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Effects and optimal integration of electric vehicle charging systems in the Tanzania electrical distribution networks using metaheuristic algorithms

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Abstract

Electric vehicles (EVs) present a viable solution for reducing carbon emissions, environmental pollution, and the effects of climate change. The EV utilizes energy stored in its battery banks, which are charged by electric vehicle charging systems (EVCS), primarily integrated with the power grid. However, integrating EVCS into grid poses significant challenges, including increased power losses, voltage deviations, harmonic injection, and grid instability. This study examines the impacts of connecting EVCS to Tanzania's electrical distribution networks and proposes an optimization approach using metaheuristic algorithms to mitigate power loss and voltage deviation challenges. The study reveals that adding one EVCS raises power loss from 13.0357 kW to 17.1963 kW, while voltage deviation increases from 0.47 V to 0.63 V, with further deterioration in system performance as more EVCS units are introduced. An enhanced Symbiotic Organism Search algorithm was employed to determine the optimal allocation and size of EVCS and PV systems. The results show that integrating 1 PV in the power system with 3 EVCSs reduced power loss to 5.26 kW from 61.42 kW. This research reveals the effectiveness of optimal PV system placement in improving the stability of the electrical network and the feasibility of an efficient EV penetration in Tanzania.

1. Introduction

Electric vehicle (EV) technology was invented at the beginning of the 20th century, competing with internal combustion engines (ICEs) in the automotive and transportation industries [1]. The EV uses electrical energy stored in the batteries. Due to the limitations of electricity access and the high cost of battery technologies, the ICE has outperformed EVs and emerged as a popular technology for many years [2]. However, the ICE relies on the combustion of fossil fuels, which fosters carbon emissions, environmental pollution, and climate change. The push for carbon-free technologies, environmental conservation, and the development of electricity and battery technologies at the beginning of the 21^{st} century led to a shift in the automobile and transportation industry towards electric vehicle (EV) technologies [3, 4].

Electric vehicles utilize electricity as a primary energy source, which is considered cleaner than energy from fossil combustion. The EV utilizes energy stored in the battery banks, which are primarily charged by electricity from the main grids or isolated renewable energy sources [1]. However, due to the large power demand posed by EVs, they are typically charged by the main grid in most cases. In peak demand, the vehicles can feed stored energy back into the main grid. The technique behind power exchange between a vehicle and the electrical grid is called vehicle-to-grid (V2G) technology[5].

The applications of V2G and EV technologies are rapidly advancing across developed and developing countries. Approximately 14 million cars were sold worldwide in 2023, with 95% of these sales occurring in China, Europe, and the United States. The trends show the rapid growth of the electric car market worldwide. Electric vehicles represented about 2% of total car sales in 2018, rising to 14% in 2022 and reaching 18% in 2023[6]. Although electric vehicles are experiencing rapid growth worldwide, their adoption in Africa remains limited. The major obstructions to the adoption of EVs in developing countries include high initial costs, the absence of clear policies and regulations, poor electricity networks, and the scarcity of public e-charging stations [7]. The study done by Malima and Moyo [8] analyzed the total Cost of Ownership (TCO) of EVs in sub-Saharan Africa to determine if they are viable options for consumers from Tanzania. The results showed that the average initial cost is more than US Dollars 40000, which makes it one of the reasons for the low adoption of EV vehicles in developing countries.

The number of vehicles in Tanzania has increased rapidly, with two-wheel (2W) vehicles, such as piki piki, and three-wheel (3W) vehicles, including Bajaji and Gutas, surpassing four-wheel (4W) vehicles. The adoption of electric vehicles in Tanzania is mostly practiced in 2W and 3W vehicles. At least four or five companies in Tanzania provide electric motorcycles, including eMo Bodaboda, Greenfoot, Sinoray, and Linkall [9]. For the 4W electric vehicles, Hanspaul Ltd and its sister company, E-motion, have ventured into assembling open-top safari vehicles for tourists. Many companies and institutions have recently ventured into studying and manufacturing electric vehicles in Tanzania, although the projects are still in the pilot stage. For example, Kaypee Motors and the University of Dar es Salaam piloted small electric flat-bed trucks in Dar es Salaam [10].

The adoption of electric vehicles in Tanzania has increased rapidly over the past few years, driven by declining costs and growing consumer awareness of electric vehicles. However, the industry is still relatively young and hindered by several factors, including high import taxes, unclear government policy, limited funding, a shortage of EV experts, and limited consumer awareness [9]. Importing vehicles in Tanzania requires processing through the Tanzania Revenue Authority. However, the process was initially made for ICE vehicles and required a CC engine size, which does not exist on electric vehicles [10]. Additionally, Tanzania has not yet established the necessary infrastructure, particularly a power system, to support electric vehicles. For example, with existing electric vehicles, charging is done through the household electrical facilities, which not only takes a long time to charge the vehicles but also may cause detrimental effects to the power system [11]. Integrating electric vehicle charging stations (EVCS) in the power system will ensure fast charging and power system safety. Therefore, this study investigates the effects of integrating EVCS into Tanzania's electrical distribution networks.

The electric vehicle charging stations (EVCS) were designed to speed up the charging time of EVs. Such fast-charging stations draw high currents from electrical systems, which may cause adverse effects on the operating parameters of electrical systems, such as increased peak load demand, voltage instability, voltage deviations, power losses, and reliability problems [12]. Most power losses in power systems occur in distribution networks where the charging stations are expected to be installed, leading to poor service quality, higher electricity costs, and utility revenue losses[13]. Distributed generators (DG) are among the tools for alleviating the problems caused by EVCS integration into the power systems. However, the DG placement in the power system is challenging. Therefore, the efficient integration of EVCS involves optimal placement of EVCSs and DGs, making it an NP-hard optimization problem. Optimal placement of EVCS and DG involves finding their location and sizes that maintain the healthy condition of the electrical system [11]. Metaheuristic algorithms are among the methods for solving such optimization problems because they can find near-optimal solutions for large and complex problems. Also, metaheuristic algorithms operate by repeated evaluation of objective functions and are particularly useful for problems where traditional optimization techniques struggle, such as non-linear, multi-modal, and non-convex problems [14].

The symbiotic organism search (SOS) metaheuristic algorithm has been employed to determine the optimal locations and sizes of EVCSs and PVs. The objective functions focused on minimizing power losses and voltage deviation. The SOS was modified by using penalty mechanisms in order to ensure the simultaneous placement of multiple EVCSs. Different parameters were considered, including the number of EVCSs and the number of PVs, with three placement cases examined. The findings indicate that incorporating photovoltaic (PV) systems significantly enhances the performance and stability of the power system by reducing power losses and voltage deviations, with greater benefits observed as the number and capacity of PV systems increase.

2. Literature Review

2.1 Metaheuristic algorithms overview

Metaheuristic algorithms are efficient computation methods for solving complex optimization problems, especially when traditional methods are impractical [15]. Metaheuristic algorithms have been applied in various fields, including engineering design, machine learning, electrical power systems, and logistics. In power systems, metaheuristic algorithms have been employed for various purposes, including solving economic dispatch problems, determining optimal DG placements, and optimizing load flow [16]. In solving the DG and EVCS placement problems in the power system, several metaheuristic algorithms have been reported.

Algorithm 1 represents basic structure of the SOS metaheuristic algorithm.

Algorithm 1: The Basic Structure of SOS [17]

```
Initialization
while t<maxite do
    Identify the best algorithm Xbest in an ecosystem
    for i=1: ecosystemssize do
        Mutualism
        Commensalism
        Parasitism
    end for
    Checking termination criteria
end while
```

2.2 Related works

Studies show that the optimal allocation of EVCS, including distributed generators such as solar photovoltaics (PV), wind energy, battery energy storage systems (BESS), and distribution static compensators (DSTATCOM), improves the power system's operational parameters. The EVCS in the electrical distribution network is the NP-hard optimization problem which employs metaheuristic algorithms, such as Teaching Learning optimization (TLBO), African vulture optimization algorithm (AVOA), Grasshopper optimization algorithm (GOA), Hybrid AVO and pattern search (HAVOPS), transient search optimization algorithm (TSOA), Whale optimization technique (WOT), non-dominated sorting genetic algorithm II (NSGA-II) and Hunter Prey Optimization (HPO) algorithm [18, 19]. Reinforcement Learning (RL) based algorithms have also been applied. Table 1 presents studies on the allocation of EVCS, along with their optimization methods and the associated electrical networks.

Table 1. Approaches for allocation of EVCS in the electrical networks using metaheuristic algorithms.

References	Optimization method	Objective functions	Electrical distribution network	Energy sources generators
[20]	TLBO	Power loss and Voltage profile	IEEE 33 and 69 bus systems	EVCS, PV and Wind energy
[21]	RL	power loss, voltage stability, installation and operation costs.	IEEE 33 and 118-bus distribution network	BESS units (EVCS) and PV
[22]	AVOA	Real power loss index and voltage stability index.	The 33 bus, 69 bus, and 136 bus systems.	EVCSs, DGs, and DSTATCOMs.
[23]	GOA	Power loss and Voltage profile	The 51-bus and 69-bus distribution networks	EVCSs, DGs, and shunt capacitors
[24]	HAVOPS	Voltage deviation, real power loss, and investment costs	33-bus and 136-bus systems	EVCS, network Reconfiguration, DG, DSTATCOM
[25]	TSOA	power loss, voltage profile and stability index	IEEE-25 unbalanced radial distribution system	EVCS and DGs
[26]	WOT	active and reactive power losses	IEEE-33 and 69-bus	EVCSs, DGs, and shunt capacitors
[19]	NSGA-II	voltage levels and power losses	IEEE 34-node test feeder	EVCSs and distributed energy resources (DERs)
[18]	HPO	Power loss and Voltage profile	IEEE-33 and 69-bus	EVCSs, PVs, and DSTATCOMs.

As presented in Table 1, most studies for the allocation of EVCS involve standard IEEE bus systems, which are the primary distribution networks and are based on theoretical assumptions. Therefore, this study proposes techniques for allocating EVCS in the secondary distribution networks. Unlike other studies, which focused on theoretical IEEE bus systems, this study involves practical electrical distribution networks from Tanzania's national electrical supply company (TANESCO), leveraging the use of advanced technologies, including resilient communications architectures [27, 28] and distributed fog computing [29]. Also, in the study by Pappu et al. [18] the number of vehicles per EVCS was fixed. This study considered optimizing the number of vehicles per charging station, which increases the complexity of the problem.

The symbiotic organism search algorithm, first reported by Cheng and Prayogo [30], is among the popular algorithms for solving DG placement issues due to its simple structure and easy implementation procedures. Since its introduction, numerous variants of SOS have been proposed to address various problems in diverse areas. The SOS was designed based on the association of organisms in the ecosystem. The SOS involves three main stages: mutualism, commensalism, and parasitism, as presented in the pseudo-code in Algorithm 1.

3. Methods

3.1 Tanzania power system

Tanzania Electric Supply Company Limited (TANESCO) is the main utility company responsible for generating, transmitting, and supplying electricity in Tanzania [31, 32]. As per the report of 2021/2022, the TANESCO distribution network comprises approximately 148,544 km of distribution lines, which includes 8,325 km of 33kV lines, 3,732 km of 11kV lines, and 12,992 km of lower voltage lines [33, 34]. The electrical distribution network is essential since it interconnects the transmission system and the users [35]. The distribution system consists of the most extensive coverage, scattered, and most households are in un-surveyed areas, which makes it complex for analysis [36]. The current EV charging trends in Tanzania, which utilize household facilities, may interfere with power system planning, potentially reducing power system performance or causing significant issues.

In studying the integration of electric vehicles into Tanzania's power system, the study area was selected from a part of the Tanzanian electrical distribution network presented in Figure 1. The area was selected from the Kinondoni North Area near Msasani Peninsula Hospital. The selected area has 79 nodes with 143 customers. Currently, there is no EVCS in this study area.

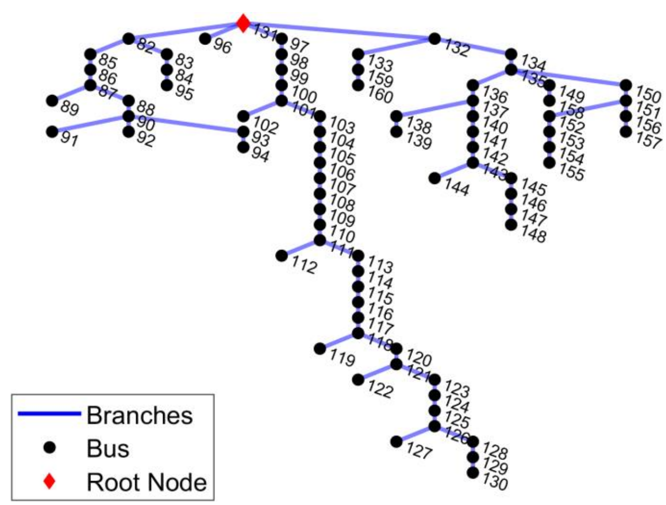

Figure 1. Electrical network of the study area [13].

3.2 Modelling of electric vehicle charging station

In V2G technology, the EVCS consists of components such as load management systems, charging stations, and electric grids. The load management system is crucial for power distribution and protection against overloading. The charging stations regulate the power exchange with the grid, ensuring safety and compatibility with the battery. The impact of EVCS on the operation of the electric grid is more significant when charging the battery. When charging, the EVCS absorbs real power from the grid. The active power expression of the EVCS can be given in equation (1) [18, 37].

$$P_{EV} = \frac{V_s \times V_c \times sin\, sin\, \beta}{\omega L_C}, \qquad (1)$$

where P_{EV} is the denotation of the real power of the EV, V_s is the grid supply voltage, V_c is the voltage of the charging station, β is the angle between V_s and V_c, ω is the angular frequency of the grid, and L_C is the total inductance contributing to the active loads, including the line inductance and the charger filter inductance between the charger and the grid.

The EVCS is connected to the electrical system's bus. In electrical power systems, active loads consume power that performs useful work (like heating or lighting), while reactive loads store and release energy but do not directly contribute to work [38]. Since it draws power from the grid, the active load, which refers to the load that consumes power for useful work, is connected to the bus and can be given as

$$P_{i(new)} = P_{i(base)} + P_{i(EV)}, \qquad (2)$$

where $P_{i(base)}$ is the active load of the system at the i^{th} bus before the EVCS is connected, $P_{i(EV)}$ is the power drawn by the EVCS from the grid at the i^{th} bus and $P_{i(new)}$ is the total load at the i^{th} bus.

3.3 Modelling of Solar Photovoltaic System Modelling

A solar photovoltaic (PV) system converts sunlight into electricity using semiconductor materials. Solar PV systems comprise solar panels, an inverter (which converts DC to AC power), and storage batteries to store surplus energy for later use, thereby addressing intermittency issues associated with solar energy [39]. Figure 2 presents a schematic diagram of the grid-connected solar PV with Solar panels, controller, inverters, and grid supply. The system can be connected to the grid or operated independently (off-grid) for residential, commercial, and utility-scale applications [40].

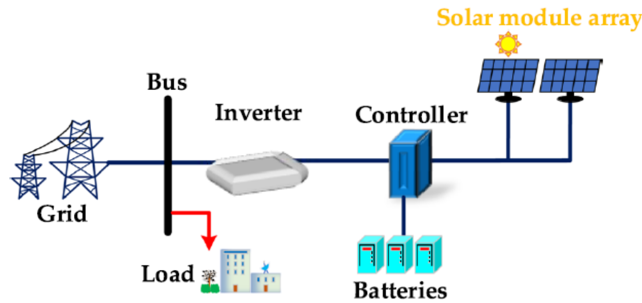

Figure 2. Schematic diagram of grid-connected solar PV [40].

A mathematical model of output power from a PV system involves an equation

$$P_{PV} = P_{PV(base)}\left[1 + \alpha_{PV}\left(T - T_{ref}\right)\right]\frac{\delta_{PV}}{100} \qquad (3)$$

representing the relationships between active power, solar irradiance, and temperature [18, 37].

The variables from (3) are defined as follows: α_{PV} represents the temperature-conversion coefficient of PV; T_{ref} represents a set reference temperature value; T and δ_{PV} represent the temperature and solar irradiance at the recording time instant, respectively; P_{PV} and $P_{PV(base)}$ represent the output power of the PV system at the recording time instant and the rated power of the PV cell, respectively.

In grid-connected mode, the PV system is connected to the bus. Since it injects the power into the grid, the active load connected to the i^{th} bus can be given as

$$P_{i(new)} = P_{i(base)} + P_{i(PV)}, \qquad (3)$$

where P_{base} is the active load of the system at the i^{th} bus before the PV is connected, $P_{i(PV)}$

represents the power injected by the PV into the grid at the i^{th} bus and $P_{i(new)}$ is the total load at the i^{th} bus.

3.4 Objective function

In low-voltage radial electric distribution networks, the active power loss is more influential than the reactive power loss [41]. Therefore, in this study, the objective functions are active power loss and voltage deviations, as presented in equations (5) and (6). The optimization method aims to minimize power loss, as presented in (7). The voltage deviation in (6) will be analyzed from optimized voltage values.

$$P_{loss} = \sum_{i=1}^{nb} I_i^2 \times R_i \tag{5}$$

$$V_d = \sum_{i=1}^{nb} (V_i - V_{rated})^2 \tag{6}$$

$$F_{obj} = \text{minimize}(P_{loss}) \tag{7}$$

where F_{obj} is the objective function, P_{loss} is the total power loss, I_i is the current through the branch i, nb is the number of buses. V_d is the overall network voltage deviation. The R_i is the resistance of the i^{th} network branch connected between i^{th} and $(i+1)^{th}$ bus. The V_i is the voltage magnitude of the i^{th} bus, expressed in p.u and V_{rated} is the rated voltage of the network, which is 1 p.u.

In the power system, changing the load or generator size at any bus causes changes in branch currents and bus voltages, which eventually cause changes in power losses, voltage deviations, and other power system performance parameters. Therefore, this study aims to determine the optimal size and number of EVCS and PV that minimize the objective function in (7).

3.5 Constraints

When operating DGs, the objective function is subjected to several constraints.

A. Power balance constraints

$$P_{PV} = P_{loss} + P_D \tag{8}$$

$$Q_{PV} = Q_{loss} + Q_D \tag{9}$$

where P_{PV} and Q_{PV} in (8) are the total active and reactive power injected by the PVs, respectively. P_D and Q_D are the active and reactive power of the load at the i^{th} bus, respectively. P_{loss} is the total active power loss of the network given in equation (5), and Q_{loss} in (9) is the total reactive power loss of the network given by equation (10).

$$Q_{loss} = \sum_{i=1}^{N} (I_i)^2 X_i \tag{10}$$

where I_i is the current through the branch i and X_i is the reactance of the branch i, and N is the total number of branches in the network.

B. Voltage constraints

$$V_{min} < V_i < V_{max} \text{ where } i = 1,2,3,\dots,n \tag{11}$$

where V_i is the voltage magnitude at i^{th} bus. The V_{max} is the upper voltage limit, and V_{min} is lower voltage limit. In this work, the minimum and maximum voltage limits are 0.9 p.u and 1.1 p.u, respectively. The values of voltage limits are according to the Tanzania electrical power system grid code, which specifies a 10% tolerance for low-voltage networks [42].

C. Photovoltaic power constraints

$$P_{i,min}^{PV} < P_i^{PV} < P_{i,max}^{PV} \tag{12}$$

where $P_{i,min}^{PV}$ is the lower active power limit of PV, $P_{i,max}^{PV}$ is the upper active power limit of PV. P_i^{PV} is the active power of the PVs at i^{th}bus, respectively.

3.6 The Proposed metaheuristic algorithm for EVCS and PV placements

In this study, the placement of EVCS was implemented using the symbiotic organism search algorithm. Installing Electric Vehicle Charging Stations (EVCS) adds to the power system load and increases power losses in electrical distribution networks. For power loss minimization problems and simultaneous placement of multiple EVCS, it is possible for multiple EVCS to be placed at the same locations. Since the simultaneous placement of multiple EVCSs aims to place each EVCS at different locations, optimizing their placement using metaheuristic algorithms becomes challenging. To enable the efficient simultaneous placement of EVCS, modifications were made to the metaheuristic algorithm by incorporating penalty mechanisms. With the penalty mechanism, the solution with repeated bus locations is penalized by adjusting its objective function value to the highest value in the population. Thus, preventing these solutions from consideration in subsequent algorithm iterations, since in minimization problems using metaheuristic algorithms, solutions with high objective function values have greater chances of being discarded. The flowchart of the proposed penalty mechanisms is presented in Figure 3.

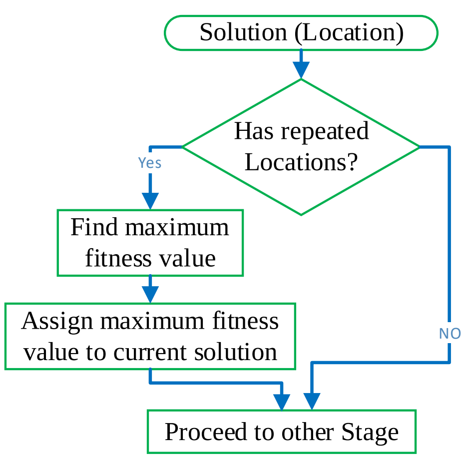

Figure 3. Penalty mechanisms for metaheuristic algorithm.

At each stage of the SOS algorithm, the organism is evaluated to determine the value of the objective function for a specific solution. The function evaluation is performed in each iteration for each organism in the ecosystem to determine the associated power loss. Since this study involves the placement of EVCS and PV, the evaluation steps are presented in Figure 4, which are explained as follows:

(i) Place the EVCS: This stage involves the placement of EVCS in the electrical bus locations as the solution proposed by the organism.

(ii) Place PV: This stage involves placing PV in the specific buses as proposed by the organism. This case is applied when the simultaneous placement of EVCS and PV is performed.

(iii) Run power flow: This stage involves running the power flow algorithm, which determines the current in each branch and the voltage in each node. This study applied the direct load flow method [31].

(iv) Calculate power loss and voltage deviation: The results from the power flow method are used to calculate the power loss and voltage deviation using (5) and (6).

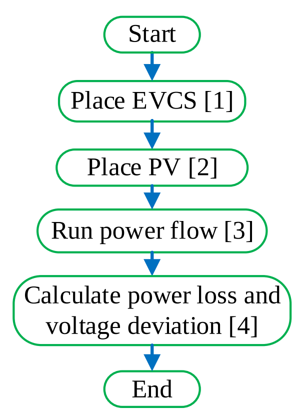

Figure 4. Objective function evaluation steps.

Based on the original SOS proposed by Chen and Prayogo [30], the penalty mechanism presented in Figure 3, and the objective functions evaluation steps presented in Figure 4, the proposed SOS variant based on penalty mechanisms for the placement of EVCS and PV in the electrical distribution networks is presented in Figure 5. In each stage of SOS, when updating the states of organisms, the penalty mechanism is applied to discard placements of multiple EVCS in the same location. Cheng and Prayogo [30] present the mathematical formulation of stages of the SOS algorithm, such as mutualism, commensalism, and parasitism.

4. Results and Discussions

4.1 Assumptions and parameter settings

In investigating the effects of integrating the EVCS and PVs in the Tanzanian power systems, the following assumptions were considered:

(i) In this study, the placement considers the charging station locations and the optimal number of vehicles to be charged simultaneously.

(ii) When considering the simultaneous placement of multiple EVCSs, no multiple EVCS should be placed in the same location.

(iii) The minimum and maximum number of vehicles per charging station were arbitrarily chosen from 0 to 100.

(iv) The capacity of vehicles is 2.5kW, which aligns with [18].

In all cases with optimized results, the proposed SOS, GWO, and SOS algorithms were considered. The parameter settings for algorithms are presented in Table 2. The algorithm incorporated an ecosystem comprising 30 organisms that ran for 200 iterations. All Simulations were carried out using MATLAB 2021b on a 3.80 GHz, 4-core i7 computer with 16 GB RAM.

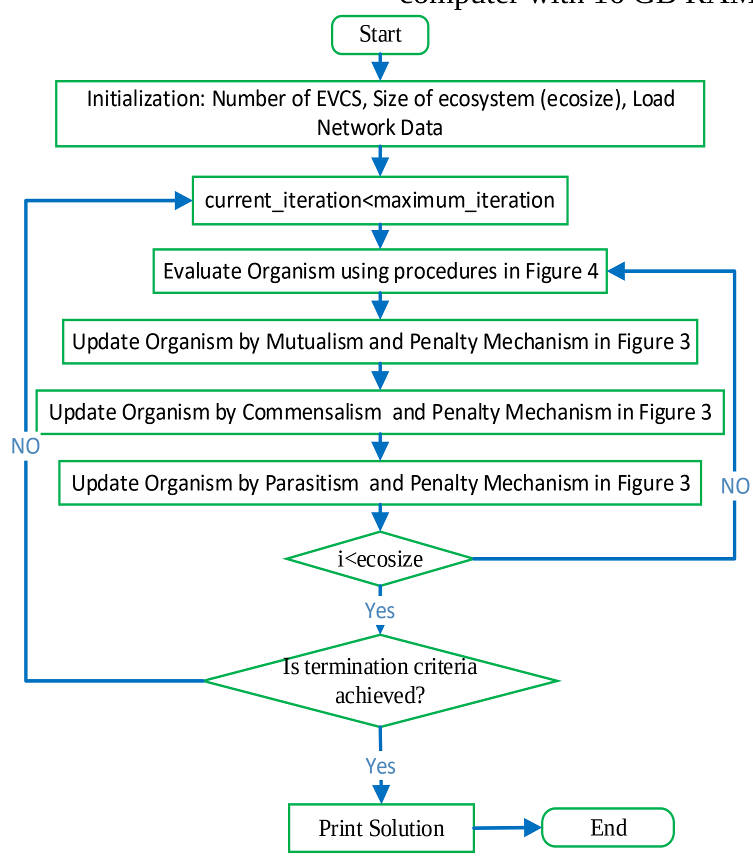

Figure 5. The Proposed SOS with penalty mechanism for placement of EVCS in electrical distribution networks.

Table 2. Parameter settings of metaheuristic algorithms.

SN	Algorithm	Parameters
1	SOS [30]	No parameter settings
2	GWO [43]	a=2 to 0 (linearly)
3	PSO [15]	w=0.9-0.4 (inertia weight)

4.2 Results for placement EVCS and PV

The proposed algorithms were tested for the placement of EVCS considering three cases: random allocation of EVCS, allocation of PV in the electrical network with existing EVCS, and simultaneous placement of EVCS and PV.

The EVCS has a fixed capacity for each charging point in practical applications, as elaborated by Ferraz et al. [19], where 4.8 kW and 2.5 kW were reported. Therefore, in this study, the size of the EVCS was fixed, while only the locations were optimized. The size of each charging station in this study was 2.5 kW, and the EVCS with 10 charging stations was considered. The number of charging stations was chosen based on the nature of the electrical network under investigation, as increasing the number could cause the network's operating parameters to exceed the required values. Investigating the impacts of mixing sizes with charging rates of 2.5 kW and 4.8 kW is possible. Still, it does not provide any significant difference to the final results as per the focus of this study.

A. Case 1: Random Placement of EVCS

In the first case, the number of vehicles per charging station was arbitrarily fixed to 10, and locations were obtained randomly. In this case, the effects of several EVCS on the power system's performance were analyzed. Four scenarios were considered; the first involved the power system without any EVCS, followed by one, two, and three EVCSs. The voltage profile, showing the voltage levels at all buses for all considered scenarios, is presented in Figure 6 and the results for power losses and voltage deviation are presented in Table 3. Figure 7 presents the results for the power loss profile, showing the power loss at all electrical network branches for all considered scenarios.

The results in Figure 6 show that as the number of EVCS increases, the voltage profiles become worse, with the most affected nodes being nodes 96 to 132. Those nodes are mostly affected because they are far from the root node. Additionally, the results in Table 3 indicate that as the number of EVCS increases, both voltage deviation and the minimum voltage of the system rise. Power system stability and quality performance require maintaining the voltage profile close to 1 p.u. with some tolerance value. Tanzania's power system implements a 10% tolerance value. Therefore, increasing the number of EVCS shifts the voltage profile beyond the required operational limits, making the power system prone to collapse.

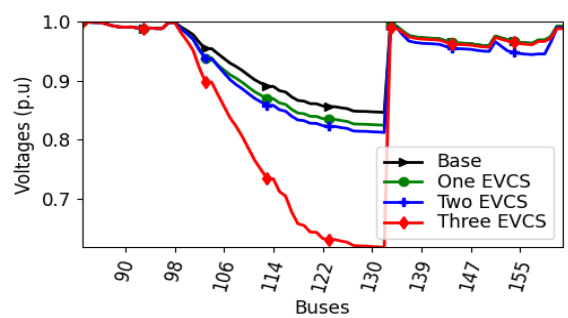

Figure 6. Voltage profile for random placement of EVCS.

The results in Figure 7 show that as the number of EVCS increases, the power loss profiles become worse, especially at branches 96 to 120. In most branches, the placement of three EVCSs results in the highest power losses, except for branches 136 and 156, where the placement of two EVCSs yields the highest values. Such variations of results are caused by the randomness in placing the EVCS. Results in Table 3 show that increasing the number of EVCS leads to higher system power losses.

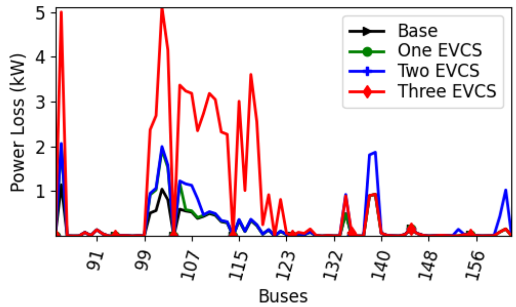

Figure 7. Power loss profile for random placement of EV.

Case 1 demonstrates that the addition of EVCS increases power system load, worsens voltage profiles, and increases power losses. The results show that power system performance parameters worsen as more EVCS are added. Therefore, some mitigation measures are necessary to ensure the optimal integration of ECVS in Tanzania's power system with minimal side effects. Some possible mitigation measures include network reconfigurations and integration of distributed generators. Network reconfiguration involves automatic restructuring of the electrical network through switching. In the Tanzania power system, especially in the secondary distribution networks, the infrastructure does not support reconfiguration due to a lack of automated switches and alternative feeders. The other mitigation measure includes DG, which has many advantages for power systems. Several DG types exist, including hydro, wind, and solar PV. Solar PV is the most commonly available in Tanzania, especially for secondary electrical distribution customers. Therefore, this study considers the optimal integration of solar PV in the electrical distribution network with EVCS, as elaborated in Case 2.

B. Case 2: Fixed EVCS with Varying Numbers of PV

Despite the dire need to integrate the EVCS into power systems, the results in Case 1 demonstrate that such integration can impact the power system's performance. To enable the integration of EVCS while maintaining improved power system performance, Case 2 investigated the inclusion of PV in the power system with EVCS. The study considered a power system with three EVCS, with sizes and locations as in Case 1, due to its considerably worse result. Then, the effects of including PV and increasing the number of PV were considered. Five scenarios were considered: the first involved the power system with three EVCSs inherited from Case 1, followed by four cases which involved the placement of one up to four PVs. Three metaheuristic algorithms: PSO, GWO, and the proposed SOS algorithm in Figure 5, were employed to determine the optimal locations and sizes of PV.

Table 4 presents the results for power losses and voltage deviation for all considered scenarios using metaheuristic algorithms. The results in Table 4 show that for the placement of 1 PV, SOS and PSO achieved the same results and outperformed the GWO. All algorithms achieved the same results when placing 2 PVs. For the placement of 3 PVs, the SOS algorithm was the best, followed by PSO. The convergence profile of the three algorithms is presented in Figure 8. The results show that the SOS algorithm provided the best profile, followed by the PSO. These results suggest that the SOS algorithm is highly competitive and can yield reliable results.

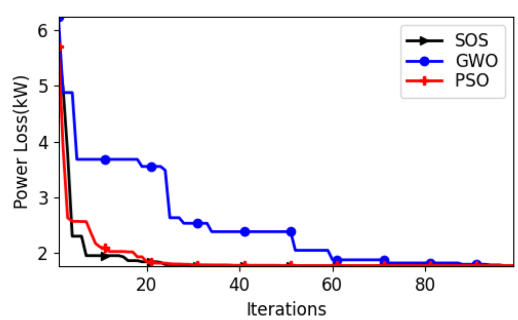

Figure 8. Convergence for profile placement of 3EVCS and 3 PVs in Case 2.

Table 3. Power and voltage profile for random placement of EVCS.

Scenario	Locations	Power Loss(kW)	Min Voltage (p.u)	VD(V)
Base	_	13.0357	0.8463	0.47152
One EVCS	103	17.1963	0.8244	0.63342
Two EVCS	106 and 156	22.8431	0.8123	0.75270
Three EVCS	116, 120, and 133	61.4207	0.6169	2.82493

Therefore, in further analyzing the effects on multiple PVs and variables, the results from the SOS algorithms were considered. The results in Table 4 indicate that as the number of PVs increases, the voltage deviation decreases, suggesting improved stability and system performance. Also, Table 4 shows that the power loss decreases as the number of PV increases.

Figure 9 presents the voltage profile showing the voltage levels at all buses for the placement of one to four PVs. The results in Figure 9 show that the inclusion of PV can significantly improve the voltage profile, with greater improvement achieved as the number of PVs increases. Similarly, the results in Figure 10 show that the minimum voltage increases as the number of PV increases, and the inclusion of PV has massively improved the minimum voltage value. That result also shows no significant change in minimum voltage value between 3 PVs and 4 PVs, implying that for any power system, there is a limiting number of PVs, which can significantly improve the voltage.

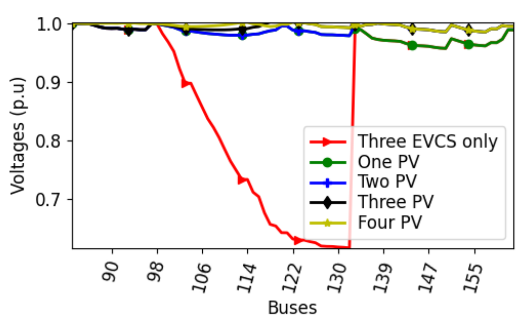

Figure 9. Voltage profile for three EVCS and increasing number of PVs.

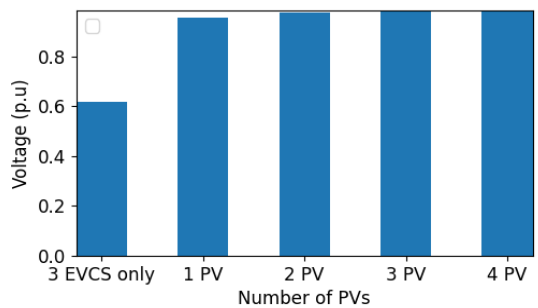

Figure 10. Minimum voltage values for three EVCS and increasing number of PVs.

Case 3: Optimal Placement of EVCS and PV

Case 2 considered the fixed placement of three EVCSs, and it was shown that increasing the number of PV in the power system improves voltage profiles and minimizes power losses. Case 3 considered the simultaneous allocation of EVCS and PVs using metaheuristic algorithms. For the case of EVCS, the algorithms were used to determine the optimal locations for fixed EVCS sizes. For the case of PVs, the algorithms were used to identify the locations and sizes. For the EVCS case, placements of one to three EVCS were considered. For each considered number of EVCS, the number of PVs was changed from one to four.

Results for the optimal placement of three EVCSs with varying numbers of PVs using three metaheuristic algorithms are presented in Table 5. The results show that for the placement of 1 PV and 2 PVs, the SOS achieved the best power loss and voltage deviations, followed by the PSO. In placing 2 PVs, the PSO produced the best power loss and voltage deviations, followed by the SOS. However, the EVCS placement results for PSO and GWO show that two EVCS were placed at the same locations, which violates the goals of placing the EVCS at three different locations and the assumption (ii) of this study. The SOS algorithm provided distinct locations for each placement case due to the incorporation of penalty mechanisms. The convergence profile of the three algorithms is presented in Figure 11. The results show that the PSO algorithm provided the best profile, followed by the SOS. Therefore, the results from the SOS algorithm were considered for further analysis of the optimal placement of EVCS in the presence of PVs.

The findings indicate that increasing the number of PVs reduces power loss. When comparing Case 2 and Case 3, the power loss and voltage deviation in Table 5 (Case 3) are lower than those in Table 4 (Case 2) for all scenarios. These outcomes demonstrate that the optimal placement of EVCSs and PVs provides the best results and can be effectively achieved using metaheuristic algorithms.

Figure 12 presents the minimum voltages for all considered scenarios. Figures 13, 14 and 15 present the voltage profiles for different numbers of PVs in the optimal placement of 1, 2 and 3 EVCSs, respectively. The results in Figure 13 show that for all considered numbers of EVCS, there is a significant change in minimum voltage between One PV and the rest of the scenarios. The changes in minimum voltage values are not very significant from two to four PV placements. The results in Figures 13, 14, and 15 show the worst voltage profile for placement of one PV in all considered scenarios. The worst voltage values are observed starting from node 141 to the last node in all considered scenarios. Figure 16 presents the results for power losses for optimal placement of EVCS and PV for all considered numbers of EVCS. The results in Figure 16 show that the power losses decrease with the increase in the number of PVs. Also, there are significant changes in power losses between One PV scenario and the rest.

Case 3 examined twelve different combinations of EVCS and PV placements. The proposed algorithms identified the optimal locations for EVCSs and PVs in each scenario while voltage deviations and power losses were calculated.

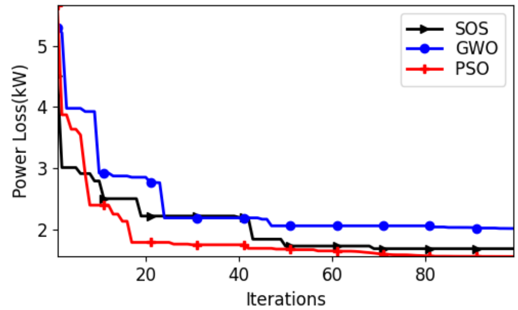

Figure 11. Convergence for profile optimal placement of 3 EVCS and 3 PVs in Case 3.

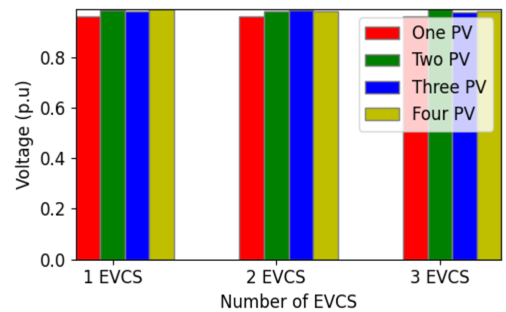

Figure 12. Minimum voltage values for optimal placement of EVCS and PV.

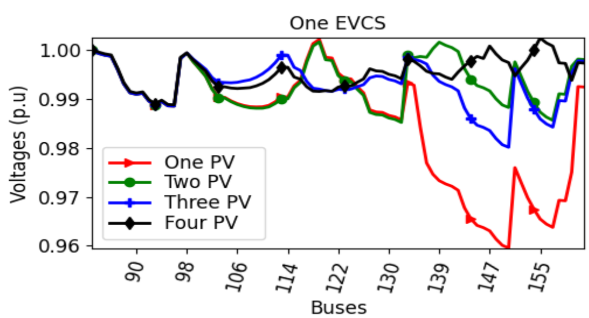

Figure 13. Voltage Profiles for optimal placement of 1 EVCS and different number of PVs.

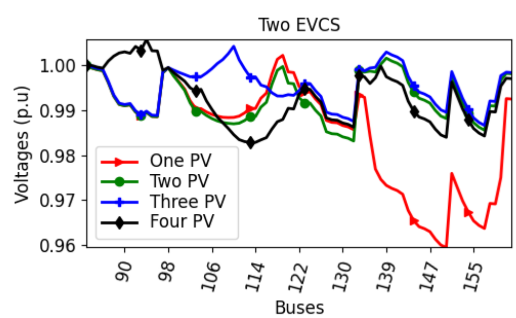

Figure 14. Profiles for optimal placement of 2 EVCS and different number of PVs.

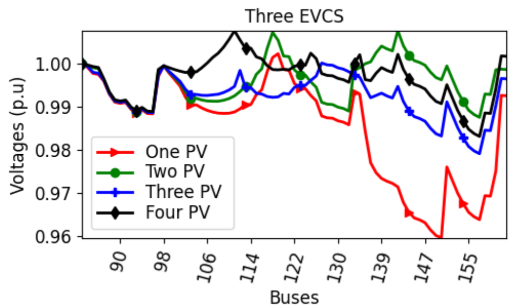

Figure 15. Profiles for optimal placement of 3 EVCS and different number of PVs.

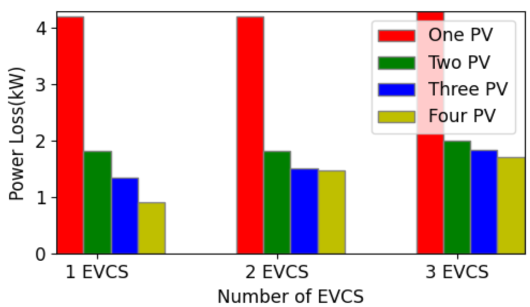

Figure 16. Power Losses for optimal placement of EVCS and different number of PVs.

5. Conclusion and Recommendations

This study explores the effects of integrating the EVCS into the electrical distribution networks, and investigates the role of PV systems in minimizing power losses and voltage deviations. Three cases were analyzed: (1) random placement of EVCS alone, (2) inclusion of PV systems in networks incorporated with EVCS, and (3) optimal placement of both EVCS and PV systems. The symbiotic organism search (SOS) algorithm, enhanced with penalty mechanisms, was utilized to optimize the placements. The symbiotic organism search (SOS) algorithm modified with penalty mechanisms was used to optimize the placements. The results show that integrating EVCS alone increases power losses and voltage deviations, which may lead to revenue losses and collapse the power systems. This effect is more pronounced with the increase in the number of EVCS. However, incorporating PV systems significantly enhances the performance and stability of the power system by reducing power losses and voltage deviations, with greater benefits observed as the number and capacity of PV systems increase. Additionally, the study reveals that considering the simultaneous optimal placement of EVCSs and PV systems is more advantageous than adding PVs to power systems already equipped with EVCSs.

In this study, power loss and voltage deviations were considered functions; however, in the optimization algorithm, the power loss function was optimized, and the voltage deviation was utilized in the analysis. Additionally, other factors can be considered when incorporating EVCS into power systems, such as PV installation costs, power system reliability indices, and dynamic network reconfigurations.

Table 4. Power loss and voltage profiles for three EVCS and an increasing number of PVS.

DG	Algorithm	Location	Size (kW)	Power loss (kW)	VD (V)
3 EVCS	Random	116	25	61.4207	2.82493
		120	25		
		133	25		
1 PV	SOS	118	100.0000	5.2648	0.03870
	GWO	118	99.6780	5.2704	0.03925
	PSO	118	100	5.2648	0.03870
2 PV	SOS	136	67.0181	2.5849	0.01175
		118	100.0000		
	GWO	136	66.8171	2.5829	0.01157
		118	100.1223		
	PSO	136	67.0181	2.5849	0.01175

Table 5: Result for optimal placement of 3 EVCS and different number of PVs.

DG	Algorithm	EVCS Locations	PV Location	PV Size	Power loss (kW)	VD(V)
1 PV	SOS	117, 82, 83	117	81.2418	4.2822	0.02899
	GWO	117, 82, 132	117	81.2418	4.5982	0.03277
	PSO	82, 95, 97	117	57.9440	4.6651	0.02902
2 PV	SOS	82,140,117	116	84.1887	2.0043	0.00329
			140	92.6288		
	GWO	82, 95, 117	117	57.85745	2.4063	0.00546
			137	62.2746		
	PSO	82, 95, 117	117	81.2419	2.0290	0.00570
			137	63.1041		
3 PV	SOS	122	123	62.5974	1.5655	0.00637
		105	136	65.9143		
		84	106	55.6428		
	GWO	82, 82, 159	83	13.5203	2.0151	0.00606
			117	56.1978		
			136	66.7436		
	PSO	109, 136, 136	109	58.7809	1.55680	0.00374
			125	30.9604		
			136	71.1139		

Therefore, future research may include other factors in the analysis or formulate a multi-objective function, which evaluates more than one function simultaneously. In this study, a modified symbiotic organism search (SOS) algorithm has been applied; future research may explore the effects of EVCS integration using other metaheuristic algorithms and investigate the computational complexity of the algorithm. This study revealed that the EVCS can be integrated into Tanzania's power system by including PV systems. The proposed algorithm can be used to suggest the optimal placement of EVCS and PV, minimizing power loss and voltage deviations, thereby enhancing the reliability and stability of the distribution network. However, upgrades to Tanzania's power distribution system network are required to include PV systems, as it was designed for one-way power flow. Furthermore, to accommodate the rapid adoption of EVs, effective policies should be implemented to address key issues, including taxation and the development of charging infrastructure.

CONTRIBUTIONS OF CO-AUTHORS

Daudi Mnyanghwalo	[ORCID:0000-0003-0476-4860]	Conceived the idea, conducted experiments and wrote the paper
Shamte Kawambwa	[ORCID:0000-0003-1937-8727]	Wrote the paper and analyzed the results

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