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COMPARATIVE ANALYSIS OF EV-MOGA AND GODLIKE MULTIOBJECTIVE EVOLUTIONARY ALGORITHMS FOR RISK BASED OPTIMAL POWER SCHEDULING OF A VIRTUAL POWER PLANT

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Abstract

An attempt has been made in this article to compare the performances of two multiobjective evolutionary algorithms namely ev-MOGA and GODLIKE. The performances of both are evaluated on risk based optimal power scheduling of virtual power plant. The risk based scheduling is proposed as a conflicting bi objective optimization problem with increased number of durations of day. Both the algorithms are elaborated in detail. Results based on the performance analysis are depicted at the end.

Keywords:

MCP (Market Clearing Price), RTO (Regional Transmission Operator), VPP (Virtual Power Plant), RES (Renewable Energy Sources), LCOE (Levelised Cost of Electricity), Distributed Generation (DG)

1. INTRODUCTION

Evolutionary algorithms (EAs) are the population-based metaheuristic optimization algorithms. They belongs to a class of stochastic optimization methods simulating the process of natural evolution. In 20^{th} century particularly after 1970s different types of evolutionary methodologies have been proposed.[1]. Evolutionary algorithms are easy to implement and often provide adequate solutions. An origin of these algorithms is found in the Darwian principles of natural selection (Darwin, 1859). In accordance with these principles, only the fittest individuals can survive in the struggle for existence and reproduce their good characteristics into next generation. There are several algorithms in EA category; genetic algorithm (GA), evolutionary strategy (ES), genetic programming (GP), and so on. Genetic algorithm (GA) has been firstly presented by J. Holland in 1975. The GA, which is the algorithm to mimic the natural evolution, is widely applied to optimization, adaptation and learning problems. Many improved algorithms are derived from the simple Genetic Algorithm.

A virtual power plant can be defined as a cluster of grid connected distributed generators (DGs) that are monitored and controlled on an aggregate level by a VPP operator for commercial or technical objectives. This cluster can then be treated as a single power producing entity. A commercial VPP has objective to participate in trade on energy markets and a technical VPP is used to lend management of some typical distribution network tasks like provision and regulation of reserve power. Some times VPP in broader sense may include renewable energy sources and controllable loads. The VPP sometimes may be centralized or decentralized depending upon the method of control used by VPP operator [2].

Optimal operation of Virtual Power Plant is studied in literature from different prospective. Self scheduling is essential for optimized operation of power plant. While self scheduling the associated risk also plays a vital role. Risk based self scheduling of power plants is not a new topic in literature.

Efforts have been made to find out Optimal scheduling in VPP by using Linear Programming [3]. Mixed Integer Linear Programming [MILP] method has been used to optimize the day-ahead thermal and electrical scheduling of a large scale VPP (LSVPP) containing many small-scale producers and consumers (“prosumers”) distributed over a large territory and energy storage along with cogeneration processes [4]. MILP has been also used to maximise profit of the VPP operator [5]. In the profit maximization problem demand side bidding for dispatchable loads, Renewable Obligation Certificate (ROC) for renewable based Distributed Generations (DGs) and the cost related to Use of System (UoS) charges to Distribution System operator (DSO) have been considered. Efforts have been also made to model a Agile VPP using quadratic programming [6]. The electricity generation costs, the total costs and loss of energy produced by generators based on renewable energy sources (green energy) of VPP has been minimized by using LCOE [7]. Operation cost has been minimized by using Linear Programming [8]. The accelerated PSO has been also used for finding out optimal dispatch of Renewable Energy Sources to maximize the profit of VPP [9].

Self-scheduling problem of a price-taker power producer by using a mixed-integer quadratic programming method has been also stated [10]. Maximization of profit considering the risk that can be tolerated as well as the optimal operation of a VPP in a microgrid considering the uncertainties of the energy and fuel prices and managing the variance/risk of the VPP’s profit with respect to these uncertainties has been studied so far [11]. Hybrid PSO has been used to optimize the operation of risk constrained VPP [12].

After having a brief introduction in section 1 about the status of study of mentioned area, the rest of paper is arranged as follows.

The main innovation of this paper are described in section 2. Section 3 details the information about the ev-MOGA multi objective optimization. Section 4 deals with GODLIKE optimization algorithm. Having introductions about the two algorithms, latter on section 5 gives brief introduction about VPP model considered in this article. Section 6 gives information about the Indian Electricity Market. Section 7 gives information about Levelised Cost of Electricity (LCOE). Section 8 deals with problem formulation. Section 9 explains the case study used for this article. Section 10 carries over the results of simulations and discussion. Finally section 11 concludes the article.

2. MAIN INNOVATIONS OF THIS PAPER

All above stated attempts [9] to [12] related to optimization of risk constrained scheduling have considered two functions mainly profit and risk for optimization. All of them have used technique presented for portfolio selection [13]. This technique uses a single objective function with the help of a risk tolerance parameter. This approach of solving multi objective optimization problem by converting it into single objective optimization is associated with invariable limitations [14]. Some of them are reproduced here:

- Requirement of anterior knowledge about the relative importance of the objectives.
- Such amalgamated function leads to only one solution per run.
- Trade-offs between objectives cannot be smoothly evaluated.
- The solution may not be possible unless the search space is convex.

As per authors knowledge only single and well attempt has been made in literature so far to solve above problem by using Multi Objective Optimization method (Pareto front method) [15]. In this attempt the authors have used MOPSO to evaluate risk constrained optimal self scheduling on hourly basis by considering the data for RTO - PJM electricity market in United States. Also for calculating the cost function the authors have used quadratic function of generator power output.

In the present article the authors envisages a novel method of risk constrained self scheduling of a VPP on 15 minutes basis by considering the data for Indian Electricity Market. Here for evaluating the cost objective another valuable metric called as Levelised Cost of Electricity (LCOE) is used. Instead of following the conventional portfolio selection method, the authors have implemented a elitist multi-objective evolutionary algorithm and a multi-objective metaheuristic optimization algorithm for scheduling and compared the both approaches.

3. ev-MOGA

ev-MOGA Multiobjective Evolutionary Algorithm has been developed by the Predictive Control and Heuristic optimization Group at Universitat Politècnica de València. This article uses the detailed version of ev-MOGA [16]. ev-MOGA is an elitist multi-objective evolutionary algorithm based on the concept of epsilon dominance.

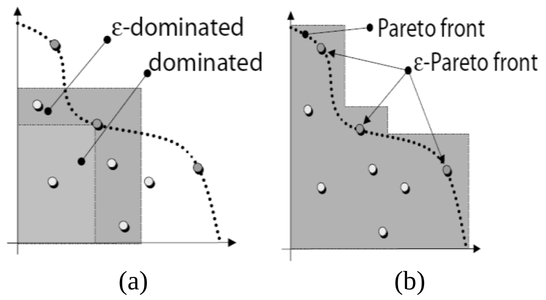

Fig.1. Concept of ε -Dominance and ε- Pareto set [17]

The Fig.1(a) and Fig.1(b) depicts the concept of ε -Dominance and ε- Pareto set. According to Fig.3(a) A ε-dominates B if ε.f(A)≥f(B). According to Fig.3(b) ε- Pareto set is defined as subset of Pareto set which ε -dominates all Pareto optimal solutions.

ev-MOGA tries to ensure that content of the archive A(t) where the result of the optimization problem is stored. converges toward an ε-Pareto set $\Theta^*_{P\varepsilon}$ in a smart distributed manner along the Pareto front $J(\Theta_P)$ with limited memory resources. It also adjusts the limits of the Pareto front dynamically and prevents the solutions belonging to the ends of the front from being lost.

A description of the ev-MOGA algorithm for obtaining an ε-Pareto front $J(\Theta^*_{P\varepsilon})$, is presented below. The algorithm, which adjusts the width ε_i dynamically, is composed of three populations:

1) Main population P(t) explores the searching space D during the algorithm iterations (t). Population size is $Nind_P$
2) Archive A(t) stores the solution $\Theta^*_{P\varepsilon}$ .Its size $Nind_A$ is variable but bounded (see Eq.(6)).
3) Auxiliary population G(t). Its size is $Nind_G$, which must be an even number.

The pseudocode of the ev-MOGA algorithm is given by

i. t: = 0
ii. A(t): = Ø
iii. P(t): = ini_ random(D)
iv. eval(P(t))
v. A(t): = $store_{ini}$(P(t),A(t))
vi. while t<t_max do
vii. G(t): = create(P(t),A(t))
viii. eval(G(t))
ix. A(t+1): = store(G(t),A(t))
x. P(t+1): = update(G(t),P(t))
xi. t: = t+1
xii. end while

4. GODLIKE ALGORITHM

The GODLIKE algorithm [18] was written as an attempt to improve the robustness of the meta-heuristic algorithms, and to do away with the need to fine-tune the algorithm of choice for each optimization problem. It tackles both single and multi-objective problems and easily includes more and different population based methods.

GODLIKE stands for Global Optimum Determination by Linking and Interchanging Kindred Evaluators, and this is exactly what it does. It uses Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and Adaptive Simulated Annealing (ASA) algorithms simultaneously (Linking), and after convergence of either of them, or exceeding certain predefined limits, it takes random members from each population and inserts then into random other populations (Interchanging) before continuing the optimization.

By using multiple optimizers simultaneously, it is essentially equal to performing four (or more) consecutive optimizations all at once, which already improves the chances of finding the global optimum; The weaknesses associated with each algorithm are negated by the strengths of another, while the strengths of all algorithms simply add up.

The interchange operator indeed destroys part of the convergence properties of either of the algorithms it uses, but that is exactly the intention the convergence one of the algorithms is experiencing might be to a local optimum, while the others might be converging to the global solution, or other local minima. By interchanging individuals between populations, GODLIKE introduces immigrants into the populations that can provide alternative good solutions to the ones already being explored by one of the algorithms. These immigrants can steer the population into other, unexplored areas of the search space, increasing the chances of locating the global minimum. By keeping the populations separate, also the principle of isolation is exploited automatically portions of the search space will be thoroughly explored by one of the populations, while not affecting the other populations. The interchange operator is extremely useful for multi-objective problems; when one population is completely non-dominated, interchanging individuals between populations will usually result in a dominated population, which continues the search for the Pareto front, instead of reporting convergence.

GODLIKE does not aim to make either of the above mentioned algorithms more efficient in terms of function evaluations, but it increases the robustness of computation at the cost of increased evaluations.

GODLIKE algorithm has its root in most popular, easiest to implement and most efficient one known, Non-dominated Sorting Genetic Algorithm II (NSGA-II). This algorithm sorts the current population according to the amount of solutions that dominate each other individual, Dominance of one individual x_i over another y_i, denoted as $x_i \prec y_i$, is defined as,

$$\begin{aligned} x_i \prec y_i \ \ & \text{if } f_j(x_i) \le f_j(y_i) \text{ for all functions } j \\ & \text{and } f_j(x_i) < f_j(y_i) \text{ for at least one function } j \end{aligned} \tag{1}$$

The NSGA-II algorithm iterates the following steps until all solutions are non-dominated:

Create an offspring population Q from the parent population P with the usual crossover and mutation operators from a GA.

Count the number of solutions y_i, that dominate the current solution x_i. Do this for all individuals from both the parent population P and the offspring population Q.

Some solutions will be found to have zero other solutions dominate them. They are non-dominated, and thus part of the Pareto front of the current populations. The solutions that have only one other solution dominate them, would have been part of the Pareto front if the members forming the true Pareto front would not have been present. Those that have two solutions dominate them would have formed the Pareto front if those solutions would also not be present, etc. Thus, the level of domination is indicative of the quality of that solution.

Next, the crowding distances are computed. These are the average distances between one solution and its surrounding solutions in the function value space.

Create a new population R, which contains individuals from the previous two populations P and Q, sorted by their level of dominance. That is, first insert all Pareto members in R, then those that have only one dominating solution, etc. Keep inserting individuals until R is the same size as P and Q.

Create a subset P_{i+1} from R by a binary tournament selection. This selection takes two random individuals from R, a_R and b_R, and lets them compete using their domination level and crowding distances as competitive factors. The "winning" individual is the one that satisfies $a_R \prec_d b_R$, defined as

$$\begin{aligned} a_R \prec_d b_R \ \ & \text{if } rank(a) < rank(b) \\ & \text{or } (rank(a) = rank(b) \\ & \quad \text{and } crowding\_distance(a) > crowding\_distance(b)) \end{aligned} \tag{2}$$

where, rank(·) indicates the rank, or domination level, of the individual. This process is repeated until the subset S is full. Usually, the size of P_{i+1} is taken to be half that Q and R.

Create a new offspring population Q_{i+1}, equal in size as the original P, Q and R, using crossover and mutation from a GA, using members from the subset P_{i+1} as parents.

After the initialization step 1, steps 2 through 7 are repeated until all individuals are non-dominated. The crowding distances in steps 4 and 6 are used to keep the spread in the solutions along the true Pareto front more or less homogeneous, when these steps are not included, the solutions tend to cluster together to the easiest-to-find compromise between the objective functions.

The greatest advantage of NSGA-II is that the entire population will simply converge to the true Pareto front, so that the number of desired solutions can easily be controlled by choosing a different population size.

Note that the genetic operators used to create Q or Q_{i+1} are completely separate Q_{i+1} from the other parts of the algorithm, so Q and Q_{i+1} can essentially be generated with any of the aforementioned meta-heuristic optimizers. This fact is used in GODLIKE algorithm.

5. VPP MODEL

In this section the details about the VPP model used for investigation are given.

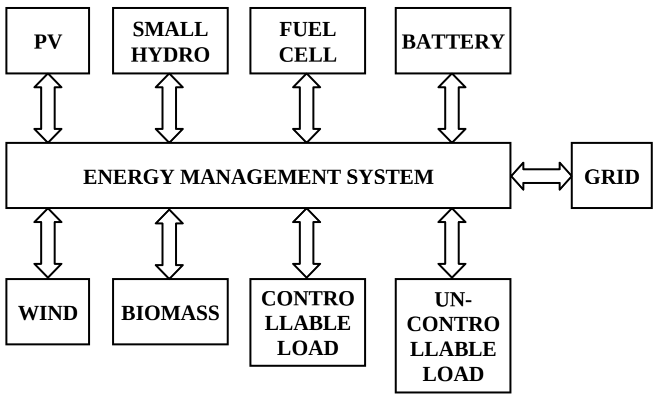

Fig.2. Virtual Power Plant Block Diagram

The Fig.2 depicts the structure of a VPP. Table.1 depicts the components of VPP under consideration.

Table.1. Components of VPP

SI. No.	Type	Rating	LCOE Rs /MWh	Energy Sale Rs / MWh
1	PV	005 MW	0.008000	0.00951
2	Wind	150 MW	0.003131	0.00486
3	Small Hydro	022 MW	0.003720	0.00419
4	Biomass	020 MW	0.002232	0.00541
5	Fuel Cell	010 MW	0.006000	0.00751
6	Battery	1557AH capacity (1000 Nos)		
7	Total Capacity	207 MW		

When generation of VPP is more than the schedule, then the excess energy generated from stochastic sources (PV and Wind) is stored in battery. Here the connected load is of two types - Controllable and Uncontrollable. The connected load can be more than the installed capacities of members of VPP. Connected uncontrollable load is nothing but the contract demand which VPP operator has to satisfy. As we are aware Solar and Wind energy is stochastic in nature. The uncertainty in their power generation can be overcome by switching off the controllable load as per the response from the consumers. If the VPP operator is still not able to satisfy the contracted demand then penalty will be imposed on VPP operator as per the agreement.

6. INDIAN ELECTRICITY MARKET

A short- term power market can help electricity providers procure unplanned and fluctuating power requirements, and on the sellers' side, enable power producers as well as procurers to sell their surplus power. VPP is commercially more related to short term transaction of electricity.

In India electricity is transacted under bilateral transactions through Inter-State Trading Licensees (only inter-state part) and directly by the Distribution Licensees (also referred as Distribution Companies or DISCOMs), Power Exchanges (Indian Energy Exchange Ltd (IEX) and Power Exchange India Ltd (PXIL)), and Unscheduled Interchange (UI)[19].

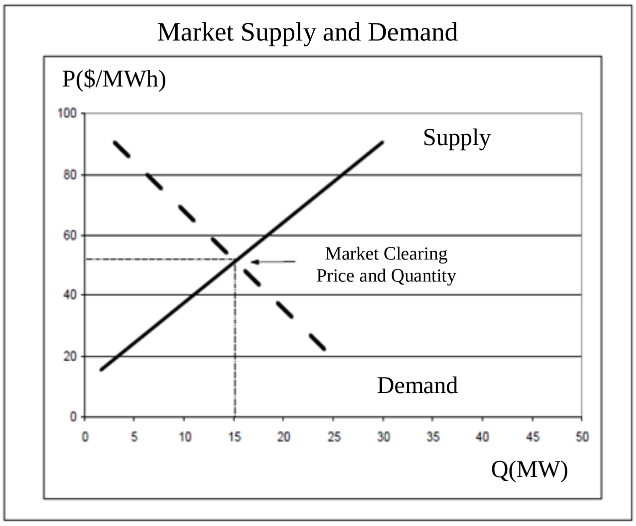

Fig.3. Market Clear Price (MCP) and MCV (Volume) [20]

At electricity exchange all purchase bids and sale offers are aggregated in the unconstrained scenario. The aggregate supply and demand curves are drawn on Price-Quantity axes. The intersection point of the two curves gives us Market Clearing Price (MCP) and Market Clearing Volume (MCV) corresponding to price and quantity of the intersection point. Results from this process are preliminary results. Based on these results the Exchange works out provisional obligation and provisional power flow.

The calculation of Market Clearing Price (MCP) is well depicted in Fig.3.

7. LEVELISED COST OF ELECTRICITY

LCOE is often considered as a convenient summary measure of the overall competiveness of different generating technologies. Since VPP consists of distributed different generation technologies, it is appropriate to use LCOE while calculating the Profit earned by VPP operator. It represents the per - kilo watt hour cost (in Rupees) of building and operating a generating plant over an predicted financial life and duty cycle. The LCOE includes different types of costs namely overnight capital costs, fossil fuel costs, fixed and variable type operations and maintenance (O&M) costs, financing costs, and an assumed utilization rate for each plant type. The importance of these different costs factors varies among the technologies. For RES technologies such as wind and solar generation which have no fuel costs and relatively small O&M costs, the levelised cost changes in rough proportion to the estimated overnight capital cost of generation capacity. For technologies having significant fuel cost, both fuel cost and overnight cost estimations significantly affect the levelised cost. The availability of various incentives offered by government can also impact the calculation of levelised cost.

Let us assume following variables.

r	Rate of interest
$Electricity_t$	The amount of electricity produced in year "t"
$P_{Electricity}$	The constant price of electricity
$(1+r)^{-t}$	The discount factor for year "t"
$Investment_t$	Investment costs in year "t"
$O\&M_t$	Operations and maintenance costs in year "t"
$Fuel_t$	Fuel costs in year "t"
$Carbon_t$	Carbon costs in year "t"
$Decommissioning_t$	Decommissioning cost in year "t"

Then,

The LCOE [21] is given by,

$$LCOE = P_{Electricity} = \frac{\sum_t \left(Investment_t + O\&M_t + Fuel_t + Carbon_t + Decommissioning_t\right) * (1+r)^{-t}}{\left(\sum_t Electricity_t * (1+r)^{-t}\right)} \tag{3}$$

8. MULTI OBJECTIVE OPTIMIZATION PROBLEM FORMULATION

The MO problem can be formulated as follows:

$$min\ J(\theta) = min[J_1(\theta), J_2(\theta), \ldots, J_s(\theta)] \quad (4)$$

subject to:

$$g_q(\theta) \le 0, (1 \le q \le r)$$
$$h_k(\theta) = 0, (1 \le k \le n)$$
$$\theta_{li} \le \theta_i \le \theta_{ui}, (1 \le i \le L) \quad (5)$$

where, $J_i(\theta)$, $i \in B := [1 \ldots s]$ are the objectives to be optimized, θ is a solution inside the L-dimensional solution space D, $g_q(\theta)$ and $h_k(\theta)$ are each of the r inequality and n equality problem constraints respectively and θ_{li} and θ_{ui} are the lower and upper constraints which defined the solution space D.

To solve the MO problem the Pareto optimal set Θ^*_P (solutions where none of them dominate any of the others) must be found. Pareto dominance is defined as follows.

A solution θ_1 dominates another solution θ_2, denoted by $\theta_1 \prec \theta_2$, if,

$$\forall_i \in B, J_i(\theta^1) \le J_i(\theta^2) \wedge \exists k \in B : J_k(\theta^1) \le J_k(\theta^2)$$

Therefore the Pareto optimal set Θ_P is given by

$$\Theta_P = \{\theta \in D \mid \nexists\ \tilde{\theta} \in D : \tilde{\theta} \prec \theta\}$$

Θ_P is unique and normally includes infinite solutions. Hence a set Θ^*_P, with a finite number of elements from Θ_P, should be obtained.

The VPP can enter in to electricity trading market by the virtue of short term / medium term / long term bilateral contracts. In case of medium or long term contracts the risk associated with the possible deviation of the random variables from their expected values have a significance contribution. While optimizing the operation with self scheduling the producer faces a trade off between maximum profit and minimum risk.

The maximization of profit problem can be formulated as [22],

$$\underset{p_1, p_2, \ldots p_T}{\text{maximize}} \sum_{t=1}^{T} \left(\lambda_t^{est} p_t - c_t\right) \quad (6)$$

subject to $\quad p_1, p_2, \ldots p_T \in \Pi$

where, λ_t^{est} is the day ahead price estimation, c_t is the production cost during hour t. Here we have considered it as LCOE. $p_1, p_2, \ldots p_T$ are the operation constraints belonging to feasible region Π.

Here operation constraints on the VPP includes:

- Maximum and minimum power output limits.
- Technical minimal production required by the respective generators.

An electrical energy price MCP is highly inconsistent in nature. Forecasting the future electricity prices is the main origin of uncertainty experienced by the VPP operator while self scheduling the generation. The most common measure of risk is variance or the standard deviation which is its square root. The effect of risk is modelled by taking into account the estimated variance of the MCP. The total risk due to price forecast uncertainty minimization problem can be formulated as,

$$\underset{p_1, p_2, \ldots p_T}{\text{minimize}} \sum_{i=1}^{T} \sum_{j=1}^{T} \left(V_{ij}^{est} p_i p_j\right) \quad (7)$$

subject to $\quad p_1, p_2, \ldots p_T \in \Pi$

where, both i and j are time indices.

In [9] the estimated covariance matrix, V^{est}, is T × T matrix and it can be estimated based on available actual and forecasted prices for last considered D days.

The actual covariance matrix V for day d is

$$V = E_{\lambda 1, \ldots, \lambda T} \{(\wedge_d^{true} - \wedge_d^{est})(\wedge_d^{true} - \wedge_d^{est})^T\} \quad (8)$$

where, $\lambda_d = [\lambda_1, \ldots \lambda_T]^T$ for day d.

If the true values of MCP as well as their estimates are available up to day d-1, the covariance matrix of day d can be estimated as,

$$V^{est} = \frac{1}{D} \sum_{i=1}^{D} (\wedge_i^{true} - \wedge_i^{est})(\wedge_i^{true} - \wedge_i^{est})^T \quad (9)$$

where, D is a convenient number of days (up to and including the day d-1) for which the estimation of prices is available. Generally the time slot dependent electricity prices have some seasonal variations, peak variations and random variation. It is necessary to normalize this data before it is used for forecasting. So exponentially weighted moving average technique [23] is used. So a better covariance matrix can be obtained by using,

$$V^{est} = (1-\alpha) \sum_{i=1}^{D} \alpha^{i-1} (\wedge_{D-i+1}^{true} - \wedge_{D-i+1}^{est})(\wedge_{D-i+1}^{true} - \wedge_{D-i+1}^{est})^T \quad (10)$$

where, D is greater or equal to 24 for making the covariance matrix positive definite. Here the past prices are weighted by a smoothing constant α which lies between 0 and 1. Here higher weights are assigned to the days nearer to day d and these weights decay exponentially as the days considered at distant away in past from day d. A VPP operator will be always interested in self scheduling which will result in a large profit with least risk (variance). To combine these contrasting objectives most popular method used in literature is of portfolio selection [14]. According to this method both objectives are combined to form a single objective function with the help of a risk tolerance parameter β whose value is limited between 0 and ∞. Then the scheduling problem takes the form

$$\underset{p_1, p_2, \ldots p_T}{\text{maximize}} \sum_{t=1}^{T} \left(\lambda_t^{est} p_t - c_t\right) - \beta \sum_{i=1}^{T} \sum_{j=1}^{T} \left(V_{ij}^{est} p_i p_j\right) \quad (11)$$

subject to $\quad p_1, p_2, \ldots p_T \in \Pi$

Here the operator uses higher value of β to lower risk and lower value of β to increase the risk. In this approach we have to implement the optimization problem in Eq.(10) repeatedly for different values of β . To avoid this repetition the authors have tried to implement the multi-objective optimization problem formed by two objectives represented by Eq.(6) and Eq.(7).

9. CASE STUDY

The authors have considered the case study of VPP whose data is given in Table.1. For forecasting the next day MCP a Neural Network analysis tool from Zaitun Time series is used. For training the neural network last six month data from PXIL is used. Table.2 lists out the forecasted MCP in Rupees/MWh for 15 minutes, 96 duration slots of a day.

Table.2. Forecasted MCP in Rs/MWh

Time Slot	MCP	Time Slot	MCP	Time Slot	MCP	Time Slot	MCP
1	2112	25	1830	49	2398	73	2287
2	2100	26	2360	50	2389	74	2778
3	2099	27	2475	51	2367	75	2798
4	2097	28	2496	52	2487	76	2762
5	2249	29	2489	53	2501	77	3012
6	2080	30	2491	54	2299	78	2694
7	2374	31	2499	55	2287	79	2689
8	2202	32	2494	56	2254	80	2693
9	2222	33	2687	57	2389	81	2686
10	2240	34	2691	58	2410	82	2705
11	2189	35	2847	59	2401	83	2693
12	2168	36	2791	60	2394	84	2698
13	1975	37	2445	61	2398	85	2651
14	1973	38	2470	62	2391	86	2559
15	2008	39	2481	63	2381	87	2594
16	2070	40	2491	64	2369	88	2591
17	2249	41	2445	65	2349	89	2473
18	2052	42	2556	66	2381	90	2489
19	2183	43	2332	67	2380	91	2467
20	2094	44	2250	68	2364	92	2492
21	2003	45	2389	69	2320	93	2398
22	1713	46	2372	70	2301	94	2396
23	1900	47	2386	71	2311	95	2397
24	1934	48	2369	72	2289	96	2391

The covariance matrix is estimated using Eq.(10) based on actual and forecasted MCP data for the last 24 days just prior to the day of the estimation day. In this article the authors have taken $\alpha = 0.98$ and $D = 24$ for the covariance matrix estimation.

10. RESULTS OF SIMULATIONS AND DISCUSSION

The elitist multi-objective evolutionary algorithm ev-MOGA has been applied to risk constraint self scheduling problem of a VPP. Fig.4 shows the pareto front obtained after applying the ev-MOGA based approach. As expected the profit earned by a VPP increases as risk level increases and vice versa. For maximum profit the scheduling of VPP is depicted in Fig.5

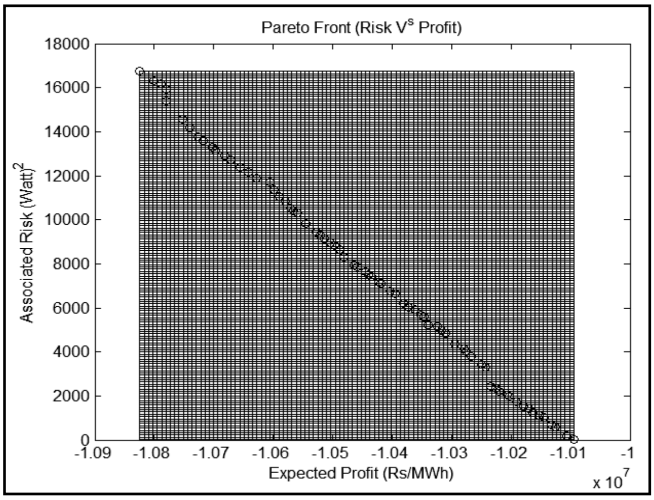

Fig.4. Pareto Front

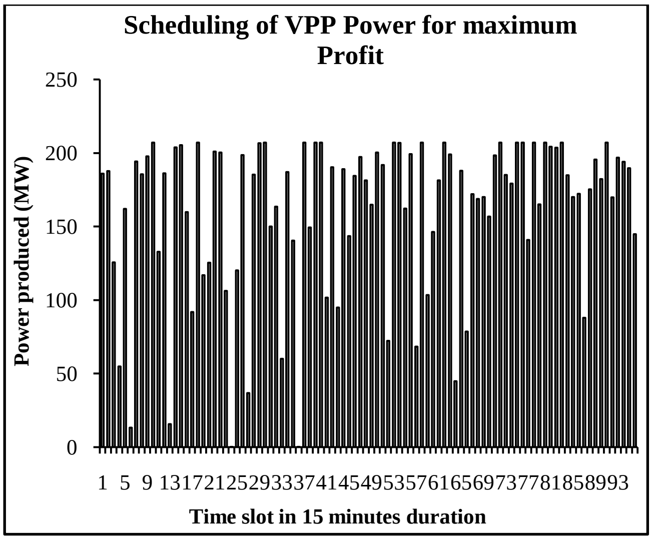

Fig.5. Maximum Profit Analysis of VPP by ev-MOGA approach

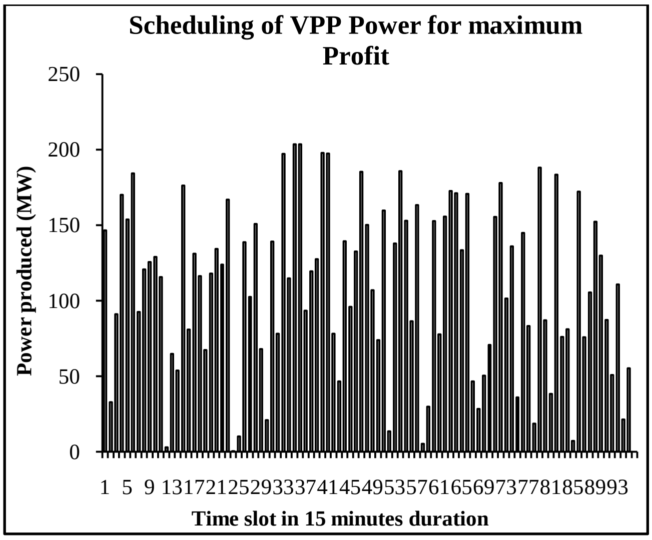

Fig.6. Maximum Profit Analysis of VPP by GODLIKE approach

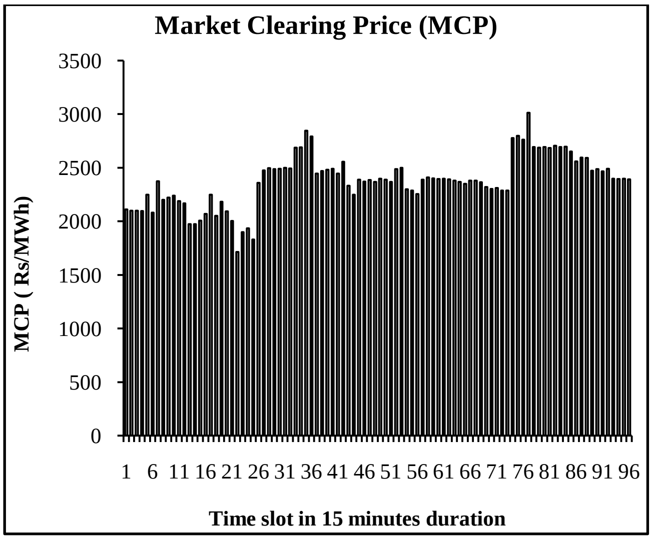

Fig.7. Market Clearing Price

The Fig.6 depicts the scheduling of VPP for maximum profit by applying GODLIKE approach. The Fig.7 depicts the variation of MCP with reference to time slot of 15 minutes. For the sake of simplicity the operation of controllable load and bi directional power flow of battery is not considered in this article. The actual data generated after optimization is shown in Table.3 in appendix.

11. CONCLUSION

If we analyze the scheduling depicted in appendix then it is found that scheduling calculated by GODLIKE is much lower than that one calculated by ev-MOGA approach. GODLIKE approach calculates about 67% lower scheduling for same amount of profit envisaged. The results exhibit that GODLIKE optimizer approach is efficient approach for calculation of scheduling of VPP.

NOMENCLATURE

Variables:

P : Power interchange with grid in kW
λ : Electrical energy price (Rs/MWh)
V : Covariance matrix
c_t : Production cost during hour

Constants:

D : Number of days for which true and estimate prices are available
T : Considered time periods in one day (96)
α : Factor used to estimate the covariance matrix
β : Weighting factor to incorporate risk into the expected profit objective function
Π : Feasible operating region of the generating machine

Miscellaneous:

$E_{\lambda 1,..\lambda T}$: Expected value operator with respect to random variables
est : Superscript that indicates estimate value
true : Superscript that indicates true value
exp : Superscript that indicates expected value

APPENDIX

Table.3. Self scheduling of dispatchable generation in VPP

Time Slot	ev-MOGA	GODLIKE	Time Slot	ev-MOGA	GODLIKE	Time Slot	ev-MOGA	GODLIKE	Time Slot	ev-MOGA	GODLIKE
1	185.9895	146.7053	25	120.2165	10.14573	49	164.8093	107.0481	73	185.1038	101.3872
2	187.7481	32.85915	26	198.684	138.8691	50	200.3564	73.96044	74	179.3145	135.9688
3	125.7142	91.19445	27	36.79811	102.5515	51	191.8209	159.6838	75	207	36.04322
4	54.90908	170.0228	28	185.2616	150.7591	52	72.21203	13.51696	76	207	144.8483
5	161.9491	153.7693	29	206.5686	68.09658	53	207	137.892	77	140.933	83.36134
6	13.3496	184.3444	30	207	20.87866	54	206.8863	185.811	78	207	18.68386
7	194.3116	92.65537	31	150.0716	139.2363	55	162.2082	152.8859	79	165.0285	188.2405
8	185.5388	120.8404	32	163.4409	78.23365	56	199.2797	86.52247	80	207	87.16777
9	197.7609	125.5367	33	60.07667	197.345	57	68.40834	163.3711	81	204.1918	38.25058
10	207	129.0096	34	187.0285	114.8166	58	207	5.279553	82	203.5036	183.5535
11	132.9269	115.5952	35	140.5343	203.6825	59	103.3632	29.97472	83	207	76.03624
12	186.0948	3.005645	36	0.2	203.6168	60	146.4383	152.7267	84	184.971	81.19298
13	15.58391	64.87841	37	207	93.45404	61	181.4372	77.73864	85	170.1103	7.110205
14	203.9187	53.82142	38	149.4544	119.5925	62	207	155.7036	86	172.2252	172.279
15	205.3782	176.2747	39	207	127.5321	63	199.1069	172.6281	87	87.91437	75.81992
16	159.9389	80.84509	40	207	197.8427	64	44.82136	171.2431	88	175.2957	105.4269
17	91.91522	131.2074	41	101.6337	197.3523	65	187.9497	133.4719	89	195.5451	152.2844
18	207	116.3581	42	190.3851	78.09213	66	78.63712	170.6925	90	182.3268	129.7972
19	116.836	67.43011	43	94.84173	46.5706	67	171.9446	46.70705	91	207	87.27059
20	125.4849	117.9442	44	189.0149	139.325	68	168.75	28.48187	92	169.7745	50.78305
21	201.1006	134.2908	45	143.4478	96.00601	69	170.0455	50.45538	93	196.8914	110.8762
22	200.4402	123.9755	46	184.4761	132.6335	70	156.7882	70.78766	94	194.0809	21.4994
23	106.2986	166.9422	47	197.3196	185.3355	71	198.3516	155.5677	95	189.6692	55.30059
24	0.2	0.445734	48	181.371	150.1797	72	207	177.976	96	144.7642	3.93E-05

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