[1]Sandeep Yadav,

2 Sanju Saini

Reactive Power Planning with FACTS under Wind Power and Load Uncertainties

Journal of Electrical Systems

Abstract: This study provides a multi-objective reactive power planning (MO-RPP) method for wind power systems that takes the uncertainty of load demand and wind power generation into account. The major goals of this work are to increase voltage stability and reduce overall active power losses. The magnitude of the generator voltage, the tap settings of the transformer, and reactive power produced by VAR sources is taken as control variables. The MO-RPP problem is resolved by using the ε-constraint approach. The IEEE 30-bus test system is used to evaluate the suggested method for its efficacy. Finally, a quick comparison of results is provided for a better understanding of the findings.

Keywords: Active Power Loss, Reactive Power Planning, Wind Farms Uncertainty, ε-constraint approach, MO-RPP problem

1. INTRODUCTION

Due to its numerous variables, constraints, and optimisation techniques, reactive power planning (RPP) in power systems is among the most difficult and sophisticated tasks [1]. It relates to the best sizing and placement of VAR sources to achieve predetermined goals, like figuring out the best placement and lowering the cost of operation [2,3]. The primary goal of RPP is the establishment of operational viability with an acceptable voltage profile in the absence of VAR support conditions. A variety of objective functions can be formulated to tackle the RPP problem in accordance with the VAR planning approach used in power systems. A cost-based objective function or an objective function that maximises or minimises an index, such as the margin for voltage stability or the loadability of the system, may be used to achieve these goals [4,5]. Additionally, the RPP can be expressed as a multi-objective optimisation problem that simultaneously optimises many objectives [1].

Additionally, due to their technical, environmental, and financial benefits, Alternative energy sources (AES) such as wind farms and photovoltaic power plants are becoming more popular for use in power systems [4-6]. The difficulties with RPP are further heightened by the high proportion of renewable energy sources (RES) in grids. The RPP may face several difficulties, one of which is the generating availability of RESs, which is unclear. The specifications of the sources are uncertain, which makes it difficult to make wise decisions while designing power systems. Moreover, electric power load needs have a stochastic nature means that RPP should consider additional uncertainties. [7] proposes a unique method for dynamic planning of VAR to enhance transient and voltage stability for short-term. In [8,9], the effect of FACTS devices on RPP is investigated. However, both studies have made an effort to frame their explanations of the issue as deterministic. [3] introduces a multi-objective RPP with a primary focus on voltage stability. However, it is modelled using a deterministic methodology. For RPP with wind generating, a multi-objective strategy is provided in [10]. Numerous goals, in this analysis considering a variety of factors related to reactive power, such as power losses and system loadability. Genetic Algorithm (GA) is used for the solution of RPP in [11] to accomplish coordination in reactive power control when FACTS devices and wind farms are present. The strategic positioning of wind farms and FACTS equipment improves the system's factor of loadability. In the case where constant power factor loads and wind farms with no uncertainty are expected., this technique is put into practise. The Benders decomposition method is used in [12] to approach the RPP problem formulated as a two-stage stochastic program while taking into account the significant penetration of wind production. In a wind integrated system, the solution of the RPP is achieved using the Differential Evolutionary Algorithm (DEA) in [13]. The

[1] [1] Electrical Engineering Department Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Haryana, India

Email: yadavsandeepee@gmail.com

[2] Electrical Engineering Department Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Haryana, India. Email: sanjusaini.ee@dcrustm.org

recommended model has a significant flaw in that it only takes wind power generation unpredictability into account. A stochastic model with multiple stages is used for the RPP problem that incorporates the uncertainty of loads is extended in [14]. But even without wind farms, the suggested model captures the probabilistic behaviour of the system.

A mixed-integer quadratic model is suggested in [15] for long-term VAR planning. Through multi-objective optimization, the objective was to minimize the investment cost and operation associated with new VAR sources, while also mitigating the risk of load shedding. Although the suggested model fully accounts for uncertainty in demand, while wind power generation uncertainty is not taken into account. This study [16] proposes a stochastic model for RPP that utilizes chance constrained programming. GA is used to resolve the suggested model. Despite being modeled, uncertainty in power generation only optimises one objective, which includes operational and cost of investment. For probabilistic RPP, a chanced restricted model is suggested in [17]. Stochastic programming is used in two stages to solve the suggested model. The suggested model's primary drawback is that it considers only the load is considered as random parameter and does not account for other sources of uncertainty. Additionally, the main objective function only considers the cost of investing in new VAR sources.

Numerous approaches, including stochastic and resilient optimization, have been proposed in recent studies to handle the short-term planning challenge. To manage the energy hubs optimally, Scheduling based on strong information decision theory established in reference [18]. Microgrids in both futures and spot markets: a stochastic algorithm is suggested in reference [19]. The physical limitations of the grid, however, have not been taken into account in these investigations. The authors of [20] use robust optimisation for multi-carrier energy microgrid short-term scheduling. The performance of the scheduling is also improved by using the decomposition technique. To serve thermal and electrical loads, a two-stage robust optimisation of a multi-energy microgrid is presented in reference [21], however the network's physical features haven't modelled with a thorough power flow analysis. In reference [22], extensive mathematical formulations are employed to represent Alternating current power flow, which is more reflective of actual microgrid operation models, but they do not look into how risk limitations affect capturing uncertainty.

The primary flaw in all of the aforementioned research projects is that they do not thoroughly explore the ideal RPP taking into account both load demand and wind power generation uncertainty. In order to minimise the overall active power losses and improving voltage stability, this study addresses RPP as a multi-objective issue. Several VAR resources are used in the current effort to regulate and correct for reactive power in energy system. These are FACTS devices and capacitor banks. In a power network, there are various FACTS device kinds that could be used.

The paper is organised as uncertainty modelling is described in section 2. Problem formulation with objective function is shown in section 3. Result and discussion are described in section 4 while section 5 is presented with concluding remarks.

2. METHOD

2.1. Uncertainty Modelling

The electricity system is subject to many random events; this section explores the load demand and wind power uncertainty modelling.

2.2. Modelling of Load demand uncertainty

Because of the stochastic loads of electrical power systems, uncertainty of demand must be modelled both during planning and during operation. A standard Gaussian distribution adequately describes the spread of burden uncertainties [23]. The load levels as well as probabilities for load scenario dth is represented by f(PD) and calculated as [24], are shown in Fig. 1.

The electricity system is subject to many random events; this section explores the load demand and wind power uncertainty modelling.

$$f(P_d) = \int_{Pmin\ D}^{P\ max\ D} \times \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(Pd-\mu d)}{2\sigma^2}}\, dP_D \quad (1)$$

where f(PD) denotes the likelihood of the dth load scenario, P_(D_d)^max and P_(D_d)^min denote its limits, of dth load and μ and σ denotes the load scenario's mean and variance, respectively.

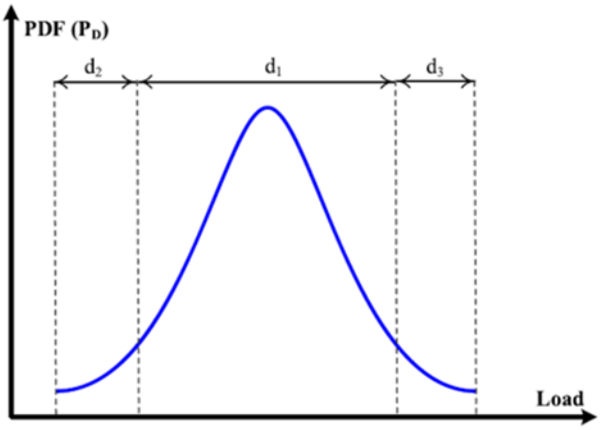

Figure 1. Load characterization PDF

2.3. Modelling of Wind power uncertainty

The location of the farm affects the wind power generation, which varies over time due to variations in wind speed. Since wind speed is unpredictable, the electricity generated by wind turbines is also unpredictable must account for the uncertainty. Weibull distributions [25] are a popular wind speed model. Fig. 2(a) displays the Weibull PDF of wind speed, which was calculated as [26].

$$PDF(U) = \left(\frac{k}{C}\right)\left(\frac{U}{C}\right)^{k-1} e^{-\left(\frac{U}{C}\right)^{K}} \quad (2)$$

where U = wind speed, k = shape factor, C = scale factor. As shown in [26], the likelihood of specific wind speed ranges in each scenario is as follows.

$$f(U) = 1 - e^{-\left(\frac{U}{C}\right)^{K}} \quad (3)$$

As seen in Fig. 2(b) and roughly expressed as [27], the relationship between the wind speed U and the active output power Pw of the WT is as follows.

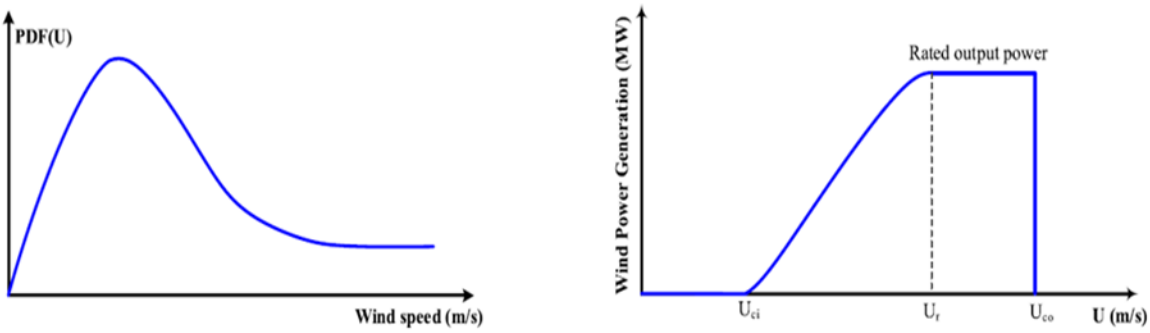

Figure 2.PDF of wind speed characterization and power curve

$$P_W = \left\{ 00 \leq U \leq U \; P_{rw} \frac{U - U_{ci}}{U_r - U_{CO}} U_{ci} \leq U \leq U_r \; P_{rw} U_r \leq U \leq U_{co} \; 0 U_{co} \leq U \right\} \quad (4)$$

2.4. Problem formulation

In power networks, the RPP can be modelled as a broad variety of objective functions, as was before mentioned. The RPP problem's control variables, state variables, and all restrictions are all significantly impacted by this issue. Therefore, a proper formulation can ensure that the problem is feasible and that all objectives and constraints are met. It is crucial to use the probabilistic variables correctly while formulating the problem since the problem's probabilistic nature has a significant influence on how it is put forth. This study focused on the finding the solution to the RPP issue when dealing with variable wind electricity and loads. The issue has been described as a multi-objective nonlinear optimisation problem as a result, and it has been resolved in a ε-constraint method.

2.4.1 Objective Functions

To satisfy two major objectives is the goal of multi-objective RPP. These goals include minimising the active power loss as well as the voltage stability index (L-index), both of which reduce overall active power losses and enhance voltage stability.

2.4.2. *Minimization the total active power losses*

The main aim in power systems is reducing the overall power losses in the transmission system for both economic and energy efficiency purposes. The following mathematical formula can be used to describe the active power losses in scenarios.

$$PL_S\left(\underline{u_s}, \underline{x_s}\right) = \sum_{i=1}^{N_g} P_{G_{i,s}} + \sum_{i=1}^{N_W} P_{W_{i},s} - \sum_{i=1}^{N_B} P_{D_{i},s} \quad (5)$$

Expected Power losses (EPL) value across all situations is taken into consideration as the first objective function. The formula is as follows

$$\emptyset_1 = EPL = \sum_{S=1}^{N_S} \pi_S \times PL_S(\underline{u_s}, \underline{x_s})) \quad (6)$$

2.4.3. Voltage stability

The definition of voltage stability is "a power system's capacity to sustain permissible voltages at each bus under typical conditions circumstances and following a disturbance" [28]. The main cause of a voltage imbalance occurs when power grids cannot supply enough reactive power. The ability of a power system to sustain voltage stability (VS) under normal and abnormal conditions is measured using the relationship between power and voltage [29]. Through several AC power flow methods, the P-V relation is discovered. Fig. 3 illustrates the relationship between system voltage and power loading. Voltage shifts result from greater transmission of energy between two network components. VSM (voltage stability margin) is calculated as the percentage of the base case loading above the failure loading [30].

$$VSM = \frac{P_{D,max} - P_D)}{P_D} \quad (7)$$

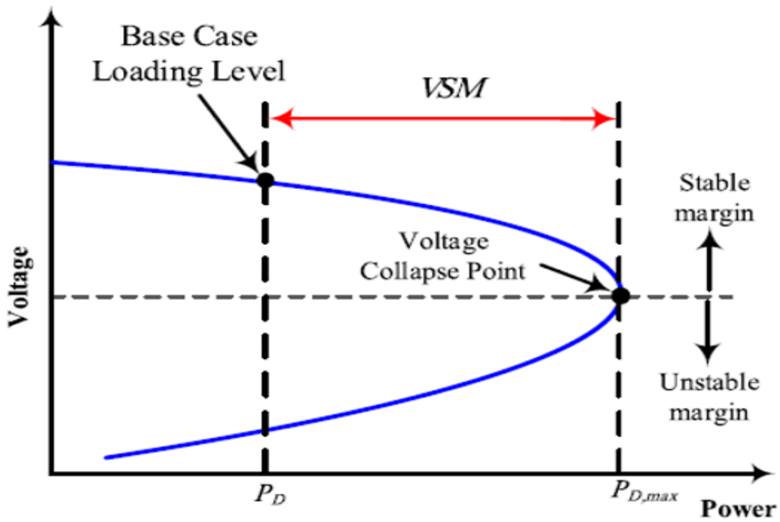

Figure 1. Power loading and bus voltage relation

The goal of this research is to formulate RPP problems in power system, not only to raise bus voltage but also to raise VSM, which will make the system more capable of handling any emergency.

2.5. Problem constraints

To make sure the technology is capable to function many requirements must be satisfied for a state to be stable and dependable. Additionally, these system constraints guarantee that the desired outcome is suitable for the power system's functional operation. Table 1 shows the problem constraints along with their equations.

$$PDF(U) = \left(\frac{k}{C}\right)\left(\frac{U}{C}\right)^{k-1} e^{-\left(\frac{U}{C}\right)^{K}} \quad (2)$$

where U = wind speed, k = shape factor, C = scale factor. As shown in [26], the likelihood of specific wind speed ranges in each scenario is as follows.

Table 1.Problem constraints

Criteria	Equation
Constraints	$P_{gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j(G_{ij} \cos\cos\delta_{ij} + B_{ij} \sin\sin\delta_{ij}) = 0 , i \in N_b$ $Q_{gi} - Q_{Di} + Q_{ci} + Q_{ci}^{O} - V_i \sum_{i=1}^{N_B} V_j(G_{ij} \sin\sin\delta_{ij} - B_{ij} \cos\cos\delta_{ij}) = 0 , i \in N_b$
Balance of active and reactive power	$V_i^{min} \le V_i \le V_i^{max}, i \in N_b$
Buses voltage limits	$\{Q_{Gi}^{min} \le Q_{gi} \le Q_{Gi}^{max} \; P_{Gi}^{min} \le P_{gi} \le P_{Gi}^{max} , \quad i \in N_b\}$
Thermal generator active and reactive power limit	$\lvert S_l \rvert \le S_l^{max} , i \in N_l$
Transmission line flow limit	$T_k^{min} \le T_k \le T_k^{max} , \; k \in N_T$
Transformer tap setting limit	$\{0 \le Q_{wi} \le P_{rw} \; Q_{wi}^{min} \le Q_{wi} \le Q_{wi}^{max} , \quad i \in N_w\}$
Wind active and reactive power limits	$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}, i \in N_{cap} \quad Q_{SVci}^{min} \le Q_{SVci} \le Q_{SVci}^{max}, i \in N_{SVC} \; -0.8x_{ij} \le x_{TSCi} \le 0.2x_{ij}, i \in N_{TCSC}$

2.6. ε-constraint method

The ε-constraint method is regarded as a classical technique for multi-objective optimization, as stated in [31,32]. This method aligns with exact approaches and is effective and straightforward, and it can be applied to both convex and non-convex issues. The multi-objective optimisation issue is reduced to a standard single-objective problem by the use of ε-constraint method [33]. By setting the appropriate value of the control parameter known as the ε parameter, all objective functions other than one are handled as inequality constraints in this technique.

$$OF = min\ (\emptyset_1) \quad (16)$$

$$\{\emptyset_2 \le \varepsilon\ Table\ 1\ \}^{s.t:} \quad (17)$$

Figure 4 and formulae (16) and (17) show that the parameter ε limits the value of φ_2 (i.e., ELmax). This parameter changes gradually from min to max value of φ_2. and Point C as shown in Fig. 4 is an example of an optimal solution derived by solving the objective problem (i.e. (16) and (17)) for any value of ε.

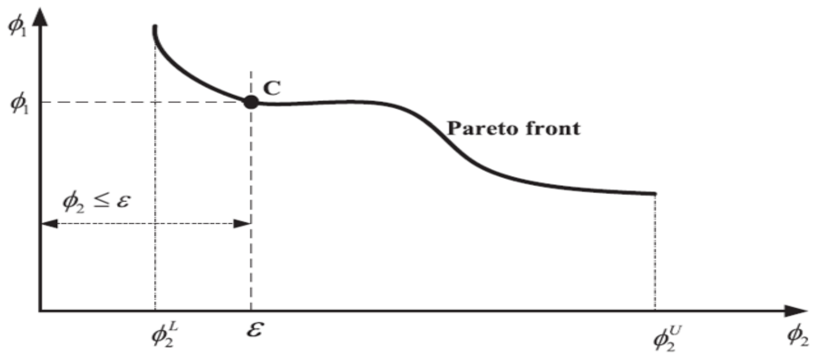

Figure 4. ε-constraint method description

3. RESULT AND DISCUSSION

The IEEE 30-bus test system has 41 individual nodes for testing purposes, including 6 generators, 4 transformers, and 30 test buses. Initial values for the tap settings of the transformers and the voltage amplitude of the generators are derived from [34]. In addition, generators' active and reactionary power outputs are calibrated to [35]. Linear and load statistics can be found in [36]. In this scenario, it is believed that there is no VAR cause. The load buses' lower and maximum value of voltage are from 0.95 p.u. to 1.05 p.u. respectively. With a step value of 0.025, the transformer tapping can be adjusted between 0.9 and 1.1 p.

First, the L-index for load buses needs to be established allocation of VAR compensation mechanisms properly. VAR compensation devices are then likely to be installed on load buses with large L-index values. After using the suggested methodology, it has been found that the loads on buses 24, 25, 26, 29, and 30 have greater L-index values than other load buses. This leads to the identification of the VAR compensator cars. The VAR compensators capacities are intended to be able to be set to zero after VAR adjustment devices have been assigned.

The findings of MO- RPP in the test system are displayed in Table 2. It is expected that the load will last for 8760 hours under maximum load conditions and with no changes to the load level. In accordance with Table 2, the ε-constraint method yields 12 Pareto optimal solutions. Following that, the fifth answer (bold) is selected as BCS by the min-max method. The BCS experiences active electricity losses of 4.8723 MW.

Table 2.Pareto optimal solutions for MO-RPP

X	$\widehat{F}_1$	$\widehat{F}_1$	$(\widehat{F}_1, \widehat{F}_1)$
1	0	1	0
2	0.4012	0.9412	0.4012
3	0.5725	0.8125	0.5725
4	0.6954	0.7754	0.6954
5	**0.7852**	**0.7023**	**0.7023**
6	0.8123	0.5645	0.5645
7	0.8917	0.495	0.495
8	0.9315	0.3954	0.3954
9	0.9505	0.2914	0.2914
10	0.9735	0.2214	0.2214
11	0.9895	0.1324	0.1324
12	1	0	0

Active power losses reduction of 9.29% over the Base Case demonstrates the pre-eminence of the ε-constraint technique. Table 3 shows that the standard voltage stability index technique is superior to the suggested approach, though.

Table 3. ε-constraint method for the BCS

	BCS	Base Case	Reduction (%)
P_{loss} (MW)	5.012	5.477	9.29
f_2	0.1072	0.1318	22.981

Monitoring voltage levels at the load lines are typically given high precedence by power system operators as a means of avoiding voltage collapse. As a result, each loading scenario's voltage profile for the load buses is displayed for BCS, as seen in Figure 5.

A MO-RPP is carried out after creating wind speed possibilities using Weibull probability distribution and power curve. In this instance, [37,38] is used to modify using the IEEE 30-bus testing system. Consequently, bus 22 gets a 40 MW wind farm attached to it. Six number of scenarios for the wind farm's output power are produced in order to assess its effects. It is believed that the load will last for 1460 hours without changing its level.

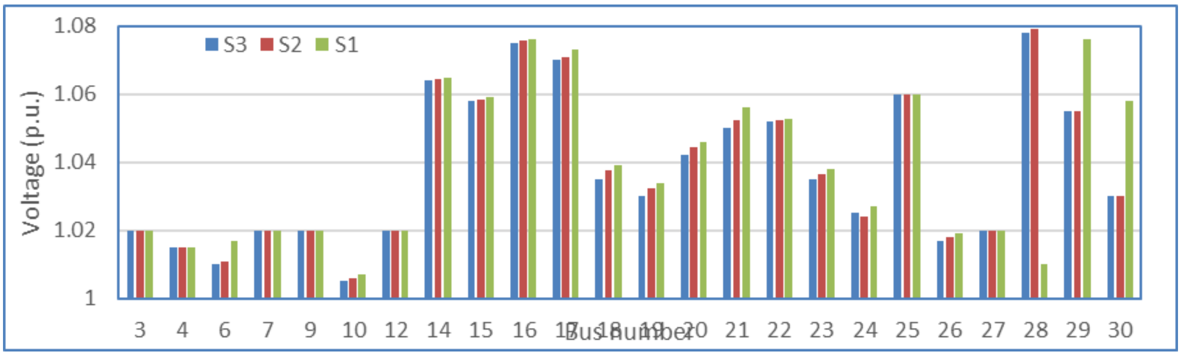

Figure 5. Voltage profile for MO-RPP considering the uncertainty of load demand

Figure 6 displays the voltage curve for the BCS's load buses. As can be seen, under all wind situations, the voltage of load buses is kept between 0.95 to 1.05 p.u. Thus, it can be inferred that power supply bus load voltage is constrained with specific limits based on an appropriate RPP and having a sufficient reactive power reserve.

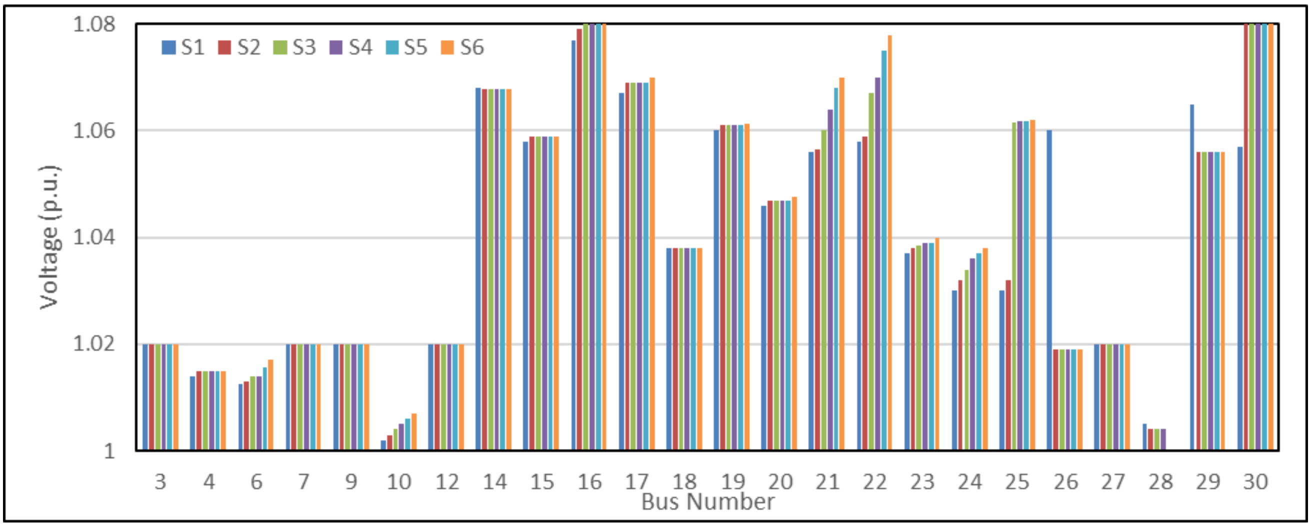

Figure 6. Voltage profile for MO-RPP considering the uncertainty of wind power generation

For each load-wind combination, the voltage profile of the load networks is shown in Figure 7 so that the effect of VAR planning on bus voltage magnitude can be studied across a variety of load-wind combinations. The voltage of load lines is shown in Fig. 7 to be constrained to 0.95 to 1.05 p.u. in all cases. This ensures that the load networks' voltage levels remain within their specifications.

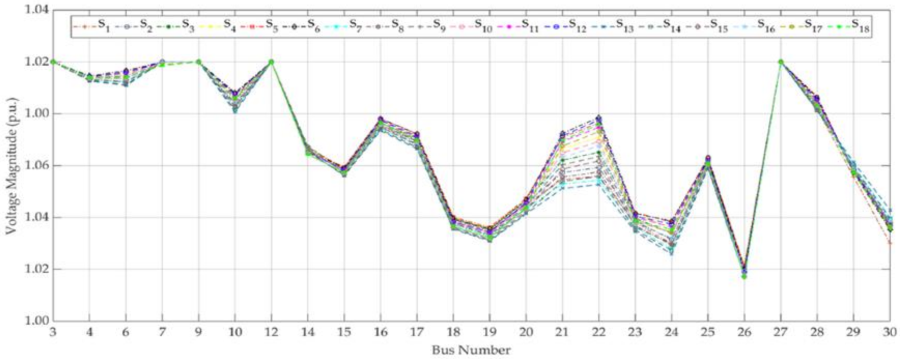

Figure 7. Voltage profile for each load-wind combination

4. CONCLUSIONS

This paper presents a multi-objective RPP structure for electricity grids with high proportions of wind power taking into account wind power generation and load demand uncertainties to minimise active power losses and enhance voltage stability level. The MO- RPP is resolved using ε-constraint method. The first step of this process involves locating the VAR compensation buses using the L-index. Then, it is looked into how exactly VAR planning studies vary from one another. Testing is performed using the IEEE 30-bus technology to evaluate the suggested method's effectiveness. According to the simulation findings, the multi-objective RPP is effective at enhancing the system's voltage stability by taking into account the uncertainties of both load demand and wind power generation. it has been explained. Future research can examine the effects of various green energy sources using additional dynamic stability indices and FACTS types.

5. ACKNOWLEDGEMENTS

This work is not supported.

6. REFERENCES

[1] Zhang, W.; Li, F.; Tolbert, L.M. Review of Reactive Power Planning: Objectives, Constraints, and Algorithms. IEEE Trans. Power Syst. 2007, 22, 2177–2186.

[2] Seifi, H.; Sepasian, M.S. Electric Power System Planning: Issues, Algorithms and Solutions; Springer: Berlin/Heidelberg, Germany, 2011.

[3] Roselyn, J.P.; Devaraj, D.; Dash, S.S. Multi Objective Differential Evolution Approach for Voltage Stability Constrained Reactive Power Planning Problem. Int. J. Electr. Power Energy Syst. 2014, 59, 155–165.

[4] Miveh, M.R.; Rahmat, M.F.; Ghadimi, A.A.; Mustafa, M.W. Control Techniques for Three-Phase Four-Leg Voltage Source Inverters in Autonomous Microgrids: A Review. Renew. Sustain. Energy Rev. 2016, 54,1592–1610.

[5] Miveh, M.R.; Rahmat, M.F.; Mustafa, M.W.; Ghadimi, A.A.; Rezvani, A. An Improved Control Strategy for a Four-Leg Grid-Forming Power Converter under Unbalanced Load Conditions. Adv. Power Electron. 2016, 2016.

[6] Mohammadi, F.; Nazri, G.-A.; Saif, M. A Fast Fault Detection and Identification Approach in Power Distribution Systems. In Proceedings of the 5th International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), Istanbul, Turkey, 26–27 August 2019.

[7] Han, T.; Chen, Y.; Ma, J.; Zhao, Y.; Chi, Y.-Y. Surrogate Modeling-Based Multi-Objective Dynamic VAR Planning Considering Short-Term Voltage Stability and Transient Stability. IEEE Trans. Power Syst. 2018, 33,622–633.

[8] Raj, S.; Bhattacharyya, B. Optimal Placement of TCSC and SVC for Reactive Power Planning Using Whale Optimization Algorithm. Swarm Evol. Comput. 2018, 40, 131–143.

[9] Bhattacharyya, B.; Raj, S. Swarm Intelligence Based Algorithms for Reactive Power Planning with Flexible AC Transmission System Devices. Int. J. Electr. Power Energy Syst. 2016, 78, 158–164.

[10] Alonso, M.; Amaris, H.; Alvarez-Ortega, C. A Multiobjective Approach for Reactive Power Planning in Networks with Wind Power Generation. Renew. Energy 2012, 37, 180–191.

[11] Amaris, H.; Alonso, M. Coordinated Reactive Power Management in Power Networks with Wind Turbines and FACTS Devices. Energy Convers. Manag. 2011, 52, 2575–2586.

[12] Fang, X.; Li, F.; Wei, Y.; Azim, R.; Xu, Y. Reactive Power Planning Under High Penetration ofWind Energy Using Benders Decomposition. IET Gener. Transm. Distrib. 2015, 9, 1835–1844.

[13] Niu, M.; Xu, Z. Reactive Power Planning for Transmission Grids withWind Power Penetration. In Proceedings of the IEEE PES Innovative Smart Grid Technologies, Tianjin, China, 21–24 May 2012.
[14] López, J.C.; Contreras, J.; Muñoz, J.I.; Mantovani, J. A Multi-Stage Stochastic Non-Linear Model for Reactive Power Planning Under Contingencies. IEEE Trans. Power Syst. 2013, 28, 1503–1514.
[15] López, J.; Pozo, D.; Contreras, J.; Mantovani, J.R.S. A Multiobjective Minimax Regret Robust VAR Planning Model. IEEE Trans. Power Syst. 2017, 32, 1761–1771.
[16] Yang, N.; Yu, C.; Wen, F.; Chung, C. An Investigation of Reactive Power Planning Based on Chance Constrained Programming. Int. J. Electr. Power Energy Syst. 2007, 29, 650–656. [CrossRef]
[17] López, J.C.; Mantovani, J.S.; Sanz, J.C.; Muñoz, J.I. Optimal Reactive Power Planning Using Two-Stage Stochastic Chance-Constrained Programming. In Proceedings of the IEEE Grenoble Conference, Grenoble, France, 16–20 June 2013.
[18] Rezaee Jordehi A, Javadi MS, Shafie-khah M, Catal~ao JPS. Information gap decision theory (IGDT)-based robust scheduling of combined cooling, heat and power energy hubs. Energy 2021; 231:120918.
[19] Geramifar H, Shahabi M, Barforoshi T. Coordination of energy storage systems and DR resources for optimal scheduling of microgrids under uncertainties. IET Renew Power Gener 2017;11(2):378-88.
[20] Shams MH, Shahabi M, MansourLakouraj M, Shafie-khah M, Catal~ao JPS. Adjustable robust optimization approach for two-stage operation of energy hub-based microgrids. Energy 2021; 222:119894.
[21] Zhang C, Xu Y, Li Z, Dong ZY. Robustly coordinated operation of a multienergy microgrid with flexible electric and thermal loads. IEEE Trans Smart Grid 2019;10(3):2765-75.
[22] Shams MH, Shahabi M, Khodayar ME. Stochastic day-ahead scheduling of multiple energy carrier microgrids with demand response. Energy 2018; 155:326-38.
[23] H. Amaris, M. Alonso, C. Ortega, Reactive power management of power networks with wind generation, Springer-Verlag London 5 (2013), https://doi.org/10.1007/978-1-4471-4667-4.
[24] S. Mohseni-Bonab, A. Rabiee, B. Mohammadi-Ivatloo, Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: a stochastic approach, Renew. Energy 85 (2016), https://doi.org/10.1016/j.renene.2015.07.021.
[25] R. Hemmati, R. Hooshmand, A. Khodabakhshian, Market based transmission expansion and reactive power planning with consideration of wind and load uncertainties, Renew. Sustain. Energy Rev. 29 (2014) 1–10, https://doi.org/10.1016/j.rser.2013.08.062.
[26] B. Magalh˜aes, Reactive Power Planning, Porto University, June 2014. PhD. thesis.
[27] 27. M. Ghaljehei, A. Ahmadian, M. Golkar, T. Amraee, A. Elkamel, Stochastic SCUC considering compressed air energy storage and wind power generation: a technoeconomic approach with static voltage stability analysis, Int. J. Electr. Power Energy Syst. 100 (2018) 489–507,
[28] https://doi.org/10.1016/j.ijepes.2018.02.046
[29] Y. Tang, Voltage Stability Analysis of Power System, Science Press, Springer, 2021, https://doi.org/10.1007/978-981-16-1071-4.
[30] H. Zhang, B. Liu, X. Liu, A. Pahwa, H. Wu, Voltage stability constrained moving target defense against net load redistribution attacks, IEEE Trans. Smart Grid (2022), https://doi.org/10.1109/TSG.2022.3170839.
[31] D. Zhou, U. Annakkage, A. Rajapakse, Online monitoring of voltage stability margin using an artificial neural network, IEEE Trans. Power Syst. 25 (3) (2010) 1566–1574, https://doi.org/10.1109/TPWRS.2009.2038059.
[32] Kalyanmoy, D. Multi-Objective Optimization using Evolutionary Algorithms; JohnWiley and Sons: Hoboken,
[33] NJ, USA, 2001.
[34] Cohon, J.L. Multiobjective Programming and Planning; Courier Corporation: North Chelmsford, MA, USA, 2004.
[35] A. Rabiee, A. Soroudi, B. Mohammadi-ivatloo, M. Parniani, Corrective voltage control scheme considering demand response and stochastic wind power, Power Syst. IEEE Trans. 29 (2014) 2965-2973.
[36] Lee, K.; Park, Y.; Ortiz, J. A United Approach to Optimal Real and Reactive Power Dispatch. IEEE Trans. Power Appar. Syst. 1985, PAS-104, 1147–1153.
[37] Christie, R. Power Systems Test Case Archive; UW Power Systems Test Case Archive: Seattle, WA, USA, 1993.
[38] Nguyen, T.T.; Mohammadi, F. Optimal Placement of TCSC for Congestion Management and Power Loss Reduction Using Multi-Objective Genetic Algorithm. Sustainability 2020, 12, 2813.
[39] Mishra, C.; Singh, S.P.; Rokadia, J. Optimal Power Flow in the Presence of Wind Power Using Modified Cuckoo Search. IET Gener. Transm. Distrib. 2015, 9, 615–626.
[40] M. Saravanan, S. Slochanal, P. Venkatesh, J. Abraham, Application of particle swarm optimization technique for optimal location of FACTS devices considering cost of installation and system loadability, Electr. Power Syst. Res. 77 (3–4) (2007) 276–283, https://doi.org/10.1016/j.epsr.2006.03.006