Stochastic Volt/Var Planning and Operation for Microgrids with Renewables

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***Abstract*—This paper presents an optimal planning and operation of wind turbines, photovoltaics, and SCs simultaneously for Volt/Var control in microgrids. In planning stage, net present value of total investment is maximized comprising investment cost, operation cost and cost of energy transaction with grid. The reactive power dispatch optimized during microgrid operation. The proposed Volt/Var model considers the probabilistic behavior of wind, solar irradiation and demand simultaneously which is solved by genetic algorithm. The proposed approach is tested on IEEE-33 bus distribution system that is used as microgrid.**

Keywords–distributed resources; distribution networks; genetic algorithm; renewable resources; shunt capacitor; volt/var control.

I. INTRODUCTION

In distribution systems, Volt/Var control (VVC) is always been an important issue to maintain smooth and steady voltage profile across system nodes. Traditionally, VVC is achieved by controlling the tap positions of On Load Tap Changers (OLTCs), Feeder Voltage Regulators (FVRs), Shunt Capacitors (SCs) etc. However, excessive operation of Volt/Var devices is not desirable as it increases tap changers wear and tear that affects the operational life of the equipment/device [1].

Nowadays, the increasing global energy crisis, greenhouse gases emission from traditional power plants and several advances in small-scale generating units have led to the large-scale deployment of Distributed Generations (DGs) in distribution systems. The quick growth of DGs in distribution systems has considerably affected the VVC, which is the one of the important duties of any distribution system operator [2]. The intermittent and uncertain power generation of solar and wind based DGs along with the load uncertainty further increases the complexity of VVC. However, DGs can also participate in VVC schemes by generator excitation control but injecting large amount of reactive power to improve the voltages may result in high field current, overheating of generator, triggering the excitation limit and disconnecting the DG from the system [3]. In comparison to DGs, variable SCs can provide cheaper VVC solution for microgrids but capacitors tap-changer may introduce voltage transients in the system.

Apart from DG integration issues, the renewable energy resources based DGs may provide pollution free and sustainable alternative source of power. The optimally integrated DGs may bring undeniable and enormous benefits to DG owner, utility and consumers such as reduced annual energy loss [3], improved voltage profile [3], enhanced reliability [3]-[5], stability [3][6], reduced energy price etc.

A variety of methods has suggested in literature to solve VVC issues in distribution systems in the presence of DGs. The literature review on VVC issues may be broadly classified into planning stage and operational stage. For planning stage, Dadkhah and Venkatesh [7], proposed a cumulant-based stochastic method to provide SCs reactive power support in wind turbine integrated distribution system. A multiobjective harmony search approach is proposed in [3] to minimize power loss and to improve voltage profile via optimal DG placement in distribution systems. The PQ and PV models of DGs are considered at specified LPF to provide reactive power support. With renewables, scenario-based stochastic multiobjective VVC control planning is proposed in [2]. A Taguchi-based approach is introduced in [8] to minimize power loss and to improve voltage profile by optimal allocation of unity power factor DGs. The reactive power and voltages are dependent variables and change in one might result in opposite effect on other [9]. Therefore, simultaneous active and reactive power planning may bring more benefits in terms of loss reduction and VVC.

Now some of the research work of operational stage is discussed. In [4], a daily VVC based on fuzzy adaptive particle swarm optimization is proposed to provide reactive power support by dispatchable DGs operated at specified Lagging Power Factor (LPF). A wireless communication based distributed VVC is proposed in [9] to find the online optimal control of regulating devices. A synchronous machine based DG is participated in VVC of distribution system in [5] via generator excitation control, however, only point of common coupling bus is considered as the voltage reference node in control scheme. Similarly, in [10], the effect of solar photovoltaic (PV) integration on voltage regulation scheme is studied by finding optimal set point of PV inverters. A time based scheduling problem to avoid unnecessary change in the state of reactive power injecting plants is considered in [6]. The VVC problem is solved by a heuristic approach.

In this paper, a stochastic Volt/Var planning and operation for microgrid is proposed comprising probabilistic model of PVs, WTs, load etc. In planning stage, the aim is to integrate PVs, WTs and SCs simultaneously such that the Net Present Value (NPV) of microgrid investment is maximized. The considered objectives for planning stage are investment cost of DGs & SCs, operation and maintenance cost of DGs & SCs and grid energy transaction cost. In second stage that is the optimal operation of microgrid, optimal dispatch of reactive power from installed SCs is determined. In this stage, annual energy loss and voltage regulation for microgrids are adopted as optimization objectives. Genetic Algorithm (GA) is adopted for both stages to solve proposed stochastic VVC problem, which is a powerful optimization technique to search the global optima [3][10][11].

II. Problem Formulations

The energy consumption depends on the customer usages behavior, which is highly uncertain and varies from customer to customer. Similarly, solar and wind power generations are intermittent and uncertain which require stochastic modeling. Moreover, local real power support from natural resource is the major motive behind DG integration in distribution systems. However, it may not be economical to supply reactive power by DG, which has significantly higher per KVA cost compared to SCs. Hence, a simultaneous integration of DGs and SCs is considered to solve microgrid Volt/Var issues in planning and operation. For the purpose, the probabilistic model of load, wind speed, and solar irradiation is used.

A. Probabilistic Modeling of Solar Power Generation and Load Demand

Generally, solar irradiation forecasting techniques are used to forecast the future solar irradiation by using previous years irradiation data. However, many researchers model the solar irradiation behavior as normal or Gaussian probabilistic distribution [2]. In this study, solar irradiation is modeled as a normal probability distribution function (PDF). The associated PDF is shown in Fig. 1. The Gaussian PDF for *i*th bus can be expressed as in [7]

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left({-(x-\mu)^2}\Big/{2\sigma^2} \right) \tag{1}$$

where μ and σ are representing mean and standard deviation of solar irradiation.

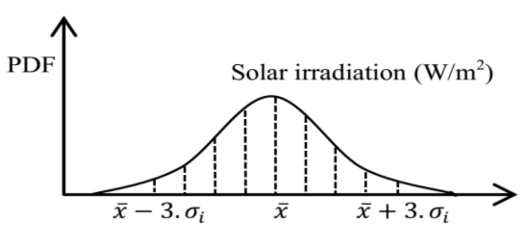

Figure 1. Gaussian PDF of annual solar irradiation.

The solar irradiation is assumed to be same for all buses of microgrid due to geographical proximity. Hence, same probability distribution parameters can be considered for all buses. In this paper, 24 hours load and generation profiles are generated from statistical analysis. Therefore, historical data of each hour is fitted in normal PDF separately as in (1). The considered interval for normal PDF is $\mu \pm 3\sigma$ with 99.7% probability that is divided into N_{PV} segments of equal size. Now, *t*th segment with average irradiation value PG_{pv} has an area or probability p_{pv}. The PVs produce real power as a function of solar irradiation and some module parameters such as panel's area, tilt angle, temperature, efficiency etc. Without loss of generality and simplicity of the problem, module parameters are assumed to be constant for all operating hours except solar irradiation. The PV power generation at *ith* bus can be expressed as linear function of solar irradiation [12].

$$PG_i^{Solar} = lin\_fun(Irradiation) \tag{2}$$

For each hour, the average data and its corresponding probability for all segments are stored for auxiliary analysis. Similarly, load demand is also follows the normal probability distribution [2][7][12]. Hence, same probabilistic model has adopted for load modeling also. The N_D number of pairs of normal distribution is kept as reference for further analysis, which contains the load factor and respective probability (PD_i^{Wind}, p_d) for each segment of each hour.

B. Probabilistic Modeling of Wind Power Generation

The wind speed is also uncertain by nature and it requires a probabilistic modeling. Many researchers have modeled the wind power generation PDF in order to analyze planning and operational issues in distribution systems [2][7][12]. In this paper, the annual wind speed is modeled as Weibull distribution function as shown in fig. 2. The Weibull PDF is expressed as in [7].

$$f(\mathrm{w}_i) = \frac{\gamma}{\beta_i^{\gamma}} w_i^{\gamma-1} \exp\left({w_i}\Big/{\beta_i} \right) \tag{3}$$

where w_i is the wind speed in m/s, γ and β_i are the shape and scale parameters of Weibull probability distribution parameters respectively. For multiple wind generators, these parameters are assumed to be same because all the are installed in a same geographical area. Now, Weibull PDF of each hour's historical data is calculated. The probability of each hour is divided into N_W segments of equal width.

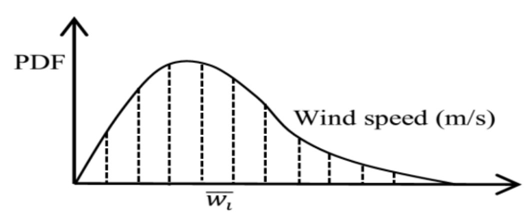

Figure 2. Weibull PDF of annual annual wind speed.

The WT produces real power as a function of wind speed and other turbine parameter such as swaping area, pitch angle, air density etc. However, these parameters can assumed to be constant for all hours except wind speed. Therefore, using appropriate transformation, wind speed can be converted into the real power as a cubic function of wind speed [12]

$$PG_i^{Wind} = cubic\_fun(wind\_speed) \tag{4}$$

The N_W pairs of wind power generation PG_i^{Wind} and its corresponding probability p_w, (PG_i^{Wind}, p_w) are kept for further studies.

C. Complete Probabilistic Modeling of System

By following the previous section, a probabilistic model of complete system has discussed in this section. In this probabilistic model, each hour has N_{PV}, N_w, and N_D set of possible values for solar, wind and load power respectively along with their corresponding probabilities. Hence, for each hour, system can have $N_{PV}\times N_w\times N_D$ number of possible states and each probable state [(w, d, pv) ε ($N_{PV}\times N_w\times N_D$)] has a probability of ($p_d\times p_w\times p_{pv}$). Fig. 3 shows the possible probabilistic outcome for wind, solar and load data for a particular time. Each sub-cube shown in fig. 3 contains the total probability, ($p_d\times p_w\times p_{pv}$) for microgrid.

D. Roulette Wheel based Stochastic Scanerio Generation

In this section, 24 hours stochastic profile of load, power generation from solar PVs and WTs are generated. In the proposed stochastic model, Roulette Wheel Selection (RWS) criteria is adopted which is itself a probabilistic model. For each hour, roulette wheel is spun to select a probabilistic outcome for system load, PVs and WTs generation. The RWS criterion selects a more probable outcome based on their respective probabilities but least probable outcome may also be selected and increases the diversity in the system.

E. Objective function

In this section, simultanious planning of PVs, WTs and SCs is formulated in order to maximize the various integration benefits. The objective is to identify optimal locations and sizes for DGs and SCs such that the NPV of the project is maximized. The proposed objective function is defines as:

$$NPV = C_{Outflows}^{Before} - C_{Outflows}^{After} \tag{5}$$

s. t.

$$C_{Before} = \sum_{y=1}^{T_P} \frac{1}{(1+d)^y}\left[\varphi \times \sum_{h=1}^{24}\sum_{i=1}^{N} C_E(h) P_i(h)\right] \tag{6}$$

$$C_{After} = \sum_{i=1}^{N}\left(\alpha_i S_i^{WT} C_{Inst}^{WT} + \beta_i S_i^{PV} C_{Inst}^{PV} + \gamma_i Q_i^{SC} C_{Inst}^{SC}\right) +$$

$$\sum_{y=1}^{T_P} \frac{24\times\varphi}{(1+d)^y}\left(\sum_{i=1}^{N}\alpha_i S_i^{WT} C_{O\&M}^{WT} + \beta_i S_i^{PV} C_{O\&M}^{PV} + \gamma_i Q_i^{SC} C_{O\&M}^{SC}\right) +$$

$$\varphi \times \sum_{h=1}^{24}\sum_{i=1}^{N} C_E(h) \times \left[P_i(h) - \sum_{a=1}^{n_{WT}} P_{WT}(h) - \sum_{b=1}^{n_{PV}} P_{PV}(h)\right]\Bigg] \tag{7}$$

$$0.95 \le V_i(y,h) \le 1.05, \quad \forall\, i \tag{8}$$

$$I_{ij}(y,h) \le I_{ij}^{Max}, \quad \forall\, i, j \tag{9}$$

where, $C_{Outflows}^{Before}$ and $C_{Outflows}^{After}$ are representing the present value of total future cash inflows in planning horizon. T_p, d, $C_E(h)$, $P_i(h)$, φ, N, S_{WT}, S_{PV}, Q_{SC}, $P_{WT}(h)$, $P_{PV}(h)$, $V_i(y,h)$, $I_{ij}(y,h)$ are representing number of planning years, discount rate, grid energy cost in hth hour, total real power drawn by microgrid at hth hour, hourly to annual cost conversion factor, total number of buses in microgrid, installed capacity of WTs, PVs, SCs , power generated from WTs, PVs in hth hour, voltage at ith bus in hth hour of year y, current in the branch connected between bus i and bus j in hth hour of year y and its maximum current carrying capacity respectively. The cost of energy purchase, installation cost of WTs, PVs, SCs, operation and maintenance cost of WTs, PVs and SC are represented by $C_E(h)$, C_{Inst}^{WT}, C_{Inst}^{PV}, C_{Inst}^{SC}, $C_{O\&M}^{WT}$, $C_{O\&M}^{PV}$, $C_{O\&M}^{SC}$ respectively. Constants α_i, β_i, and γ_i are the binary decision variable that a particular type of DG or SC is installed at bus i or not.

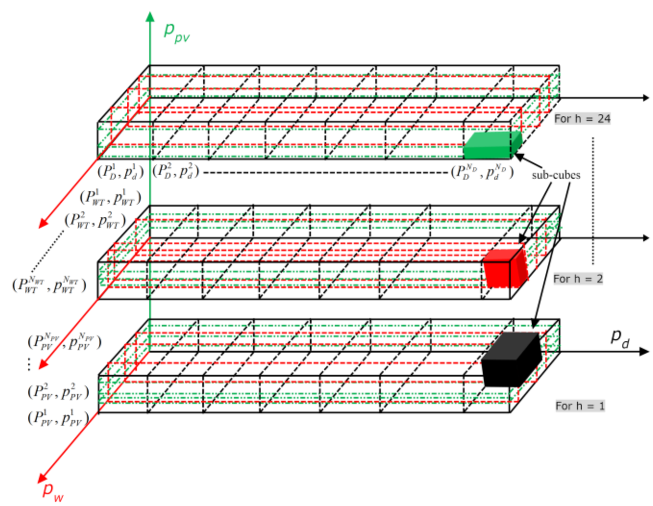

Figure 3. Probabilistic model structure of complete system.

In the proposed DG planning formulation, objective function (6) represents the present value of total cash outflows used for energy purchased by microgrid from the main grid in planning horizon before DG integration. It has assumed that before DG integration there is no alternative source of energy other than main grid. Therefore, main grid supplies the total load demand of distribution system and power loss during planning horizon. In this formulation, it has assumed that all kind of DGs and SCs investment done by utility itself. Hence, after DGs and SCs integration, some extra costs will have to be paid by the utility itself such as cost of DGs investment, operation, and maintenance. The future cash outflows of microgrid after DGs and SCs integration is given in (7). It includes cost of grid energy purchase, DG and SCs investment, operation and maintenance etc. The revenue generated from energy selling will be the same for both the cases. Voltage and thermal limit constraint are given in (8) and (9) respectively. The total DG penetration is constraint by the microgrids annual peak demand.

III. Genetic Algorithm

To solve the proposed stochastic model for DG and SC simultaneous planning, GA has adopted. GA is a bio-inspired optimization technique, which has strong ability to obtain the global optima for complex optimization problems. The technique is widely used to solve engineering problem in diversified areas [3][10]-[11]. Moreover, the researchers have proposed many improved variants of GA. In this paper, an improved variant of GA is used from [13]. The individual's structure used in this work is shown in fig. 4 that holds the location and capacities of WTs, PVs and SCs respectively.

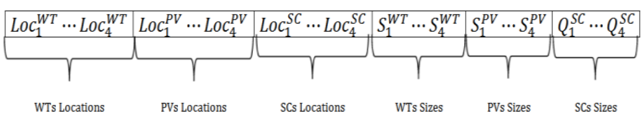

Figure 4. Individual's struture for GA.

During iterations, various infeasible population/solution may also be generated. Therefore, a correction algorithm has applied to convert all infeasible populations into the feasible population. For microgrid operation, individual structure will contain the capacitors tap positions only.

IV. Results and Discussions

In order to test the proposed stochastic planning and operation model for VVC in microgrids, a standard IEEE 33-bus distribution system has selected. The system is already used by [14] as a microgrid. The basic information of this system can be obtained from [15]. The investment & operation cost of DGs, discount rate, annual load growth, number of planning years etc. are selected from [14]. The installation cost of SCs has chosen from [11]. The annual operation and maintenance cost of SCs is equals to 525.6 \$ for each 300 kVar SC bank. The hourly grid energy price is referred from [16]. Using the proposed stochastic model in section II, φ=365 random samples are generated for each hour in order to get the stochastic hourly profile for load, wind and solar irradiation. Figure 5 shows the mean values of stochastically generated data for wind speed, solar irradiation Load Factor (LF) and deterministic load profiles.

After generating all probabilistic parameters discussed in section II, simultaneous optimal planning of WTs, PVs and SCs problem has solved by GA in order to get the their optimal location and sizes. Table I shows the simulation results of the optimal planning. The obtained optimal installed peak-peak penetration of WTs and PVs are 50% and 4% respectively, which are percentage of 1st year's annual peak demand. The calculated stochastic capacity factor for WTs, PVs, and SCs are 20.99%, 23.22%, and 19.09% respectively, which are close to the real life capacity factor of such plants.

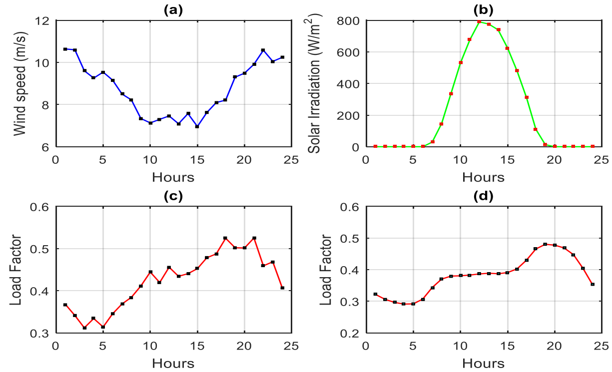

Figure 5. Annual mean profile of stochastically generated data for (a) wind speed, (b) solar irradiation, (c) LF and (d) determinstic LF.

After optimal planning, optimal control of reactive power dispatch is required for microgrids in order to minimize annual energy loss and to keep microgrid bus voltages within the specified limits. It is obtained by finding the hourly optimal tap-settings of installed SCs. Fig. 6 (a) and (b) show the optimal tap setting of each SC for 1st and 20th years of planning horizon respectively. It has observed that in 1st year, number of SCs tap staggering is high compared to 20th year due to relatively high penetration of SCs in 1st year. The box plots of system voltage profile of 20 year are shown in Fig. 7(a), 7(b) and 7(c) for base case, after VVC planning and operation respectively. Fig. 7(c) shows better voltage regulation in microgrid compared to 7(b) because of optimal VVC in microgrid operations. Fig. 7(d) shows the box plot of annual LF for 20 years.

TABLE I. Simulation Results

Scenarios	WTs Location and Sizes	PVs Location and Sizes	SCs Location and Sizes	NPV (M\$)
Base case	-	-	-	00.0000
Optimal planning	08(750), 11(750), 33(750), 29(750)	17(30) 12(210)	15(600) 07(600) 24(300) 30(900)	13.6771
Optimal operation	-do-	-do-	-do-	13.9017

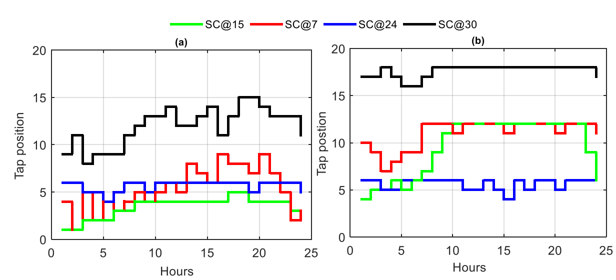

Figure 6. Optimal tap setting of SCs for microgrid VVC in (a) 1st year and (b) 20th year.

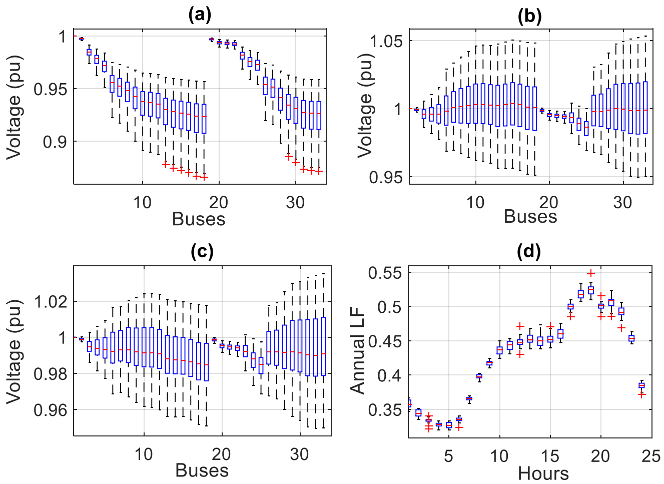

Figure 7. Box plot of microgrid voltage profile for (a) base case (b) After microgrid's VVC planning (c) optimal operation of microgrid for VVC and (d) Annual LF for Hourly generated demand

V. Conclusions

In this paper, a stochastic model of Volt/Var planning and operation for microgrids is presented comprising probabilistic behavior of load, wind speed, and solar irradiations. The simulation results show that a simultaneous DGs and SCs planning is more beneficial because SCs provide cheaper voltage regulation and reduced annual energy loss in microgrids compared to DGs. In microgrid operation, optimal reactive power dispatch via tap staggering of SCs significantly improves voltage regulation and reduces energy loss. In future, low cost dispatchable DGs or storage may be installed simultaneously with renewables and SCs to reduce the degree of renewables uncertainty for large systems.

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