# A Voltage Stability Constrained Optimal Power Flow using Multi-objective Particle Swarm Optimization Algorithm

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**Abstract**
As the global demand for energy rises, power system networks are teetering on the verge of collapsing owing to a compromise in system stability. During system disturbances, the network's inability to supply adequate reactive power causes instability and eventual collapse. As such, optimized generation scheduling during system disturbances can improve the utilization of the power plants while lowering power loss, improving voltage regulation, reducing branch loading, and ensuring the secure operation of system equipment. Since power systems have conflicting and multiple objectives, this study proposes a multiobjective optimal power flow incorporating three objective functions: generation cost, power loss, and the maximum value of the line Voltage Collapse Proximity Index. The Multiobjective Particle Swarm Optimization Algorithm is used to minimize these objectives on the IEEE 30-bus system for different case studies in normal, contingency, and stressed system conditions. Fuzzy Decision Theory is utilized for obtaining the best compromise solutions amongst a set of Pareto optimal solutions. The results show that the voltage stability of the system is improved by an average of 63.09% during system disturbances with multiobjective optimization. Simultaneous optimization of the three objective functions provides the most voltage stable condition for all system conditions, preventing possible collapse.
**Keywords:** Fuzzy decision Making, IEEE 30-Bus; MOPSO; Voltage Collapse; Voltage Collapse Proximity Index

## 1. Introduction

It has become paramount that utilities prioritize the security and stability of power system networks due to the severity and impact of blackouts. Recently, due to the rapid growth of demand in distribution networks, the threat of voltage stability and subsequent outages in distribution networks have attracted more attention from researchers (Adebayo and Sun 2020; Ashraf et al. 2017; Danish et al. 2019; Mogaka, Orenge, and Ndirangu 2021; Moghavvemi and Faruque 2013; Shakerighadi et al. 2020). Voltage instability becomes a more serious issue as the system becomes more complicated and intensively loaded. The widespread blackouts of the last two decades are evidence of this. Some of the major blackouts in Greece (July 12, 2004), WSCC, USA (July 02, 1996), West Tennessee (Aug. 22, 1987), and Belgium were caused by voltage breakdown (Aug. 04, 1982). Other severe blackouts, such as the 2003 North American blackout (Sultana et al. 2016), were also caused by it. The power system's inability to transfer reactive power to load is the primary source of instability (Opana, Charles, and Nabaala 2020). This problem can be prevented if the static voltage stability margin is increased. Controlling system parameters by incorporating the voltage stability problem into the traditional optimal power flow (OPF) problem is one effective method (Thasnas and Siritaratiwat 2019).

Specifically, Voltage Stability Constrained optimal power flow can be achieved by formulating a multiobjective optimization problem. In the power system, minimizing simply one objective function using standard OPF is insufficient because many other issues, such as transmission losses, voltage deviation, and stability, have competing aims and must be addressed simultaneously (Shang et al. 2014). As a result, in such scenarios, achieving appropriate operating points for power systems necessitates solving a multi-objective nonlinear optimization problem.

The multiobjective VSC-OPF proposed in this study incorporates a Voltage Collapse Proximity Index (VCPI) alongside other objective functions of generation cost and transmission power loss. The analyses are carried out under three different system conditions: normal, contingency, and stressed. The addition of an efficient Voltage Collapse Proximity Index in the multiobjective problem for varying system conditions is one of the research's significant achievements.

## 2. Objective Functions

In this study, three objective functions of the OPF, consisting of generation cost, transmission line losses, and maximum value of the line VCPI are considered as detailed below.

### 2.1 Minimization of total fuel cost for active power generation

The objective here is to minimize the total fuel generation cost. The function is formulated as follows; $f_1(x,u) = \sum_{i=1}^{n_g}(a_i + b_i P_{g_i} + b_i P_{g_i}^2)$ (1)

where $f_c(x)$ is the total fuel cost, $n_g$ is the number of generator buses; $a_i$, $b_i$ and $c_i$ are the $i$th generator cost coefficients; and $P_{g_i}$ is the real power injection of the $i$th generator.

### 2.2 Minimization of loss

The objective of this function is to minimize transmission loss in MW. It is given by;

$$f_2(x,u) = \sum_{k=1}^{N_{line}} G_k(V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j)) \quad (2)$$

where $G_k$ is the conductance of the *kth* line. $V_i$ and $V_j$ are the voltage magnitude at the two ends of line k. $\theta_i$ and $\theta_j$ are the bus voltage angles at the two ends of line k.

### 2.3 Minimization of the maximum line VCPI

The Voltage Collapse Proximity Index (VCPI) is incorporated into the conventional OPF problem highlighted in Equation (8). Voltage stability improvement based on VCPI is proposed as follows;

$$f_3(x,u) = max(VCPI_i) \quad (3)$$

where VCPI is given by (Khunkitti et al. 2018):

$$VCPI(power) = \frac{P_r}{P_r(max)} \quad (4)$$

$$P_r(max) = \frac{V_s^2}{Z}\frac{cos\emptyset}{4cos^2((\theta - \emptyset)/2)} \quad (5)$$

where $\emptyset = tan^{-1}(Q_r/P_r)$

With increased power flow across a transmission line, the value of VCPI steadily rises. Voltage breakdown happens when the VCPI value reaches 1. The VCPI value ranges from 0 (no load) to 1 (maximum load - voltage collapse point).

### 2.4 System Constraints

In the OPF problem, there are two types of constraints to consider. Equations (6)– (12) describe the system constraints to be handled.

#### 2.4.1 Equality Constraints

These include active and reactive power balance equations (Thasnas and Siritaratiwat 2019);

$$P_{g_i} - P_{d_i} = V_i \sum_{j=1}^{N} V_j\left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) \qquad i = 1,\dots,N \quad (6)$$

$$Q_{g_i} - Q_{d_i} = V_i \sum_{j=1}^{N} V_j\left(G_{ij}sin\theta_{ij} + B_{ij}cos\theta_{ij}\right) \qquad i = 1,\dots,N \quad (7)$$

where $P_{g_i}$ and $Q_{g_i}$ are the real and reactive power injections of the $i$th generator. $P_{d_i}$ and $Q_{d_i}$ are the real and reactive power loads at bus $i$. $V_i$ and $V_j$ are the voltage magnitude at buses $i$ and $j$. $G_{ij}$ and $B_{ij}$ are the transfer conductance and susceptance between buses $i$ and $j$, respectively. $\Theta_{ij}$ is the phase angle difference between buses $i$ and $j$. N is the total number of system buses.

#### 2.4.2 Inequality Constraints

The inequality constraints to be considered are as follows:

Generator limits:

$$P_{g_i}^{min} \le P_{g_i} \le P_{g_i}^{max}, \quad i = 1,\dots,N_g \quad (8)$$

$$Q_{g_i}^{min} \le Q_{g_i} \le Q_{g_i}^{max}, \quad i = 1,\dots,N_g \quad (9)$$

$$V_{g_i}^{min} \le V_{g_i} \le V_{g_i}^{max}, \quad i = 1,\dots,N_g \quad (10)$$

Transmission line limits:

$$\left|S_{L_i}\right| \le S_{L_i}^{max}, \quad (11)$$

Load bus voltage magnitude limits:

$$V_{d_i}^{min} \le V_{d_i} \le V_{d_i}^{max}, \quad i = 1,\dots,N_d \quad (12)$$

where $P_{g_i}^{min}$ and $P_{g_i}^{max}$ are the minimum and maximum active power generations at bus $i$. $Q_{g_i}^{min}$ and $Q_{g_i}^{max}$ are the minimum and maximum reactive power generations at bus $i$. $V_{g_i}^{min}$ and $V_{g_i}^{max}$ are the minimum and maximum generator voltages at bus $i$. $S_{L_i}$ and $S_{L_i}^{max}$ are the apparent power flow and its maximum at branch $i$. $V_{d_i}^{min}$ and $V_{d_i}^{max}$ are the minimum and maximum load voltages at bus $i$.

#### 2.4.3 Constraint Handling

In this study, quadratic constraints handling will be used to generate an augmented fitness function of the form;

$$J(x,u) = f(x,u) + K_P(P_{gslack} - P_{slack}^{limit})^2 + K_V \sum_{i=1}^{N_{load}} (V_{d_i} - V_{d_i}^{min})^2 + K_Q \sum_{i=1}^{N_{line}} (Q_{g_i} - Q_{g_i}^{min})^2 + K_S \sum_{i=1}^{N_{line}} (S_{L_i} - S_{L_i}^{max})^2 \tag{13}$$

where $J(x,u)$ is the penalized objective function; $K_P$, $K_Q$, $K_V$, and $K_s$ are the penalty factors; and $x^{lim}$ is the limit value of the dependent variables, determined as follows:

$$x^{lim} = \begin{cases} x^{max}, & if\ x > x^{max} \\ x, & if\ x^{min} < x < x^{max} \\ x^{min}, & if\ x < x^{min} \end{cases} \tag{14}$$

When the actual or active power is beyond the permitted range, the penalty function produces extremely high values; hence, the algorithm adjusts the active and reactive powers inside the allowable range to prevent a large penalty value.

## 3. Computation Procedure

### 3.1 MOPSO Algorithm

The MOPSO optimization method was utilized to solve the VSC-OPF in this research. By combining "Pareto-dominance principles" with PSO, it is utilized to address the issue of modifying weighting elements in PSO. (Abido 2011; Coello, Pulido, and Lechuga 2004) explain the MOPSO method used in this study.

### 3.2 Best Compromise Solution

To efficiently choose a candidate Pareto-optimal solution among the many possible solutions on the Pareto front, fuzzy set theory has been commonly used. Due to the nature of the decision maker's irrationality, the $i-th$ objective function of a solution in the Pareto-optimal set, $F_i$, is represented by a membership function $\mu_i$ defined as (Hemamalini and Simon 2010):

$$\mu_i = \begin{cases} 1, & F_i \le F_i^{min}, \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}}, & F_i^{min} \le F_i \le F_i^{max}, \\ 0, & F_i \ge F_i^{max} \end{cases} \tag{21}$$

where $F_i^{max}$ and $F_i^{min}$ are maximum and minimum values of the $i-th$ objective function, respectively.

For each non-dominated solution *k*, the normalized membership function $\mu^k$ is calculated as:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{j=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^j} \tag{22}$$

The number of nondominated solutions is M. The best compromise solution is the one having the highest value of $\mu^k$. The decision-maker will have a priority list of nondominated solutions if all solutions are arranged in decreasing order according to their membership function. This will guide the decision-maker, given the current operating conditions.

## 4. Results and Discussion

The study investigates the performance of the system in three operating scenarios when voltage stability is incorporated in the conventional OPF problem. The goal is to increase static voltage stability while also satisfying other objectives like lowering generation costs and reducing losses. The efficacy of VSC-OPF on various case studies of the multiobjective problem was investigated using the IEEE 30-bus system. The IEEE 30-bus is made up of 30 buses, 6 generators, 41 branches, and 4 transformers, as illustrated in Figure 1. Buses 1, 2, 5, 8, 11, and 13 have generators, whereas lines 6-9, 6-10, 4-12, and 27-28 have transformers. The total connected load is 283.4MW and 126.2MVAR. The detailed data was taken from (The University of Washington Electrical Engineering n.d.). All analyses in this work were carried out using the MATPOWER toolbox in MATLAB.

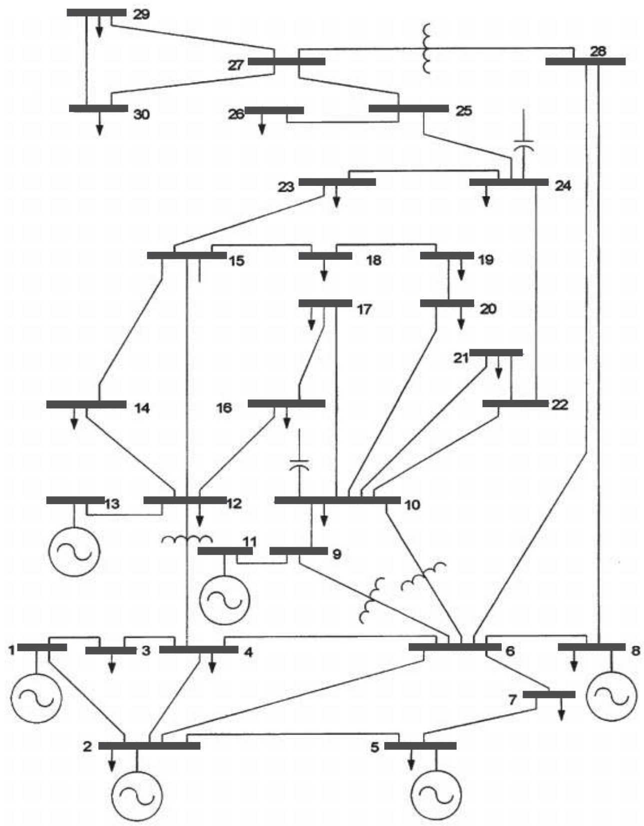


**Figure 1: IEEE 30-bus system**

### 4.1 Multi-objective optimization

#### 4.1.1 Case 1 (Generation Cost vs Power Loss)

In this scenario, two objective functions are minimized: generation cost in dollars per hour and transmission loss in megawatts. Figure 2 shows system plots the Pareto optimal solutions for all three system conditions: normal (SC-1), contingency (SC-2), and stressed (SC-3). The optimal solution is indicated as the Best Cost Solution (BCS).

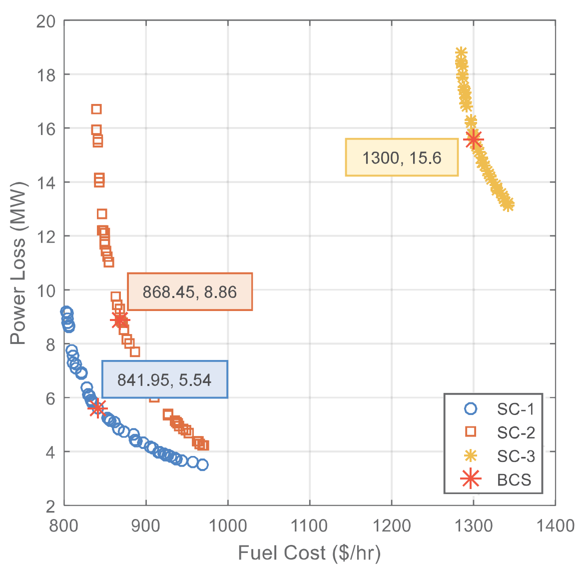


**Figure 2: Pareto optimal solutions for Case 1**

The BCS value for SC-1 for IEEE 30-bus was 841.95$/hr. for generation cost and 5.54MW for transmission loss. In this situation, the VCPI(max) was 0.3113 and the VCPI(sum) was 4.1512. The cost rises to 868.45$/hr. in contingency conditions (SC-2), while the loss and VCPI(max) rise to 8.86MW and 0.7545, respectively. The largest generating costs, losses, and voltage stability index are incurred when the network is stressed, at 1300.00$/hr., 15.60MW, and 1.11. Because 1.11 is over the voltage collapse point of 1, the system may experience voltage collapse under increased load conditions. Table 1 shows a comparison of Best Compromise Solutions to the best individual values. Individual optimization, as expected, produces the best cost and loss values since only one parameter is optimized.

**Table 1: Summary Results for Individual Best and BCS for Case 1**

| Parameter | SC-1 | SC-2 | SC-3 |
|---|---|---|---|
| Individual optimization | | | |
| Best Cost ($/hr.) | 802.39 | 840.13 | 1285.10 |
| Best Loss (MW) | 3.58 | 4.20 | 13.10 |
| Best Compromise Solution | | | |
| Cost ($/hr.) | 841.95 | 868.45 | 1300.00 |
| Loss (MW) | 5.54 | 8.86 | 15.60 |
| Pgen (MW) | 288.94 | 292.26 | 419.15 |
| Qgen (MVAR) | 90.13 | 107.88 | 183.48 |
| VCPI (max) | 0.3113 | 0.7545 | 1.1100 |
| VCPI (sum) | 4.1512 | 5.1728 | 8.1998 |

#### 4.1.2 Case 2 (Generation Cost vs VCPImax)

The objective functions in this case study are minimization of generation cost and VCPI(max). All scenarios considered for analysis are as shown in Figure 3. Table 2 indicates the best compromise solutions generated from the Pareto fronts for the IEEE 30-bus system.

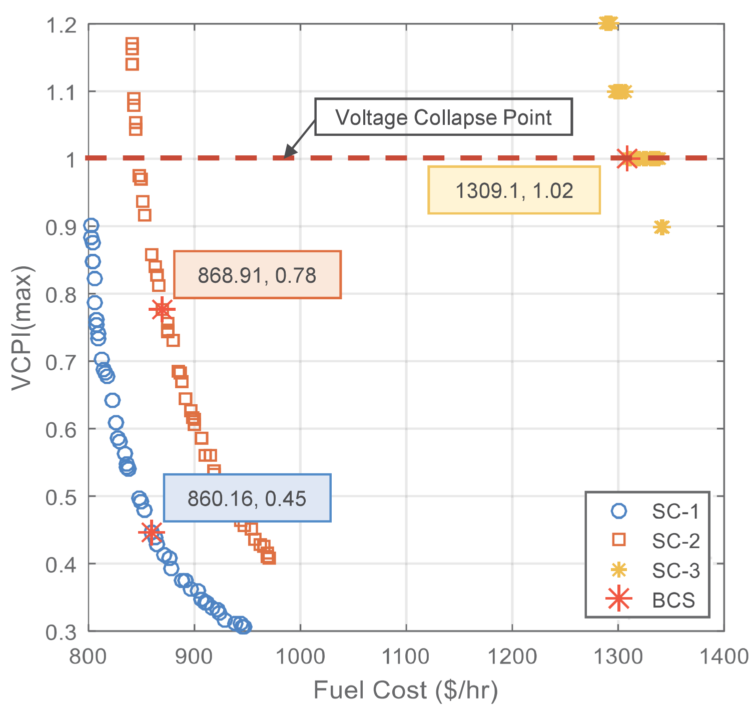


**Figure 1: Pareto Optimal Solutions for Case 2**

The results indicate that when cost and VCPI(max) are used as objective functions, the total generation cost for SC-1 is 860.16 $/hr., compared to 841.95$/hr. when only cost and loss are used. The addition of VCPI(max) does not necessarily guarantee that the system's voltage stability improves. Furthermore, when compared to Case 1, there is no substantial difference in loss performance. With contingency and stressed operating conditions, the system's generation cost, loss, and voltage stability performance all drop, as expected.

**Table 2: Summary Results for Individual Best and BCS for Case 2**

| Parameter | SC-1 | SC-2 | SC-3 |
|---|---|---|---|
| Individual optimization | | | |
| Best Cost ($/hr.) | 802.92 | 840.65 | 1288.30 |
| Best VCPImax | 0.3058 | 0.4091 | 0.9000 |
| Best Compromise Solution | | | |
| Best Cost ($/hr.) | 860.16 | 868.91 | 1309.10 |
| Best VCPImax | 0.4450 | 0.7774 | 1.0200 |
| VCPI (sum) | 4.7968 | 5.2159 | 8.6677 |
| Pgen (MW) | 288.93 | 292.37 | 421.68 |
| Qgen (MVAR) | 90.20 | 107.98 | 192.91 |
| Loss (MW) | 5.53 | 8.97 | 17.88 |

### 4.1.3 Case 3 (Generation Cost vs Power Loss vs VCPImax)

Case 3 examines the system's performance while taking into account the generating cost, power loss, and VCPI(max) as the objective functions. Figure 4 shows the Pareto fronts for the three operational scenarios for IEEE 30-bus system.

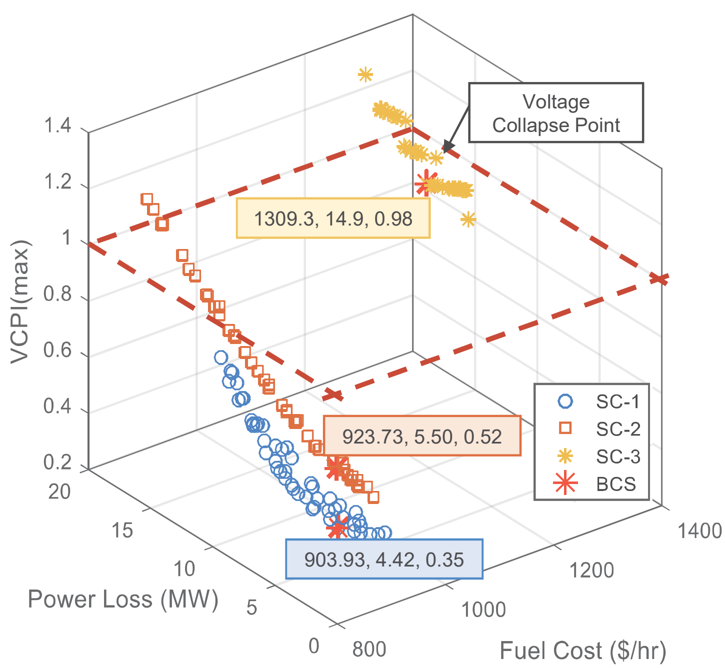


**Figure 4: Pareto Optimal Solutions for Case 2**

The network performance under normal operating settings indicates a generating cost of 903.93 $/hr., a power loss of 4.42 MW, and a VCPI(max) of 0.3502. The results show an increase in generating cost while loss and VCPI(max) decrease in all operating situations SC-1, SC-2, and CS-3.

**Table 3: Summary Results for Individual Best and BCS for Case 3**

| Parameter | SC-1 | SC-2 | SC-3 |
|---|---|---|---|
| Individual optimization | | | |
| Best Cost ($/hr.) | 802.96 | 840.09 | 1285.50 |
| Best Loss (MW) | 3.51 | 4.31 | 13.10 |
| Best VCPImax | 0.31 | 0.42 | 0.90 |
| Best Compromise Solution | | | |
| Best Cost ($/hr.) | 903.93 | 923.73 | 1309.30 |
| Best Loss (MW) | 4.42 | 5.50 | 14.90 |
| Best VCPImax | 0.3502 | 0.5153 | 0.9840 |
| VCPI (sum) | 4.4019 | 4.5358 | 8.0510 |
| Pgen (MW) | 287.85 | 288.90 | 418.47 |
| Qgen (MVAR) | 86.24 | 96.16 | 181.02 |

### 4.2 Impact on Voltage Stability

To evaluate the impact of the multiobjective optimization on the voltage stability of the network, five Case studies are assessed for comparison. Table 4 shows the different studies performed for all system conditions.

**Table 4: Case Studies For Performance Comparison**

| Case Study | Description |
|---|---|
| Base | No optimization |
| Case 0 | Single objective optimization |
| Case 1 | Multiobjective optimization (Generation Cost, Power Loss) |
| Case 2 | Multiobjective optimization (Generation Cost, VCPI(max)) |
| Case 3 | Multiobjective optimization (Generation Cost, Power Loss VCPI(max)) |

The voltage stability performance of the systems as seen in Figure 5 indicates that all operating conditions and contingency conditions, Case 3 offers the most voltage stable system condition with VCPI (max) below voltage collapse point. However, in normal operating conditions, Case 1 provides the minimal VCPI (max) value of 0.31 hence the best stability condition.

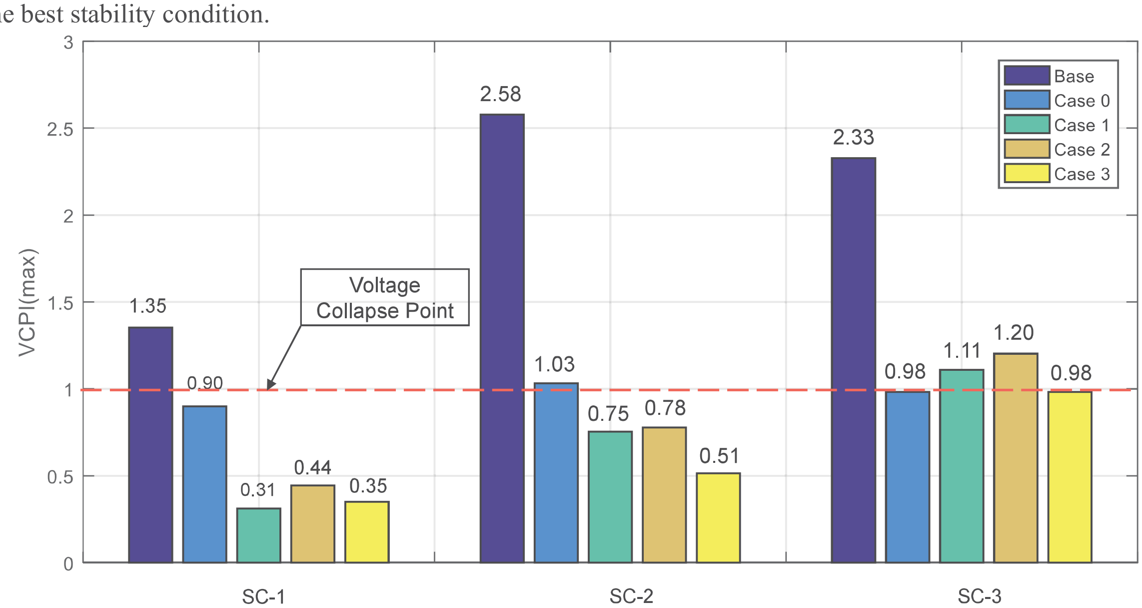


**Figure 5: Voltage Stability Performance by VCPI (max)**

### 5. Conclusion

A voltage security-constrained multiobjective optimal power flow is presented in this research. To analyze network performance in normal, contingency, and stressed settings, the suggested approach used three objective functions: the Voltage Collapse Proximity Index, generation costs, and power losses. Lower index values suggest a greater improvement in voltage stability.

When multiobjective optimization is used, the results reveal that average voltage stability improvements of 62.90%, 70.14%, and 56.25% are achieved in normal, contingency, and stressed system circumstances, respectively. This improvement comes at the expense of a higher cost of generation. As a result, a compromise is essential. Thus, a selection index can be added into these studies to advise on the ideal system parameters to ensure optimized performance of generation cost, loss, and voltage stability, allowing for improved decision-making.

## 6. Acknowledgment

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# Wind Energy Resource Prediction Techniques and BESS Optimal Sizing: A Review

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**Abstract**

Wind power integration into the electric power system has seen immense growth in many nations around the world. This is attributed by numerous advantages wind energy possesses, among which include, its environmental friendliness and the declining costs of mass production of wind turbines. However, due to its unpredictable and intermittent nature, its high penetration brings numerous challenges in the planning and operation of power systems. For instance, maintaining grid balance between the demanded power and the supplied power, which is necessary for secure grid operation, becomes a challenge. To alleviate this challenge, and to ensure accurate economic scheduling and planning unit commitments, various studies have proposed improved wind energy resource prediction and the application of Battery Energy Storage Systems (BESS). Therefore, this paper provides a detailed review of different wind energy prediction techniques, namely, traditional statistical techniques, Numerical Weather Prediction (NWP) techniques, Artificial Intelligence techniques, and hybrid prediction techniques. Various competing merits and demerits of these prediction techniques are highlighted. The paper also gives several optimal BESS sizing considerations and approaches. Lastly, the paper identifies possible areas in wind energy prediction techniques and optimal storage sizing that require further exploration.

**Keywords:** Artificial Intelligence, Battery Energy Storage System, Bio-Inspired Optimization, Wind Energy Prediction Techniques.

## 1. Introduction

Wind power constitutes the renewable generation technology which has experienced the fastest growth among all types of renewable generation technologies being currently investigated. It is considered to be the most mature in terms of commercial development in the world for meeting the energy demand from various perspectives such as environment, energy security and socioeconomic aspects without foregoing economic development and thus, a significant portion of electrical power can be generated from wind energy [1].

The capacity of wind worldwide is far larger than the world's total energy consumption and potential for development is huge [2]. Globally, total capacities of about 651 GW of wind have been installed, with a yearly production of 60.4 GW in 2019 alone according to the global wind energy council report [3]. By 2023, it is foreseen that RES will be able to meet more than 70% of worldwide electricity generation growth, led by wind and solar [4]. The development costs of wind power have decreased dramatically in recent years due to more competitive supply chains, increasing economies of scale and further technological improvements [5].

Electricity generated from wind power can be highly variable at several different timescales: hourly, daily, or seasonally. Though annual variation also exists, it is not so notable. Like other electricity sources, wind energy must be scheduled. Wind power forecasting methods are used, but predictability of wind plant output remains low for short-term operation. Because instantaneous electrical generation and consumption must remain in balance to maintain grid stability, this variability can present substantial challenges to the power system operators/planners, who have to ensure the reliable and secure grid operation when large amounts of wind power are incorporated into a grid system. If the wind energy can be scheduled employing accurate wind prediction techniques, the cost impacts of wind can be minimized considerably. System operating cost, such as unit commitment cost, at wind penetrations of up to 20% of system peak load, increases owing to the variable and uncertain nature of wind. This is according to an IEEE/PES summary. As a result, a number of utilities limit the allowable amount of wind power on their power grids. Accurate wind power prediction models can aid develop well-functional hour-ahead or day-ahead markets.

The forecast for wind-power generation is more challenging than that for solar photovoltaic. Large variations can occur within minutes. Moreover, many previous studies have shown that the designing and training of wind forecasting (WF) models such as Artificial Neural Networks (ANNs), fuzzy and Autoregressive Moving Average (ARMA) are most challenging these days. This is because the WF model designed for one site is not suitable for another site due to change in terrain, distinct wind speed patterns, distinct atmospheric parameters such as pressure, temperature or humidity. It is extremely important to periodically adjust the wind prediction models in order to cope with environment changes.

As power generation from wind energy is significantly increasing, it is of paramount importance to accurately predict the generation output of the wind energy resource as fast as possible [6]. This is for the purposes of ensuring better planning and reliable operation by the system planners and operators. Various studies have shown that wind energy will not cause the remarkable impacts on reserves if the wind power prediction techniques are improved [7].