Risk Based Day-ahead Energy Resource Management with Renewables via Computational Intelligence

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Abstract- An indeterminate and variable nature of renewable energy sources like solar photovoltaic, wind power, load consumption, electric vehicles trips and market spot prices, make the operation and control of energy management system quite complex. Also, it is expected that the system should be consistent and resilient in case of extreme events like faults, hurricanes etc. This paper has used the risk based optimization strategies considering uncertainty of aforementioned parameters to minimize the operational cost of the aggregator. A 13-bus practical distribution system with 15-scenarios (03-scenarios as extreme events with high impact) are considered as a test system. WCCI-2018 award winning, Enhanced Velocity Differential Evolutionary Particle Swarm Optimization (EVDEPSO) computational intelligence method has been used to solve this problem. The comparative analysis of EVDEPSO with most popular Differential Evolution (DE) method shows that it provides better solutions than DE method.

Keywords- Electricity Market; Energy Management; Optimization; Smart Grid.

1. Introduction

The unpredictability of power generation by renewable energy resources, such as wind, solar insolation, results in a natural cycle in renewable energy generation. Because the principle of stable operation of an electrical power system necessitates a persistent balance between generation and demand, a huge involvement of variable renewable energy sources and their uncertainty significantly increases the challenge of managing the power system from the standpoint of security and robustness [1]. Given the power system's and market's reliance on weather, determining the timeline related variability with each technology is critical [1]. The modeling of energy resources provide a framework that are frequently used to optimise the design of distributed energy systems (DES). But, uncertainty can impair the model-based strategy of DES, leading to substandard design results. This uncertainty is presented by factors such as the stochastic behavior of renewables or the unidentified upcoming global energy and economical viewpoint [2]. The completion of a detailed uncertainty characteristic is a vital initial step in any effort to investigate and include uncertainty in the design of DES [2].

The work in [3] presents a policy to decrease load shedding in islanded operating mode by properly utilizing available resources. The researchers employed mixed integer linear programming to model the normal and robust methods. Similarly, when compared to AC microgrids, the work in [4] explores the benefits of classified DC control systems in microgrids for enhancing resiliency. The work in [5] employs a self-healing approach to increase the resilience of overloaded microgrids utilising both centralized and distributed means. In the decentralized stage, the frequency of each migrogrid is utilized to specify the requirement of connections between different microgrids. At the centralised stage, the entire quantity of electricity generated by all microgrids is calculated. On other hand, extreme weather are becoming more common across the world, posing significant challenges to power grid resilience. Microgrids are a popular way to enhance the resilience of a power infrastructure. The study [6] describes how to manage battery storage system in a solar PV powered commercial building to improve resilience while lowering operational costs. To justify the uncertainty in the day-ahead energy price and solar power generation, concept of conditional value at risk (CVaR) was applied. The research work in [7] developed a novel stochastic bi-level model for optimum risk-based microgrid scheduling under load demand and renewable power generation uncertainty. In the upper and lower levels, the provided bi-level model determines the ideal size and location of Distributed Energy Resource (DER) units, as well as the best distribution of section switches to describe the boundary of microgrid. It solves microgird planning problem using a scenario-based strategy, with the Kantorovich scenario reduction method being used to achieve a balance between solution accuracy and computing burden, considering risk natural and risk averse approaches.

Several studies has implemented meta heuristic optimization techniques in microgrid applications for solving ERM problems [8,9]. The proposed methods in the work [8] and [9] are Cross-Entropy Variable Neighborhood Differential Evolutionary Particle Swarm Optimization (CE-VNDEPSO) and Hybrid Levy Particle Swarm Variable Neighborhood Search Optimization (HL_PS_VNSO) respectively. A multiple microgirds with interconnections has been proposed in [10] with optimum planning under uncertainty. To achieve an improved system operation and managing efficiency, [11] proposed stochastic resource plan method. With the inclusion of dispersed generating and energy storage devices in the system, the work in [12] proposed an integrated graph partitioning and integer programming technique for optimum loop-based construction of microgrid. An hourly based energy scheduling optimization is investigated in [13] where, the findings indicate how forecast inaccuracies, as well as contractual restrictions between the storage system, Electric Vehicle (EV) charging station and aggregator, affect the energy scheduling expenses.

A work presented in [14] is focused on optimum energy scheduling for a smart residential building where, an optimization problem is framed in which not only the ideal contract power value is determined, but also the optimal schedule of the EV charge and discharge is determined, taking photovoltaic power generation and load consumption profiles into account. The findings revealed that by combining an appropriate single contract power value with an energy management system, the power expenses may be significantly reduced. To address medium voltage (MV) networks vulnerable to economic and technical concerns, by using branch exchange algorithm, a mathematical model of a novel risk-based strategy for optimum feeder routing has been devised in [15]. Through a collection of scenarios, the proposed technique evaluates the stochastic performance of distribution system demand and local generation. Using risk analysis indexes, the suggested strategy minimizes the cost of preparing for the worst-case situations. The cost of severe occurrences is taken into account while deciding on the best setup.

A risk-based formulation for aggregators has been proposed in certain articles. A decision-making dilemma for profit maximising of a wind generating provider and the supply of Electric Vehicle (EV) and demand response (DR) aggregators, for example, is described in [16]. The risk measurement parameter is used in that effort to reduce the influence of market price uncertainty, EV and DR demand, and bids made by other wind generating organizations. A work in [17] formulates the risk-constrained stochastic power procurement issue of electrical retailers, taking into account load and pool-market pricing uncertainty. The authors suggest a risk method for achieving identical cost in all uncertainty situations, resulting in a scenario-independent procedure that costs the merchant more but carries nearly no risk..In same regards, risk curtailment strategy was fully established in [18] to limit the danger of the existence of uncertain units such as wind.

The heuristic viral colony search algorithm and the discrete non-linear programming model are used to solve the model. Considering the Robust ERM, optimum DER management for profit maximization risk analysis is incorporated in [19] using CVaR to assess the risk linked with the uncertainty of various DER. The average earnings fall as the weight allocated to risk aversion grows, and the CVaR cost increases. However, electric vehicles were not taken into account in the model used in this study. A recent work in [20] solves ERM problem where the findings reveal that even with a 4% rise in operating expenses and a 6.2 percent increase in projected costs, the risk mechanism provides for a better and more robust solution. This is achieved by lowering the risk measurement parameters (VaR and, as a result, CVaR) as well as the worst-case scenario cost. In other words, by choosing this option, the aggregator lowers its risk in the event of the worst-case scenario, with a 13.89 percent price drop in the objective function.

The proposed work in this paper, takes a platform of IEEE WCCI 2022 event [21], where energy resource management (ERM) problem considering unpredictability of power generated by renewables, variable load demand and consumption, market prices, and uncertain electric vehicles trips, similar to the works presented in [22], [23]. The stochastic nature of these restrictions is examined using a number of scenarios, each with a chance of occurrence. The peculiarity of this new test case is the inclusion of risk strategies in the formulation, which allows the aggregator to plan their operations taking into account various degrees of risk associated with various situations like risk-neutral and risk-averse considerations. By doing this, an expectation is to develop a solutions that safeguard the aggregator from severe events and developing a unique optimization model that takes into account a large number of distributed energy resources.

2. Methodology

2.1. Energy Resource Management System

In the proposed work, the Energy resource management (ERM) problem is shown in Fig. 1. And it has following features:

- Consideration of uncertainty of renewable power generation, load, EV trips and market prices.
- The use of risk analysis methodologies such as value at risk (VaR) and conditional value at risk (CVaR) measures to cope with parameter uncertainty and find solutions that protect the aggregator from severe situations.
- To cope with the computational cost of considering all conceivable scenarios with unknown parameters and the huge number of variables addressed, the method is based on current metaheuristic optimization method.
- To investigate the impact of VaR and CVaR metrics in power and energy systems over a series of case studies based on real-world data.

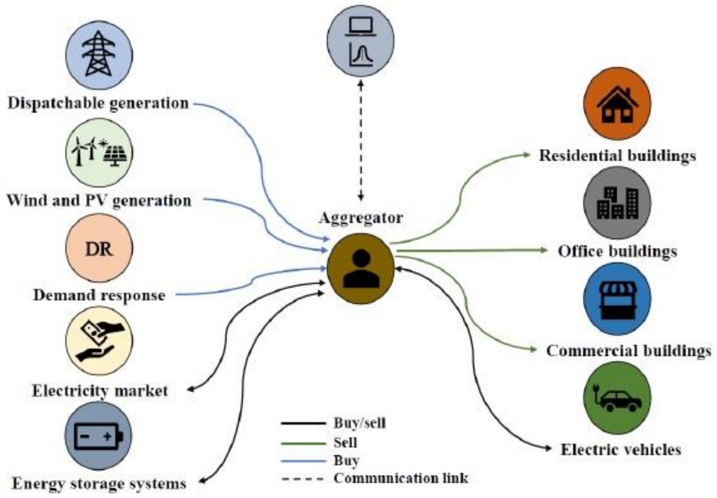

Fig.1. Risk based ERM [14]

The solution structure is a critical component of metaheuristics for representing a given solution. The 2022 competition solution representation is based on the vector form shown in Fig 2. The ERM under consideration includes 13,680 variables per individual, 570 variables distributed per period, with 21 variables forming the generators' active power and another 21 binary variables indicating the generators' status. A total of 500 EVs were investigated, with 25 different load types, two different ESSs, and one market . The fitness function that the selected metaheuristic assesses for cost reduction is shown in Fig. 3. The database containing the formed scenarios is supplied as an input to the function at first, along with the value of the risk aversion variable. The equations in the appendix section of [21] are then used to analyse each situation

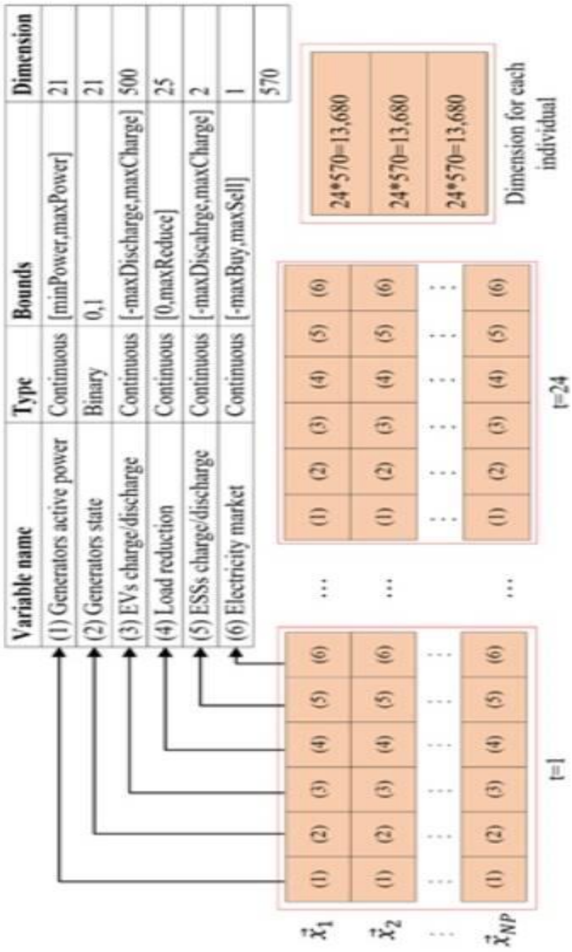

Fig.2. Solution Representation [21]

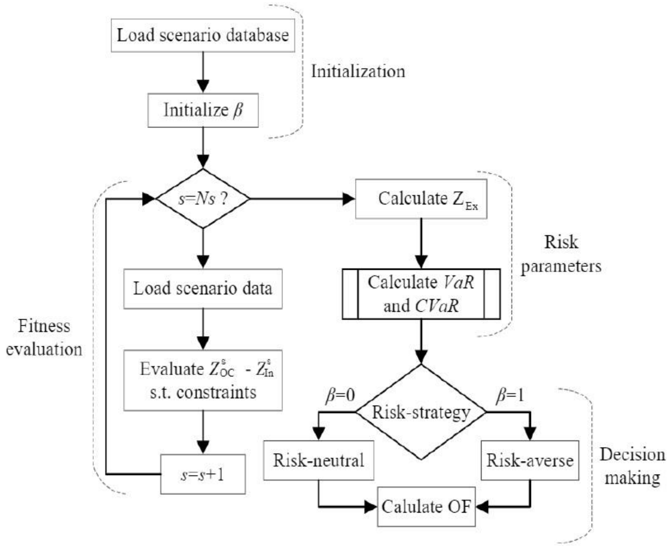

Fig.3. Fitness Function Evaluation [21]

This analysis is carried out in order to determine the cost of each scenario, which is then kept in order to compute the projected cost. According to the formula in [15], the VaR and

CVaR values are calculated using the estimated cost, the cost of each scenario, and the probability of each scenario. The aggregator initiates a judgement process based on the risk aversion factor once the risk parameters have been determined. That is, the aggregator picks the optimum method depending on the value of the Objective Function. The metaheuristic performs this evaluation task in order to reduce the Objective Function value in a specific number of iterations; hence, when, the metaheuristic will merely reduce the predicted cost. Even when the is equal to 1, the metaheuristic seeks to minimise both the estimated cost and the CVaR [11].

For the day ahead, a risk-neutral approach is being examined. ERM takes into account the unpredictability of an aggregator's technology as stated before. In this situation, the stochastic behavior of these parameters is taken into account in the strategy, which involves a series of scenarios each with a chance of occurrence. This aggregator's schedule is created depending on the predicted scenario when risk is not taken into account. The anticipated cost is the cost and value of the goal function when no risk aversion technique is used, and its formulation is provided by the equations below [21].

$$Z_s^{tot} = Z_s^{OC} - Z_s^{In} + P_s \tag{1}$$

$$Z^{Ex} = \sum_{s=1}^{N_s} (\rho_s \times Z_s^{tot}) \tag{2}$$

Where, Z_s^{tot} is the value of total objective function (OF) for each scenario s, Z_s^{OC} represents operational cost, Z_s^{In} is income in each scenario, P_s is penalty for bound violation, Z^{Ex} is expected objective function cost, ρ_s is probability of respective scenario. A risk-aversion approach examines the risk related with the previously listed technologies' unpredictability. The additional cost is $CVaR_\alpha$which is added to expected OF cost in $(1-\rho_s)$ % of scenarios having highest cost. After calculating VaR_α, the $CVaR_\alpha$ is calculated by using following equation [15].

$$CVaR_\alpha(Z_s^{tot}) = VaR_\alpha(Z_s^{tot}) + \frac{1}{1-\alpha}\sum_{s=1}^{N_s}(\rho_s \times \varphi) \tag{3}$$

Where,

$$\varphi = Z_s^{tot} - Z^{Ex} - VaR_\alpha(Z_s^{tot}) \forall Z_s^{tot} \geq Z^{Ex} + VaR_\alpha(Z_s^{tot})$$

$\varphi = 0$ Otherwise

$$VaR_\alpha(Z_s^{tot}) = z - score(\alpha) * std(Z_s^{tot})$$

Here, φ is a cost parameter connected with the worst-case situations; that is, when the cost of each scenario s goes beyond the predicted cost when the VaR_α value is added. If the reverse happens, φ is set to 0. The norminv() function in MATLAB is used to determine the z-score, which is set to 95 percent. Considering this parameter, the scheduling problem's fitness value (and OF) fluctuates depending on the degree of risk aversion considered. In this case, the model of the fitness value (or OF) is as follows:

$$OF = Z^{Ex} + \beta * CVaR_\alpha(Z_s^{tot}) \tag{4}$$

The parameter β in this case shows the proportion of aversion to risk. This option has a range of 0 to 1. When 0 is used, the OF value equals the anticipated cost, which is a risk-free approach. In contrast, a value of 1 indicates that the approach has a complete aversion to risk, giving the safest answer in the worst-case situation. For this study, β is set to 1 and operational cost and income cost calculations areas per [21].

2.2. *Enhanced Velocity Differential Evolutionary Particle Swarm Optimization (EVDEPSO) Algorithm*

The EVDEPSO method [19] (Enhanced Velocity Differential Evolutionary Particle Swarm Optimization) is an upgraded version of the Differential Evolutionary Particle Swarm Optimization algorithm (DEEPSO). Where DEEPSO is a hybrid of PSO, EA, and DE. The first stage of the EVDEPSO method is to determine the strategic parameters, after which equations (5) and (6) are used to initialize the population's location and velocity [24].

$$X_{p,d} = X_d^{\min} + (X_d^{\max} - X_d^{\min}) \tag{5}$$

$$V_{p,d} = V_d^{\min} + (V_d^{\max} - V_d^{\min}) \tag{6}$$

The starting location and velocity of the particle p for dimension d are $X_{p,d}$ and $V_{p,d}$ respectively. In this case, p=1, 2...., Np and d=1, 2...., D. Where Np is the population size and D is the solution vector's dimension, after the populations have been initialized, fitness of each particle is evaluated and calculation is done for the global best particle G_{best} according to equations in [24]. If the new velocity calculated [24] exceeds the boundary limit, it is adjusted using equation (7). After that equation (8) is used to calculate new position.

$$V_p^{new} = \begin{cases} V_p^{\min} + L.F(V_p^{\max} - V_p^{\min})...if..V_p^{new} > V_p^{\max} \\ V_p^{\min} + L.F(V_p^{\max} - V_p^{\min})...if..V_p^{new} < V_p^{\min} \end{cases} \tag{7}$$

$$X_p^{new} = D.F * (X_p + V_p^{new}) \tag{8}$$

This equation is a tweaked version of the standard new position equation that all population-based algorithms use. The vector sum of the current particle location Xp and new velocity multiplied by Deceleration Factor (D.F.) decelerates particle movement and prevents them from trapping in local minima in this equation. The concept of algorithm is shown in fig 4.

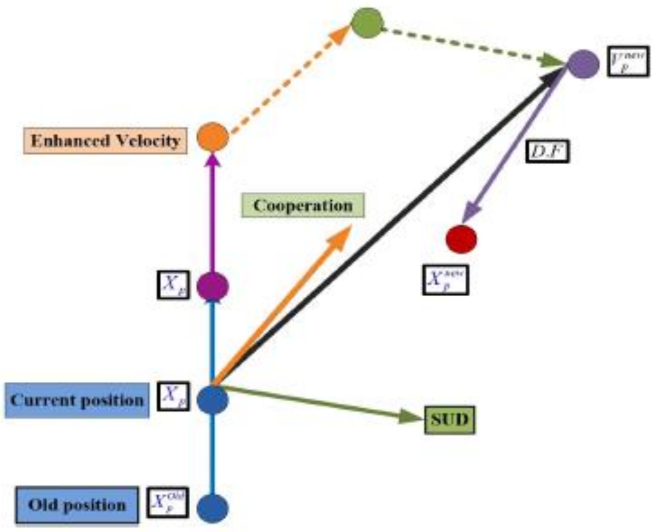

Fig.4. Illustration of EVDEPSO

The problem is solved by step by step manner as per proposed methodology. In the first step, the strategic parameters of the algorithm is set and the initialization of position & velocity of each particle has to be defined. To find the global best particle, the fitness of each initialized particle is evaluated and then EVDEPSO memory is updated with the global best particle. Iterations begin at the third phase. Copy each particle's current position and velocity, then update memory with the copied population and current global best particle. The numbers are generated randomly between 0 and 1, where, if the value is higher than local search probability then global exploration calculates new velocity and position of each particle, otherwise local exploration calculates the same. Search space limit is enforced after calculation the new velocity and position. The best particle is calculated and it is used to generate new population for next iteration. The process is repeated for global best particle. The memory of EVDEPSO is updated and next iteration takes place to check threshold limit of maximum iteration. If the threshold limit is reached, the algorithm is ended OR process starts again.

3. Test System

This case study used a medium voltage distribution network from a smart city in the BISITE laboratory in Salamanca, Spain [25]. In bus 1, there is a 30MVA substation, 15 DG units consisting of 2 wind farms and 13 PV plants, and four 1Mvar capacitor banks. This network includes 25 various loads in terms of consumption, including residential and office buildings, as well as some service buildings like hospital, fire station, and shopping mall.

For EV charging, there are four slow charging stations with 7.2kW rating and three fast charging stations with 50kW rating. Fig 5 shows line diagram of 13 bus distribution network. The specifications of energy resources are shown in table 1.

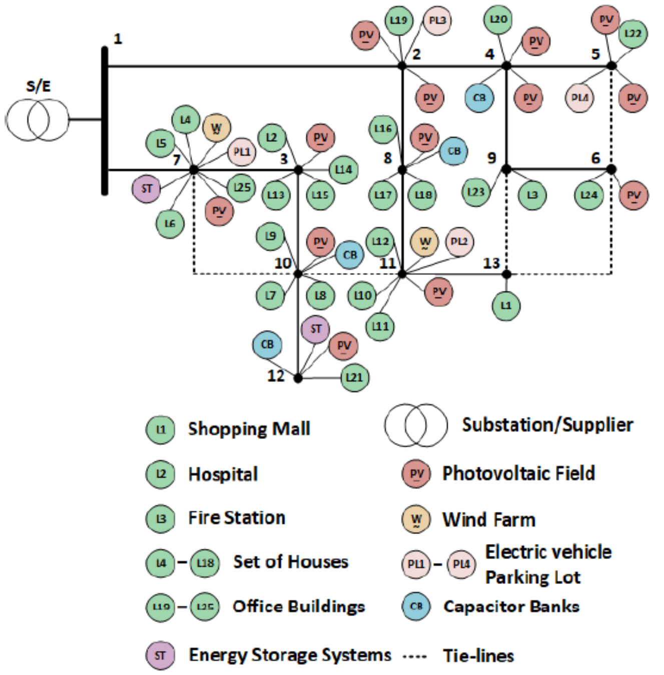

Fig.5. 13 bus system network [21]

Table 1. Energy Resources Specifications

Energy Resource	Prices (m.u./MWh) min-max	Capacity (MW) min-max	Forecast (MW) Min-max	Units
PV	29-29	--	0-0.81	13
Wind	31-31	--	0.3-3.07	2
External supplier	50-90	0-30	--	1
Storage (charge)	110-110	0-1.25	--	2
Storage (Discharge)	90-90	0-1.25	--	--
EV (charge)	0-0	0.01-0.05	--	500
EV (Discharge)	90-90	0.01-0.05	--	--
Demand Response	100-100	0-1.21	--	25
Load	0-0	--	0.01-2.38	25
Electricity Market buy & Sell	29.85-104.61	--	--	1

4. Result Analysis

In this section, the results obtained by competition organizers [21] by DE and results obtained by proposed algorithm EVDEPSO [24] are compared. The benchmark results and benchmark scenarios for DE are shown in table 2 and table 3 respectively. The benchmark results gives results of objective function, expected cost (Fex), value at risk and conditional value at risk. The benchmark scenarion results are evaluated for average, minimum, maximum and standard scanario values. The same results for EVEDEPSO will be obtained for comparative analysis.

Table 2. Benchmark Results of DE

Row	OF	Fex	VaR	CVaR
Run 1	109344.91	17412.586	49738.304	91932.321
Run 2	119560.56	18961.773	55406.232	100598.79
Run 3	120172.26	18150.121	55163.108	102022.14
Run 4	116199.83	17976.216	53212.798	98223.612
Run 5	111885.68	17654.665	50957.88	94231.014
Run 6	127374.75	18073.717	59065.031	109301.03
Run 7	109839.74	17380.123	50093.264	92459.619
Run 8	114352.43	17547.672	52332.456	96804.753
Run 9	105847.59	16987.619	48061.126	88859.969
Run 10	110171.95	17397.799	50190.539	92774.151
Run 11	121053.44	17816.645	55824.075	103236.8
Run 12	119597.93	18001.435	54941.574	101596.49
Run 13	118539.96	18661.52	54430.844	99878.441
Run 14	125988.24	18219.462	58246.364	107768.78
Run 15	112282.95	16851.466	51595.976	95431.482
Run 16	119334.54	18187.962	54957.644	101146.58
Run 17	113781.23	17571.271	52012.265	96209.958
Run 18	112914.21	17774.009	51466.054	95140.197
Run 19	112284.27	16971.381	51534.183	95312.885
Run 20	119610.87	17992.249	54931.1	101618.62

Table 3. Benchmark Scenarios of DE

Row	Avg	Min	Max	Std
	Scenario	Scenario	Scenario	Scenario
Run 1	22087.12	12551.644	130441.92	30238.742
Run 2	24812.34	12962.693	142156.84	33684.597
Run 3	23202.6	12960.698	143601.77	33536.788
Run 4	23096.49	12691.855	138705.24	32351.084
Run 5	22189.7	12960.165	133522.25	30980.191
Run 6	23253.47	12705.743	152492.75	35908.989
Run 7	22209.07	12331.82	131022.92	30454.542
Run 8	22231.04	12676.134	136588.57	31815.874
Run 9	21330.7	12529.862	126247.01	29219.09
Run 10	21901.17	12719.721	131463.76	30513.681
Run 11	22838.56	12611.131	144759.81	33938.628
Run 12	22876.83	12892.318	142925.39	33402.105
Run 13	24164.47	12988.56	141263.76	33091.603
Run 14	23500.95	12805.013	150749.45	35411.275
Run 15	21467.92	12072.165	134200.7	31368.126
Run 16	23648.66	12547.785	142429.01	33411.875
Run 17	22329.41	12598.385	135880.08	31621.212
Run 18	22602.68	12735.633	134751.28	31289.139
Run 19	21576.31	12213.764	134173.62	31330.559
Run 20	22836.69	12948.923	142954.63	33395.737

The results of benchmark and scenarios for EVDEPSO are shown in table 4 and table 5 respectively.

Table 4. Benchmark Results of EVDEPSO

Row	OF	Fex	VaR	CVaR
Run 1	114380.28	13979.1	54266.08	100401.2
Run 2	101313.84	16360.4	48508.65	84953.48
Run 3	102105.62	13848.8	47745.84	88256.83
Run 4	99807.343	15484.5	47883.44	84322.86
Run 5	116447.35	14266.3	55222.96	102181
Run 6	138798.35	19216.4	69089.6	119581.9

Run 7	98061.022	15295.6	48678.06	82765.4
Run 8	97300.882	13572	46333.16	83728.88
Run 9	145182.39	17395.8	70891.71	127786.6
Run 10	99862.396	13488.7	46874.07	86373.7
Run 11	123139.61	18081.4	61141.37	105058.2
Run 12	135236.62	19195.3	67799.62	116041.4
Run 13	85420.182	13982.9	38713.14	71437.31
Run 14	99480.817	13954.4	46270.11	85526.43
Run 15	144022.61	20008.1	71486.03	124014.5
Run 16	123763.22	16873.8	60859.26	106889.4
Run 17	93782.959	16240.5	44064.61	77542.41
Run 18	122903.77	20648	58908.18	102255.8
Run 19	87821.422	15371	42576.44	72450.46
Run 20	137081.11	17541.6	67764.56	119539.5

Table 5. Benchmark Scenarios of EVDEPSO

Row	Avg Scenario	Min Scenario	Max Scenario	Std Scenario
Run 1	18839.6	8978.2	137447.8	32991.4
Run 2	21917	10575	119536.3	29491.2
Run 3	18297.1	9221	122361.1	29027.4
Run 4	21320.1	9454.6	108074.2	29111.1
Run 5	19196.6	9197.7	139926.4	33573.2
Run 6	27075.1	11134	164044.5	42003.5
Run 7	21052.4	9344.1	115104.7	29594.2
Run 8	18587.4	8418.2	115998.7	28168.6
Run 9	24920.6	9663.6	173629.8	43099.1
Run 10	18099.8	8749.9	119612.2	28497.4
Run 11	25140.8	10753	145098	37171.3
Run 12	26998.2	11175	159357.5	41219.2
Run 13	17607.4	10202	101782.3	23535.9
Run 14	18194.1	9568.3	119109	28130.2
Run 15	28433.7	11410	162794.9	43460.4
Run 16	23717.8	9822.4	146778.3	36999.8
Run 17	21293.5	11056	110521.9	26789.4
Run 18	27641.1	13462	138097.8	35813.6
Run 19	20451.2	10125	102758.4	25884.6
Run 20	25068.2	9838.3	162968.6	41197.9

The comparison of ranking index, standard deviation, minimum deviation, maximum deviation, variance and average time for both algorithm is shown in table 6. A lower ranking index and higher value of cost saving shows that EVDEPSO gives better results than DE. The only positive side of DE is time taken for iterations.

Table 6. Benchmark Summary

	DE	EVDEPSO
Ranking Index	116006.87	113295.5893
Pstd OF	5663.1432	19310.50683
Pmin OF	105847.59	85420.18185
Pmax OF	127374.75	145182.3906
Pvar OF	127374.75	372895673.9
Avg Time	274.56178	331.0997494

The comparison of worst case objective function values obtained by DE and EVDEPSO for all 20 runs are shown in fig 6. Again these results proves EVDEPSO results better than results of DE. Considering the results of the run 6, run 9, run 12, run 15 and run 20, the results of EVDEPSO gives higher cost savings which are rarely achievable by DE.

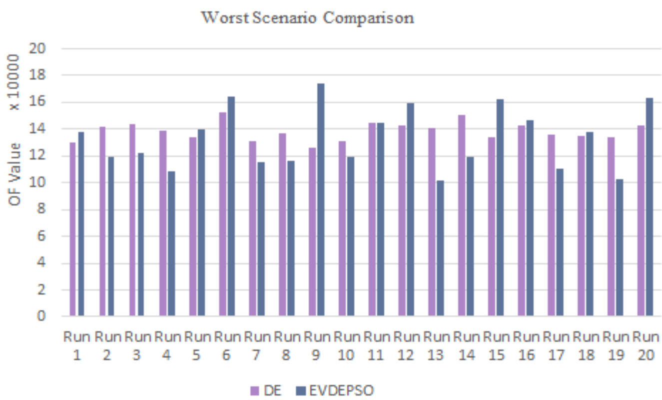

Fig.6. OF values in worst case

The bound violations in OF values for all 20 runs by both algorithms are compared in fig 7. While comparing the values of objective functions, a much better value is obtained by EVDEPSO.

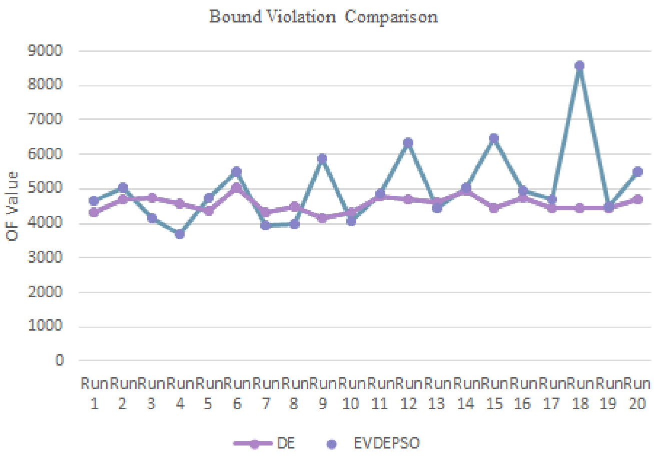

Fig.7. Bound violation in OF value

Another parameter to compare both algorithms is run time taken by them which is shown in fig 8. For higher accuracy, EVDEPSO takes more time in first 19 runs, whereas in 20th run the time taken by DE is much higher.

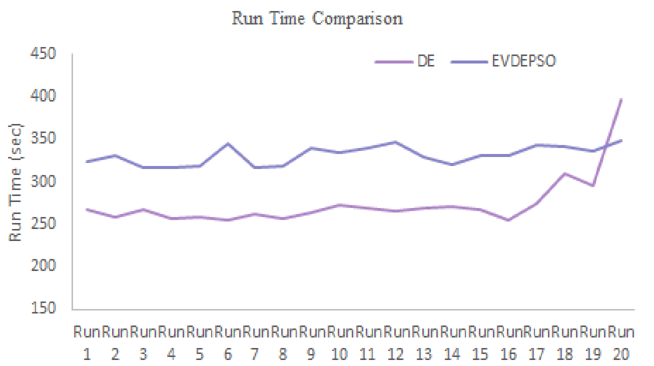

Fig.8. Run Time Comparison

Comparing overall results, a better cost savings, lower ranking index and worst case scenario results, EVEDEPSO gives better performance than DE. The future work may include optimal planning of a microgrid with wind energy [26], optimal sizing of energy resources [27], Electric vehicle [28] and smart metering [29] considering optimization techniques used in present work.

5. Conclusion

This paper has focused energy resource management for microgrid application. The uncertainty of renewable power generation under extreme conditions is taken as an optimization challenge. The results were obtained according to the rules and requirements of IEEE WCCI 2022. An optimization algorithm used in above mentioned event is DE, which is compared with EVDEPSO for IEEE 13 bus system. Both computational intelligence techniques were tested for OF value, ranking index, VaR, CVaR and run time. A significant improvement in resilience of grid operation is observed with EVDEPSO compared to DE.

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