Advanced Intelligent Dispatch Control In Power Generation

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Abstract- **With the fast development of technologies of alternative energy, the electric power network can be composed of several renewable energy resources. Time of use (TOU) pricing creates more energy-efficient and renewable-energy-friendly grid. It is possible to better utilize the energy production by incorporating an energy storage device (ESD). GA algorithm is used for creating dispatching schedules for customer-owned renewable energy systems coupled with energy storage. Genetic algorithms are adaptive search methods that simulate some of the natural processes: selection, information, inheritance, random mutation and population dynamics. Adding energy storage along with this algorithm to renewable generators would increase the rate of return for the owner of the system and help the utility to reduce peak load. In the next step PSO algorithm can be used and will compare the results**.

***Index Terms*—Distributed generation, energy storage device, genetic algorithm, renewable energy, smart grid, time of day pricing**.

I. INTRODUCTION

WITH rapid escalation in fossil fuel price as well as sharp increase in the capital cost of new central generating plant, there is a focused attention on alternate generating system with higher efficiency of energy use. A renewable resource is a natural resource with the ability to reproduce through biological or natural processes and replenished with the passage of time. Renewable resources are part of our natural environment and form our eco-system. Renewable resources are endangered by industrial developments and growth. They must be carefully managed to avoid exceeding the natural world's capacity to replenish them. A life cycle assessment provides a systematic means of evaluating renewability. This is a matter of sustainability in the natural environment.

Solar radiation, tides, winds, geothermal,biomass and other natural elements are renewable resources of energy now called renewable energies. In terms of abundance, solar energy is the most easily available source of renewable-energy. The solar rays emitted by the sun are a non-quantifiable and available for use both directly and indirectly. The ideal tool to convert the intangible solar energy into a usable energy is the photovoltaic cell. Concentrated solar power (CSP), is another effective way to convert sunlight into electricity, this technique focuses on taking the sun’s rays and placing it into a liquid that heats up and produces steam that spins an electricity producing turbine. Wind power is derived from uneven heating of the Earth's surface from the Sun and the warm core. Most modern wind power is generated in the form of electricity by converting the rotation of turbine blades into electrical currents by means of an electrical generator.
The use of renewable energy for electricity generation will increase in the future due to environmental pressures, particularly regarding global warming and emission issues. Therefore, the role of renewable energy generation will become more significant in relation to the operation and management of electrical systems.

Electric utilities and end users of electric power are becoming increasingly concerned about meeting the growing energy demand. Under deregulation and restructuring of power system, electricity market becomes highly competitive. Many people chose to own renewable generator such as residential-sized wind turbines or solar system. These help them less radiant on grid and to shrink their carbon footprint. Renewable energy resources depend on the data of the climate such as the wind speed for wind energy, solar radiation for solar energy. The main problem faced by these sources is the intermittent nature of its output. However, the initial cost of these systems often makes them hard to justify from an economic standpoint.

II. SOLAR DATA

It is noted that large buildings, trees, and even landscape have an impact on the amount of solar energy striking a surface. The annual average number of peak sun days is in the range 4 to 5. The maximum amount of solar energy is available in the time 11.00hrs to 15.00 hrs range. This may also vary for different months in a year. These variations are shown in fig 1.

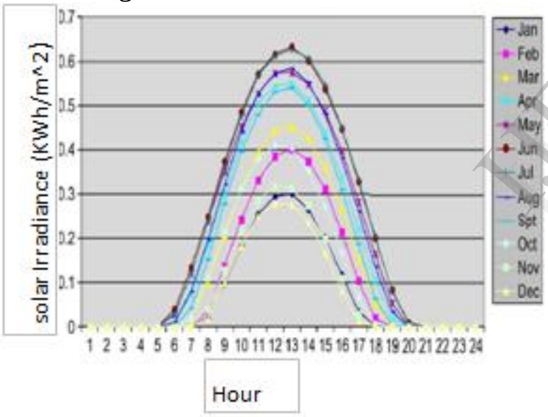


Fig 1. Average hourly sunshine on a flat surface

III. LOAD DATA

Actual load data was donated by a regional utility that serves both rural and metropolitan areas. Figure shows that the summer peak-load with an average peak demand of about 3.25 kWh from about 8 p.m. to 10 p.m. in July. The load in the two summer months of July and August is much higher than any of the other months with a well defined peak at about 7 p.m. The other months have a very flat profile and some even peak in the morning hours around 8 or 9 a.m.

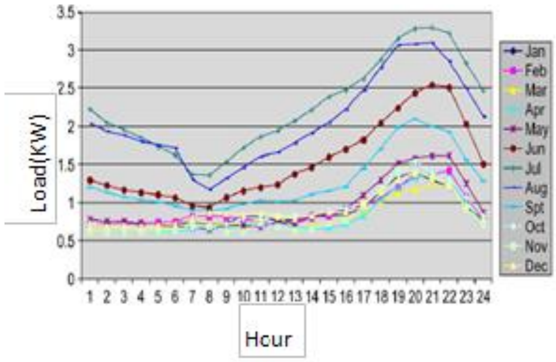


Fig. 2. Residential load data

For the better utilization of the energy produced an energy storage device is incorporated. Thus the owner gets a faster return of investment. For example, Fig. 1 shows hourly average solar irradiance and Fig. 2 shows average hourly loads. Comparing these figures it is easy to see that the peak load and peak energy production by a residential solar system do not coincide.

IV. CURRENT DG/ESD DISPATCH METHODS

A. Academic Review

Dispatching methods for small renewable generation with storage is just beginning to receive academic and industry attention.

1) *Residential photovoltaic Energy Storage System*: This paper mentions a dispatching scheme, but focuses more on the development of the hardware that could be used for switching between different operating modes and on the maximum peak power tracker that the system would be built around. Additionally this method is relevant only to solar-powered systems. The dispatching schedule used for this system is based on a prescribed load and irradiance schedule and the dispatch itself is pre-programmed into the system, which allows for little flexibility in optimizing the dispatch as conditions change. In fact, the authors state that if the characteristic of any factor is changed, the pattern of daily operation should be redesigned. Resetting the daily operation of the system would then be the responsibility of the owner of the system rather than an automated process.

While this paper did not offer a dependable means of determining the daily dispatch for customer-owned renewable energy systems with battery storage capabilities, it did propose a reliable system for switching between the different operating modes for solar systems. Therefore, a better dispatching schedule coupled with the system proposed in this paper could be implemented as an effective dispatching system for solar-based systems.

2) Optimized Dispatch of a Residential Solar Energy System: The results of the paper showed that a solar panel coupled with an energy storage element and a dispatching scheme could effectively shift customer load and, in some cases, significantly reduce the cost of the customer's energy bill. The algorithm used here considers different facts. First, selling energy back to the grid was not considered. Selling energy back to the grid allows for better utilization of the renewable generator and can further help the utility to shift or cut peak load if it is done at the proper time. Secondly, inefficiency losses of the ESD were not included in the dispatching algorithm presented in the paper. It also considers demand charges. A demand charge is based on the peak power demand of a customer in a given month.

V.ALGORITHM

Economic load dispatch (ELD) is a sub problem of the optimal power flow (OPF) having the objective of fuel cost minimization. The classical solutions for ELD problems have used equal incremental cost criterion for the loss-less system and use of penalty factors for considering the system losses. The lambda-iterative method has been used for ELD. Many other methods such as gradient methods, Newton's methods, linear and quadratic programming, etc have also been applied to the solution of ELD problems. However, all these methods are based on assumption of continuity and differentiability of cost functions. Hence, the cost functions have been approximated in the differentiable form, mostly in the quadratic form. Further, these methods also suffer on two main counts. One is their inability to provide global optimal solution and getting stuck at local optima. The second problem is handling the integer or discrete variables.

Genetic algorithms (GAs) have been proved to be effective and quite robust in solving the optimization problems. GAs can provide near global solutions and can also handle effectively the discrete control variables. GAs does not stick into local optima because GAs begins with many initial points and search for the most optimum in parallel. GAs considers only the pay-off information of objective function regardless whether it is differentiable or continuous. Consequently, the most realistic cost characteristic of power plants can be formulated. Discontinuity and non-differentiability of cost characteristics can be effectively handled by GAs.

GENETIC ALGORITHM

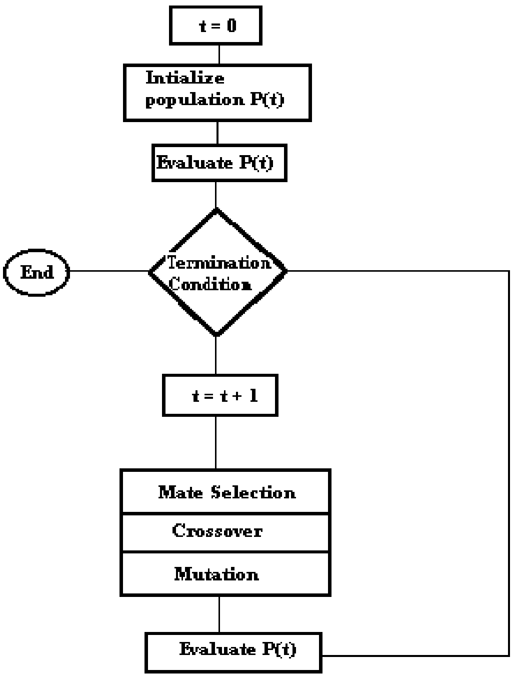
GAs is inspired from phenomena found in living nature. The phenomena incorporated so far in GA models include phenomena of natural selection as there are selection and the production of variation by means of recombination and mutation, and rarely inversion, diploid and others. Most genetic algorithms work with one large panmictic population, i.e, in the recombination step each individual may potentially choose any other individual from the population as a mate. Then GA operators are performed to obtain the new child offspring.

There are three important GA operators which are commonly used are as follows:

(i) Crossover

(ii) Mutation, and

(iii) Selection and survival of the fittest.



Basic Structure of GA

A. *Cost Function*

The most economic dispatch is found by minimizing the cost function, which includes both the total price paid for energy over the course of the dispatch period and the cost of using the equipment necessary to control the power flows. Therefore, it is the total sum of the cost of purchasing energy in each hour minus the amount of money that is made by selling energy back to the grid in each hour.
This gives buying or selling energy over a period of 24 h.

$$\sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} \qquad (1)$$

It should be noted that in reality, hourly cost would be calculated by first determining if the net energy flow from the grid was positive or negative and then multiplying by the proper rate for selling or purchasing energy.. The second part of the cost function takes into account the cost of using the ESD.

$$\text{Cycle Cost} = \frac{\text{(Cost of the ESD system)}}{\text{(Cycle life)}} \qquad (2)$$

By including this in the cost function, the GA dispatching algorithm optimizes the number of ESD cycles in a single dispatch. It is to find the best balance between maximizing the lifespan of the ESD and utilizing the system effectively, to reduce the cost of the customer's energy consumption.

$$\text{Hourly cost of cycling} = \text{(cycle cost)} \times \frac{E_{Bi}}{E_{BC}} \qquad (3)$$

$$= E_{Bi} \times R_B \text{ where, } R_B = \text{(cycle cost)} \times \frac{1}{2\,E_{BC}} \qquad (4)$$

B. Equality Constraints

The purpose of the equality constraint is to insure that the power flows from each of the sources in the system are balanced.

Reordering the equation so that the knowns and unknowns are in their proper place gives

$$E_{Pi} - E_{si} + E_{Bi} + E_{Bi-} = E_{Li} - E_{Ri} \qquad (5)$$

To prevent the GA from attempting to buy and then sell energy in the same hour when the selling price is higher than the buying price following constraints are used.

$$E_{pi} \geq 0 \qquad (6)$$
$$E_{si} \geq 0 \qquad (7)$$

The purpose of this constraint is to prevent the GA from attempting to buy and then sell energy in the same hour when the selling price is higher than the buying price. To prevent this from happening, the amount of energy either purchased or sold must be forced to zero.

C. Inequality Constraints

The purpose of this constraint is to insure the capacity of the ESD is not exceeded.

Battery charge is simply the negation of power flows into the system from the battery. Additionally, this constraint can be modified to take into account an initial battery charge, which may be present before the dispatch begins and a lower limit on the ESD as some storage devices, such as batteries, are designed to only be discharged down to a certain limit.

$0 \leq$ battery charge $\leq E_{BC}$

Where

$$E_{BC} = \begin{cases} \text{ESD capacity} \\ \textit{Battery charge} = \sum_{i=1}^{n}(-E_{Bi}) \end{cases} \quad (8)$$

EBi is negative when energy is flowing into the battery to charge it, and positive when energy is leaving the battery. Negating the already negative number makes the value positive again so that it may be compared to 0 and ESD, which is always positive.

$$-E_{B0} \leq -E_{B1} - E_{B2} - \ldots - E_{Bi} \leq E_{BC} - E_{B0} \quad (9)$$

$$1)\ -E_{B1} - E_{B2} - \ldots - E_{Bi} \leq E_{BC} - E_{B0} \quad (10)$$

and

$$2)\ E_{B1} + E_{B2} + \ldots + E_{BC} \leq E_{B0} \quad (11)$$

EB is separated into two variables with one to represent charging the ESD and one to represent discharging. The inefficiency constraints are also accounted for, e_{dis} for ESD discharging and e_{char} for ESD charging, and the inequality constraint becomes

Decision Variables

R_{Pi} - purchasing rate (cost) in period i
R_{Si} - selling rate (price) in period
R_B - cycling cost coefficient
E_{Li} - electrical load in period i
E_{Ri} - amount of energy that can be extracted from renewable resources in period i
E_{B0} - initial battery charge
E_{BCmin} - minimum ESD capacity
E_{BCmax} - maximum ESD capacity
$E_{Bdis-max}$-maximum hourly or other period, discharge
$E_{Bdis-min}$ - maximum hourly or other period, charge
e_{dis} - ESD discharging efficiency
e_{char} - ESD charging efficiency Parameters
E_{Pi} - amount of energy purchased in period
E_{Si} - amount of energy sold in period i
E_{Bi+} - amount of energy flowing from the battery in time period i (discharging)
E_{Bi-} - amount of energy flowing to the battery in time period i (charging)

$$\text{Minimize Cost} = \sum_{i=1}^{n} E_{Pi} \text{ X } R_{Pi} - \sum_{i=1}^{n} E_{Si} \text{ X } R_{si} + \sum_{i=1}^{n} E_{(B+)i} \text{ X } R_{(B-)i} - \sum_{i=1}^{n} E_{(B-)i} \text{ X } R_{(B-)i}$$

$$\text{Subject to} \quad \left.\begin{array}{l} E_{Pi} = 0 \\ E_{Si} = 0 \end{array}\right\} \begin{array}{l} \text{Dependent on guess} \\ \text{and check iteration} \end{array}$$

$$0 \leq E_{Bi+} \leq E_{Bdis-max}$$

$$E_{Bchar-max} \leq EBi \leq 0 \quad \text{when } R_{Pi} > R_{si}$$

$$0 \leq E_{Bi-} \leq 0 \quad \text{when } R_{Pi} < R_{si}$$

Where:

i – the period (typically the hour of the day)

n – the total number of periods in the dispatch schedule (typically 24, for an entire day)

D. Upper and Lower Bounds

The upper and lower bounds, shown below, insure that EB- is always negative and

$$0 \leq E_{Bi+} \leq E_{Bdis-max}$$

$$E_{Bchar-max} \leq E_{Bi-} \leq 0, \text{ when } R_{Pi} \geq R_{Si}$$

$$0 \leq E_{Bi-} \leq 0, \text{ when } R_{Pi} \leq R_{Si}$$

EB+ is always positive.

These bounds also insure that the power flow ratings of the ESD, $e_{Bdis\text{-}max}$ and $e_{Bchar\text{-}max}$, are not exceeded.

VI. RESULTS

Several simulations have been completed to test the effectiveness of this algorithm on a real system. All simulations were done using MATLAB. These simulations test the dispatching algorithm on a variety of electric rates and renewable generators supported by an ESD. All of these case studies involve 24-hour-long simulations with one-hour dispatching periods.

SIMULATION 1 LOAD, RESOURCES AND RATES

Sl.no.	Time (hrs)	Er (KW)	El (KW)	Power (KW)	R_P ($/KWh)	R_S ($/KWh)
1	0	0	1.25	1.2	0.04	0.1
2	4	1	0	1.0	0.04	0.1
3	8	1	1	0	0.04	0.1
4	12	1.20	2.5	-1	0.04	0.1
5	16	1.20	1.75	0	0.04	0.1
6	20	0	2.5	2.2	0.04	0.1
7	24	0	1.5	1.6	0.04	0.1

This data shows that the forecasted load of the residence as E_l and the forecasted hourly energy production of the solar system as Er. It also shoes the energy rates with R_P being purchasing rate and R_S being the rate at which energy can be sold back onto the grid.

SIMULATION 1 DISPATCH

Sl.no.	Time	Ep (KW)	Es (KW)	Eb (KW)	Stored Energy (KWh)
1	0	1.2	0	0	1.8
2	4	1.1	0	0	1.8
3	8	-0.2	0	-0.2	1.8
4	12	-0.8	0	-0.8	4
5	16	0	0	0	6
6	20	0.6	0	1.8	4.4
7	24	0.8	0	1.8	1.8

Dispatch results show that the excess energy produced midday is stored in the battery for use later in the day when it will be more valuable as load cutting energy rather than excess sold onto the grid.

SIMULATION 2 LOAD, RESOURCES AND RATES

Sl.no	Time	El (KW)	Er (KW)	Power (KW)	R_P $/KWh)	R_S ($/KWh)
1	0	1.2	0	1.8	0.09	0.09
2	4	1.1	0	1.8	0.09	0.09
3	8	1	1	1.0	0.09	0.09
4	12	1.1	2.2	-1.0	0.09	0.09
5	16	1.8	1.6	0	0.14	0.14
6	20	2.2	0	2.2	0.14	0.14
7	24	1.5	0	1.8	0.14	0.14

The rate structure used for the second simulation is shown here. The cost of energy increases between the hours of 1 P.M. and 6 P.M.

SIMULATION 2 DISPATCH

Sl.no.	Time	Ep (KW)	Es (KW)	Eb (KW)	Stored Energy (KWh)
1	0	1.9	0	-0.2	2.0
2	4	1.4	0	-0.1	3.0
3	8	0.8	0	-0.8	4.0
4	12	0.2	0	-1.0	8.0
5	16	0	1.2	1.4	4.8
6	20	2.2	0	0	2.0
7	24	1.5	0	0	2.0

In the dispatch generated by the algorithm, It can be seen that the system begins charging the battery from the grid even before excess energy is produced by the solar system so that it will be fully charged by the time the rates increase. When the rates do increase, the stored energy is used to both cut load and sell excess back to the grid.

V.CONCLUSION

In this paper GA algorithm creates efficient dispatching schedules. This algorithm is used along with the customer owned renewable energy systems coupled with energy storage. Simulations results will show that adding dispatchable energy storage along with this algorithm to renewable generators would increase the rate of return for the owner of the system and help the utility shave peak load.

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