Solving Economic Load Dispatch Problem with Valve Loading Effect using Adaptive Real Coded Quantum-inspired Evolutionary Algorithm

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Abstract — **Economical dispatch of power is a significant real time optimization problem in the operation of power system, which allocates the loads on the committed generating units to reduce the generation cost, while meeting all the inequality and equality constraints. Traditionally, economic load dispatch problems have been formulated as convex optimization problem and various classical methods such as gradient methods, base-point participation factor method, etc. have been used for solving them. The traditional formulation is a quadratic input-output curve or piece wise linear cost curve, which are continuous and convex, however, real generating units have valve loading effects, which make the cost curve discontinuous and non-convex and hence the economic dispatch problem is no longer simple to handle. Thus, the classical methods cannot be employed for non-convex problems. The non-convex, non-linear and discontinuous economic dispatch (ED) problem can be better solved by metaheuristic approaches. Such approaches often require tuning of their respective evolutionary parameters. Although, solution to such type of problem have already been solved by different meta-heuristic optimization techniques in previous studies as well, however, the algorithm employed in this paper to solve Power Economic Load Dispatch (PELD) problem is adaptive real coded quantum-inspired evolutionary algorithm, which does not require tuning of evolutionary parameters and performs better than some of the existing techniques on standard 6-bus 3 machine system and IEEE 14 bus 5 unit system.**

Keywords—Non-linear Optimization; Metaheuristic; Quantum Entanglement; Two Qubit Representation.

I. INTRODUCTION

Power system is a vast sector consisting of generating units that supply output power; transmission system that transfers power from generating station to distribution centers; and distribution system that provides power to small load centers like homes and industries. As per the statistics mentioned in reference [1], thermal power plants are catering to about 71% of the electricity consumed in India and electricity demand of more than 62 % in India is met by the country's coal reserves. Thermal power plant's total cost depends on various factors like availability of coal, cost of coal transportation, cost of land, running cost etc. Due to these factors electricity produced by thermal power plant is more costly (running cost) than hydro power plant. Thus, there is a need to operate power system economically to reduce the price paid by the end customer. The constantly increasing prices of coal, salary, wages etc., are also making it essential to run production in most economical and efficient way. Some installed generator-turbine units are more cost effective than other units, so such units should contribute more in generation of power. Further, the cost curves are not linear, so allocation of load is not straight forward [2]. Power Economic Load dispatch (PELD) tries to allocate a part of total load on each generator to optimally minimize the overall cost of operation, while meeting all the constraints. Thus, PELD is formulated as a problem of allocating generation among committed unit such that the total generation cost can be minimized satisfying all inequality and equality constraints. The basic equality constraint is that total output power of generating units must be equal to total demand and losses in the power system. Losses can be found by using Kron's formula [3] or load flow analysis. Inequality constraints in economic load dispatch problem are ramp rate constraint [4, 5], valve point effect [5], prohibited operating zones [5, 6], security constraints [7], emission constraint [5, 8] etc. The committed power of each generator unit must be within prescribed limits.

Classically, the cost of fuel of conventional thermal unit is formulated using a quadratic function as it is assumed that each unit uses one fuel and there is no consideration of irregularities like valve point effects etc. Conventional methods such as dynamic programming [9], gradient method [13], base-point participation factor method [14, 15] etc. are used to solve linear PELD problems. In today's scenario, the cost curve become very complicated as multiple fuels are used and irregularities in cost function like valve point effects are also considered [16, 17]. Non-convex and non-linear PELD problems cannot be solved by classical technique. Evolutionary programming technique is considered to be one of the methods to solve non convex problems [18, 19]. Various heuristic and meta-heuristic techniques such as Simulated Annealing (SA) [20], Tabu Search (TS) [21],

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Particle swarm optimization (PSO) [18, 22-24] and Genetic algorithm (GA) [25] are used to solve these problems. Simulated annealing can find a global optimal solution for an optimization problem. It employs search technique with probabilistic approach to accept individual solution so that it can come out of local optima solutions. However, choosing an appropriate control parameter and speed of operation are major drawbacks of this algorithm. Tabu search has a disadvantage of short term memory structure. GA is a potential method to solve PELD problems, where the actual parameters are encoded first and then various genetic operators (reproduction, crossover and mutation) are applied on it until near global optimal solution is found. However, encoding and decoding waste a lot of computer space and time. The problem with heuristic methods is that it gets trapped in local optimal solutions but they provide reasonable solution in finite time. That's why meta-heuristic methods are getting popular these days. However, parameter tuning is often necessary in meta-heuristics. Hence, Adaptive Real-coded Quantum-inspired Evolutionary Algorithm (ARQEA) [26-28] is employed to optimize the generation cost, wherein it is proposed that cost curve of committed units will have valve point effects along with transmission losses. ARQEA does not require tuning of parameters in evolutionary operators and still provides high quality solution and faster computation as compared to various known techniques on two systems: Standard 3-unit 6-bus and IEEE 5-unit 14-bus system.

This paper has been divided in to five sections. Section II describes the background and formulation of PELD in a power system. Section III contains the detail of the technique proposed. To validate our employed technique, it is compared with GA, Hybrid GA, Hybrid method and Gumption method [2] and the results obtained are discussed in Section IV. Section V presents the conclusions of the paper.

II. Power Economic Load Dispatch with Valve-Point effect

Power Economic Load dispatch (PELD) is an important task in the economic operation of power plant, which targets at allocation of generation by committed units to meet load demand and losses in minimum possible cost while taking care of all the equality and inequality constraints in power system. Power Economic dispatch can be a convex or non-convex problem. Convex PELD problems are those whose input-output characteristic is piecewise linear and monotonically increasing.

A. Convex Power Economic Load dispatch problem

Traditionally cost curve of the committed generator is represented by the quadratic equation (1).

$$F_j(P_j) = a_j P_j^2 + b_j P_j + c_j \tag{1}$$

The fixed term c_j in quadratic equation (1) represent the fixed cost associated with the jth generator like salary or cost of land. b_j represent the variable cost which changes proportionally with power demand like cost associated with fuel input of the *j*th generator and a_j represent the cost associated with losses of the *j*th generator. $F_j(.)$ is the function to find fuel cost of the jth generator. The cost curve of generating unit is shown graphically in Fig.1. The objective of PELD is to optimally minimize the overall cost of generation given by:

$$C_t = \sum_{j=1}^{n} F_j(P_j) \tag{2}$$

where $F_j(P_j)$ is the cost of fuel of the '*j*'th generating unit, P_j is the output power of '*j*'th generating unit, n is total nunber of generating units and C_t is total generation cost of the plant.

The objective function is subjected to following constraints

$$\sum_{j=1}^{n} P_j = P_d + P_L \tag{3}$$

$$P_L = \sum_{j=1}^{n}\sum_{k=1}^{n} P_j B_{jk} P_k + \sum_{j=1}^{n} B_{0j} P_j + B_{00} \tag{4}$$

$$P_{j\,\min} \le P_j \le P_{j\,\max} \tag{5}$$

where total demand is designated by P_d, P_{jmin} designates the minimum active power output, P_{jmax} designates the maximum active power output of jth generating unit, P_L is the transmission loss and B_{jk}, B_{0j}, B_{00} are transmission loss formula coefficients.

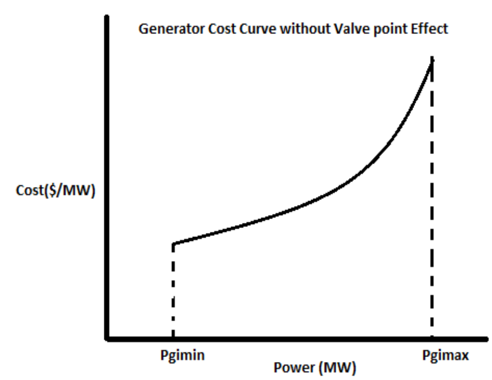

Fig. 1. Cost curve of generator without valve point loading effect

B. Non-convex Power Economic Load Dispatch problem

In practical system, a large number of generator units are employed to meet the power demand. Active power output of a steam power plant is controlled by steam input. Steam input to the turbine is further controlled by number of steam valves which open in succession. When input increases, there is a decrease in incremental heat rate between consecutive valve openings. The cost curve shows ripple when a new valve starts to open. The objective function of economic dispatch involving valve effect is given by combination of sine function with quadratic equation.

$$F_j(P_j) = a_jP_j^2 + b_jP_j + c_j + \left|e_j \sin(f_j(P_{j\,\min} - P_j))\right| \quad (6)$$

Where e_j and f_j are the coefficients of cost function of the 'j'th generator with valve point loading effect. The graphical representation of modified cost curve with valve point loading effect is shown in Fig.2.

III. Proposed Method

Quantum Mechanical Systems can be used for simulation of other quantum mechanical processes was first proposed by Feynman. Subsequently, it was shown that quantum computers running quantum algorithms can outperform classical computers on tasks like searching, factorization etc. But quantum algorithms can only run on quantum computer which are still in nascent stage of evolution. However, quantum paradigms are conjectured to be more powerful than classical paradigm. Thus, quantum inspiration can be a good candidate for improving classical algorithms [26]. Quantum-inspired Evolutionary Algorithms (QEAs) are such integration between Evolutionary algorithm and Quantum mechanics. Thus, QEAs are a type of evolutionary algorithm, which employ the principle of quantum mechanics in evolutionary framework [26]. Quantum mechanics have four important principles: superposition, measurement, entanglement, interference. QEA in [29] was proposed for improving the diversity during search process by using superposition and measurement principles in form of probabilistic nature of qubit, Q-bit and a linear operator, rotation gate for updating the Q-bits. The rotation gate requires tuning of eight parameters [29]. In order to overcome, the tuning of parameters in rotation gate, Adaptive Real-coded Quantum-inspired Evolutionary Algorithm (ARQEA) was proposed which utilizes two qubits (analogous to classical bit in quantum system) representations to utilize entanglement and superposition principles both. To generate new population an adaptive parameter free quantum crossover operator has been used which is inspired by rotation gate.

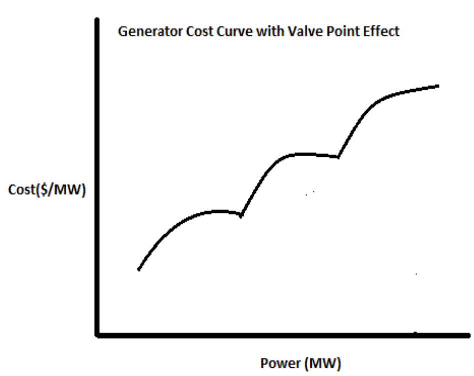

Fig. 2. Cost curve of generator with valve point loading effect

A. *Representation*

The qubit, which is quantum analogous of classical bit, is a basic information element in quantum computer. '0' or '1' are two states of a classical bit whereas a quantum bit can be in a superposition of its basis states, |0> and |1>. In Hilbert space, it is described by a vector $|\psi>$ as follows:

$$|\psi> = \alpha|0> + \beta|1> \quad (7)$$

Where $|\alpha|^2$ is the probability of qubit to be in state |0> and $|\beta|^2$ is the probability of qubit to be in state |1>.

Given condition should be satisfied:

$$|\alpha|^2 + |\beta|^2 = 1 \quad (8)$$

ARQEA has two sets of qubits per solution vector, of which, the first set $|\psi_{1i}>$ is assigned the present value of the ith variable as amplitude α_{1i} which can take values between zero and one. That is the minimum and maximum output of ith generator is scaled between zero and one. As amplitude β can be calculated from equation 8, it is not stored in quantum register. In quantum register QR_1, the number of qubits is equal to the number of generators to be loaded in the problem. The qubits are stored in quantum register. The number of quantum register is 10 times the number of variables in this work. Thus, making it function of number of variables. In order to use the profit of quantum rotation and superposition in EA, the number of QR_1 is kept high. The structure of QR_1 is given below, where small n is the number of generators:

$QR_{1,1} = [\alpha_{1,1,1}, \alpha_{1,1,2} \ldots \alpha_{1,1,n}]$

$QR_{1,2} = [\alpha_{1,2,1}, \alpha_{1,2,2} \ldots \alpha_{1,2,n}]$

....

$QR_{1,10n} = [\alpha_{1,10n,1}, \alpha_{1,10n,2} \ldots \alpha_{1,10n,n}]$ (9)

The objective function value for the ith solution vector is ranked with respect to objective function value for all other solution vectors and is subsequently scaled between [0, 1]. This scaled value is stored in second set of qubits $|\psi_{2i}>$ as amplitude α_{2i}. "1" is assigned to the value of objective function for fittest vector and "0" is assigned to worst vector. The value between 0 and 1 is assigned to rest of the solution vector's objective function value. Alternatively, we can normalize the value of objective function for a solution vector between 0 and 1 and assigning it to α_{2i}.

In quantum computing paradigm, Quantum gates are used for producing next generation of qubits. In Grover's algorithm, Quantum phase rotation gate was used for amplitude amplification for searching the desired element in the unprocessed database [11, 12]. An adaptive variation operator based on entanglement principle has been utilized in the ARQEA and is called as Adaptive Quantum Rotation based variation operator [26]. It is adaptive and parameter tuning free variation operator. The angle of rotation is calculated from amplitude of 2nd qubits for evolving the 1st qubit. The expression for this purpose is given below:

$$\psi_{1i}(n+1) = \psi_{1i}(n) + f(\psi_{2i}(n), \psi_{2j}(n)) * (\psi_{1j}(n) - \psi_{1i}(n)) \quad (10)$$

where n is generation number and ψ_{1j} can be the most-fit vector or a randomly chosen vector.

The function $f(\psi_{2i}(t), \psi_{2j}(t))$ is used for fine and gross search. Presently, $f(\psi_{2i}(t), \psi_{2j}(t))$ generates a arbitrary number either between α_{2i} and α_{2j} or $|\alpha_{2j}|^2$ and $|\alpha_{2i}|^2$. The value $|\alpha_{2j}|^2 - |\alpha_{2i}|^2$ is used for fine search and $\alpha_{2j} - \alpha_{2i}$ is used for gross search, thus former is smaller than later. The important characteristics of the variation operator is that it modifies each variable in the solution vector adaptively and is driven by problem vector rather than user driven. A balance is maintained between exploration and exploitation by the variation operator by using three attractor selection technique viz. Rotation towards Best (R-I), Rotation away from worse (R-II) and Rotation towards Better (R-III). In R-I, all chosen solution vectors are rotated towards most-fit solution vector. In R-II, the attractor vector is randomly chosen and the inferior solution is rotated towards better vector. In R-III, the most-fit solution vector is rotated far away from the inferior solutions.

B. *Constraint Handling technique*

In constrained optimization, one of the main issue is constraint handling as its selection can impact the efficiency and efficacy of the overall optimization technique. There are many techniques which are suggested for constraint handling [28] like feasibility rules and penalty factor method etc. These techniques introduce penalty parameters to penalize infeasible solutions. These penalty parameters need fine tuning which becomes a complex optimization problem. Feasibility rules method give preference to feasible solution over infeasible solution. It has three rules through which comparison can be made between two solution vectors. It is robust in nature and free from fine tuning. Therefore, feasibility rules [10] have been used for constraint handling in this work and is implemented as follows:

1) *The solution with better objective function value wins if both solutions being compared are feasible.*
2) *If out of the two solutions being compared, the one that is feasible wins if the other solution is infeasible.*
3) *If none of the solutions being compared are feasible then one with lesser constraint violation wins.*

Feasibility rules method is a parameter free technique that is it does not have any parameters, which may require tuning, however, it is known to reduce the diversity of the population. Therefore, EAs using feasibility rules often incorporate niching and other associated techniques for improving diversity during search. However, ARQEA does not require any such technique that is it is able to maintain diversity through its variation operator, in spite of using feasibility rules.

In addition to feasibility rules, a novel repair technique is used for handling power balance (equality) constraint, which ranks the generator according to their loading and provides the deficit (excess) power as far as possible from the generator in the order of their load ability (non-load ability). Repair is tried for five times iteratively to make the solution feasible; otherwise, infeasible solution is passed in the evolutionary process. The selection for next generation of solution vector has been made by using tournament selection method by comparing the present generation solution vector with their respective best evolved vector in that generation.

C. *Pseudo code for the ARQEA*

1) Quantum register QR_1 is initialized, Set Iteration Count While (!termination criteria){
2) If (CV > 0.0001) Repair QR_1
3) Compute fitness of QR_1.
4) QR_2 is assigned on the basis of fitness of QR_1.
5) Apply Adaptive Quantum Rotation crossover on QR_1.
6) By Feasibility Rules, QR_1 next generation is selected.}

D. *Description of Algorithm*

1) The first set of quibit in QR1 is randomly initialized. Quantum register QR1 stores the α scaled between [0,1] corresponding to the solution vectors of the population. It is storing the decision variables, P_j, power allocated to j^{th} generator and the value of P_j is scaled between [0, 1] using its minimum and maximum generation value. The number of quantum register is 10 times the number of variables.

2) Fitness of each qubit in QR_1 is validated by checking the constraint voilation (CV) which should be less than 0.0001 where

$$CV = \sum_{j=1}^{n} P_j - P_D - P_L \tag{11}$$

Repair QR_1 till the Constraint Violation are satisfied or maximum number of attempts is reached, which is five in this implementation.

3) Compute the fitness using eq. (6) and (11)

4) For ith solution vector in QR_1, QR_2 stores the ranked and scaled objective function value as α_{2i} scaled between [0,1]. *1* is assigned to fittest vector and *0* is assigned to worst vector. Other solution vectors are ranked between 0 and 1.

5) Adaptive Quantum Variation operator is implemented utilizing 3 strategies R-I, R-II and R-III on QR_1. In order to test the effectiveness of rotation startegies, three configurations have been tried out, which are standard configuration (SC-I), second configuration (SC-II) and third configuration (SCIII). SC-I has employed all the three rotation strategies R-I, R-II and R-III as described in section 3. SC-II also uses the three rotation strategies R-I, R-II and R-III as described in section 3 but in SC-I, randomly generated values based on QR_2 are being used for determining the degree of rotation but in SC-II, degree of rotation is determined deterministicaly using α values of QR_2. SC-III uses R-I and R-II of SC-I i.e. random exploration R-III is turned off. The results in Table 1 show that random rotation is a better design option than deterministic rotation as SC-I has performed better than SC-II and SC-III. Therefore, R-III is performing its function.

6) Individual parents are compared with their best child and tournament selection is applied to select the solution vector for next generation using feasibility rules [10].

Termination criterion is selected by chosing maximum no. of generations, which in this paper is 500.

IV. VALIDATION WITH BENCHMARK FUNCTIONS

To evaluate the performance of ARQEA, the algorithm was tested on standard load dispatch problem. The different benchmark system considered is as follows:

A. Standard 3 machine 6 bus system

The total demand of Standard 3-unit system is 210MW+losses [2]. For 3-unit 6 bus system, we have used 30 number of qubit registers. Total generation number is 500.

B. IEEE 14 bus 5 machine system

The total demand of 5-unit system is 259MW+losses [2].In 5 unit system, no. of qubit register used is 50 and total generation number is 500.

Cost coefficient of the generator for two systems is given in [2]. The B-coefficient of two systems is taken from [2]. ARQEA has been programmed in ‘C’ language and was run in Windows environment on DELL laptop having Intel Core i3 processor.

C. Result Analysis

The results of testing of SC-I, SC-II and SC-III configurations of ARQEA using IEEE 14 bus 5 machine system is shown in Table I. It depicts that SC-I gives the best results amongst all the three configurations. Hence the result from SC-I is compared with known popular techniques, which is shown in Table II and Table III for standard 3 machine six bus system and IEEE 14 bus 5 machine system respectively. In both the cases discussed, it is shown that ARQEA has achieved least cost of generation as compared to existing ‘state of art’ methods. The result obtained for standard 3-unit system in Table II shows that the cost of generation obtained by ARQEA is approximately 1.6% less than minimum cost from GA and 2.9% less than minimum cost from hybrid GA method; approximately 0.4 % decrease from hybrid method and more than 0.3% decrease in cost from gumption method. Fig. 3 depicts the graphical representation of reduction in cost with the use of ARQEA technique.

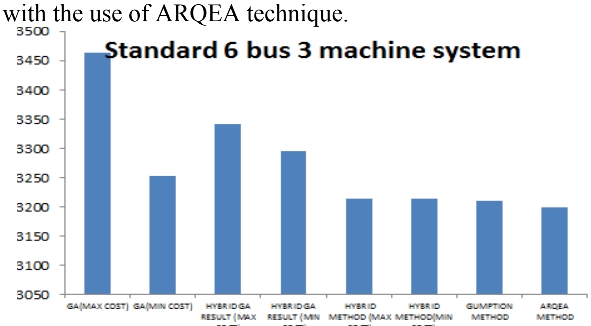

Fig. 3 Generation cost by different algorithm for standard 3 machine 6 bus system.

For IEEE 14 bus 5 unit system, results are shown in Table III. The comparative study demonstrates that ARQEA with SC-I strategy gives approximately more than 10% decrease in minimum cost from GA and hybrid GA method; approximately 8% decrease from hybrid method and more than 6% decrease in cost from gumption method. Figure 4 shows the graphical representation of reduction in cost with the use of ARQEA technique for IEEE 14 bus 5 machine system.

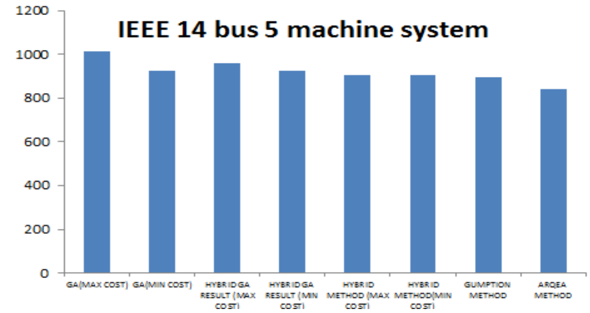

Fig. 4 Generation cost by different algorithm for IEEE 14 bus 5 machine system.

V. Conclusions and Future Work

Power economic load dispatch problem considering valve point loading effect is a real world complex optimization problem, which has been solved using Adaptive Real-coded Quantum-inspired Evolutionary Algorithm. ARQEA established better balance between exploitation and exploration by using 2 qubit approaches and entanglement principle of quantum mechanics. The simulation results shown for standard 6 bus 3 machine system and IEEE 14 bus 5 machine system clearly demonstrates that ARQEA give better results as compared to existing ‘state of art’ methods.

ARQEA algorithm has been tested and found to be working well for relatively small power systems. In future, investigations will be made on larger power system problem as well.

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TABLE I. RESULTS WITH ARQEA IN CONFIGURATION SC-I, SC-II AND SC-III ON IEEE 14 BUS, 5 GENERATOR SYSTEM

	ARQEA (SC-I)		**ARQEA (SC-II)**		**ARQEA (SC-III)**	
	Max	**Min**	**Max**	**Min**	**Max**	**Min**
P_1	200.00	200.00	150.66	200.00	186.18	150.60
P_2	34.15	20.18	28.21	33.62	23.71	52.03
P_3	15.00	15.02	35.33	15.04	32.47	28.99
P_4	10.00	23.74	23.40	10.03	12.18	21.74
P_5	10.00	10	27.60	10.43	12.96	12.90
P_L	10.15	9.93	6.20	10.12	8.51	7.28
P_{total}(MW)	269.15	268.94	265.20	269.12	267.51	266.28
Cost($/MW)	870.93	838.96	916.95	869.98	901.02	870.68

TABLE II. COMPARISON RESULT OF VARIOUS METHODS FOR 3 UNIT 6-BUS SYSTEM WITH P_{DNEW}=210MW+P_L

	GA result corresponding to		**Hybrid GA corresponding to**		**Hybrid method result for**		**Gumption method**	**ARQEA**
	Max cost	***Min cost***	***Max cost***	***Min cost***	***Max cost***	***Min cost***		
P_1	77.89	53.26	61.64	54.45	50	50	50	**50**
P_2	67.47	88.96	95.16	115.68	86.03	86.06	90	**76.29**
P_3	72.13	74.46	60.54	47.58	79.74	79.71	75.87	**90.57**
P_L	7.53	6.99	7.34	7.71	6.85	6.85	6.91	**6.86**
P_{total}(MW)	217.52	216.99	217.35	217.72	216.85	216.85	216.91	**216.86**
Cost($/MW)	3463.36	3252.45	3341.77	3294.54	3213.386	3213.38	3210.394	**3199.77**

TABLE III. COMPARISON RESULT OF DIFFERENT METHODS FOR 5 UNIT 14-BUS SYSTEM WITH P_{DNEW}=259MW+P_L

	GA result for		**Hybrid GA result for**		**Hybrid method result for**		**Gumption method**	**ARQEA**
	Max cost	***Min cost***	***Max cost***	***Min cost***	***Max cost***	***Min cost***		
P_1	118.30	172.76	131.52	172.76	180.57	181.12	150	**200**
P_2	46.07	26.62	78.83	26.62	46.72	46.75	80	**20.18**
P_3	48	24.83	27.27	24.83	19.16	19.15	18.32	**15.02**
P_4	33.87	23.41	10.89	23.41	10.58	10.18	10	**23.74**
P_5	18.05	19.18	17.45	19.18	10.90	10.77	10	**10**
P_L	5.30	7.82	7.02	7.82	9.08	9.12	8.48	**9.93**
P_{total}(MW)	264.29	266.80	266.02	266.80	268.06	268.1	267.48	**268.94**
Cost($/MW)	1012.44	926.55	960.52	926.55	906.59	905.66	896.20	**838.96**