasted price is considered in market-based ED.ED based on cost is a simple optimization problem. The objective function of the cost-based ED is minimizing the cost while satisfying equality, inequality, and other technical constraints. The equality constraint is balancing the generation and the load demand of electricity. The total generation should always be equal to the total load demand at every instant of time. Generators should lie in the inequality constraint between their lower and upper limits of generation. Other technical constraints, such as ramp limits, valve point loading, etc., should be satisfied during optimization. In the price-based ED, the objective function is the maximization of profit of the generation company. Profit is the difference between income and the operating cost. The income of the generation company is dependent on the day-ahead electricity price and the power sold. The cost is the expenditure in the generation. The difference between the cost and the price-based ED is the satisfaction of the equality constraints. There is no need to balance demand and supply in price-based [3]. The load demand should always be more than the generation in price-based ED. Other technical constraints should be satisfied in price-based ED as in cost-based ED.

Economic emission dispatch is a multi-objective problem in which both the cost and emission are minimized [4–6]. The emission may be taken as a constraint, with fuel cost minimization as a prime objective. A trade-off solution is obtained between cost and the emission in MEED. The Pareto optimal front solution provides a compromise solution between both cost and emission. Different AI techniques have been used to optimize a compromise solution of cost and emission. For several decades, conventional power systems with huge investment costs along with the emissions of NO_X, SO_X, and carbon emissions have been in existence.

μG is a small-scale generation including RES, CG, Energy storage system, and load close to the generation [5]. RES and ESS in μG have a good capability to reduce cost and emission. μG and smart grid with recent technologies with RES have several advantages like reduction in cost, emission, and improved reliability. μG may be operated in grid-connected or isolated mode. RES, like WTG and PVM, are the main generation sources in μG . Uncertainty and randomness are among the main issues with RES [7, 8]. RES randomness may be the reason for instability. Effect of demand and weather uncertainty is a critical issues in power systems [9].

ESS, such as BESS, flywheel, ultra-capacitors, etc., can play a significant role in uncertainty management. ESS can store energy during low load periods and excessive generation. ESS can discharge during peak load and low generation periods. Hence ESS can optimize cost in ED by optimal charging and discharging. Demand response may be a good alternative in the management of power systems. Change or reduction in demand during peak load can reduce costs in ED.

1.2. Literature Review

ED problem with equality, inequality, and other technical constraints has been optimized in previous literature work. In the Equality constraint, total generation must be equal to total demand at every interval of time. The power generation must lie between their boundary limits in inequality constraint. The solution should satisfy technical constraints, such as wind curtailment should be less than the total available wind. Combined economic emission dispatch using PSO, GA and other techniques [3], optimal solution with multi-microgrid including emission [1, 10, 11], optimal dispatch with demand response [12] ,Optimal dispatch using water cycle algorithm in power system and optimal scheduling [13] with ESS and electric vehicle ,ED solution using PSO [14], ED problem [15] using MILP, time-varying PSO [4] for multi-objective optimization, the Cost based DED with wind integration [16], Demand response in ED [17], RES and demand response strategy in μG [15], MPC application in ED using hybrid ESS and μG uncertainty MPC [18] approach with CHP has been discussed. A smart energy dispatch unit model based on fuzzy to utilize available energy optimally has been presented in a hybrid power system. Researchers presented a Dynamic economic emission dispatch with wind uncertainty [19]. WOA to solve economic emission dispatch and compare existing algorithms with GAMS in this paper [5].

Wind and solar curtailment are one of the important problems in modern power systems. Wind and solar curtailment is the reduction in the generation of electricity below its well-functioning maximum capacity. There may be several reasons for curtailment, like transmission congestion, high generation during low load periods, uncertainty, etc. Curtailment of RES affects both cost and emission adversely. RES curtailment is a bad outcome of modern power systems.

Energy storage systems(ESS) such as Battery energy storage systems (BESS), flywheels, pumped storage, and super-capacitors are essential to manage the intermittency or uncertainty problem [20, 21]. ESS can store energy during off-peak hours and may be discharged during peak hours to manage load and generation balance in the way of cost reduction in ED.

Microgrid (μG) is an integration of small distributed energy sources (DES) and local loads with storage systems. It has several advantages like uninterrupted power supply and hence reliability increases [22]. DES may be CG or RES. RES are in tradition due to a number of advantages over CG. μG may be connected to the main grid or operated in islanded mode [23].In connected mode, μG can exchange power with the main grid through a point of common coupling (PCC). μG is disconnected from the main grid and supplies power to the small geographical area in islanded mode.

A day ahead and real-time dispatch are two different ED problems. Generation and load demand before a day are committed in a day ahead market [3, 24]. In real-time ED, the schedule of generation and load demand varies in real-time. Economic emission dispatch and energy storage systems [18], RES, and μG have been studied in literature [15]. Cost-based and market-based ED [25],

Table 1. Comparison of the proposed method with different studies

Reference	Uncertainties	Curtailment of RES	Sensitivity Analysis
[2]	✓	✓	×
[7]	✓	×	×
[8]	✓	×	×
[9]	✓	×	×
[18]	✓	×	×
[33]	✓	×	×
[39]	✓	×	×
[40]	✓	×	×
[41]	✓	×	×
[43]	✓	×	×
Proposed Method	✓	✓	✓

ED optimization using water cycle algorithm [13], cost-based ED with renewable integration [26] and model predictive control with ESS and combined heat and power [18] has been discussed in the literature. RES curtailment is a fundamental issue associated with modern power systems. Curtailment is the reduction in generation capacity below it,s maximum generation capacity [27]. There may be specific reasons for the curtailment, such as the over generation and congestion in the energy market. The value of curtailment cost defines the cost per unit energy quantity and hence establishes the loss of generation. Load curtailment is the reduction in load in the same way as that of RES curtailment.

Renewable energy curtailment is a challenging issue, and this loss of generation has an adverse effect on the economy. Economic dispatch with Combined heat and power (CHP) is a technology that generates both heat and electrical power. Operating cost in CHP units depends upon the heat level and electricity generation. Literature has given Optimal operation using Whale optimization algorithm (WOA) for MEED in CHP plants [28]. The optimal function of CG decides the unit commitment in the power system. Unit commitment is the on-off status of units [29].

Various optimization techniques have been used for optimal scheduling in μG with uncertainty, demand response and ESS [30–33]. μG optimal dispatch using meta heuristic methods has been analyzed [34, 35]. Energy management in μG has been discussed [36]. Stochastic operation of virtual power plants considering contingencies using GAMS has been proposed [37]. Optimal scheduling with demand response and uncertainty of RES have been discussed [38–43]. Table 1 shows the comparison of proposed method with different studies.

1.3. Research Necessity on the basis of gap in literature

Several techniques have been proposed in the literature to find out the multi-objective solution between cost and emission with uncertainties. The disadvantages of PSO are untimely convergence and local optimal solutions. Population diversity is another disadvantage of PSO. Unguided mutation and tuning time of control parameters are the main problems with NLP. Not much emphasis was proposed using GAMS for ED, EMD, and MEED. This gap in literature motivated the authors to study GAMS optimization for optimal dispatch problems. Sensitivity analysis of ramp rate limits is very important for optimal scheduling. CPLEX solver in GAMS has been proposed for optimal dispatch including emission. CPLEX solver is very suitable for econometric models like optimal scheduling in μG. Uncertainty of RES in terms of curtailment cost for multi-objective economic dispatch is a gap in the literature. Random numbers for the uncertainty of RES,s have been generated in GAMS and provide optimal results for MEED. Sensitivity analysis of load demand, Ramp rate sensitivity, and optimal solution of MEED with curtailment due to uncertainty using GAMS is the main literature gap. CPLEX solver in GAMS provides automatic differentiation for NLP, and there is no need to show gradients, and it optimizes large-scale NLP very quickly. GAMS supports good global solvers such as Baron. GAMS results have been compared with some algorithms, and it shows better results. Local optimal solution, convergence, and unguided mutation problems in various algorithms may be fulfilled using GAMS very easily.

1.4. Novelty and main contribution of the paper

- Static ED, EMD, and MEED analysis for test system-1 and better comparison results with PSO and NLP.
- To elaborate the results in test system-1 with load sensitivity between the minimum and maximum generation limits of generation.
- Dynamic ED and MEED optimization for twenty-four hour at an interval of one hour in test system-2 with better results.
- Ramp rate sensitivity analysis has been provided for test system-2 to check the proposed method's effectiveness.
- Uncertainty due to RES curtailment on test system-2 has been analyzed, and comparative results are better.

1.5. Organization of the paper

Problem formulation with constraints has been proposed in Section 2. The proposed methodology has been presented in Section 3. Section 4 is the results and discussion part of this paper. Section 5 concludes the paper and presents the future scope of the proposed work.

2. Modeling

2.1. Economic Dispatch

Load sharing between CG in such a manner so that the operating cost may be reduced for the scheduled load is a quadratic constrained problem. ED problem with different constraints problem is formulated as [2, 3]. The cost equation with cost coefficient and generated power output is formulated as [3]:

$$CG(P_{i,t}) = m_i P_{i,t}^2 + n_i P_{i,t} + o_i \tag{1}$$

where,
$CG(P_{i,t})$ is operational cost (\$/hr) of i_{th} CG.
$P_{i,t}$ is power generated by i_{th} CG at time t.
m_i(\$/MW^{2}h), n_i(\$/MWh) and o_i(\$/h) represents the coefficients of cost of i_{th} CG.

Cost coefficients m_i, n_i, and o_i are critical factor in ED. The value of cost coefficients determines the power production of the corresponding CG. CG with the lower value of cost coefficient will be used first and share the load economically. n_i coefficient represents the linear multiplication with output power. o_i is independent of power, and it is a fixed cost coefficient.

Economic dispatch is a constrained problem, which is non-linear. ED Problem should satisfy equality, inequality, ramp constraints, and other technical constraints.

1) Equality constraint: Total generation should be equal to the total load demand at every interval of time [3].

$$\sum_{i,t} P_{i,t} = LD_t \tag{2}$$

Where,

LD_t Shows the load demand.

2) Inequality constraint: CG should be restricted in between their minimum generation ($P_{i,min}$) and maximum generation capacity ($P_{i,max}$) [3].

$$P_{i,min} \leq P_{i,t} \leq P_{i,max} \tag{3}$$

3) Ramp limit constraint: The ramp limit constraint determines the sudden change in the upper and lower limits of power generation by CG. CG can not increase or decrease power after a specific

limit. These upper and lower limits are known as ramp-up and ramp-down limits, respectively [3].

$$P_{i,t} - P_{i,t-1} \leq RU_i \tag{4}$$

$$P_{i,t-1} - P_{i,t} \leq RD_i \tag{5}$$

Where,
RU_i represents the ramp up limits of i_{th} CG.
RD_i represents the ramp down limits of i_{th} CG.

2.2. Emission Dispatch

Emission of SO_x, NO_x, and CO_2 etc. is formulated in terms of CG power production. This is a non-linear problem similar to the cost equation with different emission coefficients. Emission dispatch (EMD) reduces the harmful pollutants [2].

$$EG(P_{i,t}) = q_i P_{i,t}^2 + r_i P_{i,t} + s_i \tag{6}$$

Where,
$EG(P_{i,t})$ is Emission of CG (Kg/hr).
q_i(Kg/MW^{2}h), r_i(Kg/MWh), and s_i (Kg/h) are the coefficients of emission of i_{th} CG.

2.3. Multi-objective Economic emission Dispatch

In multi-objective EED, both cost and emission are minimized simultaneously. We can not attain both value minimum at the same time. A compromised solution of both the cost and emission is obtained. Various methods, such as price penalty factor, weighting sum, fractional programming, and Pareto method etc. may be used to determine the compromised solution. Pareto optimal solution using the fuzzy satisfaction method has been proposed in this paper to determine a compromised solution [2].

$$\min_{TV} TC = \sum_{i,t} CG(P_{i,t}) + \sum_{i,t} EG(P_{i,t}) \tag{7}$$

Where,
TV is total variable.
$TV \forall [P_{i,t}, PV_t, WT_t]$

Pareto optimal front is used to determine the compromise solution between cost and emission. Procedure of minimization is as follows:
1) Find maximum value of the cost function and emission function.
2) The emission function will be added as a constraint.

$$E \leq \eta \tag{8}$$

3) η is a variable between EG_{min} and EG_{max} and cost function will be minimized.
4) To find the best solution in the pareto front, fuzzy method with a assigned membership function will be used.
5) Find the minimum value of both cost and emission in the membership function.

Figure 1 shows the proposed model with multi-objective minimization. Various generation sources such as CG, WTG, and PVM have been used for generation. CG emits harmful pollutants. The generation side includes renewable curtailment and VPC (value of photovoltaic curtailment), and VWC (value of wind curtailment).VWC and VWC represent the energy quantity($\$/MWh$) and cost of curtailment. Load shedding is another option for optimal scheduling in terms of loss of load. Demand response is the management of load from the distribution side. Demand response is not considered in this paper.

2.4. Economic Dispatch including RES curtailment

RES curtailment is a significant problem in the power system. When this available generation from RES is not injected into the grid, power producers miss their opportunity to generate more power, increasing the overall cost [44]. There may be several reasons for RES curtailment. RES curtailment due to uncertainty is modeled as [2]:

$$\min_{TV} TC = \sum_{i,t} CG(P_{i,t}) + \sum_{t} PVC(PV_t) + \sum_{t} WTC(WT_t) \tag{9}$$

Where,
$TV \forall [P_{i,t}, PV_t, WT_t]$
TV is total variable
TC is total cost.
PVC is photovoltaic power curtailment (MW)
WTC is wind turbine generator power curtailment (MW)
PV_t is photovoltaic power production at time t.
WT_t is wind turbine generator power production at time t.

Objective function with curtailment should satisfy equality constraint.

$$\sum_{i,t} P_{i,t} + PV_t + WT_t = LD_t \tag{10}$$

2.5. Multi-objective Economic emission dispatch including RES curtailment

RES curtailment in multi-objective problems includes the cost of CG, wind curtailment, and solar curtailment costs, along with emission cost and constraint should be followed for multi-objective problems. The total cost to be minimized is formulated as [2].

$$\min_{TV} TC = \sum_{i,t} CG(P_{i,t}) + \sum_{t} PVC(PV_t) + \sum_{t} WTC(WT_t) + \sum_{i,t} EG(P_{i,t}) \tag{11}$$

2.6. RES with uncertainty

RES like wind and solar are unpredictable and depend upon weather conditions at different times of the day. Uncertainty may be modeled using some stochastic and robust approach. Uncertainty may be modeled as [45]:

$$PVM_{uncer.}^{t} = SDPVM_{uncer.} \times RN_1 + PVM_{forc.}^{t} \tag{12}$$

$$SDPVM_{uncer.} = 0.7 \times \sqrt{PVM_{forc.}^{t}} \tag{13}$$

$$WTG_{uncer.}^{t} = SDWTG_{uncer.} \times RN_2 + WTG_{forc.}^{t} \tag{14}$$

$$SDWTG_{uncer.} = 0.8 \times \sqrt{WTG_{forc.}^{t}} \tag{15}$$

$SDPVM_{unct.}$ is standard deviation in PVM. RN_1 and RN_2 are random number functions with zero standard deviation and mean 1. $PVM_{uncer.}^{t}$ is PVM output with uncertainty. $PV_{forc.}^{t}$ is solar forecasting at time t. $SDWTG_{uncer.}$ is the standard deviation in WTG output. $WTG_{uncer.}^{t}$ is WTG output with uncertainty. $WTG_{forc.}^{t}$ is forecasted WTG output at time t.

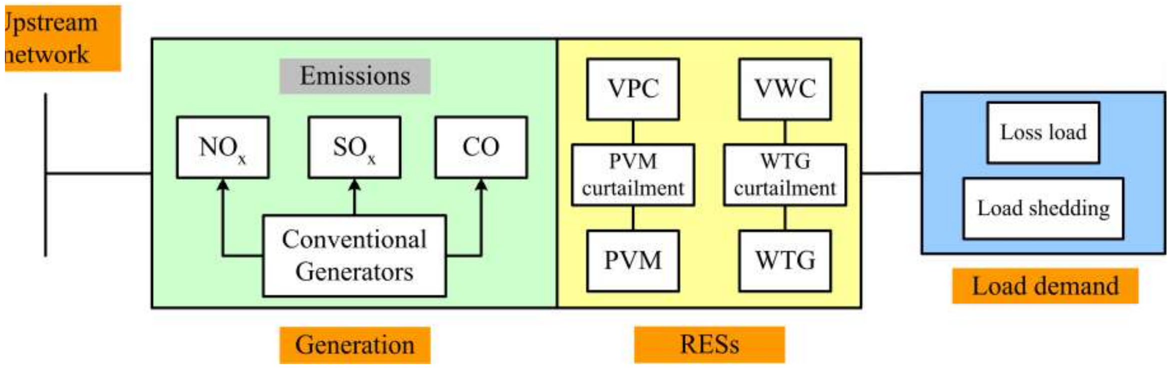

Fig. 1. Proposed model in microgrid

2.7. Economic Dispatch with Energy Storage system

ESS may play a significant role in power system uncertainty management by optimal charging and discharging. ED with energy storage system may be modeled efficiently [3]. Equation (1) can be minimized using ESS with the following equations and constraints [3].

$$SC_t = SC_{t-1} + (P_t^{ch}\eta_{ch} - \; P_t^{dis}/\eta_{dis})\delta_t \tag{16}$$

$$P_{min}^{chg.} \leq P_t^{chg.} \leq P_{max}^{chg.} \tag{17}$$

$$P_{min}^{disch.} \leq P_t^{disch.} \leq P_{max}^{disch.} \tag{18}$$

$$SC_{min} \leq SC_t \leq SC_{max} \tag{19}$$

$$\sum_{i,t} P_{i,t} + P_t^{disch.} = LD_t + P_t^{chg.} \tag{20}$$

$$\sum_{i,t} P_{i,t} + P_t^{disch.} + P_t^{wtg} + P_t^{pvm} = LD_t + P_t^{chg.} \tag{21}$$

Equation (16) represents the state of charge at the time (t) with the state of charge at the previous time ($t-1$), including charging and discharging efficiency. Equations (17)-(19) represent charging, discharging, and charging state limits of operation. Equation (20) shows that the generation with battery should always be equal to load demand. Discharging power is generation, and charging power is load in ESS. Equation (21) shows the equality constraint with renewable energy sources.
SC_t = Battery charging state at time t.

$P_t^{chg.}$ = Battery charging power

$P_t^{disch.}$ =Battery discharging power

$\eta_{chg.}$ = Efficiency of charging

$\eta_{disch.}$ =Efficiency of discharging

δ_t= Scheduling time interval (1 hour)

P_t^{wtg}= Wind turbine generated power at time t

P_t^{pvm}= Power generated by photo-voltaic module at time t

3. PROPOSED ALGORITHM

3.1. GAMS

A general algebraic modeling system (GAMS) is an available tool for optimization and modeling. The main three elements of optimization are input, output, and interconnection of modeling with equations. Input element are defined in the form of sets, tables, and fixed values. The input parameters are the total number of generators, cost and emission coefficients, the limit of generators, load demand, and uncertainty of RES. Variables value needs to be solved. The variables are generated power output, cost, emission, and multi-objective cost. Modeling of equations interconnects the input data with variables, which should be defined in GAMS. The cost equation and emission equation with operating constraints are the modeling equations. Output parameters are total operating cost and optimal generated power output. Solve statements need to be defined according to the nature of the problem. ED is a quadratic-constrained problem(QCP). Different solvers may be used for specific problems. CPLEX solver has been used in this modeling. In this problem, the multi-objective solution needs to be determined between cost and emission. Iteration will specify the minimum and maximum value of cost and emission. But it is challenging to decide on the best-compromised result. Fuzzy method is used to determine the best solution. Membership functions are need to defined for each objective function. A membership function is defined in equation [3] (16) for both objective functions.

$$\alpha^{B_j(X_i)} = \begin{cases} 0, & elsewhere \\ B_j^{max} - B_j(X_i), & \text{if } B_j^{min} \leq B_j(X_i) \leq B_j^{max}. \end{cases} \tag{22}$$

The final solution regarding decision is minimum satisfaction and maximum dissatisfaction is obtained by equation [3] (17).

$$\max_{i=1:N} \big(\min_{j=1:2} \alpha^{B_j(X_i)} \big) \tag{23}$$

Maximum value in all iterations from 1 to N is best compromise solution.

Figure 3 shows the flow chart used for ED, EMD, and MEED optimization. Table 2 shows the data for test system 1. The input parameters are cost coefficients, emission coefficients, and minimum-maximum limits of generators. Equations relate the input and output parameters. Output parameters are cost, emission, and optimal output of generators.

3.2. Steps of proposed algorithm

The following steps have been used for optimization.

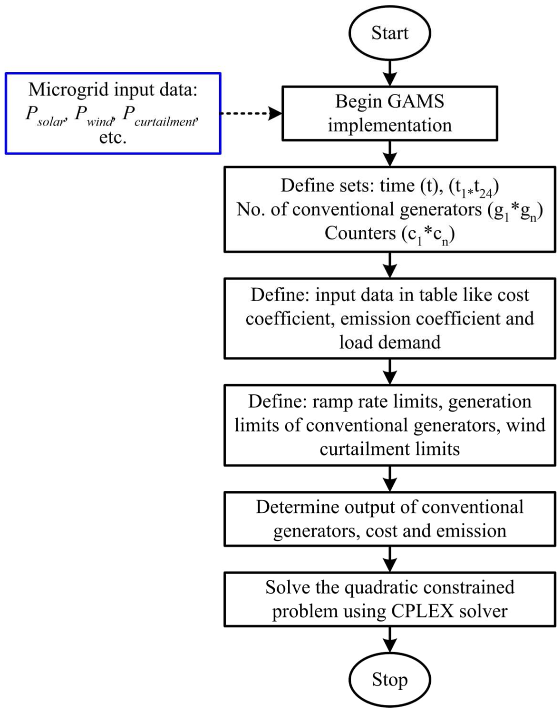

Fig. 2. Flow chart of GAMS

1) Sets: Initial step for CPLEX optimization is sets. It provides indices like the number of generators, time period and counters, etc.
2) Input Data: Input data such as cost and emission coefficient, ramp limits, minimum and maximum limits of generators, etc., need to be defined over the sets. They may be defined in the form of fixed value or tabular value.
3) Variable: Variables are the unknown before optimization, such as total cost, generated power of plants, and total multi-objective cost, etc.
4) Equations: Equations provide the relation between predefined input data and unknown variables. Proposed system contain equations such as objective function and some constraints.
5) Model and solve statement: Model name and solve statements like minimization or maximization will be defined with the model name in this step. The solver option is also available for different kinds of optimization problems. CPLEX solver has been used in the proposed study.
6) Output: Output with global solution determines the optimal value of variables required.
7) Display and summary: Output display statements like TC.l and $P(g,t)$.l will display the best value of a variable. The output summary will provide the global results with the total execution time of the problem.

4. Simulation Result

4.1. Description of test systems

Test system one consists of six CG [46]. Data for test system one is shown in Table 2. The input parameters are cost coefficients, emission coefficients, and minimum-maximum limits of generators. The output parameters are the total operating cost with an optimal power output of generators. Load sensitivity analysis has been provided between the summation of the maximum and minimum power of all CG. Static ED, EMD, and MEED Problem has been optimized using a CPLEX solver installed on a personal computer with specifications of intel corei3 processor 2.00 GHz and 4GB RAM. Test system two consists of four CG, One WTG, and One PVM [2]. This test system consists of a grid connected μG through a point of common coupling [2]. Transmission losses through energy transfer network have been neglected for simplicity. Case study for test system two has been considered for total capacity of grid connected. Cost and emission parameters are shown in Table 3 for test system two. This test system considers WTG and PVM curtailment cost due to uncertainty [2]. Uncertainty reasons may be aging, change in wind speed, change in solar radiation, and other technical reasons like wiring issues. Wind and solar curtailment with load curtailment have been considered in test system two. Forecasting of the load demand, WTG, and PVM power is shown in Table 4.

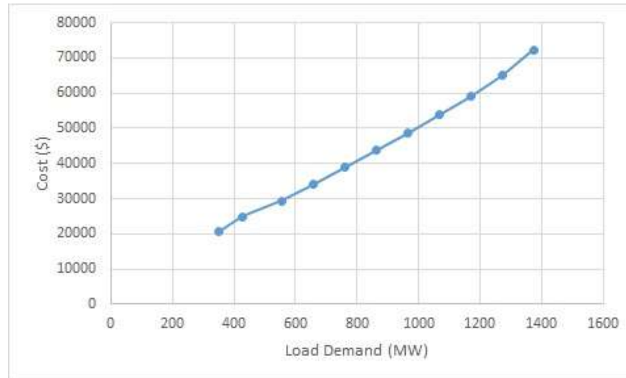

Fig. 3. Load demand vs cost for test system-1

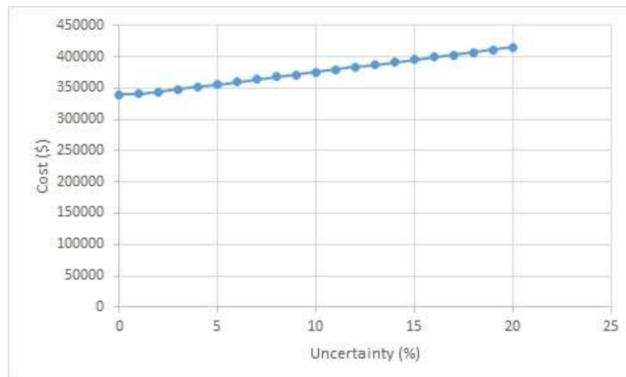

Fig. 4. Uncertainty vs cost for MEED in test system-2

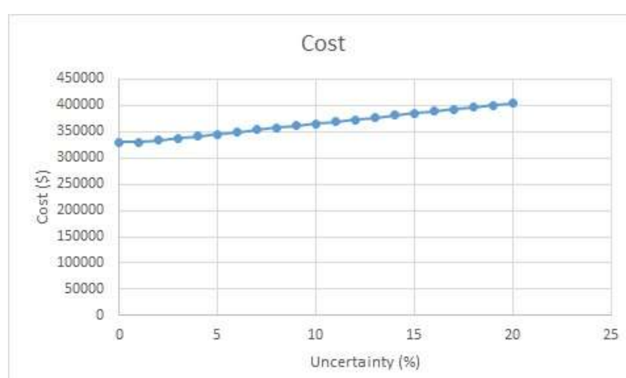

Fig. 5. Uncertainty vs cost for ED in test system-2

Table 2. Data for CG [46]

CG	$P_{i,min}$	$P_{i,max}$	$m_i(\$/MW^2h)$	$n_i(\$/MWh)$	$o_i(\$)$	$q_i(Kg/MW^2h)$	$r_i(Kg/MWh)$	$s_i(Kg)$
G1	10	125	.15247	38.5397	756.79886	.00419	.32767	13.85932
G2	10	150	.10587	46.1591	451.32513	.00419	.32767	13.85932
G3	40	250	.02803	40.3965	1049.3251	.00683	-.54551	40.26690
G4	35	210	.03546	38.3055	1243.5311	.00683	-.54551	40.26690
G5	130	325	.02111	36.3278	1658.5696	.00461	-.51116	42.89553
G6	125	315	.01799	38.2704	1356.6592	.00461	-.51116	42.89553

Table 3. Data of CG for test system-2 [2]

CG	$P_{i,min}(MW)$	$P_{i,max}(MW)$	m_i	n_i	o_i	q_i	r_i	s_i	$RU_i(MW)$	$RD_i(MW)$
G1	25	210	.16	38.50	789	1.6	5	13	35	35
G2	23	290	.11	46.15	483	2.4	4.24	16.3	39	39
G3	32	195	.03	40.39	1030	1.2	2.15	15.6	43	43
G4	21	263	.04	38.30	1149	1.8	3.99	16.3	51	51

Table 4. WTG, PVM Generation and Load Demand forecasting of power for test system-2 [5]

Time(Hours)	Forecasted load demand (MW)	Forecasted wind Power (MW)	Forecasted PV Power (MW)
1	530	51.1	0
2	540	56.5	0
3	531	63.7	0
4	525	152.7	0
5	561	212.1	32
6	571	317.1	72
7	671	368.2	105
8	691	337.2	119
9	748	281	236
10	754	336.1	265
11	749	434.1	312
12	770	411	445
13	759	456.2	482
14	730	551.7	415
15	691	521.1	407
16	730	520.5	375
17	718	491.8	207
18	781	386.6	55
19	721	392.4	0
20	700	307.3	0
21	671	327.6	0
22	514	342.4	0
23	579	411.4	0
24	512	434.4	0

Table 5. ED Cost (in $) comparison with PSO and NLP(test system-1)

	Unit	PSO [46]	NLP [46]	GAMS
Generated Power(MW)	G1	32.450	32.490	32.497
	G2	10.720	10.810	10.816
	G3	143.69	143.64	143.646
	G4	143.15	143.03	143.032
	G5	287.16	287.10	287.104
	G6	282.80	282.90	282.905
Total cost ($/h)	–	45463.49	45463.49	45463.47
Total emission (Kg/h)	–	795.110	795.070	795.018

Table 6. Emission (in Kg) comparison in EMD of micro-grid (test system-1)

	Unit	PSO [46]	NLP [46]	GAMS
Generated Power(MW)	G1	116.99	116.99	116.993
	G2	116.99	116.99	116.993
	G3	135.69	135.69	135.694
	G4	135.69	135.69	135.694
	G5	197.31	197.31	197.313
	G6	197.31	197.31	197.313
Total cost ($/h)	–	48051.22	48051.51	48051.21
Total emission (Kg/h)	–	646.12	646.81	646.11

Table 7. Multi-objective EED cost (in $) comparison of micro-grid (test system-1)

	Unit	PSO [46]	NLP [46]	GAMS
Generated Power(MW)	G1	68.86	36.02	68.860
	G2	66.77	16.66	66.768
	G3	143.77	143.79	143.769
	G4	156.01	146.54	156.010
	G5	244.55	278.73	244.538
	G6	220.01	274.24	220.010
Total cost ($/h)	–	46112.09	46248.23	46112.083
Total emission (Kg/h)	–	682.32	775.48	682.316

Table 8. Optimal cost in ED sensitivity analysis with different loads (test system-1)

Load Demand (MW)	Cost (in $)
350.0	20578.137
425.5	24933.190
555.0	29431.729
657.5	34051.453
760.0	38792.360
862.5	43654.453
965.0	48635.784
1067.5	53746.606
1170.0	59095.149
1272.5	65078.572
1375.0	72357.409

Table 9. Optimal output of CG in ED (test system-1)

Load Demand (MW)	G1(MW)	G2(MW)	G3(MW)	G4(MW)	G5(MW)	G6(MW)
350.0	10.000	10.000	40.000	35.000	130.000	125.000
452.5	15.601	10.000	51.740	70.383	165.070	139.707
555.0	19.478	10.000	72.830	87.053	193.073	172.566
657.5	23.355	10.000	93.919	103.724	221.076	205.426
760.0	27.232	10.000	115.009	120.395	249.079	238.285
862.5	31.109	10.000	136.099	137.066	277.082	271.145
965.0	34.829	14.174	156.329	153.057	303.944	302.666
1067.5	40.503	22.346	187.195	177.456	325.000	315.000
1170.0	49.381	35.132	235.487	210.000	325.000	315.000
1272.5	85.439	87.061	250.000	210.000	325.000	315.000
1375.0	125.000	150.000	250.000	210.000	325.000	315.000

Table 10. Optimal output of CG for ED in test system-2

Time(Hours)	Demand (MW)	G1(MW)	G2(MW)	G3(MW)	G4(MW)	WTG (MW)	PV (MW)
1	530	48.985	36.477	195.000	198.438	51.1	0
2	540	49.697	37.514	195.000	201.289	56.5	0
3	531	47.187	33.863	195.000	191.249	63.7	0
4	525	38.108	23.000	156.260	154.932	152.7	0
5	561	50.426	38.574	113.260	114.640	212.1	32
6	571	25.000	23.000	70.260	63.640	317.1	72
7	671	25.000	23.000	70.671	79.129	368.2	105
8	691	25.000	23.000	91.814	94.986	337.2	119
9	748	25.000	23.000	88.828	94.172	281	236
10	754	25.000	23.000	45.829	59.071	336.1	265
11	749	25.000	23.000	32.000	21.000	434.1	312
12	770	25.000	23.000	32.000	21.000	411	445
13	759	25.000	23.000	32.000	21.000	456.2	482
14	730	25.000	23.000	32.000	21.000	551.7	415
15	691	25.000	23.000	32.000	21.000	521.1	407
16	730	25.000	23.000	32.000	21.000	520.5	418
17	718	25.000	23.000	32.000	21.000	491.8	375
18	781	25.000	23.000	67.784	69.616	388.6	207
19	721	27.463	23.000	110.784	112.353	392.4	55
20	700	45.659	31.641	153.784	161.616	307.3	0
21	671	60.000	62.000	110.784	110.616	327.6	0
22	514	25.000	23.000	67.784	59.616	342.4	0
23	579	25.000	23.000	53.414	66.186	411.4	0
24	512	25.000	23.000	32.000	21.000	434.4	0

4.2. Analysis of results

Results for test system one are shown in Tables 5, 6, and 7 for ED, EMD, and MEED, respectively. Results are compared with NLP and PSO with the proposed method. The generators' power outputs are shown in Tables 5, 6, and 7 for ED, EMD, and MEED, respectively. Load sensitivity analysis is provided between 350 and 1375 MW of load demand for ED. The total cost for intermittent load is shown in Table 8. The optimal power output of generators for different load demands is shown in Table 9. The sum of the minimum power of all generators is 350 MW, and the sum of the maximum power is 1375 MW. These values are operating boundary limits for test system -1. The operating cost with 350 MW is 20578.137 \$ and 72357.409 \$ with 1375 MW. Cost is changing by 71.56% from minimum to maximum feasible load demand. Results for test system-1 are shown for static load demand.

Results for test system-2 are analyzed with RES curtailment in terms of uncertainty. Cost-only and multi-objective cost and emission results have been compared with RES curtailment. For uncertainty analysis, twenty values from 0 to 20% have been considered in the simulation. This uncertainty will increase the cost of ED and MEED. Uncertainty reasons may be uncertain weather conditions or the aging effect of equipment. Figure 4 shows the variation of cost with uncertainty (0 to 20%) for MEED. Cost increases linearly with uncertainty, and curtailment cost is a sensitivity variable. Cost variation with uncertainty for ED is shown in Figure 5. The power output of generators for cost only and multi-objective optimization are shown in Tables 10 and 11, respectively. Ramp rate sensitivity analysis has been provided, and variations of cost and emission with different ramp limits have

Table 11. Optimal output of CG for MEED in test system-2

Time(Hours)	Demand (MW)	G1(MW)	G2(MW)	G3(MW)	G4(MW)	WTG (MW)	PV (MW)
1	530	122.586	81.967	164.894	109.448	51.1	0
2	540	123.768	82.757	166.467	110.503	56.5	0
3	531	119.607	79.978	160.918	106.792	63.7	0
4	525	95.209	63.695	128.322	85.071	152.7	0
5	561	81.118	54.821	107.645	73.203	212.1	32
6	571	46.119	30.375	64.646	40.649	317.1	72
7	671	50.367	33.757	68.442	45.123	368.2	105
8	691	59.869	40.104	81.125	53.590	337.2	119
9	748	58.894	39.452	79.821	52.721	281	236
10	754	38.836	26.047	53.044	34.862	336.1	265
11	749	25.000	23.000	32.000	21.000	434.1	312
12	770	25.000	23.000	32.000	21.000	411	445
13	759	25.000	23.000	32.000	21.000	456.2	482
14	730	25.000	23.000	32.000	21.000	551.7	415
15	691	25.000	23.000	32.000	21.000	521.1	407
16	730	25.000	23.000	32.000	21.000	520.5	418
17	718	25.000	23.000	32.000	21.000	491.8	375
18	781	47.182	31.623	64.186	42.289	388.6	207
19	721	69.832	46.752	94.428	62.466	392.4	55
20	700	100.448	67.198	135.312	89.738	307.3	0
21	671	83.714	63.823	111.112	84.747	327.6	0
22	514	48.714	24.824	68.113	33.748	342.4	0
23	579	42.640	28.579	58.131	38.249	411.4	0
24	512	25.000	23.000	32.000	21.000	434.4	0

Table 12. Ramp rate sensitivity analysis and it,s effect on cost and emission for test system-2

Ramp Rate (%)	cost($)	Emission (Kg)
100	329696.560	864266.931
98	329844.297	864668.264
96	329994.304	865390.114
94	330148.295	865445.397
92	330314.363	863070.005
90	330490.717	861366.369
88	330690.087	857188.270
86	330910.831	851966.206
84	331153.295	847216.837
82	331416.887	842661.864
80	331714.400	838846.264
78	332089.058	837549.178
76	332476.447	836535.259
74	332876.601	835784.171
72	333289.815	835250.741
70	333799.229	835251.975

been proposed in Table 12. Ramp rate variation from 100 to 70 % shows an increase in cost by 1.24 % and a decrease in emission by 3.35 %. Results for cost only and multi-objective cost and emission dispatch are compared with the proposed method for 20% uncertainty in terms of curtailment and show better results. ED cost Without curtailment is 329696.439 $. ED cost with curtailment is 365200.978 $. In MEED, emission without RES curtailment is 700112.273 kg. In MEED, emission with curtailment is 700109.113 kg. Uncertainty results for multi-objective cost and emission dispatch and ED are shown in Tables 13 and 14,

Table 13. Variation in cost due to uncertainty variation in multi-objective problem for test system-2

Uncertainty	cost(in $)
0	339766
1	340162
2	343721
3	347666
4	351611
5	355556
6	359501
7	363446
8	367391
9	371336
10	375281
11	379226
12	383171
13	387116
14	391061
15	395006
16	398951
17	402896
18	406841
19	410786
20	414731

Table 14. Variation in cost due to uncertainty variation in only cost minimization for test system-2

Uncertainty	cost(in \$)
0	329696
1	329891
2	333641
3	337586
4	341531
5	345476
6	349421
7	353366
8	357311
9	361256
10	365200
11	369146
12	373091
13	377036
14	380981
15	384926
16	388871
17	392816
18	396761
19	400706
20	404651

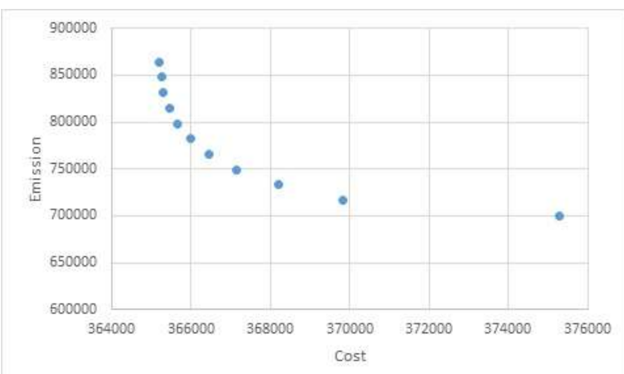

Fig. 6. Pareto optimal solution

Table 15. Comparison of results in terms of cost for test system-2

Methods	cost (\$) [2]	Cost (\$) (GAMS)
ED -Without curtailment	3.30×10^5	329696.439
ED-with curtailment	3.65×10^5	365201.078
MEED-without curtailment	3.40×10^5	339776.459
MEED-with curtailment	3.75×10^5	375281.766

Table 16. Comparison of results in terms of emission for test system-2

Methods	Emission (in Kg) [2]	Emission (Kg) (GAMS)
ED -Without curtailment	8.64×10^5	864271.345
ED-with curtailment	8.64×10^5	864177.089
MEED-without curtailment	7.00×10^5	700112.273
MEED-with curtailment	7.00×10^5	700109.135

Table 17. Comparison of results in terms of percentage improvement for test system-2

Methods	Cost (\$) [2]	GAMS
ED	9.70%	9.58%
MEED	9.46%	9.33%

respectively. Comparisons in terms of cost and emission have been shown in Tables 15 and 16, respectively. A membership function for cost (β_{cost}) and emission ($\beta_{emission}$) have been shown in Table 18. Membership function values have been assigned between 0 and 1. The minimum value (β_{cost},$\beta_{emission}$) of both membership functions have been determined in the last column of Table 18 as per the procedure of the Pareto solution. The maximum value of min(β_{cost},$\beta_{emission}$) is .703 in the 9th iteration, and it shows the optimal compromised solution.

In MOEED solution with curtailment, Cost is changing by 9.33% from 3.40 $\times$ 10^5 to 3.75 $\times$ 10^5. In ED solution with curtailment, Cost is changing by 9.58% from 3.30 $\times$ 10^5 to 3.65 $\times$ 10^5. As compared to MOEED with ED, Cost is increasing by 2.66 % from 3.65 $\times$ 10^5 to 3.75 $\times$ 10^5, but the emission is decreasing by 18.98 % from 8.64 $\times$ 10^5 to 7.00 $\times$ 10^5. Percentage improvement in results for test system-2 has been shown in Table 17.

4.3. Results obtained and the main achievements

Three comparative studies have been done for test system -1, i.e., ED, EMD, and MEED. For ED, only cost has been minimized without any concern of emission by harmful pollutants. The total cost is 45463.47 \$, and the emission is 795.018 kg with an execution time of 4.834 seconds. For EMD, only emission has been minimized without any cost concern, and results have been shown in Table 6. Execution time is 4.981 seconds. In MEED, both cost and emission have been minimized, the total cost is 46112.083 \$, and the emission is 686.316 kg with an execution time of 6.997 seconds. There are various methods to determine the multi-objective solution. This paper uses a Pareto optimal solution with fuzzy decision-making to determine the compromised solution. Load sensitivity analysis provides the feasible operation limits of test system-1. The optimal output of generators for load sensitivity has been shown in Table 9, and the execution time is 8.823 seconds. Execution time comparison has been shown in table 19 for old PC and new updated PC.

Test system -2 with 4 CGs, one WTG, and a PVM have been studied. Two comparative case studies have been analyzed, i.e., ED and MEED. Two sub-studies have been analyzed, i.e., with and without curtailment cost due to uncertainty for ED and MEED. Comparison Table 15 and 16 shows the cost and emission results, respectively. Comparison in terms of percentage improvement for test system-2 has been shown in Table 17. For ED, the cost has been reduced by 9.58 % as compared to 9.70 % in the literature. For MEED, the cost has been reduced by 9.33 %as compared to 9.46 %. Pareto optimal results with fuzzy decision making have been shown in Table 18. Variations in cost due to uncertainty (0-20%) for MEED and cost have been shown in Tables 13 and 14, respectively.

The proposed methodology using GAMS for MEED has been compared with the weighting method (WM). Different weights may be assigned for cost and emission according to priority. MEED problem has been converted into scalar optimization. Equal weights have been assigned for both the cost and emission. Similarly, the proposed method has been compared with NNC and price penalty factor (PPF). The penalty has been imposed in terms of the ratio of cost to the emission. The proposed method has been compared with different methods in terms of cost and emission in Table 21 and 22, respectively. Execution time with the updated PC

Table 18. Pareto optimal results with fuzzy satisfaction method for test system-2

Iteration	η	Total cost($)	Emission (Kg)	β_{cost}	$\beta_{emission}$	min(β_{cost},$\beta_{emission}$)
1	864266.931	365201.078	864177.089	1.000	0.000	0.000
2	847851.711	365225.178	847850.903	0.997	0.099	0.099
3	831436.491	365301.900	831435.809	0.989	0.199	0.199
4	815021.270	365439.264	815017.345	0.976	0.299	0.299
5	798606.050	365656.340	798603.274	0.954	0.399	0.399
6	782190.830	365980.909	782187.158	0.922	0.499	0.499
7	765775.609	366459.230	765775.378	0.875	0.599	0.599
8	749360.389	367159.261	749359.977	0.805	0.699	0.699
9	732945.169	368188.968	732942.462	0.703	0.799	0.703
10	716529.948	369838.885	716526.590	0.539	0.899	0.539
11	700114.728	375281.766	700109.135	0.000	1.000	0.000

Table 19. Comparison of Execution time with new upgraded PC (test system-1)

Problem	Old PC (Seconds)	New updated PC (Seconds)
ED	5.103	4.834
EMD	5.314	4.981
MEED	7.409	6.997
ED sensitivity	9.072	8.823

Table 20. Comparison of Execution time with new upgraded PC (test system-2)

Problem	Old PC (Seconds)	New updated PC (Seconds)
ED	10.769	10.063
MEED	12.081	12.673
Ramp rate sensitivity	13.523	13.102
ED with uncertainty	11.721	11.147
MEED with uncertainty	14.709	13.927
Pareto optimal solution	14.018	13.671

for test system-2 has been compared with the old PC in Table 20 for various problems.

BESS may be a better alternative for uncertainty management. The ED problem with the battery's charging and discharging have been formulated in equations (16-21). The main contribution of the proposed scheme is the reduction in cost, emission, and execution time. The comparison table shows the optimal solution and better results.

5. Conclusion and Future Scope of Work

In this paper, two test systems have been analyzed. Results of test system one have been compared for static ED, EMD, and MEED. A comparison of results shows the effectiveness of the proposed method. Load sensitivity analysis has been proposed for different load demands within feasible generation limits for ED in test system one. The feasible range of load is 350 MW to 1375 MW. ED, MEED, and RES curtailment due to uncertainty has been analyzed in test system two. Ramp rate sensitivity analysis provides the effect on cost and emission with the change in ramp limits from 100% to 70%. Major contributions of this paper are

- Static ED, EMD, and MEED results have been compared with different techniques in test system one.
- Load sensitivity analysis for test system-1 provides the 71.56 % change in cost from minimum to maximum feasible load demand.
- MEED study shows the increment in cost by 2.66 % but emission is decreasing by 18.98 %. A comparison of results in test system two shows the effectiveness of the algorithm.

Table 21. Comparison of results in terms of emission for MEED (Test system-2)

Methods	WM	PPF	NNC	GAMS
MEED-without curtailment	700117.425	700118.523	700117.536	700112.273
MEED-with curtailment	700113.619	700114.802	700113.048	700109.135

Table 22. Comparison of results in terms of cost for MEED (Test system-2)

Methods	WM	PPF	NNC	GAMS
MEED-without curtailment	339779.853	339780.002	339784.417	339776.459
MEED-with curtailment	375286.493	375287.162	375289.098	375281.766

- Reduction in cost due to uncertainty in ED is 9.58% as compared to 9.7%.
- Cost has been reduced in MEED by 9.33% as compared to 9.46%.

  Future scope of the proposed work: Purposed work may be extended using different kinds of generation sources like biomass, geothermal and tidal, etc. ESS with demand response may be used for a better optimal schedule. Sensitivity analysis of different parameters may be imposed on standard IEEE test systems and multi micro-grid. The proposed problem may be optimized using good global solvers such as Baron in GAMS. GAMS have some minor limitations. GAMS requires some other software tools to visualize results like MATLAB. It requires solver selection according to the nature of optimization problem. Purposed work may be extended by optimal dispatch of different generation types with virtual energy storage systems such as hydrogen storage systems and virtual power plants with contingencies. Optimal sizing of battery for proposed model may be better future scope.

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