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.**

***Index Terms*—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].

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 optimally integrated DGs may bring undeniable and enormous benefits to DG owner, utility and consumers such as reduced annual energy loss [2], [3], improved voltage profile [3], enhanced reliability [3]-[5], stability [3], [6], reduced energy price etc.

The prominence 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, injecting large amount of reactive power from the DGs for improvement of voltage profile may lead to high field current, overheating of generator, triggering the excitation limit and disconnection of the DG from the system to protect the generator [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.

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. The reactive power and voltages are dependent variables and change in one might result in opposite effect on other [8]. The PQ and PV models of DGs are considered at specified Lagging Power Factor (LPF) to provide reactive power support. Moreover, simultaneous active and reactive power planning may bring more benefits in terms of loss reduction and VVC. 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. A scenario-based stochastic multiobjective VVC control planning with renewables is proposed in [2]. A Taguchi-based approach is introduced in [9] to minimize power loss and to improve voltage profile by optimal allocation of unity power factor DGs.

Now some of the research work of operational stage is discussed. Ref. [4] proposed a daily VVC based on fuzzy adaptive particle swarm optimization to provide reactive power support by dispatchable DGs operated at specific LPF. A wireless communication based distributed VVC is proposed in [8] to find the online optimal control of regulating devices. A synchronous machine based DG is introduced in VVC of distribution system in [5] via generator excitation control. However, only the point of common coupling bus is considered as the voltage reference node in the 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] and the VVC problem is solved by a heuristic approach.

In available literature, VVC problem is solved either in planning or in operation stage. In this paper, the problem is solved simultaneously for planning and operation. A stochastic Volt/Var planning and operation for microgrids

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is proposed comprising probabilistic model of PVs, WTs, load etc. In planning stage, the aim is to optimally integrate PVs, WTs and SCs simultaneously such that the Net Present Value (NPV) of microgrid is maximized. The considered objectives for planning stage comprises of investment, operation and maintenance cost of DGs & SCs and grid energy transaction cost in the planning horizon. For the optimal operation of microgrid, dispatch of reactive power from installed SCs is determined to maximize the benefit of installed DG and SCs. In this stage, the annual energy loss and voltage regulation of microgrid system comprise the optimization objectives. Genetic Algorithms (GA) is a well-established and proven method to solve similar mixed integer, non-linear optimization problems and has the capability to explore global optima efficiently [3], [10]. [11]. Therefore, GA is adopted for both stages to solve proposed stochastic VVC problem.

II. Problem Formulation

The energy consumption depends on the customer usage behavior, which is highly uncertain and varies from customer to customer. Similarly, renewables are intermittent and uncertain by nature. An approximated stochastic modeling is required to deal with the uncertainty and intermittency of load and generation. The local real power support from natural resources is a major motivation 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. 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 are considered

A. Probabilistic Modeling of Solar Power Generation and Load Demand

Generally, solar irradiation forecasting techniques are used to forecast the solar irradiation by using previous years irradiation data. However, many researchers have modelled 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]

$$f(x) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left({-(x_i-\mu_i)^2} \Big/ {2\sigma_i^2} \right) \qquad (1)$$

where μ_i and σ_i represent mean and standard deviation of solar irradiation for bus i.

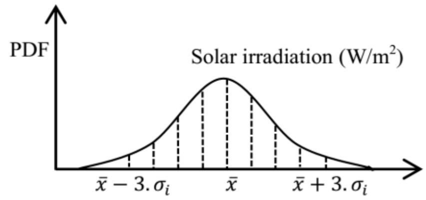

Figure 1. Gaussian PDF of annual solar irradiation.

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. Unlike in [2], [7], [12], data of each hour is fitted in normal PDF to generate 24 hours load and generation profiles for statistical analysis. The considered interval for normal PDF is $\mu \pm 3\sigma$ with 99.7% probability, which is further divided into N_{PV} segments of equal size. The *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 constant during operating hours except solar irradiation. The PV power generation at *ith* bus can be expressed as linear function of solar irradiation [12].

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

For each hour, the average data and its corresponding probability for all segments are stored for auxiliary analysis. Similarly, load demand also follows the normal probability distribution [2], [7], [12]. Hence, same probabilistic model has been adapted for load modeling. 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 uncertain by nature thus requires 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].

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

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 assume to be same, as all WTs install in a same geographical area. Next, Weibull PDF of each hour's historical data is calculated. The probability of each hour is divided into N_W segments of equal width.

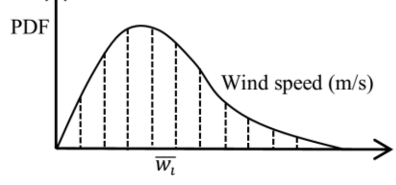

Figure 2. Weibull PDF of annual wind speed.

The WT produces real power as a function of wind speed and other turbine parameter such as sweeping area, pitch angle, air density etc. However, these parameters 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]

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

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

Following the previous section, a probabilistic model of complete system is 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 $(p_d\times p_w\times p_{pv})$ [12]. However, it is not always true as these are dependent parameters. 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.

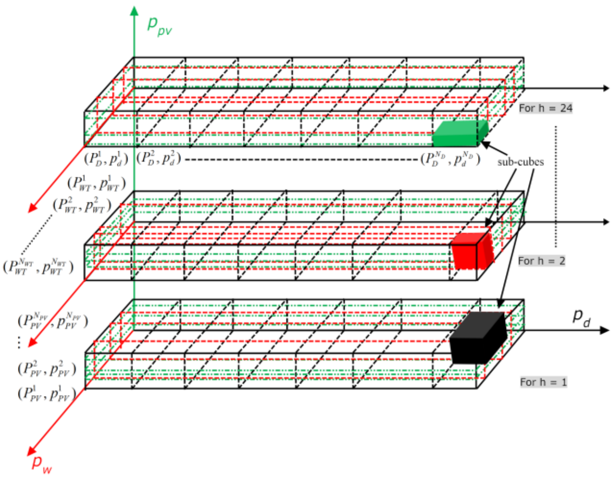

Figure 3. Structure of probabilistic model of complete system.

D. Roulette Wheel Based Stochastic Scenario Generation

In this section, stochastic profile of load, power generation from solar PVs and WTs are generated for 24 hours. 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 independently unlike the model proposed in [12]. The RWS criterion selects a more probable outcome based on their respective probabilities but least probable outcome may also get select and increases the diversity of the system model.

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 objective considered for optimal operation of microgrid is to minimize real power loss and voltage deviation. The objective function is defined as:

$$obj_{planning} = NPV = C^{Before}_{Outflows} - C^{After}_{Outflows} \tag{5}$$

$$obj_{operation} = \sum_{y=1}^{T_P}\frac{\varphi}{(1+d)^y}\sum_{h=1}^{24}\sum_{i=1}^{N}\sum_{j=1}^{N}\left|1-V_i\right| I_{ij}^2 r_{ij} \tag{6}$$

s. t.

$$C_{Before} = \sum_{y=1}^{T_P}\frac{1}{(1+d)^y}\left[\varphi\times\sum_{h=1}^{24}C_E(h)P_{Grid}^{Before}(h)\right] \tag{7}$$

$$\begin{aligned} C_{After} = {} & \sum_{i=1}^{N}\left(\alpha_i S_i^{WT}C_{Inst}^{WT}+\beta_i S_i^{PV}C_{Inst}^{PV}+\gamma_i Q_i^{SC}C_{Inst}^{SC}\right)+ \\ & \sum_{y=1}^{T_P}\frac{24\times\varphi}{(1+d)^y}\left(\sum_{i=1}^{N}\alpha_i S_i^{WT}C_{O\&M}^{WT}+\beta_i S_i^{PV}C_{O\&M}^{PV}+\gamma_i Q_i^{SC}C_{O\&M}^{SC}\right)+ \\ & \varphi\times\sum_{h=1}^{24}C_E(h)\times\left[P_{Grid}^{After}(h)-\sum_{i=1}^{N}\left(\alpha_i P_i^{WT}(h)-\beta_i P_i^{PV}(h)\right)\right] \end{aligned} \tag{8}$$

$$0.95 \le V_i(y,h) \le 1.05, \quad \forall\ i \tag{9}$$

$$I_{ij}(y,h) \le I_{ij}^{Max}, \quad \forall\ i, j \tag{10}$$

where, $P_{Grid}^{Before}(h)$ and $P_{Grid}^{After}(h)$ represent power purchase from the grid before and after DG integration in hth hour. T_p, d, $C_E(h)$, $P_i(h)$, φ, N, S_{WT}, S_{PV}, Q_{SC}, $P_i^{WT}(h)$, $P_i^{PV}(h)$, $V_i(y,h)$, $I_{ij}(y,h)$, r_{ij} represent number of planning years, discount rate, grid energy cost, total real power drawn by microgrid in 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, current in the branch connected between bus i and bus j in hth hour of year y and its maximum current carrying capacity, resistance respectively. The cost of energy purchase, installation, 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.

It has assumed that before DG integration main grid supplied the total load demand of distribution system. Hence, (5) comprises the total cash outflows used for energy purchased from the main grid in planning horizon before DG integration. The future cash outflow of microgrid is expressed in (7). It includes the cost of grid energy purchase, various investment and running costs etc. The revenue generated from energy selling will be the same for both the cases; hence, does not affect the NPV. Equation (9) and (10) express the Voltage and thermal limit constraints respectively. The total DG penetration is constraint by the microgrids annual peak demand.

III. Genetic Algorithm for DG & SC Integration

To solve the proposed stochastic model for DG and SC simultaneous planning, a powerful optimization technique GA has adopted. GA is a bio-inspired optimization technique, which has strong ability to obtain the global optima for complex optimization problems compared to MIP and analytical methods. The technique is widely used and successfully solved engineering problem of 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 for this work is shown in Fig. 4, which holds the location and capacities of WTs, PVs and SCs respectively.

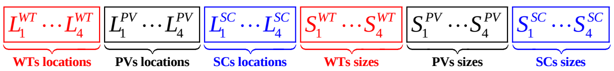

Figure 4. Individual's structure for GA.

Various infeasible population/solution may generate by GA. Therefore, to convert all infeasible population/s into the feasible population a correction algorithm is applied. For optimal operation of microgrid, individual structure will contain the capacitors tap positions only.

IV. Results and Discussions

In order to test the proposed stochastic planning and operation model of VVC for microgrids, we selected standard IEEE 33-bus distribution system as a microgrid. The system is used in [14] as a microgrid. The basic information of this system can obtain from [15]. The investment & operation cost of DGs, discount rate, annual load growth, number of planning years etc. are taken 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 considered planning horizon is T_P = 20 years. The hourly grid energy price referred from [16].

Initially, φ = 365 random samples are generated for each hour by using RWS discussed in Section II. In order to reduce computation burden and without loss of generality of proposed model mean value of generated data for each hour is considered. The mean values of stochastically generated data for wind speed, solar irradiation, and Load Factor (LF) along with deterministic LF are shown in Fig. 5. These profiles used to do calculation for planning and operations of microgrid. Table I shows the optimal locations and sizes of DGs and SCs for microgrid.

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.

Due to load and generation variability, an optimal control of reactive power dispatch from installed SCs is required in order to minimize energy loss for 20 years and to keep microgrid bus voltages within the specified limits. This is achieved by finding the hourly optimal tap-settings of installed SCs. The taps assume to be set on each 50 kVar. Hence, each SC bank can have maximum of six taps. Fig. 6a and 6b show the optimal tap setting of SCs for first and last (i.e. 20th) year respectively.

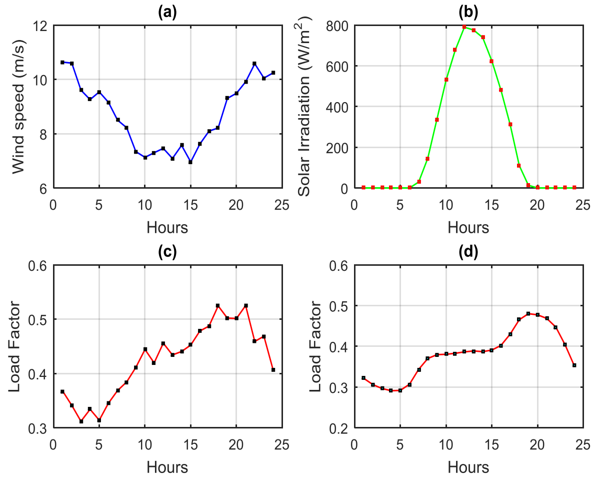

Figure 5. Mean profile of stochastically generated data for (a) wind speed (b) solar irradiation (c) LF and (d) deterministic LF.

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-	Variable	13.9017

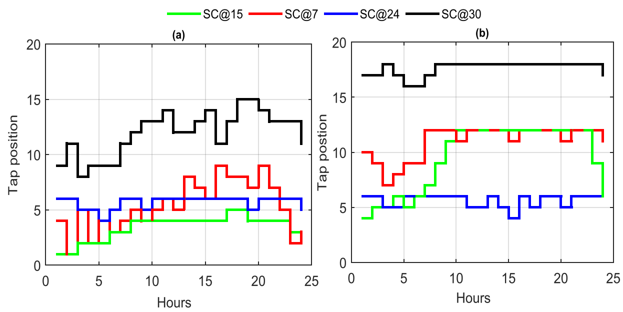

Figure 6. Optimal tap settings of SCs in (a) 1st year and (b) 20th year.

In this work, variable SCs are the only units, which control the microgrid bus voltages, as DGs are non-dispatchable and assumed to be operating at unity power factor. All SCs control the voltages simultaneously. From the figure, it is observed that the number of tap staggering in 1st year are high compared to 20th year due to relatively high penetration of SCs in 1st year.

The box plots of voltage profiles of all 20 years are shown in Fig. 7a, 7b and 7c for base case, after VVC planning and operation respectively. It shows that no bus violates the voltage limit constraint in both planning and operation of microgrid. Fig. 7c shows better voltage regulation in microgrid compared to 7b because of optimal VVC in microgrid optimal operation. Fig. 7d shows the box plot of 20 years stochastic load variations.

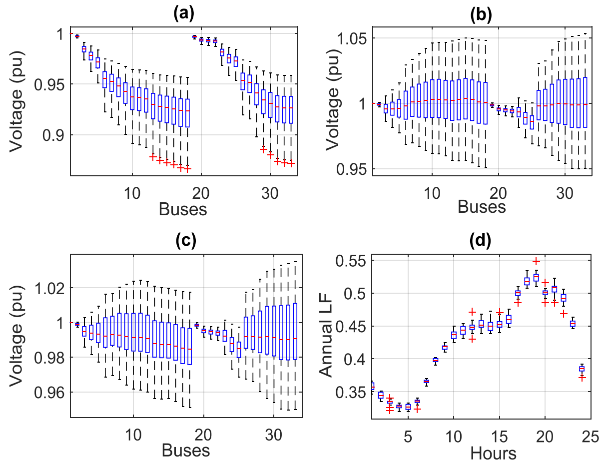

Figure 7. Box plots of 20 years microgrid VVC (a) voltage profile for base case (b) voltage profile after planning (c) voltage profile after operation and (d) stochastic LF.

V. Conclusion

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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