Research article

Under voltage load shedding using hybrid ABC-PSO algorithm for voltage stability enhancement

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ABSTRACT

Voltage collapse tends to occur due to the voltage instability created during large faults. As a last resort, under-voltage load shedding (UVLS) is performed after all the available power operation and control mechanisms have been exhausted. Load shedding techniques have advanced from the conventional and adaptive methods that are less optimal compared to computational intelligence-based techniques. Recent works have identified hybrid algorithms to give more optimal solutions for UVLS problems with multi-objective functions. In this paper, a novel hybrid ABC-PSO algorithm, adapted from a software estimation project, is used to perform UVLS on a modified IEEE 14-bus system. Eight overload conditions are imposed on the system ranging from 105% to 140% loading, where FVSI ranking is used in identifying weak buses. The load shedding is then performed following decentralized relay settings of 3.5 seconds, 5 seconds and 8 seconds, which gives an overall 99.32% recovery of voltage profiles. The proposed hybrid ABC-PSO algorithm is able to shed optimal amounts of load, giving an 89.56% post-contingency load, compared to GA’s 77.04%, ABC-ANN at 84.03% and PSO-ANN at 80.96%. This study has been simulated on MATLAB software, using the Power System Analysis Toolbox (PSAT) graphical user and command-line interfaces.

1. Introduction

The ability of power systems to remain stable during large faults is a key area of study amongst researchers. Protection and control techniques have been improving to factor in the complex nature of power systems [1]. Power blackouts have been a long persisting challenge to all power systems globally, directly affecting overall productivity in industries and other socio-economic environs [2, 3]. One of the main power outages recorded in history is the US-Canada blackout in 2003 that lasted 96 hours, affecting over 50 million people. Human error and overgrown vegetation along a major transmission line contributed to this outage. The blackout report attributed the cascading collapse of the grid to the failure of control operators to detect the extent of the damage to the larger power system [4]. Since then, significant efforts have been made by researchers and utility companies to prevent voltage collapse caused by both natural and technical faults [5].

For a power blackout to occur, the transmission network gradually degrades due to imbalances in demand and supply, especially for reactive power. As a result, a stressed power system is most susceptible to power outages, characterized by long transmission distances, strict economic limitations for grid expansion and an ever-increasing load demand [6]. Traditionally, load shedding has been used in power systems to achieve a power balance to prevent voltage collapse. Based on the parameters monitored, under-frequency load shedding (UFLS) and under-voltage load shedding (UVLS) are the typical classifications. UFLS relies most on active power balance while UVLS relies on reactive power balance. The latter is often desirable in systems with a dynamic generation where Automatic Voltage Regulators, tap changers and synchronous condensers are installed [7]. Over the last decade, blackout reports cite voltage instability as the root cause of cascading grid failure. UVLS schemes have evolved in approach from the use of conventional and adaptive load shedding methods to the current implementation of optimal power flow (OPF) equations used to evaluate optimal load shedding. Since voltage stability dynamics are often considered to be slow, a static approach is expected to give a better estimate of the system’s voltage stability [8, 9].

In this study, several factors have been considered in the implementation of the UVLS with reference to previously done studies. In [10, 11], the authors showed how Artificial Intelligence (AI) has been

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integrated into modern-day power system operations, especially in load shedding schemes. Computational Intelligence Techniques (CITs) came into focus in the advent of grid automation. CITs include evolution techniques like Differential Evolution (DE) and Genetic Algorithms (GA); swarm intelligence methods like Particle Swarm Optimization (PSO); Fuzzy Logic Control (FLC) and Artificial Neural Networks (ANN), among others, which have been implemented in UVLS schemes [12, 13, 14, 15, 16, 17]. These metaheuristic algorithms are considered to be robust, scalable, and more accurate in solving modern-day scientific problems [10].

An ABC algorithm proposed in [18] showed that higher power transfer to heavily loaded buses was achieved as compared to conventional methods, namely projected augmented Lagrangian method (PALM) and the gradient-technique based on Kuhn-Tucker theorem (GTRBKTT). However, the voltage operation conditions achieved ranged from 0.95 to 1.17 p.u., falling outside the required range for voltage stability to be maintained. Similarly in [19], a hybrid of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) was used to optimize a UVLS scheme in IEEE 14-bus and IEEE 57-bus test systems. It showed an improved per unit voltage profile of +0.022 p.u. The researchers also indicated a 53% improvement in terms of convergence time, brought about by the PSO algorithm, compared to using GA alone.

In [20], comprehensive learning particle swarm optimization (CLPSO) was used in an IEEE-33 bus radial distribution system. The UVLS scheme targeted the islanding of individual sub-systems which had distributed generation (DG) sources. The hybrid metaheuristic was then tested on the Egyptian 66 kV, 45-bus system. By simulating the loss of the main distribution feeder, both radial and meshed Egyptian systems showed effective minimization of the amount of load shed and savings on related costs. The use of the CLPSO algorithm is said to achieve voltage stability post-disturbance, at 0.95 ≤ V ≤ 1.05 p.u. The optimal performance of the algorithm highlighted the costs saved, the amount and the location of load shed but did not mention the convergence time. Similarly in [15], a hybrid metaheuristic of Particle Swarm Optimization (PSO) algorithm and Modal Analysis was tested on an Iranian system. Initialization of the UVLS for the three buses was done at values ranging from 0.85 to 0.9 per unit, at 0.5 seconds intervals. From the PV curves, 34 MW of the load demanded was shed in a 500 MW system. However, despite the reduced amounts of load shedding achieved, the convergence time became slower and only adaptable to that specific network only.

Existing UVLS techniques face a common challenge of sub-optimal performance as the complexity of the power systems increases. These performance challenges include suboptimal amounts during load shedding, long convergence time, and the failure to achieve voltage stability [21, 22]. PSO-based schemes often fall into local minima in high-dimensional search spaces, failing to achieve optimal load shedding. ABC-based techniques have a triple-search mechanism, which is advantageous but has a relatively slower convergence time as compared to PSO. Similarly, GA has a slow convergence time due to the mutation in its algorithm. When combined, researchers show an improvement in solutions obtained as the strengths of two algorithms increases their effectiveness, such as hybrid GA-PSO [19].

This paper focuses on implementing a hybridized metaheuristic algorithm (ABC-PSO) to solve the UVLS problem [23]. The choice of ABC and PSO is guided by their combined performance in [8], which is a novel research performed on a software-based project. The ability of the ABC algorithm to optimize solutions in larger systems aids PSO in its limitation of finding local minima solutions in large search spaces; while the relatively faster convergence speed of PSO improves the time taken by ABC in narrowing down on a solution during its triple search approach. Novel hybrid metaheuristics are constantly emerging, both in the Power System and Computer-related fields of study. The integration in UVLS aims at increasing the system efficiency in load shedding operations.

The rest of the paper covers the problem statement in Section 2, relevant literature review in Section 3 and the methodology used to study various load models on an IEEE 14-bus test system (in Section 4). The results and discussion of the findings are in Section 5, with a conclusion drawn in Section 6.

2. Problem formulation

This study aims to find a feasible solution for UVLS for an IEEE 14-bus test system using a hybrid of ABC and PSO algorithms. The implementation of the hybrid algorithm is done in three steps: (i) developing a test model with static loads and synchronous generators, (ii) analyzing the voltage stability of the system during overload contingency conditions; and (iii), implementing the hybrid algorithm for optimal load shedding. The validation of the algorithm’s performance is done by comparing it to other algorithms from existing literature. Since load shedding is a complex, nonlinear optimization problem, a multi-objective optimization approach is used. The mathematical formulation is as follows:

2.1. Multi-objective function

The objective functions considered in this paper are minimization of: (i) the amount of load to be shed, (ii) the costs incurred (interruption costs), and (iii) the voltage deviation.

(i) Minimization of the amount of load shed

The primary aim of load shedding schemes is to reduce the power demand in the system such that power balance is restored. This objective function is given by:

\[ OF_1 = \min \left( \frac{\sum_{i \in \text{bus}} (P_{\text{shed}})}{P_i} \right) \]  \hspace{1cm} (1)

where \( P_{\text{shed}} \) is the difference between the active power during fault and at the snapshot time, after stepwise load change; and \( P_i \) represents the total active power demand in the system. The data is obtained from the power flow analysis of the test system, where \( i \) represents the sending end bus and \( b_{\text{shed}} \) is the set of buses selected for load shedding. The \( P_{\text{shed}} \) is obtained by ranking the buses using the Fast Voltage Stability Index [18].

(ii) Minimization of the Penalty/Interruption Cost

The penalty/interruption cost is incurred by a utility to avoid inconveniencing customers due to preventable downtime. It is introduced as an economic constraint which ensures that the UVLS is a last resort, within which the cost of disconnection varies by consumer type. In this paper, the priority of each load is considered before UVLS is applied as highlighted in Section 2-D [18]. The objective function for minimization of the penalty cost is given by:

\[ OF_2 = \min \left[ \frac{\sum_{i \in \text{bus}} (P_{\text{shed}} \times \beta_i)}{\sum_{i \in \text{bus}} (P_i \times \beta_i)} \right] \]  \hspace{1cm} (2)

where \( \beta_i \) represents the penalty cost associated with each load bus and \( P_i \) is the active power demand at each bus. The \( P_{\text{shed}} \) is obtained from Eq. (1) where the bus \( i \) is an element of the selected buses \( b_{\text{shed}} \) for load shedding, \( N \) is the maximum number of buses in the test system.

(iii) Minimization of the Voltage Deviation

To improve on the power quality in a power system, voltage profiles must be maintained within a given limit. Voltage deviation is minimized using the following equation:

\[ OF_3 = \min |V_i| \]  \hspace{1cm} (3)

where \( V_i \) represents the voltage magnitude at each bus. This objective function is used in finding the absolute voltage deviation from the range.
of voltages (0.95 – 1.06p.u.) for each bus (i) as part of the optimal solution of the algorithm [24].

Considering the three objective functions described above, the overall multi-objective function for the UVLS is given as:

$$\min f = (w_1 \times OF_1) + (w_2 \times OF_2) + (w_3 \times OF_3)$$  

(4)

where $w_1 = 50\%$, $w_2 = 20\%$ and $w_3 = 30\%$. Weights for multi-objective problems can be obtained either through the Pareto optimization or scalarization method [25]. In the first method, the solution obtained is normally updated continuously. In the scalarization method, each objective function is multiplied by user-specific weights. These can be equal weights, rank order centroid weights or rank-sum weights. In this paper, the weighted sum method has been used, in which the weights are assigned in proportion to the relative importance of the objective, with a sum value of 1 [26].

### 3.2. Equality and inequality constraints

The real and reactive power flow equations given in (5) and (6) are used to compute the power mismatches between the sending end (s) and the receiving end (r) as shown in Figure 1 [8].

$$P_d - P_s + \Delta P_s = \sum_{j=1}^{N} |V_i||V_j|Y_{ij}\cos(\delta_j - \delta_i - \delta_f)$$  

(5)

$$Q_d - Q_s + \Delta Q_s = - \sum_{j=1}^{N} |V_i||V_j|Y_{ij}\sin(\delta_j + \delta_i - \delta_f)$$  

(6)

where $\Delta P$ and $\Delta Q$ denote the active and reactive power losses on line starting from a given bus ‘i’, respectively, resulting from the overload conditions subjected to the system. The voltage magnitudes ($V_i$, $V_j$) and phase angles ($\delta$ and $\theta$) are obtained from the power flow analyses, where $\delta_i$ and $\delta_j$ represent the voltage angles at bus $i$ and $j$, respectively; and $\theta_{ij}$ represents the difference of admittances angle at buses $i$ and $j$. $Y_{ij}$ represents the admittance of line ‘ij’.

The inequality constraints are defined within the components in the simulation toolbox during modeling, such as the transmission line limits, given by (7)-(10):

$$V_i^{\min} \leq V_i \leq V_i^{\max} \text{ for } i \in N$$  

(7)

$$|P_i| \leq P_i^{\max} \forall ij \in \text{transmission lines}$$  

(8)

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$  

(9)

$$Q_i^{\min} \leq Q_i \leq Q_i^{\max}$$  

(10)

where $V_i^{\min}$ is the minimum voltage limit (0.95 p.u.) and $V_i^{\max}$ is the maximum voltage limit (1.05 p.u.), with an exception of the slack bus at (1.06 p.u.). $P_g$ is the active power flowing between the sending end bus $i$ and receiving bus $j$ for the transmission line limits. $P_g$ sets the active power limits and $Q_g$ the reactive power limits for the synchronous generators. Additionally, the load shedding amount limits are set to a minimum of 5% for each bus selected in the FVSI selection, and a maximum of 20% [19].

To identify the weakest lines and consequently the buses to load shed, the Fast Voltage Stability Index (FVSI) is used to evaluate the possibility of voltage collapse. For stable operation of a power system, the magnitude of the FVSI should be less than 1, with the value for each line ‘ij’ computed using Eq. (11).

$$\text{FVSI}_{ij} = \frac{4Z^2Q_i}{V_i^2X_i}$$  

(11)

where $Z$ represents the impedance of the line and $X$ its reactance; $Q_i$ represents the reactive power at the receiving end; $V_i$ represents the sending end voltage [27].

### 3.3. Penalty costs

Penalties considered in load shedding can be set either by the energy supplier or the consumer. They ensure that the least priority loads are shed first before affecting higher priority loads. The buses are assigned penalties as shown in Table 1. Any load shed in the lower penalty ranges would incur minimum charges, and if the system remains unstable, after which higher priority loads would be considered [28].

### 3. System modeling

The data for this study is obtained from a modified IEEE 14 test-bus system as presented in [29]. The load characteristics are considered to establish a comparison between the static loads often used for UVLS studies. Static analysis is said to give accurate results for modelling and testing of protection and control instruments in long-term voltage stability studies. This study aimed at analyzing the effects of dynamic generation characteristics in UVLS problem-solving to depict real-life grid conditions. Therefore, the literature supporting the study revolved around:

| No. | Type of load | Penalty cost [$/MWh] |
|-----|-------------|---------------------|
| 1   | Residential | 5                   |
| 2   | Commercial  | 8                   |
| 3   | Industrial  | 12                  |
| 4   | Municipal  | 15                  |
| 5   | Agricultural | 8                  |

**Figure 1. Two-bus system.**
3.1. Types of loads

Static load models are used to represent loads that vary instantaneously with changes in the voltage and/or frequency at the load bus. Static load models can be used in both static and dynamic simulations. The majority of electrical utilities use constant power in their load flow calculations. On the other hand, the Power System Analysis Toolbox (PSAT) converts all loads into constant impedance loads when performing time-domain simulations. Constant impedance loads represent both active and reactive power as a function of the square of the voltage magnitude. That is, electrical loads that are of constant impedance nature require less power whenever the voltage is low, e.g. an incandescent lamp [30].

Static loads express active ($P$) and reactive ($Q$) powers at any instant of time as exponential or polynomial functions of the bus voltage magnitude ($|V|$) and frequency simultaneously. Constant impedance, constant current and constant power loads, known as (ZIP) models are expressed by polynomial Eqs. (12) and (13) as:

$$P = P_0 \left[ a_1 \left( \frac{V}{V_0} \right)^2 + a_2 \frac{V}{V_0} + a_3 \right]$$  \hspace{1cm} (12)

$$Q = Q_0 \left[ a_4 \left( \frac{V}{V_0} \right)^2 + a_5 \frac{V}{V_0} + a_6 \right]$$  \hspace{1cm} (13)

where $P$ and $Q$ are the active and reactive powers at an instant and $P_0$ and $Q_0$ are the initial active and reactive powers; with corresponding voltage values ($V$). The ZIP loads can also be expressed using the exponential Eqs. (14) and (15):

$$P = P_0 \left( \frac{V}{V_0} \right)^a$$  \hspace{1cm} (14)

$$Q = Q_0 \left( \frac{V}{V_0} \right)^b$$  \hspace{1cm} (15)

Figure 2. Modified IEEE 14-bus test system.
where powers $a$ and $b$ are the voltage exponent values. These values define the load composition for either active or reactive power as 0, 1 or 2, that is, constant power load, constant current load or constant impedance load respectively [31, 32].

Figure 2 shows the modified IEEE 14-bus PSAT model used, namely `d_014_dyn10.mdl` in the tests' toolbox. The modification is specifically on the types of loads used and the dynamic components at the generation buses. One bus (bus 14) is selected to examine the effect of various static load types, specifically using Voltage-Dependent Load Model (VDLM). Since by default, IEEE test systems use constant power loads, a polynomial (ZIP) model is used to account for the voltage-dependency of the loads. The voltage exponents of a VDLM are defined as (0,0) for constant power loads ($P$), (1,1) for constant current loads ($I$) and (2,2) for constant impedance ($Z$) loads. ZIP models are an example of static load models.

In the PSAT model selected, various components include cost blocks ($\$$) which define a PV bus for bifurcation and market studies; Automatic Voltage Regulators (AVRs) and Turbine Governors (TGs), which are included as voltage control blocks based on studies in [18] and [33]. They are considered helpful in reducing the amount of load shed by compensating the power mismatches, thus improving the overall results of the UVLS scheme. The synchronous machines and PV blocks are for conventional load flow studies [34]. In actual power systems, other components like under-load tap changers (ULTC) and over-excitation limiters (OEL) are usually connected [35].

The system data for the above model is as shown in Tables 2, 3, and 4.

### 3.2. Impact on voltage stability

Voltage instability occurs when bus voltages decline gradually and uncontrollably, whereby the acceptable tolerance for transmission systems is ±5%, and ±6% for distribution systems. The parameters affecting voltage stability considered include:

- Generator Characteristics e.g., presence of AVRs.
- Transmission Line Characteristics, e.g., Surge Impedance Loading (SIL).
- Load Characteristics as discussed in part III.A.

The expected graphical illustrations resulting from loading a system to its tipping point (Saddle Node Bifurcation Point – SNB) is given in Figure 3.

### Table 3. Generator data for the IEEE 14-bus model.

| Bus no. | P (gen) [MW] | Q (gen) [MVAr] | Q (max) [MVAr] | Q (min) [MVAr] | V (gen) [p.u.] | P (max) [MW] | P (min) [MW] |
|--------|-------------|---------------|---------------|---------------|---------------|-------------|-------------|
| 1      | 232.4       | -16.9         | 10            | 0             | 1.06          | 332.4       | 0           |
| 2      | 40          | 42.4          | 50            | -40           | 1.045         | 140         | 0           |
| 3      | 23.4        | 24            | 0             | 0             | 1.01          | 100         | 0           |
| 4      | 0           | 12.2          | 24            | -6            | 1.05          | 100         | 0           |
| 5      | 0           | 17.4          | 24            | -6            | 1.05          | 100         | 0           |
| 6      | 0           | 23.4          | 10            | 0             | 1.06          | 332.4       | 0           |
| 7      | 40          | 42.4          | 50            | -40           | 1.045         | 140         | 0           |
| 8      | 23.4        | 24            | 0             | 0             | 1.01          | 100         | 0           |
| 9      | 0           | 12.2          | 24            | -6            | 1.05          | 100         | 0           |
| 10     | 0           | 17.4          | 24            | -6            | 1.05          | 100         | 0           |
| 11     | 0           | 23.4          | 10            | 0             | 1.06          | 332.4       | 0           |
| 12     | 40          | 42.4          | 50            | -40           | 1.045         | 140         | 0           |
| 13     | 23.4        | 24            | 0             | 0             | 1.01          | 100         | 0           |
| 14     | 0           | 12.2          | 24            | -6            | 1.05          | 100         | 0           |

4. Implementation of the hybrid ABC-PSO algorithm

The UVLS problem is solved by integrating the PSO's velocity and position-finding into the framework of the ABC algorithm. The ABC algorithm relies on the exploitation of food sources by the employed bees, while the unemployed bees (comprising of the scout and onlooker bees) perform random food searches and wait for information from the employed bees respectively. On the other hand, the PSO algorithm updates its randomly initialized particles by searching for optima and updating its entire population. The hybrid ABC-PSO algorithm is achieved in the following steps [36]:

#### 4.1. Initialization of data sets

The ABC algorithm's initialization phase is used to define the data variables to be used in the optimization. The variables are defined within their minimum and maximum limits.

**Step 1:** Random initialization of food sources, computed using upper and lower bounds of the amount of load to be shed (5–20%), the number of food sources (Food Number = 50), which is half the colony size (CS = 100 bees), and the problem dimension (D = 14 buses). The base apparent power is specified as 100 MVA.

Additionally, the PSO parameters to be used for the velocity computation are also initialized as: Coefficients $c_1$ and $c_2 = 2$ and Inertia weight $w = 1$ [36].

**Step 2:** Setting the iteration start point at $r = 0$ and the iteration limit at 100.
4.2. Employed bee phase

In this phase, the employed bees forage the neighboring places nearest their current food source positions. If the new position is better, it is swapped to replace the old position. Contrary to PSO where all positions are updated once, each employed bee can only have one food source updated in the following steps:

**Step 3:** Evaluation of the fitness of the food source based on Eq. (16). The OF denotes the objective functions which are evaluated individually as per Eqs. (1), (2), and (3).

\[
\text{fitness}_i = \begin{cases} 
\frac{1}{1 + \text{OF}_i}, & \text{if } \text{OF}_i \geq 0 \\
\frac{1}{1 + \text{abs}(\text{OF}_i)}, & \text{if } \text{OF}_i < 0 
\end{cases}
\]  
(16)

**Step 4:** Determining the parameters to be changed randomly and ensuring that the neighbor food source chosen and the current value are not the same.

**Step 5:** In the ABC algorithm, Eqs. (17) and (18) are used to compute the velocity of the food source and update its position respectively:

\[
v_{ij} = x_{ij} + \varphi_{ij} (x_{ij} - x_k) 
\]  
(17)

Table 4. Branch data for the IEEE 14-bus model.

| Line number | From bus | To bus | Resistance R [p.u.] | Inductance X [p.u.] | Susceptance (B/2) [p.u.] | Transformer tap ratio |
|-------------|----------|-------|--------------------|---------------------|--------------------------|----------------------|
| 1           | 2        | 5     | 0.057              | 0.1739              | 0.034                    | 1                    |
| 2           | 6        | 12    | 0.1229             | 0.2558              | 0                        | 1                    |
| 3           | 12       | 13    | 0.2209             | 0.1999              | 0                        | 1                    |
| 4           | 6        | 13    | 0.0662             | 0.1303              | 0                        | 1                    |
| 5           | 6        | 11    | 0.095              | 0.1989              | 0                        | 1                    |
| 6           | 11       | 10    | 0.0821             | 0.1921              | 0                        | 1                    |
| 7           | 9        | 10    | 0.0318             | 0.0845              | 0                        | 1                    |
| 8           | 9        | 14    | 0.1271             | 0.2704              | 0                        | 1                    |
| 9           | 14       | 13    | 0.1709             | 0.348               | 0                        | 1                    |
| 10          | 7        | 9     | 0.0194             | 0.0592              | 0.0528                   | 1                    |
| 11          | 1        | 2     | 0.047              | 0.198               | 0.0438                   | 1                    |
| 12          | 3        | 2     | 0.067              | 0.171               | 0.0346                   | 1                    |
| 13          | 3        | 4     | 0.054              | 0.223               | 0.0492                   | 1                    |
| 14          | 5        | 4     | 0.0534             | 0.0421              | 0.0128                   | 1                    |
| 15          | 2        | 4     | 0.0561             | 0.1763              | 0.0374                   | 1                    |
| 16          | 5        | 6     | 0                  | 0.252               | 0                        | 0.932                |
| 17          | 4        | 9     | 0                  | 0.5562              | 0                        | 0.969                |
| 18          | 4        | 7     | 0                  | 0.2091              | 0                        | 0.978                |
| 19          | 8        | 7     | 0.0194             | 0.0592              | 0.0528                   | 1                    |
| 20          | 14       | 13    | 0.1709             | 0.348               | 0                        | 1                    |
\[ x_{d} = x_{d}^{min} + r (x_{d}^{max} - x_{d}^{min}) \]  

where \( i \) represents the employee bee, \( j \) is the random index based on the problem dimension, \( k \) represents the random neighboring index to \( i \) and \( \phi \) is a random number between 0 and 1. \( r \) is a real number between 0 and 1, and \( d \) is the problem dimension with minimum and maximum limits. However, for the hybridization, the PSO algorithm is integrated using Eqs. (20) and (21) shown after Step 10.

Step 6: The greedy selection is applied to the new food source and its corresponding variable using an "if-else" statement.

### 4.3. Onlooker bee phase

The information obtained from the employed bees is then evaluated using a probabilistic approach by the onlooker bees. The higher the probability associated with the new food source, the more likely it is to be selected as the new food source. The worst probability will be abandoned if not, the trial counter increases by 1.

Step 7: The onlooker bee performs a probability evaluation given by:

\[ P_i = \frac{fit(x_i)}{\sum_{i}^{S_{pop}} fit(x_i)} \]

where \( fit(x_i) \) shows the suitability of the \( i \)th food source, associated with the objective function; \( S_{pop} \) represents the population size of the food sources.

Step 8: If the food source selected by the onlooker bee is fit and better than the older variable, the employed bee memorizes this new position and the trial counter is reset. If not, the trial counter increases by 1.

Step 9: The neighbor of the food source selected is then randomly computed, its fitness evaluated and the greedy selection reapplied.

### 4.4. Scout bee phase

This phase is applied based on the number of solutions that can be enhanced, activated only when the probability value of the food source is not improving over a preset value. Only one scout bee phase can occur in each ABC iteration.

Step 10: A scout bee searches for the next food source randomly, independent of previous history and in incremental steps of the iteration counter (\( \tau = \tau + 1 \)).

### 4.5. Hybrid of the algorithm

The 5th phase of the ABC algorithm is the Termination Phase. However, the PSO algorithm substitutes Eqs. (17) and (18) in phase 2 with Eqs. (20) and (21):

\[ v_{new}(t) = w_{1} v_{old}(t - 1) + c_{1} r_{1} (x_{best} - x_{old}) + c_{2} r_{2} (G_{best} - x_{old}) \]

\[ X_{new}(t) = X_{old}(t - 1) + v_{new}(t) \]

where \( v_{new} \) and \( X_{new} \) represent the new food source's velocity and position respectively. Constant \( w \) represents the inertia weight (1), which gives a balance between the global and local search abilities of PSO. Constants \( c_{1} \) and \( c_{2} \) represent the acceleration coefficients (2), which influence the maximum step size taken in each iteration. Variables \( r_{1} \) and \( r_{2} \) and random numbers ranging between 0 and 1, which affect the algorithm's stochastic nature. \( X_{best} \), also referred to as \( P_{best} \), is the best position of the food source, and \( G_{best} \) is the global best position of the food source in the entire population. The global best solution doesn't need to be used directly in the ABC algorithm to find a new food position [36].

### 4.6. The stopping criteria

**Step 11:** This is based on the maximum number of iterations and the set limit, computed from the employee bees (Food Number) and problem dimension as the best food source and particle fitness are updated [18, 36]. Figure 4 shows a flow chart of the hybrid algorithm used in the UVLS study.

All data used is obtained from power flow analysis and time domain simulations done in both command prompt and the PSAT graphical user interface. All tests have been done on an Intel core i7 processor with the following specifications: 2.5GHz CPU, 8GB RAM.

### 5. Results and discussion

#### 5.1. Effect of load characteristics on SNB point

ZIP modelling as shown in Figure 5 affects the SNB point by slightly increasing the loading margin by 0.2, which is an 8.7% load increase. This test is done to show the differences of the static loads, particularly voltage-dependent loads. In real-life power systems, loads are predominantly source-dependent. That is,

i. **Constant Power Loads – Active and reactive powers are independent of the voltage.** For instance, a mechanically-loaded motor at maximum capacity having a decrease in rotational speed compensates by increasing the slip, consequently increasing the current to provide the initial torque. IEEE models adopted the use of constant power loads in the '90s for ease and simplicity of studying power systems. It also has the least SNB point, creating a 'worst-case scenario’ of minimum loading margin compared to constant current and constant impedance loads [37]. However, these loads lead to system instability because thy tend to increase the current, to maintain constant power even though the voltage drops. This often leads to a further drop in the voltage. On the other hand, constant impedance loads tend to damp voltage oscillations.

ii. **Constant Current Loads – Active and reactive powers are proportional to voltage.** e.g., street light control systems in airports. The lamps are meant to operate at a constant current with the help of transformers that regulate the current. A change in system parameters directly impacts their illumination. This is represented in Figure 5 by the voltage exponents (1,1), whose loading margin is slightly higher than that of the constant power loads.

iii. **Constant Impedance Loads - Active and reactive powers are proportional to voltage squared.** The starting of a motor exhibits characteristics of a constant impedance load before it becomes a constant power load. This load has the largest loading margin of the three, represented by the voltage exponent (2,2) in Figure 5, and exhibits the lowest voltage dips in a dynamic analysis in [38].

Therefore, the applications of the ZIP models vary for different application areas. For this study, the purpose of using VDLM in comparison to the default constant power loads is to show the changes to the SNB point, which is a useful feature of voltage stability. PSAT converts all loads to constant impedance loads during time-domain simulations, hence for the voltage collapse analysis done in this study, voltage exponents (2,2) are used.

#### 5.2. Voltage collapse analysis

To determine the overloading conditions for the analysis, the system is loaded in steps of 5% until the occurrence of voltage collapse shown in Figure 6. Bus 14 is then picked for analysis being the weakest bus as it had the lowest Saddle Node Bifurcation (SNB) point when running the Continuation Power Flow for the test system.
The maximum loading parameter is 2.375 p.u., representing a function of active & reactive power for each load. From the curves, bus 14 has the lowest PV curve, which peaked at approximately 0.65 per unit of voltage. Therefore, bus 14 is analyzed in time-domain as shown in Figure 7, where loads are increased in steps until attaining a point of voltage collapse. The fault created is a simultaneous loss in two transmission lines nearest the generators, i.e., between buses 1–2 and 2–5.

Whenever a fault occurs in transmission lines, the load is normally redistributed to other lines during the outage period (until the fault is cleared, in this case at 10 seconds). The momentary shift in load causes more strain to the weak buses in a system. The Fast Voltage Stability Index (FVSI) is evaluated for multiple load increment values between 105% and 140% loading. Figure 8 shows the comparison in FVSI values for all lines during initial operating conditions (100% loading) and at...
maximum overload (140%). The FVSI values rank the weakest of the 20 lines used in the supply of power between the buses.

From the graph in Figure 8, line 18 (located between buses 4 and 9) has an FVSI value of 0.366 pre-contingency and 0.5274 during contingency, ranking it the highest value nearest unity. Other lines high in the ranking are 3, 9 and 12, linked to buses 13 and 2. The buses to which the loads are connected are considered weak buses, such that, when other factors like voltage deviation and penalty costs are considered, they are the first buses to undergo load shedding. The FVSI values are therefore, able to quantify how close a particular bus is to the steady-state voltage stability margin.

During the contingency simulation, the total load demand of the system changes from 259MW and 81.4MVAr initially, to 362.6MW and 113.96MVAr loading, whereby the voltage fails to recover after the fault occurrence at 3 seconds. The pre-fault voltage for bus 14 is 0.89p.u., which fails to sustain the load during the fault, thus causing the voltage collapse in that bus. Similarly, the impact of the dynamic generation for the test system is represented in Figure 9, in which the power generated increased proportionally to the load increment. This is due to the presence of Type 2 AVRs and Turbine Governors at the generators. A static system analysis normally ignores the action of dynamic components, although, for long-term voltage stability, the parameter changes are said to be constant.

The combination of all the above conditions is then factored in the formulation of the hybrid load shedding algorithm.

5.3. Under voltage load shedding

There are three expected outcomes from this study, namely: the location, and amount of load to shed and voltage enhancement of the system.

i) Location of Load Shed

The use of voltage stability indices (VSIs) gives more optimized results for the location of load to shed as shown in Table 5, in which FVSI is used. For the implementation of the algorithm, the maximum FVSI value is set to 0.15, beyond which the bus is selected for load shedding.

The comparison for the FVSI ranking compared to studies in [24] show that the eigenvalue analysis shed one additional bus for the same system.

ii) Amount of Load Shed

Figure 10 shows the amount of active power shed after the 140% loading considering load prioritization. The comparison of the active power with and without load prioritization is also shown in Figure 11. There is a 5.81$/MW cost saving when loads are prioritized for UVLS, and 85.5%, compared to 85.02%, of load is maintained post-contingency by considering load prioritization.

iii) Voltage Recovery

In order to perform UVLS, the criterion set up for decentralized relays, in which each relay remotely monitors a given bus is:

- When voltages drop to 90% and below, 5% of the load is tripped at the specified bus for 3.5 seconds.
- When the bus voltages drop lower than 92%, a 5% additional load is tripped for 5.0 seconds.
- When the bus voltages are still below 92% an additional load of 5% is tripped for 8.0 seconds [13].

Figure 12 shows the voltage profiles of the recovered system following the above UVLS criterion.

The voltages are restored to almost the initial values, despite the minimal load shed. The range of voltages at each instance is recorded as:

- Initial bus voltage magnitude: 0.9995p.u. (bus 14) to 1.06p.u. (slack bus).
- Voltage during contingency: 0 p.u (buses 3–5) to 0.9983p.u. (slack bus).
- After 5% load shed: 0.823p.u (bus 5) to 1.0764p.u. (slack bus).
- After 10% load shed: 0.8444p.u. (bus 5) to 1.103 (slack bus).
- After 15% load shed: 0.9908p.u. (bus 14) to 1.06p.u. (slack bus).

The set voltage range is 0.95p.u to 1.05p.u with an exception for the slack bus at 1.06p.u. The power generated post contingency is then
captured as 261.17MW and 54MVar, in comparison to the initial 232.58MW and 40MVar. This is a 15% increment in power generated as compensated by the AVRs and TGs.

5.4. Validation of hybrid algorithm

The validation of the algorithm is done in comparison with similar works in [19] and [24] as shown in Table 6. The active load post-contingency is given in comparison to existing algorithms while considering the load prioritization.

In the above results, buses 5, 10 and 14 are have the least deviation ranging from 0.26% to 3.96%. Buses 2 and 13, assigned the penalty cost of residential loads (5$/MW), had the most amount of load shed compared to buses 4 and 14, which are assigned to be a industrial loads which has a higher penalty cost of 12$/MW. The prioritization of load saved an overall 5.81$/MW for the 40% overload contingency. At the same time, voltage stability is restored by simultaneously achieving optimal cost saving and optimal amount of load shedding.

Figure 13 shows the convergence of the proposed solution (hybrid ABC-PSO) in comparison to the ABC algorithm used in this study. In evaluating the convergence of the solution, an Intel Core i7 processor of specifications 2.5GHz CPU and 8GB RAM has been used for the two algorithms. The average computation time for the ABC algorithm for the 50 iterations is 7.54 seconds, while that of the proposed solution is 5.63 seconds, achieved in 35 iterations. The difference in convergence time, as compared to [19], is attributed to the addition of the penalty factor in which a selection criteria for least priority loads is added to the algorithm. The hybrid algorithm achieves a 25% decrease in convergence

| Overload condition | No. of buses to load shed | Bus No. for UVLS |
|--------------------|--------------------------|-----------------|
| 105%               | 1                        | 9               |
| 110%               | 1                        | 9               |
| 115%               | 1                        | 9               |
| 120%               | 3                        | 13, 2, 9        |
| 125%               | 4                        | 13, 2, 6, 9     |
| 130%               | 4                        | 13, 2, 6, 9     |
| 135%               | 9                        | 12, 13, 11, 10, 14, 9, 2, 4, 6 |
| 140%               | 9                        | 12, 13, 11, 10, 14, 9, 2, 4, 6 |

Figure 8. FVSI values at 40% overload.

Figure 9. Dynamic behavior of the generators during overload conditions.

Figure 10. Amount of active power shed.
time, having 30% fewer iterations. Thus, its performance is significantly improved from the use of a single metaheuristic approach.

6. Conclusion

From this study, the first objective on the impact of load modelling shows that load modification on bus 14 gives an 8.7% bandwidth in loading margin. This shows that variation in systems’ loads creates a difference in SNB points, which can cause delayed voltage collapse in cases where loads are dependent on voltage variations. In achieving optimal UVLS, load prioritization, achieved using the second objective function, creates an overall saving of 5.81 $/MW as compared to UVLS without considering the load priority. The resulting amounts of load shed restores active power at 89.56% post fault compared to 77.04%, 84.03% and 80.96% in GA, ABC-ANN and PSO-ANN respectively. Lastly, voltage stability is restored in intervals of 3.5, 5 and 8 seconds, as per the decentralized relay settings. The average voltage profile is also restored by 99.32% of the initial voltage profile before fault. Therefore, the
novelty of this hybrid ABC-PSO algorithm is its ability to compute the multi-objective functions, giving a wider perspective on the UVLS problem. It proves that Computational Intelligence Techniques are useful in optimizing power system solutions.

**Declarations**

**Author contribution statement**

Susan Mumbi Kisengeu: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Christopher Maina Murithi: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

George Nyauma Nyakoe: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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**Data availability statement**

Data included in article_supp. material/referenced in article.

**Declaration of interests statement**

The authors declare no conflict of interest.

**Additional information**

No additional information is available for this paper.

**References**

[1] C. Taylor, Power System Voltage Stability, McGraw-Hill Companies, California, 1994.
[2] C. Zhai, H. Zhang, G. Xiao, T.C. Pan, A model predictive approach to protect power systems against cascading blackouts, Int. J. Electr. Power Energy Syst. 113 (May) (2019) 310–321.
[3] Prinessa Naidoo, R. Vollgraaff, "South Africa’s Record Rolling Blackouts Raise Recession Risk, 2019.
[4] B. Liscouski, W. Elliot, U.S.-Canada power system outage task force, System 40 (April) 2004 238.
[5] I.H. Alhelou, M.E. Hamedani-Golshan, T.C. Njenda, P. Siano, A survey on power system blackout and cascading events: research motivations and challenges, Energies 12 (4) (2019) 1–28.
[6] H. Shiraki, S. Ashina, Y. Kamayama, S. Hashimoto, 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. 114 (Feb. 2016) 81–94.
[7] S. Rai, V. Kumar, G. Agnihotri, Under voltage load shedding for contingency analysis to optimize power loss and voltage stability margin, Electr. Electron. Eng. An Int. J. 3 (4) (2014) 57–64.
[8] M. Usman, A. Amin, M.M. Azam, H. Mokhlas, Optimal under voltage load shedding scheme for a distribution network using EPSO algorithm, in: Proc. 2018, IEEE 1st Int. Conf. Power, Energy Smart Grid, ICPESG 2018, no. September 2019, 2018, pp. 1–6.
[9] R.M. Lalik, M.W. Mustafa, M.N. Aman, A critical review of the state-of-art schemes for under voltage load shedding, Int. Trans. Electr. Energ. Syst. 29 (5) (2019) 1–26.
[10] J.A. Laghari, H. Mokhlas, A.H.A. Bakar, H. Mohamad, Application of computational intelligence techniques for load shedding in power systems: a review, Energy Convers. Manag. 75 (2013) 130–140.
[11] A.P. Engelbrecht, Computational Intelligence: an introduction, 2007.
[12] B. Mozafari, T. Amraee, A.M. Ranbar, An approach for under voltage load shedding using particle swarm optimization, IEEE Int. Symp. Ind. Electron. 3 (2006) 2019–2024.
[13] C. Mozina, Undervoltage load shedding, in: Power Syst. Conf. Adv. Metering, Prot. Control. Commun. Distrib. Resour. PSC 2007, no. April 2007, 2007, pp. 39–54.
[14] R.M. Lalik, M.W. Mustafa, S. Qazi, N.H. Mirjat, Under voltage load shedding scheme to provide voltage stability, Energy, Environ. Sustain. Dev. 2016 (November) (2016) (EESD 2016).
[15] S. Jaliijazadeh, S.H. Hossein, M. Derashtian-Maram, Optimal load shedding to prevent voltage instability based on multi-objective optimization using modal analysis and PSO, in: 2010 Int. Congr. Ultra Mod. Telecommun. Control Syst. Work., 2010, pp. 371–376.
[16] M. Guichon, M. Melo, A.C. Nieto, M. Vignolo, N. Yedrezewski, A. Introduction, Automatic Load Shedding Calculated with Genetic Algorithms – DAC-CMAG, ”Transm. Distrib. Lat. Am. Conf. Expo., IEEE/PES, 2012, pp. 1–7, no. Sixth.
[17] M. Ben Hessine, H. Jouini, S. Chebbi, Load shedding strategy application using fuzzy logic, Int. Conf. Electr. Eng. Softw. Appl. ICESSA 3 (6) (2013) 2012–2015.
[18] R. Magreshvarana, T. Jayabarath, Steady state load shedding to prevent blackout in the power system using artificial bee colony algorithm, J. Teknol. (Sciences Eng. 8 (2) (2015) 113–124.
[19] R.M. Lalik, M.W. Mustafa, M.N. Aman, T.A. Jumani, S. Sajid, M.K. Panjwani, An improved algorithm for optimal load shedding in power systems, Energies 11 (7) (2018) 1–16.
[20] A. El-zonkoly, M. Saad, R. Khalil, Electrical Power and Energy Systems New algorithm based on CLPSO for controlled islanding of distribution systems, Int. J. Electr. Power Energy Syst. 45 (1) (2013) 391–403.
[21] R. Verayiah, A. Mohamed, H. Shararef, I. Zainal Abidin, Review of under-voltage load shedding schemes in power system operation, Prz. Elektrotechniczny 90 (7) (2014) 99–103.
[22] V. Tamiiselvan, T. Jayabarathi, A hybrid method for optimal load shedding and improving voltage stability, Ain Shams Eng. J. 7 (1) (2016) 223–232.
[23] W. Chan-Feng, L. Kui, S. Pei-Ping, Hybrid artificial bee colony algorithm and particle swarm search for global optimization, Math. Probl. Eng. (2014) 2014.
[24] V. Tamiiselvan, A hybrid PSO-ABC algorithm for optimal load shedding and improving voltage stability, Int. J. Manuf. Technol. Manag. 34 (6) (2020) 577–597.
[25] X. C. Yang, Multi-objective optimization, Nature-Inspired Optim. Algorithms (2014) 197–211.
[26] N. Gunantara, A review of multi-objective optimization: methods and its applications, Cogent Eng. 5 (1) (Jan. 2018) 1–16. http://www.editorialmanage r.com/cogenteng.