A Review on Optimal Operation of Distributed Network Embedded to Wind-Battery Storage System

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Abstract: ***Energy is a vital requirement for today's socio-economic welfare and development. But due to the continuous increase of the demand the conventional energy resources are depleting day by day and on the verge of extinction. Hence more renewable generation units are emphasised to integrate to the power network to supply the required demand. This incorporation of the distributed generation into the distributed network has the advantages of controllability, flexibility and tremendous potential if it can be exploited properly. However, due to their intermittent and unpredictable nature, there is a need for energy storages to ensure continuous operations, i.e., to meet the load all the time. There are many possible options for energy storage, but the most popular and technologically sound option is battery storage. Along with this battery storage system (BSS), a power conditioning system (PCS) has to be connected for generation of both active and reactive power from the BSS which in turn increases the overall installation cost of BSS. Moreover, the energy storage cost is a function of the storage device power, energy capacities and their specific costs depending on the chosen technology of optimization. Thus, profit from those renewable energy producers have to be maximized, and losses are to be minimized by using dynamic optimization techniques. But along with the advantages there comes the complexities due to the inclusion of distributed generation and the additional energy storages in the power system network. Moreover, it is highly critical to operate the vast system optimally. Hence there are lots of research had been done or are in process for finding the proper approach of optimization of the system. This paper presents a review of the current state of the optimization methods applied to renewable and sustainable energy source embedded with the Energy storage for maximization of the revenue obtained from the power trading to the network.***

Keywords: Distributed Generation (DG), Distributed Network (DN), energy storage, Battery storage system (BSS), power conditioning system (PCS),Dynamic optimization techniques, Energy Management System (EMS)

1. Introduction

Renewable Power Generation systems are being increasingly preferred for clean power generation, to reduce the dependency on fossil fuels and to cease greenhouse gas emissions. Many countries have implemented various terms and policies to promote renewable energy in the distribution network. Many researches have been recently carried out for making the wind farms dispatchable. This can be accomplished by integrating a Battery Storage System (BSS) with these wind farms [1]. It was shown that the only economically feasible BSS technology is Zn/Br [10]. With high Photo Voltaic (PV) and wind penetration in some regions, there is a surplus power available, which is utilized for charging the Battery Storage System during low demand and deliver power during high demand. From the consumers' point of view, use of a BSS can lower the electricity costs as it can store electricity bought at lower prices during off-peak, which can be used during peak load periods in the place of expensive power [7]. The potential of BSS can be well understood from Fig. 1.

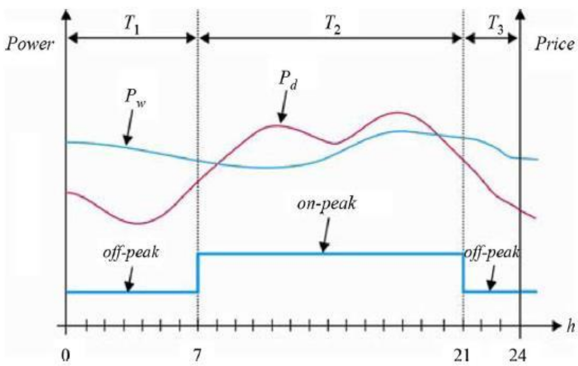

Fig. 1: Daily wind-demand power profiles and electricity price model

Fig. 1 schematically shows the daily demand and Wind Power profiles. It can be seen that, during time periods of T_1 and T_3 (off-peak), the excess energy can be stored in BSS. This stored energy can be used during the time period of T_2 (peak), in which the demand is more than the wind power penetration. In a research by A. Gabash and P. Li [2], a method based on genetic algorithms (GA) is applied to evaluate the impact of the cost of energy storage on the economic performance of a distribution substation .Thus by optimizing the daily /weekly scheduling of the renewable generating plants integrated with the BSS should be done in order to maximize the total revenue [1]. BSS should be connected to the AC power system through PCS which is a Flexible AC Transmission System (FACTS) device used for accommodating the bidirectional power conversion between AC and DC system.

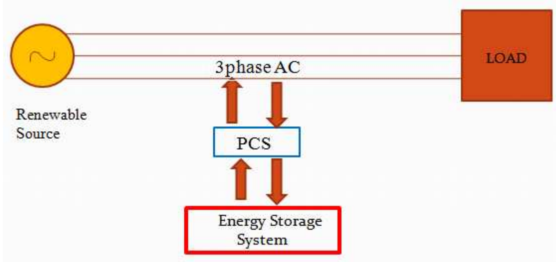

Fig. 2: Arrangement of Storage system and PCS

2. Optimization Techniques

The best suitable or the most acceptable design of all feasible conceptual designs can be said as the optimum design of a system. This process of designing the optimum system by satisfying some objective is called optimization; it follows a process or methodology of making something fully perfect, functional, or effective as possible; specifically by using the mathematical procedures. Simply, optimization is the process of maximizing of a desired quantity or minimizing of an undesired one [17]. Whereas, the various techniques used for designing the optimum model are known as the optimization techniques. In terms of Electrical Energy System, the optimized power system should minimize the fuel cost or minimize the losses, keep the power outputs of generators, bus voltages, shunt capacitors/reactors and transformer's tap-setting within their secure bounds and maximize the total profit.

Some of the classical optimization techniques are direct method, gradient methods, linear programming method (LP) and interior point method. Some of the advanced optimization technique includes simulated annealing, evolutionary optimization algorithms (Genetic algorithm(GA), Particle swarm optimization(PSO), Ant colony optimization (ACO), Estimation of distribution algorithm (EDA), Differential Evolution(DE), Evolutionary Strategy(ES), Evolution Programming(EP), Bacteria Forging Algorithm (BFA), Bee's colony Algorithm (BCA) etc.). The choice of suitable optimization method depends on the type of optimization problem. Due to the fast development of digital computers, there are major advances in optimization techniques. Techniques like GA and PSO have become very popular and powerful tools in power engineering to minimize the electricity cost in the electricity market from consumers' point of view and also to enhance the profit derived from power trading. The classical optimization techniques are also useful for single as well as multi-dimensional optimization problems, but there are some drawbacks and they are less effective and reliable compared to the advanced techniques; because unlike advanced optimization method, classical methods do not use the information gathered from previously solved points [18]. Moreover, in the gradient method, the algorithm terminates as the gradient of the objective function reaches very close to zero. The slope or gradient of the function indicates what direction to move locally. Thus, it uses the knowledge of derivative information to find the local optimum point, not the global optimal point [19]. Again, for the LP method, there lies the condition of both objective and constraints being linear. Thus, the classical methods are inferior for finding global optimum; moreover, they are highly sensitive to the initial conditions. This suggests that to solve the complex, non-linear, discrete, continuous or mixed variables, multiple conflicting objectives, discontinuity etc., as the power flow optimization problem of the power system, there is a need of some robust techniques. Hence, advanced optimization methods come into play. Among them, for the problems having a very large number of decision-variables and non-linear objective functions, Evolutionary algorithms are often used. The evolutionary algorithms are based on population-based search methods that incorporate random variation and selection. The first evolutionary-based optimization technique was the genetic algorithm (GA) [18]. Eventually, more optimization algorithms like Particle Swarm Optimization (PSO) [16], Ant Colony Optimization (ACO) and Estimation of Distribution Algorithm (EDA) etc. came into existence.

According to the characteristics of the evolutionary algorithm, one algorithm cannot be superior to the other in all kinds of cases. Hence, for a class of problem, one has to observe which algorithm is reliable to obtain an optimized result. Another popular approach of solving optimization problem is the implementation of the Algebraic Modeling Languages (AML) like General Algebraic Modeling System (GAMS) [25], Advanced Interactive Multidimensional Modeling System (AIMMS) [26], A Mathematical Programming Language (AMPL) [27], LINDO [28], etc. AML are high-level computer programming language, which uses different algorithms called solvers to handle different mathematical problems. They are also suitable for modelling of linear, nonlinear, mixed integer, large scale and complex optimization problems, as they are proficient in high-level mathematical computations. Hence, AML can easily be implemented to the power flow optimization problems.

3. Optimal Power Flow

The finding of the real and reactive powers scheduling of power plant in a way that it minimizes the overall operating cost of the interconnected power system by satisfying some set of operating constraints is known as the optimal power flow (OPF) problem. The OPF was first formulated by Carpentier in1962, and it was proved to be a very difficult problem during those days. There are commonly three types of problem in power system. They are load flow, economic dispatch and OPF, while economic load dispatch and load flow are the sub-problem of OPF. For a very large system, the modern trend is to use the metaheuristic algorithms to solve the non-convex, non-linear, complex OPF [20]. A metaheuristic algorithm is a higher-level procedure to find a near optimal solution; it guides the search space. These metaheuristics can be both local/ global search based. As OPF is population-based optimization, hence global search metaheuristics are applicable. Such global search metaheuristics include the evolutionary computation, GA, PSO, ACO etc. [21]. Even though, the cost of generation and real power generation can be found out using the versatile Newton-Raphson (NR) method. However, by using the developed Constraint, GA-OPF through crossover and mutation operations can further reduce the cost of generation [21].OPF is a large-scale, static optimization problem with both continuous and discrete control variables. The discrete control variables are the switchable shunt devices, transformer tap positions, and phase shifters and due to their presence, it becomes complicated to derive the problem solution. In the research by L. L. Lai, J. T. Ma, R. Yokoyama and M. Zhao [21], a simple genetic algorithm (SGA) is applied for OPF solution. The control variables taken in their work are generator active power outputs, voltages, shunt devices, and transformer taps. Complexity arises when the number of control variables increases. The GA-OPF approaches do not have the limitations of the conventional methods in the modelling of non-convex cost functions and discrete control variables. However, they do not scale easily to larger problems, because the solution weakens with the increase of the chromosome length, i.e., the number of control variables. Thus, the existing GA-OPF is limited to very small problems. So in addition to the basic genetic operators of the SGA [21], the advanced and problem-specific operators are used to enhance the performance of GA. The three basic genetic operators are parent selection; crossover and mutation. Thus with the incorporation of the problem, specific operators such as Gene Swap operator (GSO), Gene Cross Swap Operator (GCSO), Gene Copy Operator (GPO), Gene Inverse Operator (GIO) and Gene Max-Min Operator (GMMO) the GA can solve larger OPF problems [7]. But, unfortunately, recent researchers have identified some fault in the performance of GA [23]. Hence evolutionary computation PSO was introduced to solve the OPF problem for its simple concept and flexibility. It can be observed from some researchers, like the results obtained by M. A. Abido [24], that PSO technique is highly effective and superior over the classical techniques and genetic algorithm. In addition to these hybrid heuristic algorithms (i.e. use of two optimization techniques together) are also used for solving OPF problem in order to get better results [30]. Optimization of the power network can also be done using AML [25-29].

4. Optimization of a Combined System

The electrical power system is a network of a large number of electrical components used for supplying, transferring and utilizing power. Economically, electricity (both power and energy) can be bought, sold and traded. The profit derived from the power trading should be always more than all other costs (like generation cost, operation and maintenance cost etc.), which in turn will affect the electricity pricing. Hence, optimization plays a great role in such condition. Hence, ACOPF is solved every year for power system planning, every-day for the day-ahead market, every hour and in-fact for every 5 minutes [31]. OPF finds out the optimal solution to an objective function subject to the power flow constraints and other operational constraints such as generator constraints, thermal stability constraints and voltage constraints and many more according to the requirement. But, when the renewable generation units are integrated to the power network, the designing of an optimum model becomes more complex; because along with the renewable source, other auxiliaries will also be incorporated such as BSS, PCS etc. Hence, to find the optimal operation of such an integrated system, there may be a need for designing multiple objective functions. As a result, the complexities of the power system increases further.

5. Optimal Operation of Wind-Storage System

Energy storage is one of the efficient and effective solutions to store and use energy on demand. It provides flexibility throughout the grid and enhances stability, power quality and reliability of supply. Hence energy storage systems, when embedded with the renewable energy generation, provide a wide range of ways to manage power supplies and develop a more stable energy infrastructure, and as a result, the cost of energy for utility providers and consumers get reduced as well as it brings down the operating cost of generation. Despite, the optimal BSS capacity is closely associated with the shape of load curves and parameters of all generating units in a power system [3].

Energy storage systems are comprised of three main modules:

a) The Battery storage, i.e., BSS

b) The Power Conditioning System (PCS), which helps the energy the energy conversion from AC to DC or DC to AC

c) The control system that controls the operation of the energy storage system

Since several decades, the optimization techniques are applied to the power system problems, and there seems to be a competition among the optimization algorithms, applied to the growing complexity of power system planning and operations related problems [4]. Optimization of ESS includes the optimal operation of the storage system with the least losses during charging and discharging. Moreover, the losses during AC-DC conversion also should be less. For the Renewable Embedded Storage System (RESS) the optimal scheduling of generation should be done for supplying power demand to the network. In the work by A. Gabash and P. Li [1], the operation of Wind-Battery stations is considered which is composed of two main substations. First, a wind farm substation, which can dispatch power hourly. Second, a Battery substation in which its power and capacity are selected initially through simulation procedures for satisfying the electricity market requirements at the same time [1].

The wind farm (WF) is designed to generate the active and reactive power. During low demand, the excess power is used to charge the battery through PCS. While during high demand, the power to the network is supplied by the wind farm as well as the battery.

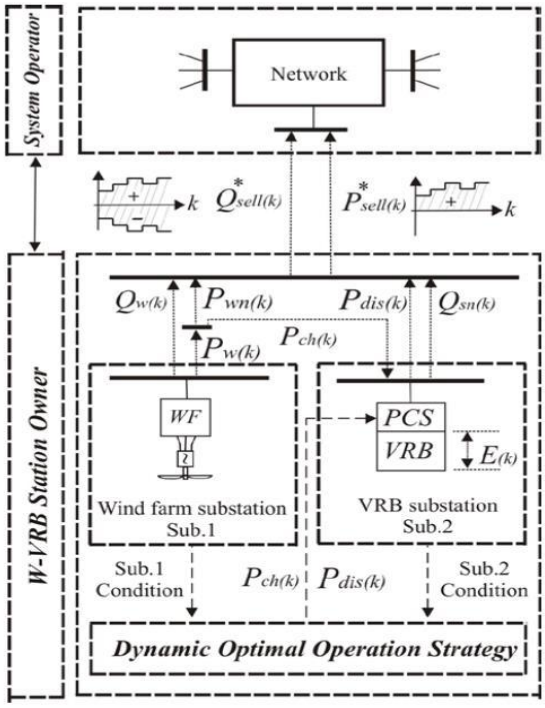

Fig. 3: Structure of the proposed W-Battery station and the total operating scheme

In Fig. 3, $P_{sell}(k)$ is the hourly active power to be sold to the electrical power system, $P_{ch}(k)$ is the hourly active power used for charging the battery substation and $P_{dis}(k)$ is the hourly active power discharged to the network from the battery substation respectively. Typically, the power factor (PF) of a wind farm is controllable from 0.95 inductive to 0.95 capacitive [5]. For simplicity 0.962 inductive power factor is assumed for the wind farm substation, which means absorbing reactive power, $Q_w(k)$ [1]. During charge/discharge processes, there are power losses. Generally, charging efficiency is assumed to be 80% and during the discharge, the efficiency is assumed to be 75% [6].

6. Profit Maximization

Besides optimizing the operation of the battery, if active power and reactive power are optimized separately using optimal power flow (OPF), then the total profit derived can be increased hence the efficiency of the power network can be improved [7]. The profit can be farther increased if combine Active-Reactive Optimal Power Flow (AROPF) is formulated in Distributed Networks (DNs), which is embedded with wind generation and battery storage, satisfying all the operational constraints. The solution provides an optimal strategy, which ensures the feasibility and efficiency and enhances the profit significantly. The optimized output obtained from the optimization of energy storage is implemented for optimizing the AROPF [2]. Generally, the solution for Active Reactive Optimal

Power Flow is obtained considering the fixed length of the charge and discharge cycle of BSSs. This can lead to a low profit because the profiles of renewable generation, demand and energy prices vary from day-to-day. Due to the dynamic behaviour of renewable energy sources (e.g., wind and solar), demand, and energy prices leads to a complex process and needs adaptive strategies to deal with. The integration of the BSS to the energy supply networks can help in controllability of charging and discharging time interval [10]. Hence, if the charging/discharging time of BSS can be controlled with respect to the input parameters, the profit output can be increased. The lifetime of a battery storage depends on a fixed number of charge/discharge cycles and days of operation. This can be represented by a replacement period (in years) by the formula [5]:

$$r = \frac{p}{n \times D}$$

where p is the total number of charge/discharge cycles in the lifetime, D is the annual operation days, and n is the number of charge/discharge cycles per day. Generally, the number of charging or discharging cycle is kept to be one in order to increase the replacement period of the battery and for optimal planning and operation [10]. Thus, the whole system of optimization wind battery embedded system can be represented by three objective functions.

6.1 Objective function for Energy Storage Optimization

When the ESS is embedded with a wind farm, the objective function can be formulated as [1]:

$$R_{max} = \sum_{k=1}^{24} [Cpr(k)Psell(k) - Cch(k)Pch(k) - Cdis(k)Pdis(k) - \beta\{\{(Pch(k+1) - Pch(k)\}^2 + \{Pdis(k+1) - Pdis(k)\}^2\}] \quad \ldots\ldots(i)$$

where $C_{pr}(k)$ represents a vector of hourly active power prices, $C_{ch}(k)$ is the charge operation cost, $C_{dis}(k)$ is the discharge operation cost. The objective is to maximize profit. The first summation term gives the total profit from active power trading in which the losses in the revenue by charging/discharging are subtracted. The second summation term is formulated to reduce the differences of control variables between two successive time intervals in order to evaluate the minimum constant reactive power capability. In the work by A. Gabash and P. Li [1], a weighting factor β is used to formulate a multi-objective model where the generation cost and system network loss is combined together.

6.2 Objective function for AROPF

In the work by A. Gabash and P. Li [2], the objective function for combined AROPF in DNs with embedded wind generation and battery storage is given by:

R_{max} = (total revenue from active power trading of wind farm) – (cost of energy losses) ….(*ii*)

Total revenue

$$= \sum_{h=1}^{T} Cpr(h) \sum_{i=1}^{N} [Pw(i,h)\, \beta_0\, (i,h) + Pdis(i,h) - Pch(i,h)$$

Cost of energy losses

$$= \frac{1}{2}\sum_{h=1}^{T} Cpr(h) \sum_{i=1}^{N} \sum_{j=1}^{N} G(i,j)(Vr^2(i,h) + Vim^2(i,h) + Vr^2(j,h) + Vim^2(j,h) - 2\{Vr(i,h)Vr(j,h) + Vim(i,h)Vim(j,h)\})\}]$$

Where G(i,j) is the real component of the complex admittance matrix elements. $P_w(i,h)$ is the active power of wind generation at bus i during hour h. $V_r(i,h)$ is the real component of complex voltage at bus i during hour h. $V_{im}(i,h)$ is the imaginary component of complex voltage at bus i during hour h. β_0 is the wind power curtailment factor, which is responsible for maintaining the capacity of the BSS (i.e., to spill a part of the power when the installed capacity of the BSS is not sufficient to accommodate the whole power or it may violate the other system constraints) [2]. The range of β_0 is 0 to 1. If there is no wind power $\beta_0 = 1$ or $\beta_0 \leq 1$

6.3 Objective function for finding the optimal time duration of charging and discharging of the battery

In another work by A. Gabash and P. Li [10], it is shown to be a two-stage iterative framework because the whole optimization problem is divided into two sub-problems. In each iteration, the integer variables (hours of charge and discharge periods) will be optimized with an efficient search method in the upper stage, while the continuous variables are handled by a Non-Linear Programming (NLP) solver in the lower stage. This forms a complex Mixed-Integer Nonlinear Program (MINLP). The optimization problem will have three additional integer variables (the three time variables) along with the continuous control variables for AROPF (i.e., active power charge, active power discharge of BSSs, reactive power dispatch of BSSs and wind power curtailment).

The objective function of general AROPF depends on the time variable. The function for maximizing the profit is represented by

$R_{max} = F(x, u, t)$ .... (*iii*) where x is the vector of state variables of the system, i.e., real and imaginary component of complex voltage at PQ buses, active and reactive power injected at slack bus and energy level of BSS. u is the vector of continuous control variables including active power charge/discharge of BSS and reactive power dispatch of BSSs. Lastly, t is the vector of the integer control variables, i.e., the number of charge/discharge hours per day. In eqn.(iii), the function F is the total revenue from wind power and BSSs minus the total cost of energy losses (includes the cost of active energy losses in the grid) [2].

Subjected to

$g(x,u,t) = 0$ .... (iv)

$x_{min} \leq t_1 \leq x_{max}$ ....(v)

$u_{min} \leq t_2 \leq u_{max}$ ....(vi)

where, g(x,u,t) in eqn.(iv) represents the equality constraints including active and reactive power balance equations (they are nonlinear terms). The energy balance equations for BSSs are also included in eqn.(iv). The inequality constraints in eqn.(v) and eqn.(vi) include voltage bounds, active and reactive bounds at the slack bus, and main feeder bounds. The operational constraints in eqn.(vii) and eqn.(viii) are also included in the inequality constraints.

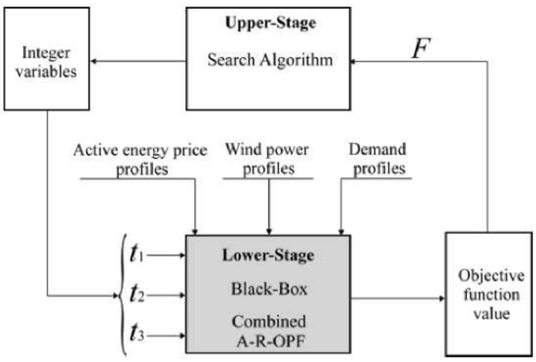

Fig. 4: Input-output model for the combined A-R-OPF with a search algorithm.

The two-stage model gives the sub-objective function for eqn.(iii). They are given by eqn.(a) and eqn.(b).

The upper stage solves the following problem.

Max F [x(t),u(t),t] .... (a)

Subjected to:

$t_1 + t_2 + t_3 = t_{max}$,where t_{max}= 24 and t_{min}= 0 ......(vii)

$$\left.\begin{array}{l} t_{min} \leq t_1 \leq t_{max} \\ t_{min} \leq t_2 \leq t_{max} \\ t_{min} \leq t_3 \leq t_{max} \end{array}\right\} \text{.....................} \quad \text{(viii)}$$

where t_{min} and t_{max} are the minimum and maximum bounds on time variables, respectively. The cycle of charge is determined by two integer variables representing the time periods (hours) of charge (t_1 and t_3). The cycle of discharge is defined by one integer variable representing the hours of discharge (t_2). As the daily operation of BSSs are considered, so t_{min}= 0 and t_{max} = 24 .

With the optimum value of t delivered from the upper stage, the lower stage solves the following NLP problem, i.e., AROPF becomes:

R_{max} = F(x,u) .... (b)

Subjected to

g(x,u) = 0 .... (c)

And inequality constraints are given by eqn.(v) and eqn.(vi). The solution of the lower stage provides the objective function value for the upper stage, where an update will be made for the next iteration until it reaches an optimum result.

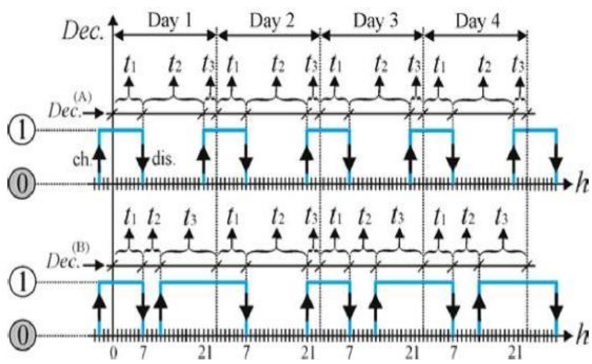

Fig. 5: Illustration for one charge/discharge cycle every day. A, and B stand for fixed and flexible operations of BSS, respectively

The model equations formulated by A. Gabash and P. Li, [1,2] for the system, describe the active power exchanges in the designed model as well as the change in the energy level in the BSS.

$P_{sell}(k) = P_{wn}(k) + P_{dis}(k)$ …………...……….. (ix)

$P_w(k) = P_{wn}(k) + P_{ch}(k)$ ..…………….……… (x)

where k = 1……..24, $P_{wn}(k)$ is the hourly active power delivered to the network by the wind farm, $P_w(k)$ is the hourly available wind power for a given wind speed.

The energy level of the battery is given by hourly energy balance equation in each storage unit. For optimization, it is commonly recognized that the energy level in the storage unit at the final time interval should be equal to that at the initial time point [1].

$E(k) = E(k\text{-}1) + \eta_{ch} P_{ch}(k)\Delta t - (1/\eta_{dis}) P_{dis}(k)\Delta t$
(for k = 1…….24) ……………………..…………(xi)

Where,

$E(k)$ = the energy storage level in the Battery substation in k^{th} hour
η_{ch} = charging efficiency of BSS
η_{dis} = discharging efficiency of BSS
The time interval Δt in research of A. Gabash and P. Li [1] is considered to be one hour.

Finally, the feasibility, capability and efficiency of the proposed model are verified with the IEEE 41-Bus test system. Taking into consideration of various equality and inequality constraints of the system for optimization of energy storage could be obtained by using the optimizing tools like General Algebraic mathematical system (GAMS), Genetic Algorithm (GA) or Particle Swarm optimization (PSO) etc. [8].

After solving the optimization problem for the objective given by eqn.(i), the optimal scenario of $P_{ch}(k)$ and $P_{dis}(k)$ can be obtained. Thereby, the reactive power from the Battery substation $Q_{sn}(k)$ [hourly available] can be calculated as follows [9]

$$Q_{sn}(k) = \sqrt{(S_r^2 - P_{ch}^2)} \text{ if charging } (k = 1,..,24) \quad \text{…. (xii)}$$

$$= \sqrt{(S_r^2 - P_{dis}^2)} \text{ if discharging } (k = 1,..,24) \quad \text{..(xiii)}$$

where S_r is the rated apparent power of the selected PCS, suitable for the battery station. Again the hourly reactive power available from the wind farm substation $Q_w(k)$ is given by

$$Q_w(k) = P_w(k) \tan \Phi \quad \text{……………...………….. (xiv)}$$

where $Q_w(k)$ is set to work with the fixed power factor ($\cos\Phi$ = 0.962) lagging (i.e. absorbing reactive power) [1]. Thus, the available reactive power to be sold to the electrical power system $Q_{sell}(k)$ can be calculated using relation:

$$Q_{sell}(k) = Q_w(k) + Q_{sn}(k) \quad \text{…………………...….. (xv)}$$

Therefore, the reactive power capability from the wind-battery station can be controlled using suitable PCS [1]. This reactive power can satisfy the local reactive power requirement of the wind farms and provide sufficient, constant and fully controlled reactive power to the electrical power system. In addition, it can also be used in a hybrid reactive power sources system by dynamic optimal operation at the W-B station. The reactive power could also be sold to the electrical power system for increasing power quality, voltage regulation, power losses minimization etc. Moreover, it increases the individual profit of wind farms through their reactive power compensation capabilities. Hence, the necessity of installing other reactive power compensators such as Static Synchronous Compensator (STATCOM) and Mechanically-Switched Capacitors and Reactors (MSCR) will get reduced in future. The optimization problem that is defined can be solved under the MATLAB environment, using FMINCON function [1], which can find a minimum/maximum of a constrained nonlinear multivariable function.

When a combined problem is formulated for active-reactive optimal power flow (A-R-OPF) for DNs with embedded wind generation and battery storage the objective was to maximize the total profit meanwhile the maximization of the amount of available reactive power. It was shown by A. Gabash and P. Li [2] that a large amount of reactive power can be achieved by an optimal operation of Wind-battery system embedded to DN. The formulated equations of the system show it to be a highly Non-Linear system; hence the Newton Raphson Power Flow Method is most suitable for finding the bus voltages of the required system. However, the initial values in the A-R-OPF method also has an impact on both the feasibility and computational efficiency of the system [2]. Hence the initial values are generally chosen to be a flat start for all computations, i.e.,

$P_{ch} = P_{dis} = Q_{disp} = V_{im} = P_s = Q_s = E = 0$
Whereas
$V_r^{(0)} = 1$

For different initial values, the solution converges to the same results, but the CPU time is different. Only when the initial values are very far from the flat start, a convergence problem may occur. The problem of AROPF in the work of A. Gabash and P. Li [2] with the objective function, as shown in eqn.(ii), is solved by using GAMS satisfying all the operating constraints. In addition, the NLP solver or algorithm used for solving the AROPF is CONOPT3, which is suitable for solving models with highly nonlinear constraints.

But in AROPF, even though charging-discharging power is flexible, the battery operation was restricted as the charging/discharging time of the battery was considered to be fixed. So the A-R-OPF method is extended by developing flexibility in the battery management system. This can be accomplished by optimizing the lengths (hours) of charge and discharge periods of BSSs for each day (24 hours). This, together with the A-R-OPF formulation, leads to a complex mixed-integer nonlinear programming (MINLP) problem, which cannot be readily solved by available approaches. GA has been successfully applied in solving many optimization problems in power systems, especially when both integer and continuous variables are present. The authors Anastasios G. Bakirtzis *et al.* [7] presented an enhanced GA for the solution of OPF with both continuous and discrete control variables. Since all these methods treat the continuous and integer variables simultaneously, they are not suitable to be used for the large-scale complex MINLP problem framework to decompose the optimization problem. Thus, a two-stage model is designed represented by (i) and (ii). In the upper stage, the time variable (i.e., hours of charge and discharge periods) are optimized based on the day-to-day profiles and delivered to the lower stage. In the lower stage, the A-R-OPF problem is solved by a Non-linear programming solver and the resulting objective function value is sent to the upper stage for the next iteration.

The search method for selecting the optimal time interval is a complex problem. It is demonstrated with the help of a search space shown in Fig. 6(a) and 6(b) [10].

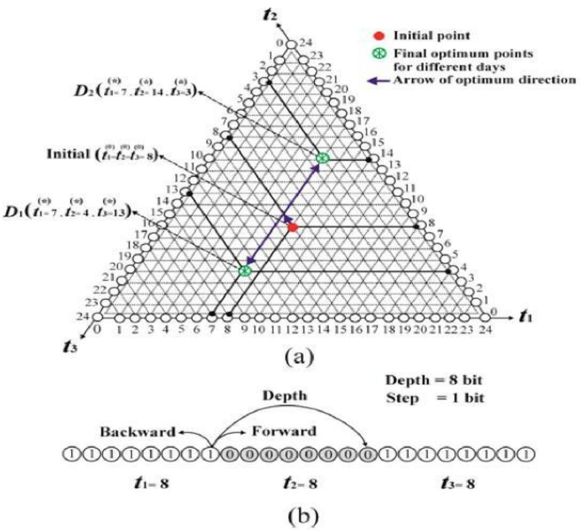

Fig. 6: (a) Illustration of the search space (b) String-structure.

In the search space, there is a total of 325 combinations as can be seen from Fig. 6(a). At first, an initial combination is selected (say $t_1 = t_2 = t_3 = 8$, i.e., at the center of the triangle) and this initial combination is provided to the lower stage for evaluating the objective function then the fitness value is recorded. Then keeping one of the variables fix (say t_3) and sweeping another variable (t_1) bit by bit backwards or forward from its initial value, different combinations are set. For each string, different fitness is recorded and among them, the best is selected for t_1. Then again, keeping t_1 fix for that value, sweeping is done with t_3 and the best value, which is obtained from it, is the best string found; its fitness represents the optimal operations for a specific day. Thus, the optimal lengths of charge/discharge cycle of BSSs for daily operations or even multiple days can lead to a considerably higher profit in comparison to that from a fixed operation strategy [10].

7. Conclusion

Many power related issues influence the operation of the Distributed Network (DN); and when Wind-Battery system is embedded with DN, the system becomes more complex to carry out the optimal operation of the network. Thus, many studies are done or still going on to find the most acceptable and feasible optimization technique that could be implemented to the power system for deriving the optimal operation. It can be concluded that the choice of suitable optimization method totally depends on the type of optimization problem formulated. In the case of deriving an optimized result of a wind-battery embedded system integrated into the power network, the problem is divided into parts then optimization is applied to maximize the profit of the overall system. Moreover, Energy Storage facilitates many advantages for optimal operation of the power network and has a great impact on profit maximization, specially when the generation is unpredictable. As the input parameters of the network are variable, a flexible and adaptive optimized operation strategy of storage systems can control the power flow and reduce the power losses, thereby enhancing the derived revenue from the power trading to the network. However, there is a very limited number of studies done related to the storage systems in grids such as design, dimension, location, operation planning and control of BSSs [10]. Hence, there lies immense opportunities and potential of BSS yet to be explored in the field of optimal power flow, which if explored will be promising in the future energy networks.

References

[1] A. Gabash and P. Li, “Evaluation of Reactive Power Capability by Optimal Control of WRedox Battery Stations in Electricity Market”, *Renewable Energy Power Quality Journal*, Vol. 1, Issue 9, May 2011, pp. 1154-1159. Doi: https://doi.org/10.24084/repqj09.583

[2] A. Gabash and P. Li, “Active-Reactive optimal power flow in distribution networks with embedded generation and battery storage”, *IEEE Transactions on Power Systems*, Vol. 27, Issue 4, Nov. 2012, pp. 2026-2035.

[3] C. H. Lo and M. D. Anderson, “Economic Dispatch And Optimal Sizing Of Battery Energy Storage Systems in Utility Load-Leveling Operations”, *IEEE Transactions on Energy Conversion*, Vol. 14, Issue 3,

September 1999, pp. 824-829. Doi: https://doi.org/10.1109/60.790960

[4] D. Chattopadhyay, "Application Of General Algebraic Modeling System to Power System Optimization" *IEEE Transactions on Power Systems*, Vol. 14, Issue 1, February 1999, pp. 15-22. Doi: https://doi.org/10.1109/59.744462

[5] E. DÍaz-Dorado, C. Carrillo and J. CidrÁs, "Control Algorithm for Coordinated Reactive Power Compensation in a Wind Park", *IEEE Transactions on Energy Conversion*, Vol. 23, Issue 4, Dec. 2008, pp. 1064-1072. Doi: 10.1109/TEC.2008.2001432

[6] D. K. Khatod, V. Pant, and J. Sharma, "Optimized daily scheduling of wind-pumped hydro plants for a day-ahead electricity market system", *Proc. of 2009 International Conference on Power Systems*, Kharagpur, Dec. 2009, pp. 1-6. Doi: 10.1109/ICPWS.2009.5442767

[7] A. G. Bakirtzis, P. N. Biskas, C. E. Zoumas and V. Petridis, "Optimal Power Flow By Enhanced Genetic Algorithm", *IEEE Transactions on Power Systems*, Vol. 17, Issue 2, May 2002, pp. 229-236. Doi: 10.1109/TPWRS.2002.1007886

[8] F. A. Chacra, P. Bastard, G. Fleury and R. Clavreul, "Impact of energy storage costs on economical performance in a distribution substation", *IEEE Transactions on Power Systems*, Vol. 20, Issue 2, May 2005, pp. 684–691. Doi: 10.1109/TPWRS.2005.846091

[9] E. Muljadi, C. P. Butterfield, R. Yinger and H. Romanowitz, "Energy Storage and Reactive Power Compensator in a Large Wind Farm", *Proc. of 42nd AIAA Aerospace Sciences Meeting and Exhibit, Aerospace Sciences Meetings*, Reno, Nevada, 5-8 Jan. 2004, pp. 1-10. Doi: https://doi.org/10.2514/6.2004-352

[10] A. Gabash and P. Li, "Flexible Optimal Operation of Battery Storage Systems for Energy Supply Networks", *IEEE Transactions on Power Systems*, Vol. 28, Issue 3, August 2013, pp. 2788 – 2797. Doi: 10.1109/TPWRS.2012.2230277

[11] P. Poonpun and W. T. Jewell, "Analysis of the cost per kilowatt hour to store electricity", *IEEE Transactions on Energy Conversion*, Vol. 23, Issue 2, Jun. 2008, pp. 529–534.

[12] G. Coppez, S. Chowdhury and S. P. Chowdhury, "The Importance of Energy Storage in Renewable Power Generation: A Review", *Proc. of 45th International Universities Power Engineering Conference (UPEC2010)*, Cardiff, Wales, 31 Aug. - 3 Sept. 2010, pp. 1-5.

[13] T. Bouktir, L. Slimani and M. Belkacemi, "A Genetic Algorithm For Solving The Optimal Power Flow Problem", *Leonardo Journal of Sciences*, Issue 4, 2004, pp. 44-58. Retrieved from https://www.researchgate.net/publication/26444444

[14] P. F. Ribeiro, B. K. Johnson, M. L. Crow, A. Arsoy and Y. Liu, "Energy Storage Systems for Advanced Power Applications", *Proceedings of the IEEE*, Vol. 89, Issue 12, Dec. 2001, pp. 1744-1756. Doi: 10.1109/5.975900

[15] S. M. Schoenung and W. V. Hassenzahl, "Long- vs. Short-Term Energy Storage Technologies Analysis: A Life-Cycle Cost Study: A Study for the DOE Energy Storage Systems Program", SAND2003-2783, *Technical Report, Sandia National Laboratories, United States Department of Energy's National Nuclear Security Administration*, August 2003. Doi: https://doi.org/10.2172/918358

[16] T. Blackwell, J. Branke and X. Li, "Particle Swarms for Dynamic Optimization Problems", in *Swarm Intelligence: Introduction and Applications*, C. Blum and D. Merkle (eds.), pp. 193-217, Springer, Berlin, Heidelberg, 2008. Retrieved from https://link.springer.com/content/pdf/10.1007/978-3-540-74089-6_6.pdf

[17] A. De, "Module 5: Design for Reliability and Quality", in *Design For Manufacturing, NPTEL Lecture Notes*. [Online]. Available: https://nptel.ac.in/courses/112101005/ (Accessed: 12 Feb. 2017)

[18] S. Mishra, *Optimization Studies for Physics Problems in Indian PHWRs*, Ph.D. Thesis, Homi Bhabha National Institute, India, April 2012, pp. 26-36. Retrieved from http://hdl.handle.net/10603/11449

[19] R. Kumari J., *Reliability of Metallic Framed Structures*, Ph.D. Thesis, University of Kerala, May 2012, pp. 43-51. Retrieved from http://hdl.handle.net/10603/62316

[20] C. N. Ravi, C. C. A. Rajan, "Optimal power flow Solutions using Constraints Genetic Algorithm", *National Journal on Advances in Computing and Management*, Vol. 3, Issue 1, April 2012, pp. 48-54. Retrieved from http://journals-sathyabama.com/archives/acm/07ravi.pdf

[21] L. L. Lai, J. T. Ma, R. Yokoyama and M. Zhao, "Improved genetic algorithms for optimal power flow under both normal and contingent operation states", *International Journal of Electrical Power & Energy Systems*, Vol. 19, Issue 5, 1997, pp. 287–292. Doi: https://doi.org/10.1016/S0142-0615(96)00051-8

[22] T. Numnonda and U. D. Annakkage, "Optimal power dispatch in multinode electricity market using genetic algorithm," *Electric Power Systems Research*, Vol. 49, Issue 3, April 1999, pp. 211-220. Doi: https://doi.org/10.1016/S0378-7796(98)00139-4

[23] D. B. Fogel, *Evolutionary Computation: Toward a new philosophy of machine intelligence*, IEEE Press, 1995, New York.

[24] M. A. Abido, "Optimal power flow using particle swarm optimization", *International Journal of Electrical Power & Energy Systems*, Vol. 24, Issue 7, Oct. 2002, pp.563-571. Doi: https://doi.org/10.1016/S0142-0615(01)00067-9

[25] D. Chattopadhyay, "Application of General Algebraic Modeling System to Power System Optimization", *IEEE Transactions on Power Systems*, Vol. 14, Issue 1, February 1999, pp. 15-22. Doi: 10.1109/59.744462

[26] "AIMMS", *Wikipedia*. [Online]. Available: https://en.wikipedia.org/wiki/AIMMS (Accessed 12 March 2017)

[27] R. Fourer, D. M. Gay and B. W. Kernighan, "A modeling language for mathematical programming", *Management Science*, Vol. 36, Issue 5, May 1990, pp. 519-554. Retrieved from https://www.ampl.com/REFS/amplmod.pdf

[28] L. E. Schrage, *Linear, Integer and Quadratic Programming with LINDO*, Third Edition, Scientific Press, CA, 1986,

[29] "LINDO", *Wikipedia*. [Online]. Available: https://en.wikipedia.org/wiki/LINDO (Accessed 12 March 2017)

[30] S. Makhloufi, A. Mekhaldi, M. Teguar, D. Saheb-Koussa and A. Djoudi, "Optimal power flow solution including wind power generation into isolated Adrar power system using PSOGSA", *Revue des Energies Renouvelables*, Vol. 16, Issue 4, 2013. pp. 721-732. Retrieved from https://pdfs.semanticscholar.org/48d7/1e960fd44c81338ede289257e242effd971a.pdf

[31] M. B. Cain, R. P. O'Neil and A. Castillo, "History of Optimal Power Flow and Formulation: Optimal Power Flow Paper 1", *Staff Paper, Federal Energy Regulatory Commission*, USA, Dec. 2012, pp. 1-36. Retrieved from https://pdfs.semanticscholar.org/3dc0/62a0e5fc363c3e08194d756069e8bcc0115c.pdf