

Under Voltage Load Shedding using Hybrid Metaheuristic Algorithms for Voltage Stability Enhancement: A Review

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Abstract— Power blackouts are experienced globally, more so with increasing load demand and ageing infrastructure. The high failure rate of conventional and adaptive load shedding techniques is prevalent during multiple contingencies. This paper analyses existing UVLS tools, and the potential of hybrid computational intelligence techniques (CIT) to optimally solve the voltage instability problem. Researchers have implemented UVLS with single-solution and population-based algorithms, bringing out strengths and limitations of different methods. Features like: (1) accuracy in load shedding amount, (2) ease of handling of multi-objective functions, and (3) speed of convergence are desired in modern power systems to maintain voltage stability. This paper, therefore, explores the implication of hybridizing metaheuristic algorithms to achieve optimal solutions, while enhancing voltage stability post-contingency.

Index Terms-- Computational intelligence, hybrid intelligence systems, load shedding, voltage stability.

I. INTRODUCTION

Over the last three decades, millions of people have been directly affected by power blackouts. The causes of these blackouts are either natural-occurring (such as high wind speeds of over 100km/h) or human-related/ technical errors. A survey done in the last decade highlights cases such as a cascading grid failure that occurred in Sudan in 2018. In the 24-hour duration it took to restore power, over 40 million people had been affected. The more frequent the occurrence of these blackouts, the more hospitals, banks, transport, telecommunication and multiple industries are disrupted[1].

Stressed power systems are the most susceptible to power outages. Most power systems globally have the following similarities: (1) the generation units are located far away from the load centers; (2) the transmission distances tend to be long, with strict economic limitations for expansion; (3) the load demand keeps increasing with urbanization and industrialization trends[2]. In recent times, blackout reports are repeatedly citing voltage instability, rather than underfrequency, to be the root cause of cascading grid failure[3]. Under voltage load shedding (UVLS) schemes are

often used to regain voltage stability as a last resort and a relatively cost-effective control measure. Voltage instability arises from the imbalances between demand and supply of reactive power to connected loads. The imbalance is often attributed to shortages of reactive power supply within the grid and/ or transmission system limitations[4].

The complexity of the non-linear equations arising from the grid parameters has led to the adoption of computational intelligence techniques (CIT). Researchers have implemented various metaheuristic optimization techniques in performing UVLS. These algorithms are considered to be accurate, flexible and robust in handling complex, nonlinear systems, unlike the conventional methods[5]. For voltage stability analysis, existing methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have shown different strengths and limitations[5]. This paper reviews the pros and cons of existing metaheuristic algorithms, and how their combined strengths can be used to enhance voltage stability during UVLS.

The rest of the paper is structured as follows: Section II gives the theoretical concepts of voltage instability. Section III covers load shedding concepts and performance evaluation of the UVLS schemes. A review of computational intelligence techniques used in UVLS is covered in section IV. Lastly, suggested guidelines for hybridization for UVLS are given in section V, followed by a conclusion of this detailed review.

II. VOLTAGE INSTABILITY

By definition in [4], *voltage stability* refers to the ability of a power system to maintain steady voltages at all buses after being subjected to a disturbance. Electrical utilities usually define healthy bus voltage levels to be within $\pm 5\%$ for normal transmission lines operation. *Voltage instability* is said to occur whenever the bus voltages decline gradually and uncontrollably after a disturbance, such that the voltage falls below 0.95 per unit. For most stressed systems, *voltage collapse* is inevitable as low voltage profiles lead to partial or total blackouts.

A. Factors Contributing to Voltage Instability

According to [4], bus voltages are influenced by synchronous machines. The factors contributing to voltage instability are clustered into the following three categories.

Generator Characteristics: Disturbances experienced in a power system can be caused when the reactive power limit of connected generators is exceeded. Automatic Voltage Regulators (AVRs) are long-existing control mechanisms used in regulating the output voltage. Current carrying limitations associated with the generators are the armature heating, field heating and stator-end iron heating, which limit the nominal rated voltage, the reactive power production and absorption, respectively[6].

Transmission Line Characteristics: Increasing the power transfer demand to connected loads, as is the case with growing load demand, leads to voltage instability. Surge impedance loading (SIL) is used to predict the maximum loading ability of the transmission lines. It describes the real power (P) in [MW] at which natural reactive power (Q) in [MVar] balance occurs. The transmission network characteristics vary based on the load characteristics and they require sufficient reactive power compensation for effective power transfer[4], [6].

Load Characteristics: Loads can be of resistive, capacitive, reactive or a combination the three, often dynamic in nature in real power systems. In supplying power to the loads, equipment such as tap changing transformers are used to meet the voltage consumption needs. Cases of voltage instability occur when the demand of reactive power goes beyond the capability of the generating and compensating devices; or when the on-load tap changers reach the end of their tapping range. [4], [6].

The operation and control mechanisms for maintaining voltage stability requires the consideration of the above characteristics, alongside proper operation of protection relays, to avoid extreme disturbances in the network.

B. Countermeasures against Voltage Collapse

There are preventive and corrective measures taken in dealing with voltage instability. Since low voltage profiles in stressed systems tend to lead to voltage collapse, various methods are used to prevent it. Studies in [4], [6] include methods like:

- Switching shunt capacitors
- Blocking on-load tap changing (OLTC) transformers
- Rescheduling power generation
- Load shedding, often used as a last resort.

Under *preventive measures*, any occurrence with a reasonable likelihood to happen, such as slow cascading outages, is handled by either manual or automatic control actions such as economic dispatch (ED) and switching on of compensating devices. However, *corrective measures* are engaged using automated and special protection schemes (SPS). UVLS is, consequently, important in handling extreme measures, such as having a second contingency before fixing the initial fault[7].

III. LOAD SHEDDING

Load shedding is defined in [8] as the process of temporarily shutting down the electrical power supply to selected loads, in order to achieve the balance between the power supply and demand, aiming to preventing a power system breakdown. It is a control technique used to either prevent or assist with the recovery of a power system from a disturbance.

A. Classification

The two most common types are Under-Frequency Load Shedding (UFLS) and Undervoltage Load Shedding (UVLS). The latter, which is the main subject in this review, is specifically more practical for long-term voltage instability issues, as there are better methods to cater for fast-voltage-decaying power systems. The types of load shedding are classified in [7], [9]–[11] based on:

- Outage circumstances (forced or scheduled outages)
- Area of occurrence (centralized or decentralized)
- Parameters being monitored (frequency or voltage)
- Network topology (closed or open loop)
- Decision-making (algorithmic or rule-based)

In this review, undervoltage load shedding (UVLS) schemes are evaluated under the algorithmic and rule-based decision making, and how they have evolved in related research work.

B. Load Shedding Techniques

The first is *conventional load shedding*. It comprises of the traditional UFLS and UVLS methods that relied on relays to measure frequency or voltage at given buses. They operate in a static nature, taking a snapshot of the system at the onset of mismatching parameters. The measured values are usually compared to a pre-defined threshold beyond which the system becomes unstable. For instance, UVLS relays are set at voltage steps at which the minimum voltage is set at 0.9pu[12].

The second is the *adaptive load shedding*, in which a dynamic approach is adopted. The relay response, in this case, depends on the level of disturbance at each phase. The reference parameters involved are frequency and voltage, with UFLS being the most common scheme. The swing equation is mostly used as it quantifies the relative motion between all the connected synchronous machines. The simplification of this swing equation often results in power system instability, making load shedding to be erroneous[4].

Computational intelligence forms the third classification. It is defined in [13] as a branch of Artificial Intelligence, which helps address reliability issues through fast, robust and accurate solution optimization. The conventional and adaptive techniques tend to have sub-optimal load shedding where they either over- or under-shed. CITs factor in algebraic and differential equations of a network model for static modelling, often in their complex form. Since voltage stability dynamics are usually slow, computational methods using static methods are a reliable method of load shedding[5].

Despite the advantages of computational intelligence methods, they have two main challenges. The first is the *variation in the accuracy of results* whenever new cases are tested with previously used techniques. The inability to duplicate the CITs makes it unsatisfactory for commercial application. Second is the *suboptimal performance* of the algorithms with ongoing research on hybridization of metaheuristic algorithms.

C. Performance Evaluation of UVLS Tools

To test the performance of the optimization tools used in UVLS, the following load shedding criteria has to be addressed:

- Minimum amount of the load shed
- Accuracy in locating the weak buses
- Speed of the convergence time of the solution
- Ability to restore voltage stability

These four evaluation criteria form the basis of the review for CITs that have been used in previous UVLS schemes[3], [14].

D. UVLS Problem Formulation

Optimal power flow (OPF) equations are usually used in computational intelligence methods for UVLS schemes. In order to analyze existing works on UVLS schemes, the definition of the problem is illustrated using mathematical models. The optimization scope is defined using the equations (1-3).

1) Objective Function

UVLS can be expressed using multi-objective, complex and nonlinear mathematical equations which help in evaluating the load shedding tool used. In this case, P and Q are the real and reactive powers at any given node *i*, for *j* number of branches; V is the normalized voltage at the sending-end bus; Z the line impedance and ρ is the total load demand[15].

The first objective is to minimize the amount of load shed so as to ensure minimum interruption of connected loads, as expressed in (1).

$$\min f_1 = \left[\sum_{i=1}^j \left(\frac{P_i^2 + Q_i^2}{|V_i|^2} \right) \times Z_i \right] / \rho_i \quad (1)$$

The second is to minimize the voltage deviation by keeping the voltage of each bus within defined limits so as to improved power quality, as shown in (2).

$$\min f_2 = \frac{|1 - V_{\min}|}{1 \text{ p.u.}} \quad (2)$$

Lastly, the economic evaluation of proposed load shedding schemes expresses the viability of the solution in real life application. Therefore, *minimizing the interruption cost* is expressed in (3), relying on the sensitivity $(\delta\lambda/\delta P)$, where λ is the loading margin.

$$\min f_3 = \sum_{i=1}^{N_g} C_i \left(\frac{\Delta P_{Di}}{\delta\lambda} \frac{\delta\lambda}{\delta P_i} \right) \quad (3)$$

2) Equality Constraints

These show the initial operating conditions and contingency conditions, which are to be observed when performing the UVLS. Real and reactive power flows are assigned tolerance levels at each node in the network, restricting the operation of the system when the constraints are unmet. Researchers in [15] have defined these constraints for both normal and contingency operating conditions.

3) Inequality Constraints

Fast Voltage Stability Index (FVSI) is one such constraint used in [14] to locate weak buses during contingency. Voltage Stability Indices (VSI) are often used in optimization of power system operation and control schemes. In UVLS, they are used as indicators for the voltage collapse point in a given power system. Other limits include voltage and power limits given in [3], [14] to define the network limits.

IV. REVIEW OF COMPUTATIONAL INTELLIGENCE ALGORITHMS

Figure (1) shows the general categorization of metaheuristic algorithms that are commonly used in UVLS. This paper proceeds to analyze some of the methods used in previous works and how hybridization can improve the performance of UVLS tools[16].

Population-based algorithms <i>Swarm intelligence e.g. PSO and Evolutionary computing e.g. GA</i>
Single solution-based algorithms <i>e.g. Simulated Annealing (SA), Tabu-Search, Local Search</i>
Hybrid Algorithms <i>Low and high level hybrids for relay and teamwork performance</i>

Figure 1: General classification of metaheuristic algorithms

A. Fuzzy Logic Control (FLC)

In [17], fuzzy logic control (FLC) is used to optimize a UVLS scheme, where the input parameters are the difference of power supply and demand; and the rate of change of the difference. Eigenvalue analysis is used to identify weak buses, and the testing of the load quantity to shed is done on an IEEE 14-bus test system. Voltage stability is only assumed with load shedding proportions. From the evaluation criteria of UVLS schemes in section III, the FLC doesn't give comprehensive analysis in terms of time and improvement of the voltage stability. The solution is also difficult to use on large, complex power systems due to the setting up of and the lack of replicability on a universal scale.

B. Particle Swarm Optimization (PSO)

PSO has been frequently used in power system optimization problems. It is described in [18] as a relatively simple concept, easy to implement, robust for multiple control parameters, and highly efficient when compared with mathematical algorithms and other heuristic optimization techniques. For UVLS application in [19], PSO is tested on an IEEE-39 test bus system. The notable achievements are in the identification of collapse points by plotting P-V curves. By using the loading margin as a constraint, voltage stability is achievable. Additionally, the interruption cost is quantified and convergence time considered faster as compared to Genetic Algorithm (GA). However, PSO is not repeatable as it easily falls into local minima in large search spaces. Its accuracy in minimizing the amount of load shed is not guaranteed, hence making it perform sub-optimally.

C. Artificial Bee Colony (ABC)

The ABC algorithm was tested in [15] on both small and medium sized IEEE test systems. On the IEEE 14 and 30 bus systems, contingency was introduced through generation loss and overloads. The authors in this study record higher power transfer to heavily loaded buses and compares the results obtained with conventional methods such as: Projected Augmented Lagrangian method (PALM) and the Gradient-Technique Based on Kuhn-Tucker Theorem (GTBKTT). For the medium systems, IEEE-57 and IEEE-118 bus systems are subjected to the same contingencies as the smaller systems. The results obtained show a reduction in load amounts shed, achieving voltage operation conditions of between 0.95 and 1.17p.u. The shortcoming of the proposed ABC algorithm is in the inconsistent results as the system becomes larger.

D. Genetic Algorithm (GA)

This metaheuristic algorithm has outranked individual techniques in the accuracy in attaining optimal load shedding amounts. It has also become a core metaheuristic technique in hybrid optimization solutions [7], [9], [20].

Used independently in [20], GA was tested on a 500kV power system in Uruguay. Using incremental loading, the load shedding is achieved leaving no network component overloaded. The study factors in a module that runs DC load flow ensure no current violations in connected equipment. Convergence time, however, is the biggest limitation to GA-based solutions. In this study, for instance, an exhaustive search for optimal solutions takes between 5 to 8 minutes in different computers. For a system likely to suffer from multiple contingencies in a shorter duration, voltage collapse would be unavoidable. Therefore, research on hybridizing GA targeted improving the convergence time taken in the mutation process.

Other algorithms used include Firefly Algorithm (FA), Self-Organizing Maps (SOM), Differential Evolution (DE), as highlighted in [3]. The most recent developments point to hybridization of metaheuristics as described in the next section.

V. GUIDELINES FOR HYBRIDIZATION

Recently, researchers have adopted the combination of individual metaheuristics to create better UVLS optimization tools. The individual algorithms can be combined for:

- Multi-objective problem solving
- Large scale neighborhood searching
- Parameter tuning and initialization [16]

A. Hybridizing Genetic Algorithms

Researchers in [21], hybridize GA with Artificial Neural Networks (ANN) and apply it in two stages for UVLS. First, to frame the optimization model and second, to generate data set for the ANN load shedding model. Tests on IEEE 6-bus and 14-bus systems show minimum load shedding amounts and minimum voltage deviations. In [14], GA is combined with PSO each performing individual tasks to optimize a UVLS scheme. Testing the hybrid on an IEEE 30-bus system, results obtained show an improved per unit voltage profile of +0.022p.u. The study also indicates a 53% improvement in terms of convergence time, as compared GA used autonomously. Working the hybrid algorithm simultaneously also improves the voltage profile, outperforming PSO by >2%, according to the study.

B. Assessing Strengths and Limitations of Metaheuristics

Table (1) highlights some of the pros and cons of algorithms popular in UVLS optimization. Hybrids such as Evolutionary PSO (EPSO), Firefly Algorithm and PSO (FA-PSO), PSO- Simulated Annealing (PSO-SA) have been used to formulate UVLS schemes as assessed in [3].

Table 1: Strengths and Limitations of Individual Metaheuristics

Individual algorithm	Strengths	Limitations
GA	Relatively the most accurate	Slow convergence time
PSO	Fast convergence	Local minima in large search spaces
ABC	Optimum solution	Can be slow because of the triple search solution

C. Recommendation

Therefore, in solving the voltage instability problem using UVLS, the different aspects of the modern grid can be considered for hybrid CIT implementation.

System Modeling – the ability of the CIT to tune and initialize parameters should be explored to assess load dynamic responses, distributed generation (DG), and FACTS devices.

Grid dynamics - It is also assumed that the system frequency remains unchanged when tackling UVLS. CITs could evaluate the interactions of the on-load tap changing transformers and generator limits. The performance of combined UFLS and UVLS schemes in [22] can be explored using hybrid metaheuristic algorithms to compute the multi-objective functions faster.

Compatibility of hybrid algorithms – the effectiveness can be evaluated based on the processes taken up, and the paralleling/ simultaneous action of a section or complete algorithm. Novel hybrids such as ABC-PSO in [23], designed for software projects, solves the limitation of local minima for PSO and long convergence time for the triple search mechanism for ABC.

By hybridizing the CITs, there is potential in designing more practical and optimal UVLS schemes. Achieving faster convergence through novel hybrid metaheuristics can then improve voltage stability and prevent widespread voltage collapse. From the reviewed metaheuristic techniques, the hybridization trend shown in section V proves that improved performance of CITs in UVLS is achievable. The algorithms are continually being developed and tested, providing room for more hybrid combinations.

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REFERENCES

- [1] H. H. Alhelou, M. E. Hamedani-Golshan, T. C. Njenda, and P. Siano, "A survey on power system blackout and cascading events: Research motivations and challenges," *Energies*, vol. 12, no. 4, pp. 1–28, 2019.
- [2] H. Shiraki, S. Ashina, Y. Kameyama, S. Hashimoto, and T. Fujita, "Analysis of optimal locations for power stations and their impact on industrial symbiosis planning under transition toward low-carbon power sector in Japan," *J. Clean. Prod.*, vol. 114, pp. 81–94, Feb. 2016.
- [3] R. M. Larik, M. W. Mustafa, and M. N. Aman, "A critical review of the state-of-art schemes for under voltage load shedding," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 5, pp. 1–26, 2019.
- [4] P. Kundur, *Power System Stability and Control*. McGraw Hill, 1994.
- [5] J. A. Laghari, H. Mokhlis, A. H. A. Bakar, and H. Mohamad, "Application of computational intelligence techniques for load shedding in power systems: A review," *Energy Convers. Manag.*, vol. 75, no. August 2003, pp. 130–140, 2013.
- [6] H. Saadat, *Power System Analysis*, 2nd, illustr. ed. McGraw-Hill, 2002.
- [7] R. Verayiah, A. Mohamed, H. Shareef, and I. Zainal Abidin, "Review of Under-voltage Load Shedding Schemes in Power System Operation," *Prz. Elektrotechniczny*, vol. 90, no. 7, pp. 99–103, 2014.
- [8] C. N. Raghu and A. Manjunatha, "Assessing Effectiveness of Research for Load Shedding in Power System," *IJECE*, vol. 7, no. 6, pp. 3235–3245, 2017.
- [9] R. M. Larik, M. W. Mustafa, S. Qazi, and N. H. Mirjat, "Under Voltage Load Shedding Scheme to Provide Voltage Stability," *Energy, Environ. Sustain. Dev. 2016 (EESD 2016)*, no. November, 2016.
- [10] S. Rai, Y. Kumar, and G. Agnihotri, "Under Voltage Load Shedding for Contingency Analysis to Optimize Power Loss and Voltage Stability Margin," *Electr. Electron. Eng. An Int. J.*, vol. 3, no. 4, pp. 57–64, 2014.
- [11] C. Mozina, "Undervoltage load shedding," *Power Syst. Conf. Adv. Metering, Prot. Control. Commun. Distrib. Resour. PSC 2007*, no. April 2007, pp. 39–54, 2007.
- [12] H. Haes Alhelou, M. E. Hamedani Golshan, T. C. Njenda, N. D. Hatziaargyriou, Prinesha Naidoo, and R. Vollgraaff, "An Overview of UFLS in Conventional, Modern, and Future Smart Power Systems: Challenges and Opportunities," *Electr. Power Syst. Res.*, vol. 179, no. February, p. 106054, 2020.
- [13] A. P. Engelbrecht, *Computational intelligence: An introduction*. 2007.
- [14] R. M. Larik, M. W. Mustafa, M. N. Aman, T. A. Jumani, S. Sajid, and M. K. Panjwani, "An improved algorithm for optimal load shedding in power systems," *Energies*, vol. 11, no. 7, pp. 1–16, 2018.
- [15] R. Mageshvarana and T. Jayabarathib, "Steady State Load Shedding to Prevent Blackout in the Power System using Artificial Bee Colony Algorithm," *J. Teknol. (Sciences Eng.)*, vol. 8, no. 2, pp. 113–124, 2015.
- [16] A. Memari, R. Ahmad, and A. R. A. Rahim, "Metaheuristic Algorithms: Guidelines for Implementation," *J. Soft Comput. Decis. Support Syst.*, vol. 4, no. 6, pp. 1–6, 2017.
- [17] M. Ben Hessine, H. Jouini, and S. Chebbi, "Load shedding strategy application using fuzzy logic," *2013 Int. Conf. Electr. Eng. Softw. Appl. ICEESA 2013*, vol. 3, no. 6, pp. 2012–2015, 2013.
- [18] K. Y. Lee and J. B. Park, "Application of particle swarm optimization to economic dispatch problem: Advantages and disadvantages," in *2006 IEEE PES Power Systems Conference and Exposition, PSCE 2006 - Proceedings*, 2006, pp. 188–192.
- [19] B. Mozafari, T. Amraee, and A. M. Ranjbar, "An approach for under voltage load shedding using particle swarm optimization," *IEEE Int. Symp. Ind. Electron.*, vol. 3, pp. 2019–2024, 2006.
- [20] M. Guichon, M. Melo, A. C. Nieto, M. Vignolo, N. Yedrzejewski, and A. Introduction, "Automatic Load Shedding calculated with Genetic Algorithms – DAC-CMAG," *Transm. Distrib. Lat. Am. Conf. Expo.*, no. Sixth IEEE/PES, pp. 1–7, 2012.
- [21] V. Tamilselvan and T. Jayabarathi, "A hybrid method for optimal load shedding and improving voltage stability," *Ain Shams Eng. J.*, vol. 7, no. 1, pp. 223–232, 2016.
- [22] S. Rahmani, "Voltage and Frequency Recovery in Power System And Microgrids using Artificial Intelligent Algorithms," Toronto, Ontario, 2019.
- [23] T. T. Khuat and M. H. Le, "A Novel Hybrid ABC-PSO Algorithm for Effort Estimation of Software Projects Using Agile Methodologies," *J. Intell. Syst.*, vol. 27, no. 3, pp. 489–506, 2018.