Optimal Placement of FACTS Devices Using Filter Feeding Allogenic Engineering Algorithm

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Abstract

Flexible Alternating Current Transmission System (FACTS) are a useful tool for power system stability improvement and control. This research developed a new algorithm for optimal placement of FACTS devices named the Filter Feeding Allogenic Engineering (FFAE) algorithm inspired by the filter feeding and the motile behaviour of Allogenic Engineers. Kenya's 87-Bus, 25-Generator, 132 kV and 220 kV transmission network was used as the test case in Matlab's environment. The said algorithm was used to solve the twin objectives on minimization of active power loss and voltage deviations. One meta-heuristic technique—the whale optimization algorithm (WOA)—and one sensitivity based method—the fast voltage stability index (FVSI)—were used to test the accuracy of the proposed method. The computation time was 0.283 s and 0.308 s for FFAE and the whale optimization algorithm respectively mainly because of the use of Kalman filtration to achieve targeted iterations and using a more robust algorithm. The FFAE algorithm summed the total active power losses to 99.911% whereas the whale optimization algorithm gave a total of 99.770% indicating superior computational ability of the new method.

Keywords Allogenic Engineers · Filter Feeding · FVSI, Kalman Filtration · Whale Optimization

Introduction

Flexible Alternating Current Transmission System (FACTS) devices provide an excellent tool for controlling power flow and regulating bus voltages in a power system for improved voltage and rotor angle system stability. They are a power electronic based devices that provide control of one or more power system parameters to improve system control, power transfer capability and stability by way of adjustment of voltage, angle and system impedance [1]. FACTS devices have been instrumental in making the best use of the existing power network and avoiding or deferring the need to construct new power infrastructure due to the huge capital outlay required. Power system network expansion is also constricted by increased land pressure and growing environmental issues.

Power system series installed FACTS devices modify the line impedance to increase the transmittable active power.

Shunt FACTS devices work as a controllable current source. Due to their high initial installation and maintenance costs, placement of the said devices in the optimal location in a power system is of paramount importance. As a matter of fact, continuous improvement of the existing FACTS devices placement techniques as well as the development of new placement methods continue to attract a lot of research interest [2].

The techniques for optimal location of FACTS devices are broadly classified into three categories, namely the classical optimization methods, sensitivity based methods and meta-heuristic methods [3].

Classical optimization methods are based on mathematical formulation. They include but are not limited to curved space optimization [4], Newton–Raphson algorithm (Padmavathi 5, non-linear optimization programming [6], dynamic optimization programming techniques [7], mixed integer linear programming [8] and mixed integer non-linear programming [9]. These methods have a number of drawbacks, namely, the convergence challenge occasioned by the non-linear nature of power system equation formulation, inability to effectively deal with many variable constraints, high computational time and difficulty in achieving a global optima.

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Sensitivity based methods are designed to track the changes in a power system output parameters on continuous variation of the input variables until a set threshold is achieved. They include but are not limited to Jacobian matrix index [10], line stability index (Aung 11, augmented matrix [12], system reactive power loss sensitivity indices [13], voltage stability indices [14], eigen value analysis [15] and real power flow performance index [16]. Their computational efficiency is highly degraded when handling non-linear, multi-variable and constrained practical power systems [16].

Meta-heuristic based methods are inspired by human, natural biological systems intelligence and laws of nature and physics. They are broadly classified into four categories as shown in Fig. 1 below [17]:

They provide a robust tool for solving multi-modal, discrete, stochastic-based and multi-objective non-linear constrained power system problems with a very high degree of computational efficiency. Examples include but not limited to genetic algorithm [18], particle swarm optimization [19], brainstorm optimization [20], moth-flame algorithm [21], adaptive cuckoo search algorithm [22], strength pareto multi-objective evolutionary algorithm [23], differential evolution [24], biogeography based optimization [25], gravitational search algorithm [26], fuzzy logic [27], artificial neural network [28], harmony search [29], Grey wolf optimization [30], hybrid fruit fly firefly optimization [31], bee colony algorithm [32], opposition krill herd algorithm [33], flower pollination algorithm [34] and firefly algorithm [35].

Meta-heuristic placement techniques have superior computational ability, high versatility when handling various system operational constraints among other advantages over classical and sensitivity based methods. As a result of their excellent performance, there has been a lot of research work geared at combining two or more meta-heuristic methods so

as to take advantage of the superior characteristics of each of the individual algorithms. Examples are Bat-particle swarm optimization algorithm [36], particle swarm optimization-gravitational search algorithm [37], gravitational search algorithm-sequential quadratic programming [38], genetic algorithm-ant colony optimization [39] and tabu search-simulated annealing [40].

There has been continuous and sustained effort to develop new meta-heuristic optimization methods. Recent examples include immune algorithm [41], lightning flash algorithm [42] teaching-learning based optimization algorithm [43], symbiotic organism search algorithm [44], enhanced firework algorithm [45], modified differential evolution [46], adaptive charged system search algorithm [47], distributed auction optimization algorithm [48], water cycle algorithm [49], mine blast algorithm [50], Grey wolf optimizer (Jurado 2018) and the adaptive grass hopper optimization algorithm [51] and [52]).

Despite their superior computational ability, meta-heuristic optimization techniques have a number of operational challenges. These are mainly occasioned by the nonlinear, complex and stochastic interaction of the various components in metaheuristic algorithms. The said drawbacks include but not limited to low convergence rate (cuckoo search algorithm), falling into regional optimum (differential evolution), getting trapped in the local maxima (genetic algorithm, flower pollination algorithm and firefly algorithm), partial optimism and premature convergence (particle swarm optimization), undefined convergence time (ant colony optimization), need for parameter tuning (bat algorithm and bee algorithm) and high computation time (invasive weed optimization). As such, continuous development of new nature inspired optimization techniques as well as fine tuning of the existing methods will continue in the foreseeable future [53].

Fig. 1 Meta-heuristic optimization methods

Swarm-based methods have been shown to be superior to evolutionary techniques because they preserve the search space information over subsequent iterations as opposed to the evolutionary methods that get rid of old information as soon as a new population is developed ([54], [55] and [56]). As such, the development of new robust nature-inspired, swarm-based, meta-heuristic and hybrid optimization methods will continue to grow in the near future as power systems become interconnected, bigger and more complex. It is for this reason that this research sought to develop a new method of optimal placement of FACTS devices named the filter feeding allogenic engineering (FFAE) algorithm inspired by the filter feeding and the environmental stimuli motile behaviour of allogenic engineers.

The obtained results were benchmarked with an existing meta-heuristic placement method-whale optimization algorithm-and a sensitivity based optimal placement method-FVSI. It is instructive to note that the new method performed much better as compared to the two other existing placement techniques. The computation time was 0.283 s and 0.308 s for FFAE and the whale optimization algorithm respectively mainly because of the use of Kalman filtration to achieve targeted iterations and using a better algorithm. The FFAE algorithm summed the total active power losses to 99.911% whereas the whale optimization algorithm gave a total of 99.770% indicating a more robust computational ability of the newly developed algorithm method.

The rest of the paper is organized as follows: Section two gives the formulation of the two algorithms in use, section three details the simulation methodology. Section four presents the simulation results. Section five discusses the results and finally section six gives a conclusion of the work.

Developed Algorithms

Problem Formulation

The two main research objectives were the minimization of the active power loss and voltage deviations using optimally placed shunt and/or series FACTS devices as formulated below.

The minimization of active power loss is formulated as:

$$F(x_1, x_2) = P_{\text{loss}} = \sum_{j=1}^n [G_i(V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij})] \quad (1)$$

whereby,

$$x_1 = [Q_{G1}, \dots, Q_{GNPV}, V_{L1}, \dots, V_{LNPQ}, S_{L1}, \dots, S_{LNL}] \quad (2)$$

$$x_2 = [T_1, \dots, T_{NT}, \dots, V_{G1}, \dots, V_{GNPV}, Q_{C1}, \dots, Q_{CNC}] \quad (3)$$

where x_1 is the vector of dependent variables consisting of reactive power output of generators Q_{G1}, L, Q_{GNPV} , load voltages V_{L1}, L, V_{LNPQ} and transmission lines loading S_{L1}, L, S_{LNL} . And x_2 is the vector of control variables consisting of transformer tap settings T_1, L, T_{NT} , generator voltages V_{G1}, L, V_{GNPV} and reactive power injections Q_{C1}, L, Q_{CNC} . and n indicates the number of buses in the system.

In this case, G_i is the conductance of branch i , V_i and V_j are the magnitude of voltages at sending bus and receiving bus respectively and δ_{ij} is the phase angle difference between i^{th} bus and j^{th} bus [57].

The equality constraints are represented by the power balance equations. The practical implication of this is solving the load flow problem with the bus active and reactive power constraints as formulated below:

$$P_{gi} - P_{di} - \sum_{j=1}^{87} V_i V_j (G_{ij} \cos \theta_{ij} - B_{ij} \sin \theta_{ij}) = 0 \quad (4)$$

$$Q_{gi} - Q_{di} - \sum_{j=1}^{87} V_i V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \quad (5)$$

where

$i=1, 2, \dots, n$ = number of buses in the system

$$\theta_{ij} = \theta_i - \theta_j$$

P_i, Q_i injected active and reactive power at bus i

P_{di}, Q_{di} active and reactive power demand at bus i

V_i, θ_i bus voltage magnitude and angle at bus i

G_{ij}, B_{ij} conductance and susceptance of the (i,j) element in the admittance matrix

The inequality constraints reflects the limits on the physical power system equipment as well as the limits in place to ensure power system security. They are:

$P_{gimin} \leq P_{gi} \leq P_{gimax}$ = lower and upper bounds on active power generation set at 10–90% of the machine rated value

$Q_{gimin} \leq Q_{gi} \leq Q_{gimax}$ = lower and upper bounds on reactive power generation for each machine

$t_{ijmin} \leq t_{ij} \leq t_{ijmax}$ = given lower and upper bounds on the transformer tap ratio

$\alpha_{ijmin} \leq \alpha_{ij} \leq \alpha_{ijmax}$ = lower and upper bound on phase shifting of variable transformers

$|P_{ij}| \leq P_{ijmax}$ = Upper limit on the active power flow of line $i-j$

$|S_i| \leq S_i^{\text{max}}$ = transmission line loading capacity limit

$V_{imin} \leq V_i \leq V_{imax}$ = lower and upper bounds on
the bus voltage magnitude set at 0.9 to 1.05 per unit

$$(6) \quad \frac{dC_m}{dt} = (k_m - \sum_{n=1}^N k_{mn} C_n - k_h) C_m + k_h C_{mo} \quad (8)$$

The minimization of voltage deviation is expressed as:

$$VD = \sum_{i=1}^n |V_{b_i} - 1.0| \quad (7)$$

where n is the total number of buses in the transmission network and V_b is the bus voltage.

The proposed optimization algorithms are employed to solve models given in Eq. (1) to Eq. (7) in order to obtain the optimal location of FACTS devices for improvement of the voltage system stability whilst minimizing the power system's active power loss.

Filter Feeding Allogenic Engineering Algorithm

Filter feeding allogenic engineering has its roots from oceanography and is inspired by the feeding and motile behavior of allogenic engineers (part of ecosystem engineers) such as herring clams, sponges, baleen whale, krill and ameiboid protozoa. Ecosystem engineers affect the availability of resources to other organisms either from a direct result of the structure that they create (Autogenic engineers) or by the modulation of biotic and abiotic forces caused by their structure and biological activity (Allogenic engineers). Allogenic engineers remove large quantities of suspended material from the water by filter feeding as they move around largely due to stimuli caused by food nutrients within their environment. They affect the availability of resources to other organisms by the modulation of biotic and abiotic forces through their body structure and biological activity. They are able to interfere with abiotic factors such as water residence time, hydrodynamic conditions and availability of light by water filtration thus providing a residential habitat for other marine species [58].

As a result of the response to various stimuli-actively moving away or towards the environmental stimuli-the allogenic engineers act as environmental monitors e.g. if something in the water goes bad, they are the first to show the effects. This is the inspiration used to develop this optimization method. The power network environment will be scanned in real time for set parameters so as to determine the global optimal solution for the minimal fuel cost and losses in the same way the allogenic engineers respond to real time stimuli in the water environment [59–61].

The equation below shows the time rate of change of a given nutrient-main stimuli for Allogenic Engineers movement in sea water:

where:

c_m = concentration of a given nutrient in sea water
 N = total number of constituents (dependent variables)
 c_{mo} = the most influential chemical in the given water ecosystem e.g. nitrogen
 t = time
 k_m = net production rate of the given nutrient-minus natural decay, respiration and sinking processes
 k_{mn} = rate coefficients for uptake of c_m by other constituents c_n
 k_h = reciprocal of the hydrodynamic residence time

The above equation takes care of a large number of coefficients, majority of which are a function of c_n , light, temperature and turbidity. It can be reduced to the prey-predator equations written as:

$$\frac{dP}{dt} = k_p - \frac{F}{h} BP \quad (9)$$

$$\frac{dB}{dt} = -k_b B + \alpha \beta_1 \beta_2 FPB \quad (10)$$

where:

P = a given nutrient concentration
 B = filter feeders population
 k_p = given nutrient growth rate
 k_b = filter feeders mortality rate
 F = specific filtration rate for a given filter feeder
 h = water depth
 α = conversion coefficient of the most influential chemical component e.g. nitrogen to the given type of nutrient
 β_1 = (filter feeders) feeding efficiency
 β_2 = filter feeders nutrient conversion coefficient

Equation (9) and Eq. (10) shows that the time rate of increase of a given nutrient equals to the most influential chemical conversion efficiency minus the rate of removal through filter feeding. The iterative determination of α , β_1 , β_2 , k_p and k_b is used to solve for P and B . The highest nutrient concentration (P) will act as the stimuli to attract the largest number of filter feeders (B) which will be our optimal solution equivalent to given generator outputs and power losses obtained by solving Eq. (4) and Eq. (5) [61].

The particular load data and generators with set power output constraints will be equated to given parameters that affect the nutrient(s) concentration in the sea water. This

is the stimuli that normally results in the movement of a majority of allogenic engineer species towards the direction with the highest nutrient concentration in the sea. The optimization will begin with a number of initial solution guesses and after a few iterations, Kalman filtration will be applied to zero in on the most probable solutions which will be iterated to the end. The filtration process will be used to predict which of the initial guesses has higher chances of convergence by way of walking the entire probability distribution of each after a few iterations. This enables mathematical distinction between phenomena and noumena by way of a complete statistical characterization of the estimation problem at hand [62].

The Whale Optimization Algorithm

This algorithm was inspired by the humpback whale species communal hunting behavior. Humpback whales are part of a small group of mammals that have the spindle cells to handle rapid information processing and transfer. They are able to think, learn, judge, communicate in their species dialect and even exhibit emotions.

Humpback whales hunt for small groups of fish using a unique hunting method called the bubble-net feeding method. They swim in a synchronized shrinking circle, blowing bubbles and creating a loud and intense sound that ultimately forces fish upwards as they herd and corner them together. The noise makes it very hard for the fish to escape from the trap. The lead whale dives deep from where it begins to blow air to create bubbles. The rest of the team members follows creating a shrinking fence around the fish prey. The whales then gather inside the forming bubble-net and rise to the surface with their mouths wide open to swallow the fish [63, 64].

Bubble-net hunting involves three distinct steps. The first one being to identify the position of the target prey and circle them. The algorithm adopts the current solution as the best fit. After defining the best search agents, the remaining agents will attempt to update their position targeting the best search agent. This is modelled as:

$$\vec{D} = |\vec{C} \cdot \vec{X}^* - \vec{X}(t)| \quad (11)$$

$$X(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (12)$$

where t denotes the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, $\vec{X}^*$ is the position vector of the best solution obtained so far, $\vec{X}$ is the position vector and $||$ is the absolute value, and $\cdot$ is an element-by-element multiplication. $\vec{X}^*$ should be updated if there is a better solution.

The vectors $\vec{A}$ and $\vec{C}$ are computed as:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (13)$$

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (14)$$

where $\vec{a}$ is linearly decreased from 2 to 0 during the course of the iterations in both the exploration and exploitation phase and $\vec{r}$ is a random vector within the $[0, 1]$ space.

The bubble-net attacking method (exploitation phase $|\vec{A}| < 1$) can be formulated mathematically by using two approaches.

The first approach is the shrinking encircling mechanism where the value of $\vec{a}$ is decreased in Eq. (13). The variation range of $\vec{A}$ is also decreased by decreasing $\vec{a}$ i.e. $\vec{A}$ is a random value in the interval $[-a, a]$ where a is decreased from 2 to 0 in the course of the iterations. The current position of the search agent can be updated to a new position that can be defined anywhere between the actual position and the position of the current best agent. This can be achieved by randomly setting the values for $\vec{A}$ in $[-1, 1]$.

The other approach is by the use of spiral updating position. Here, the separation between the whale and the prey located at (X, Y) and (X^*, Y^*) respectively is computed first. A spiral equation is then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as:

$$\vec{X}(t+1) = \vec{D} \cdot e^{bl \cos(\pi l)} + \vec{X}^* \quad (15)$$

where $\vec{D} = |\vec{X}^*(t) - \vec{X}(t)|$ indicates the distance between the i^{th} whale and the target prey (current best solution), b is a constant that defines the logarithmic shape of the spiral, l is an arbitrary number in the range $[-1, 1]$ and $\cdot$ is an element-by-element multiplication.

The humpback whales swim around the prey by means of a shrinking circle and along a spiral-shaped path simultaneously. Each has an equal chance of being chosen by the whale at any given time and is modelled as:

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} = \vec{D} \cdot e^{bl \cos(2\pi l)} + \vec{X}^*(t) \quad (16)$$

for $p < 0.5$ and $p \geq 0.5$ respectively, where p is a random number in the range $[0, 1]$.

In addition to the bubble-net method, the humpback whales do a random search for prey according to the position of each other (exploration phase $|\vec{A}| \geq 1$). In this case, $\vec{A}$ is used with the arbitrary values that lies between $+1$ to -1 to trigger the search agent to move far away from the reference whale. In contrast to the exploitation phase, the position of a search agent in the exploration phase is updated according to a randomly chosen search agent instead of the best search agent found so far. This practice and $|\vec{A}| > 1$ stresses the exploration and allows the whale optimization

Fig. 2 Two-Bus Line Model

algorithm to perform a global search whose mathematical model is given as:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{\text{round}} - \vec{X} \right| \quad (17)$$

$$\vec{X}(t+1) = \vec{X}_{\text{round}} - \vec{A} \cdot \vec{D} \quad (18)$$

where $\vec{X}_{\text{rand}}$ is a random position vector (a random whale) selected from the existing population.

The Fast Voltage Stability Index(FVSI)

Voltage stability indices(VSI) are part of the sensitivity based methods of optimal placement of FACTS devices based on tracking of a power system output variables as the inputs are varied until a set threshold is met. The VSI are classified into two, namely the Jacobian matrix VSI and the system variables based VSI. Jacobian matrix based VSI compute the voltage collapse point and hence determine the voltage stability margin. The system variables based VSI

makes use of the admittance matrix and some system variables such as bus voltages [65].

In this work, we will make use of one reactive power adjustment method called the FVSI owing to the fact that voltage stability and by extension loss reduction are key objectives of the study as outlined above. This is the method used in Kenya to determine the weak system buses for interventions in power system stability improvement because of its simplicity in execution. The FVSI utilizes the admittance matrix and voltage and reactive power measurements.

The two-bus model in Fig. 2 below is used to derive the FVSI:

The derivation starts with the equation for the current in a line between two buses i and j above as:

$$I_{ij} = \frac{u_i - u_j}{z_{ij}} \quad (19)$$

i and j represent the sending and receiving ends respectively and bus i is taken as the reference bus with its voltage angle set to zero.

The apparent power at bus j is computed by multiplying Eq. (19) with the voltage at bus j as:

$$I_{ij} = u_j \left(\frac{u_i - u_j}{z_{ij}} \right)^* = P_j + jQ_j \quad (20)$$

The imaginary part of Eq. (20) is the reactive power received at bus j given as:

$$Q_j = \frac{u_i u_j (R_{ij} \sin \delta + X_{ij} \cos \delta - X_{ij} u_{ij}^2)}{R_{ij}^2 + X_{ij}^2} \quad (21)$$

Fig. 3 The FFAE optimization algorithm flow chart

Fig. 4 Flow chart of the Whale Optimization Algorithm on Kenya's Transmission Network

Table 1 Voltage Profiles, active power losses and loadability limits

Bus	FFAE			WOA			FVSI		
	% Bus Voltage deviation	Active power loss as a % of total system loss	Rank	% Bus voltage deviation	Active power loss as a % of total system loss	Rank	FVSI	Load-ability (MVar)	Rank
Kindaruma 132.00	0.636363636	0.345576619		0.613636364	0.34063981				
Gitaru 132.00	0.590909091	0.320892575		0.507575758	0.315955766				
Githambo 132.00	4.371212121	2.468404423	12	4.356060606	2.458530806	12	0.9039	35.7	12
Kamburu 132.00	0.560606061	0.34063981		0.560606061	0.335703002				
Garissa 132.00	0.575757576	0.370260664		0.575757576	0.365323855				
Meru 132.00	0.560606061	0.315955766		0.515151515	0.315955766				
Kutus 132.00	0.424242424	0.38507109		0.424242424	0.380134281				
Masinga 132.00	0.553030303	0.390007899		0.333333333	0.38507109				
Olkaria I 132.00	0.515151515	0.404818325		0.515151515	0.399881517				
Athi river 220.00	4.895454545	3.949447077	7	4.904545455	3.93957346	7	0.9298	27.6	7
Wote 132.00	0.651515152	0.345576619		0.651515152	0.345576619				
KDP3 132.00	0.090909091	0.202409163		0.598484848	0.202409163				
Tiomin 132.00	0.515151515	0.375197472		0.515151515	0.375197472				
isinya 220.00	0.645454545	0.25671406		0.645454545	0.25671406				
Vipr 132.00	0.439393939	0.232030016		0.439393939	0.232030016				
Mangu 132.00	3.795454545	2.221563981	13	3.78030303	2.196879937	13	0.9021	36.5	13
Menengai 132.00	0.575757576	0.25671406		0.575757576	0.261650869				
Msac 132.00	0.318181818	0.38507109		0.318181818	0.390007899				
Sarm 132.00	0.363636364	0.320892575		0.545454545	0.320892575				
Olkau2 132.00	0.507575758	0.261650869		0.507575758	0.266587678				
Olkau 220.00	0.463636364	0.30114534		0.463636364	0.30114534				
Olkaria 4 132.00	0.621212121	0.38507109		0.545454545	0.38507109				
Oau 132.00	0.613636364	0.38507109		0.613636364	0.38507109				
Tsavo 132.00	0.560606061	0.320892575		0.560606061	0.320892575				
Eldoret 132.00	2.181818182	0.888625592	20	2.166666667	0.888625592	20	0.8865	52.4	20
Muhoroni 132.00	4.704545455	3.455766193	8	4.689393939	3.455766193	8	0.9233	29.4	8
Isiolo 132.00	0.545454545	0.25671406		0.545454545	0.25671406				
Kisumu 132.00	5.901515152	11.35466035	1	6.053030303	11.34478673	1	0.9523	21.6	1
Webuye 132.00	4.560606061	2.962085308	10	4.575757576	2.962085308	10	0.9219	31.2	9
Kiganjo 132.00	0.628787879	0.320892575		0.628787879	0.320892575				
Kilifi 132.00	4.606060606	3.20892575	9	4.606060606	3.20892575	9	0.9121	33.1	11
Kato 132.00	0.651515152	0.370260664		0.651515152	0.370260664				
Narok 132.00	0.628787879	0.276461295		0.628787879	0.276461295				
Musaga 132.00	4.507575758	2.715244866	11	4.484848485	2.715244866	11	0.9204	32.7	10
Lessos 132.00	5.393939394	8.886255924	2	5.424242424	8.876382306	2	0.9503	22.3	2
Tororo 132.00	0.560606061	0.12835703		0.560606061	0.12835703				
Lanet 132.00	1.984848485	0.789889415	21	2.007575758	0.789889415	21	0.8833	54.1	22
Kitale 132.00	1.636363636	0.691153239	22	1.636363636	0.691153239	22	0.8792	55.6	23
Loiya 132.00	0.545454545	0.355450237		0.545454545	0.355450237				
Naivasha 132.00	0.507575758	0.370260664		0.507575758	0.370260664				
Sultan 132.00	0.613636364	0.350513428		0.613636364	0.350513428				
Kiboko 132.00	0.393939394	0.30114534		0.393939394	0.30114534				
Voi 132.00	0.287878788	0.335703002		0.287878788	0.335703002				
Soilo 132.00	0.265151515	0.370260664		0.265151515	0.370260664				
Makutano 132.00	1.545454545	0.592417062	23	1.53030303	0.592417062	23	0.8843	53.2	21
Ruaraka 132.00	3.060606061	1.481042654	16	3.045454545	1.481042654	16	0.8972	40.3	16
Nrbn 220.00	5.204545455	7.898894155	3	5.236363636	7.884083728	3	0.9478	22.9	3

Table 1 (continued)

Bus	FFAE			WOA			FVSI		
	% Bus Voltage deviation	Active power loss as a % of total system loss	Rank	% Bus voltage deviation	Active power loss as a % of total system loss	Rank	FVSI	Load-ability (MVar)	Rank
Mumias 132.00	2.545454545	1.234202212	17	2.53030303	1.234202212	17	0.8924	45.9	18
Sondu 132.00	0.621212121	0.355450237		0.621212121	0.355450237				
Kieni 132.00	0.560606061	0.325829384		0.560606061	0.325829384				
Kamburu 220.00	0.509090909	0.335703002		0.509090909	0.335703002				
mwingi 132.00	0.545454545	0.34063981		0.545454545	0.34063981				
Athi 220.00	2.331818182	1.184834123	18	2.331818182	1.160150079	18	0.8969	42.8	17
Kiambere 132.00	0.621212121	0.306082148		0.621212121	0.306082148				
Rangala 132.00	0.439393939	0.370260664		0.439393939	0.370260664				
Turkwel 132.00	0.537878788	0.320892575		0.537878788	0.320892575				
Olkaria II 132.00	0.613636364	0.370260664		0.613636364	0.370260664				
Sangoro 132.00	0.439393939	0.370260664		0.439393939	0.370260664				
Embakasi 220.00	1.356060606	0.493680885	24	1.356060606	0.493680885	24	0.8745	58.7	25
Ishiara 132.00	0.522727273	0.335703002		0.522727273	0.335703002				
Dandora 220.00	1.113636364	0.46899684	25	1.095454545	0.46899684	25	0.8769	57.1	24
Kakuyuni 220.00	0.654545455	0.335703002		0.654545455	0.335703002				
Rabai 220.00	0.609090909	0.350513428		0.609090909	0.350513428				
Garsen 220.00	0.527272727	0.103672986		0.527272727	0.103672986				
Suswa 220.00	0.518181818	0.133293839		0.518181818	0.133293839				
City 220.00	0.977272727	0.419628752	26	0.977272727	0.419628752	26	0.8734	60.2	26
Gasoi 132.00	0.507575758	0.375197472		0.507575758	0.375197472				
Kwale 132.00	0.621212121	0.360387046		0.621212121	0.360387046				
Juja rd 132.00	5.143939394	6.911532385	4	5.166666667	6.911532385	4	0.9421	23.8	4
Lessos 220.00	5.159090909	5.924170616	5	5.163636364	5.916765403	5	0.9388	24.9	5
Maungu 132.00	0.568181818	0.306082148		0.568181818	0.306082148				
Rabai 132.00	0.606060606	0.315955766		0.606060606	0.315955766				
KDP1 132.00	0.333333333	0.335703002		0.333333333	0.335703002				
Jomvu 132.00	0.439393939	0.390007899		0.439393939	0.390007899				
Nbam 132.00	0.333333333	0.365323855		0.333333333	0.365323855				
RBPL 132.00	0.090909091	0.34063981		0.090909091	0.34063981				
Konza 132.00	0.318181818	0.157977883		0.318181818	0.157977883				
Lamu 220.00	0.813636364	0.414691943	27	0.804545455	0.414691943	27	0.8722	61.2	27
Orpower 132.00	0.553030303	0.370260664		0.553030303	0.370260664				
Nbnorth 220.00	4.963636364	4.936808847	6	4.913636364	4.926935229	6	0.9306	26.2	6
Nanyuki 132.00	0.78030303	0.409755134	28	0.787878788	0.409755134	28	0.8707	63.4	28
Ndhiwa 132.00	3.143939394	1.727883096	15	3.136363636	1.727883096	15	0.9014	37.8	14
Awendo 132.00	2.310606061	1.086097946	19	2.318181818	1.086097946	19	0.8873	48.8	19
Kega 132.00	3.590909091	1.974723539	14	3.568181818	1.974723539	14	0.9004	38.9	15
Sotik 132.00	0.742424242	0.404818325	29	0.742424242	0.404818325	29	0.8693	65.7	29
Bomet 132.00	0.659090909	0.394944708	30	0.689393939	0.394944708	30	0.8594	67.2	30
Csit 132.00	0.568181818	0.350513428		0.575757576	0.350513428				
		99.91113744			99.7703839				

This can be rewritten u_j as:

$$u_j^2 - u_j u_i \left(\frac{R_{ij}}{X_{ij}} \sin \delta + \cos \delta + X_{ij} + \frac{R_{ij}^2}{X_{ij}} \right) Q_j \quad (22)$$

The FVSI states that the system remains stable as long as there are only real solutions to Eq. (22) i.e.

$$\left[\left(\frac{R_{ij}}{X_{ij}} \sin \delta + \cos \delta \right) u_i \right]^2 - 4 \left(X_{ij} + \frac{R_{ij}^2}{X_{ij}} \right) Q_j \geq 0 \quad (23)$$

Simplifying Eq. (23) above and assuming that the angle difference δ is normally very small ($\delta \approx 0, R_{ij} \sin \delta \approx 0$ and $X_{ij} \cos \delta \approx X_{ij}$) gives:

$$(X_{ij} u_i)^2 \geq (4X_{ij} + R_{ij}^2) Q_j \quad (24)$$

FVSI is then defined as:

$$\text{FVSI} = \frac{4Z_{ij}^2 Q_j}{u_i^2 X_{ij}} \leq 1 \quad (25)$$

i.e. As seen in Eq. (25) above, the power transmission through line i-j is stable as long as the $\text{FVSI} \leq 1$.

Methods

FFAE Simulation

The FACTS devices optimal placement process started with the collection of Kenya's transmission system data complete with the applicable inequality constraints as shown in the appendix Tables 4, 5 and 6. The Power System Analysis Toolbox (PSAT) running on Matlab's simulink platform plot Figure 7 was used to obtain the system's Y-Bus matrix [66]. Two critical variables of power system operation, namely the minimization of the active power losses and maintaining the voltage profiles within the acceptable limits of 0.90 to 1.05 per unit were considered in this research work. Kenya's recorded peak demand of 1960 MW was used.

The filter feeding Allogenic Engineering algorithm was developed as outlined in Sect. 2.2 above and Matlab's optimization toolbox [67]. This was executed as shown in the Fig. 3 below:

The active power loss Eq. (1) and equality constraints Eq. (4) and Eq. (5) were formulated on Kenya's transmission network and solved using the new optimization algorithm. The parameters P and B were solved iteratively to

give the various transmission buses voltage and power losses respectively.

Kalman filtration was used to speed up the iteration process by zeroing in on the most probable solutions with a high likelihood of convergence.

Simulation of the Whale Optimization Algorithm

The Whale optimization algorithm is a meta-heuristic optimization algorithm that was used to test the accuracy of the newly developed optimization algorithm. This was done using the guidelines and applicable source code in Matlab [68], [69]. The simulation done is as summarized in Fig. 4 below:

Continuous iterations were then carried out during which parameters a, A, C and the system's Y-Bus matrix were continuously updated. A comparison of the fitness solution value with the search agent solution obtained for each iteration was done. The iterations were terminated once the set maximum number of 1,000 iterations was achieved. The fitness values obtained were treated as the best solution for optimal placement of the FACTS devices.

Parameters A and C represent the various transmission buses voltage magnitude and active power loss respectively as ranked in the results section below.

The FVSI Simulation

The FVSI is a sensitivity based placement method that was used to further test the accuracy of FFAE. A load flow solution was done out on Kenya's 87-Bus transmission network Matlab's PSAT platform and data in the appendix part of this paper. The voltage was capped to 1.05 per unit. The load flow solution gave the magnitude and phase angle of voltage at each bus and the real and reactive power flowing in each transmission line. This data formed the basis for the FVSI computation for optimal placement of FACTS devices.

The FVSI were calculated by a slow increase of the reactive power at a given load bus until the load flow solution fails to converge (instability tipping point) while maintaining the real power constant at the said load bus. This was repeated for all load buses.

At the instability tipping point, the connected load at a given bus was determined as the maximum loadability for the bus. This was sorted in ascending order with smallest value being ranked highest for all the load buses using Eq. (25). Highest rank implies the weakest bus in this case thus the best candidate for placement of FACTS devices.

Table 2 Convergence Characteristics of FFAE and WOA Algorithms

Algorithm	Computation time(s)	Number of Iterations
FFAE	0.283	776
WOA	0.308	852

Results

The bus voltage magnitude (P) and active power loss (B) were solved iteratively to give the various transmission buses voltage and active power losses respectively using the filter feeding algorithm. For the whale optimization algorithm, parameters A and C representing the transmission bus voltage magnitude and power loss respectively were computed as well.

The buses have been ranked from the weakest to the strongest with the first thirty buses having been tabulated. For the purposes of this research, the rest of the buses have minimal losses and have not been ranked.

The FVSI was used to determine the maximum loadability of the various load buses and the same have been ranked.

The results obtained for the three placement techniques of FFAE, WOA and FVSI were as shown in Table 1 below:

The total active power loss stood at 202.56 MW or 10.33% of the total system peak demand of 1960 MW.

The convergence characteristics of the algorithms are as shown in Table 2 and Fig. 5 below:

Figure 6 below shows the active power loss as a percentage of the total system loss for the 87no. buses in the Kenyan system:

Discussion

The weakest eight buses account for 55% of the total system losses and have the biggest bus voltage deviations thus forming the best candidates for placement of FACTS devices.. The said eight buses are listed in Table 3 below starting with the weakest (Kisumu 132 kV) to the strongest (Muhoroni 132 kV):

In FFAE algorithm, the buses with the highest amount of active power loss and the largest percentage of voltage deviation as determined as the weakest buses as seen in Tables 1 and 3. This was done by iterative and simultaneous solution of Eqs. (9) and (10).

Kisumu 132 kV and Lessos 132 kV buses are the weakest buses in Kenya's transmission network thus the best candidates for placement of FACTS devices. Both are the leading load centers of the western part of the country. This is partly because of the long distance from the geothermal power generation hub of Naivasha (in the central part of the country). The western part of the country has very low generation levels as compared to the load demand. The Muhoroni 28 MW peaking gas plant's main role has been to generate reactive power during system peaks but it has not matched the heavy energy demand of the West Kenya load center of Kisumu and its environs.

The next two candidates in line are in the capital city of Nairobi-Juja 132KVA and Nrbn 220 kV. This can be

Fig. 5 Convergence curve of the WOA and FFAE

Fig. 6 Active power loss as a percentage of the total system loss for the Kenyan transmission network

Table 3 Weakest Buses for optimal location of FACTS devices

Bus	Rank
Kisumu 132.00	1
Lessos 132.00	2
Nrhn 220.00	3
Juja Road 132.00	4
Lessos 220.00	5
Nairobi North 220.00	6
Athi River 220.00	7
Muhoroni 132.00	8

attributed to the abnormally high load demand in the capital city metropolis which stands at 58% of the national aggregate. The main challenge is constrained energy transmission from Coast, Naivasha and Mount Kenya to the capital city at system peak that is normally recorded at 8 pm in the evening. The Ibrafrica diesel power plant in Nairobi was installed to support voltage during the system peak.

A big number of the buses with very low voltage deviations are the buses at the power generation sites with minimal load in the vicinity. Examples include Gitaru, Masinga, Olkaria and many more as seen in Table 1 above.

FFAE had faster computation time of 0.283 s as compared 0.308 s by the whale algorithm as can be seen in Table 2 and convergence curve Fig. 5 above. This is mainly because of the use of Kalman filtration to achieve targeted iterations for a more compressed algorithm. The algorithm also gave a much better active power loss summation when compared to the whale optimization algorithm. The sum of total active power loss as a percentage of total system loss was 99.911% and 99.770% for the filter feeding optimization algorithm and the whale optimization algorithm respectively. This represents 202.38 MW and 202.095 MW for FFAE and WOA respectively against a total system loss of 202.56 MW indicating superior computational ability of the new algorithm. Figure 6 above further illustrates the better computational

efficiency in terms losses as each of the 87no. buses in the Kenyan transmission network.

It is instructive to note that the two meta-heuristic methods gave similar results in terms of the ranking of the buses. The sensitivity based method results differed slightly for eleven buses ranked number nine onwards as can be seen in Table 1 above. This can be linked to the degraded computational efficiency when dealing with non-linear, multi-variable and constrained real world power systems. The FVSI is manual and prone to human errors and tends to do a simple estimate of the solution as per Eq. (25). As power systems become bigger, multi-variable, highly non-linear, more complex and interconnected, sensitivity based methods tend to become inaccurate.

Conclusion

The use of probabilistic filtration to zero in on the most probable solution played a big role in enhancing the speed of iterations.

As power systems become bigger and more complex coupled with deeper penetration of renewables, the development of more efficient algorithms to carry out system simulations and computations will remain a key area of research interest.

Optimal utilization of the existing network is critical amidst the capital and environmental challenges to the expansion of power networks. Thus the development of a new swarm-based FACTS devices optimal placement technique that hinges on accurate summation of active power loss and voltage stability rhymes well with the agenda of enhanced power infrastructure utilization.

As seen in the introduction part, each of the existing metaheuristic optimization methods has its own drawbacks, thus one area of improvement is combining the new method with an existing method so as to take advantage of the strong traits of each of the said algorithms.

equations as marine biologists continue to study and understand the ecosystem engineers better.

Figure 7

Fig. 7 Kenya's 87-Bus, 25-Generator data 132 kV and 220 kV Transmission Network modelled in Matlab's Simulink

Table 4 Kenya's 132 kV and 220 kV Transmission lines data

From	To	Line R (pu)	Line X (pu)	Susceptance (p.u.)	Rating (MVA)	Length (KM)
Kindaruma 132.00	Kamburu 132.00	0.019	0.0452	0.0086	81	18.4
Gitaru I 132.00	Kamburu 132.00	0.008	0.0186	0.0036	73	7.7
Gitaru II 132.00	Kamburu 132.00	0.0078	0.0186	0.0036	73	7.7
Kamburu I 132.00	Masinga 132.00	0.0076	0.0456	0.0084	150	18.4
Kamburu II 132.00	Meru 132.00	0.051217	0.307304	0.056609	150	124
Masinga 132.00	Kutus 132.00	0.05305	0.1071	0.0208	73	44.25
Olkaria I 132.00	Olkaria II 132.00	0.0006	0.00357	0.00508	150	4
Olkaria I 132.00	Domes 132.00	0.002519	0.014519	0.014519	150	6
Olkaria I 132.00	Naivasha 132.00	0.0097	0.0559	0.0108	150	23.1
Ulu 132.00	Juja rd 132.00	0.06455	0.1534	0.02875	81	62.5
Ulu 132.00	Sultan Hamud 132.00	0.06455	0.1534	0.02875	81	62.5
Kipevu I 132.00	Rabai 132.00	0.0204	0.0411	0.008	73	17
Kipevu II 132.00	Rabai 132.00	0.0204	0.0411	0.008	81	17
Kipevu III 132.00	Rabai 132.00	0.0105	0.0431	0.0085	150	18
Manyani 132.00	Mtito Andei 132.00	0.04645	0.11055	0.0207	81	45
Manyani 132.00	Voi 132.00	0.04645	0.11055	0.0207	81	45
Mangu 132.00	Juja rd 132.00	0.047505	0.112992	0.021606	81	46
Mangu 132.00	Kindaruma 132.00	0.109949	0.261516	0.050006	81	106.47
Juja rd 132.00	Dandora 132.00	0.0008	0.0048	0.0009	150	2
Juja rd I 132.00	Dandora 132.00	0.0008	0.0048	0.0009	150	2
Juja rd 132.00	Ruaraka Tee 132.00	0.0058	0.012	0.0023	73	5
Juja rd II 132.00	Ruaraka Tee 132.00	0.0058	0.012	0.0023	73	5
Samburu 132.00	Maungu 132.00	0.04425	0.10555	0.01975	81	43
Samburu 132.00	Mariakani 132.00	0.04425	0.10555	0.01975	81	43
Kipevu IV 132.00	Rabai 132.00	0.0105	0.0431	0.0085	150	18
Kokotoni 132.00	Rabai 132.00	0.01245	0.0255	0.000495	73	10.5
Kokotoni 132.00	Mariakani 132.00	0.01245	0.0255	0.000495	73	10.5
Rabai 132.00	Tsavo 132.00	0.0295	0.05943	0.01146	73	24.6
Rabai 132.00	Galu 132.00	0.05996	0.12079	0.02329	73	50
Eldoret 132.00	Lessos 132.00	0.0385	0.0779	0.015	73	32.1
Muhoroni 132.00	Kisumu 132.00	0.0581	0.1177	0.0225	73	48.5
Muhoroni 132.00	Chemosit 132.00	0.0368	0.0745	0.0143	73	30.7
Muhoroni 132.00	Lessos 132.00	0.068	0.1376	0.0266	73	56.7
Kisumu 132.00	Sondu 132.00	0.041667	0.119722	0.023611	150	50
Chemosit 132.00	Kisii 132.00	0.05	0.143666	0.028333	150	60
Webuye 132.00	Musaga 132.00	0.0216	0.0437	0.0084	73	18
Kiganjo 132.00	Nanyuki 132.00	0.0617	0.1246	0.0242	73	51.5
Kiganjo 132.00	Kutus 132.00	0.05305	0.1071	0.0208	73	44.25
Kilifi 132.00	Bamburi 132.00	0.0583	0.11744	0.02265	73	48.6
Owen Falls I 132.00	Tororo 132.00	0.1618	0.2755	0.0515	73	112
Owen Falls II 132.00	Tororo 132.00	0.1618	0.2755	0.0515	73	112
Tororo I 132.00	Musaga I 132.00	0.0845	0.171	0.0329	73	70.5
Tororo II 132.00	Musaga II 132.00	0.0845	0.171	0.0329	73	70.5
Musaga I 132.00	Lessos 132.00	0.0784	0.1585	0.0308	73	66
Musaga II 132.00	Lessos 132.00	0.0784	0.1585	0.0308	73	66
Musaga 132.00	Mumias 132.00	0.0324	0.0648	0.0135	81	27
Lessos I 132.00	Kapsabet 132.00	0.035981	0.072804	0.014019	73	30
Lessos II 132.00	Kabarnet 132.00	0.027294	0.157295	0.03039	150	65
Lessos III 132.00	Makutano 132.00	0.0685	0.15215	0.0296	73	63

Table 4 (continued)

From	To	Line R (pu)	Line X (pu)	Susceptance (p.u.)	Rating (MVA)	Length (KM)
Lessos III 132.00	Makutano 132.00	0.0685	0.15215	0.0296	73	63
Lanet 132.00	Naivasha 132.00	0.0803	0.1626	0.0315	73	67
Lanet I 132.00	Naivasha 132.00	0.0803	0.1626	0.0315	73	67
Lanet 132.00	Soilo 132.00	0.010892	0.024192	0.004706	73	10.017
Lanet II 132.00	Soilo 132.00	0.010892	0.024192	0.004706	73	10.017
Naivasha I 132.00	Ruaraka Tee 132.00	0.0828	0.1725	0.0323	73	71.2
Naivasha 132.00	Ruaraka Tee 132.00	0.0828	0.1725	0.0323	73	71.2
Sultan Hamud 132.00	Kiboko 132.00	0.0441	0.1056	0.0198	73	43
Kiboko 132.00	Mtito Andei 132.00	0.0888	0.2111	0.0395	81	86
Voi 132.00	Maungu 132.00	0.0289	0.0687	0.0129	81	28
Soilo I 132.00	Makutano 132.00	0.057609	0.127958	0.024894	73	52.983
Soilo 132.00	Makutano 132.00	0.057609	0.127958	0.024894	73	52.983
Ruaraka I Tee 132.00	Ruaraka I 132.00	0.0018	0.0036	0.0007	81	1.5
Ruaraka II Tee 132.00	Ruaraka II 132.00	0.0018	0.0036	0.0007	81	1.5
Mumias 132.00	Rangala 132.00	0.014277	0.082277	0.015896	150	34
Sondur 132.00	Sangoro 132.00	0.005993	0.012134	0.002329	73	5
Kamburu I 220.00	Kiambere 220.00	0.0074	0.0302	0.0459	250	35
Kamburu II 220.00	Gitaru 220.00	0.0014	0.008	0.0114	250	9
Kamburu III 220.00	Dandora 220.00	0.0161	0.0959	0.1364	250	107.5
Kamburu IV 220.00	Dandora 220.00	0.0164	0.0977	0.1389	250	109.5
Kiambere 220.00	Embakasi 220.00	0.0229	0.1344	0.192	250	151
Kiambere 220.00	Rabai 220.00	0.0925	0.3752	0.5767	210	440
Turkwel 220.00	Lessos 220.00	0.0458	0.1879	0.2856	210	218
Olkaria II 220.00	Nbnorth I 220.00	0.0103	0.0615	0.0875	250	69
Olkaria II 220.00	Nbnorth II 220.00	0.0103	0.0615	0.0875	250	69
Olkaria II 220.00	Olkaria III 220.00	0.001045	0.006239	0.00888	250	7
Dandora 220.00	Embakasi 220.00	0.0026	0.0108	0.0164	250	12.5
Dandora I 220.00	Embakasi 220.00	0.0026	0.0108	0.00164	250	12.5
Dandora I 220.00	Nbnorth 220.00	0.0076	0.0455	0.0647	250	51
Dandora II 220.00	Nbnorth 220.00	0.0076	0.0455	0.0647	250	51
Rabai 220.00	Malindi 220.00	0.024304	0.105738	0.16343	210	124
Malindi 220.00	Garsen 220.00	0.02156	0.0938	0.14498	210	110
Garsen 220.00	Lamu 220.00	0.018522	0.080583	0.12455	210	94.5
Olkaria II 220.00	Suswa I 220.00	0.0103	0.0615	0.0875	250	64
Olkaria II 220.00	Suswa II 220.00	0.0103	0.0615	0.0875	250	65
Olkaria II 220.00	Orpower 132.00	0.0103	0.0615	0.0875	250	52
Lanet 132.00	Lessos 132.00	0.0008	0.0048	0.0009	81	125
Lanet 132.00	Lessos 132.00	0.0008	0.0048	0.0009	81	143
Juja rd 132.00	Naivasha II 132.00	0.0289	0.0687	0.0129	81	93
Juja rd 132.00	Naivasha II 132.00	0.008	0.0186	0.0036	81	93
Juja rd 132.00	Konza 132.00	0.008	0.0186	0.0036	81	86
Voi 132.00	Kiboko 132.00	0.06455	0.1534	0.02875	81	166
Maungu 132.00	Rabai 132.00	0.008	0.0186	0.0036	81	111
Rabai 132.00	Mariakani 132.00	0.06455	0.1534	0.02875	81	16
Rabai 132.00	KDP1 132.00	0.0289	0.0687	0.0129	81	68
Rabai 132.00	Jomvu 132.00	0.0828	0.1725	0.0323	73	375
Rabai 132.00	Nbam 132.00	0.0828	0.1725	0.0323	81	33
Rabai 132.00	RBPL 132.00	0.0289	0.0687	0.0129	81	26

Table 5 Kenya's 132 kV and 220 kV Primary Sub-station Transformers data

From	To	R (pu)	X (pu)	Rating (MVA)
Olkaria II 132.00	Olkaria II 220.00	0.003376	0.09992	90
Juja rd 132.00	Dandora 220.00	0.0002	0.105	200
Juja rd 132.00	Dandora 220.00	0.0002	0.105	200
Kiambere 132.00	Kamburu 220.00	0.002403	0.11205	270
Kiambere 132.00	Kamburu 220.00	0.002403	0.11205	270
Rabai 132.00	Rabai 220.00	0.003141	0.106893	90
Rabai 132.00	Rabai 220.00	0.003141	0.106893	180
Lessos 132.00	Lessos 220.00	0.032775	0.09999	23
Lessos 132.00	Lessos 220.00	0.032775	0.09999	23
OAU 132.00	OLKAU 220.00	0.032775	0.09999	90

Table 6 Kenya's Power System Generation data

Station	Installed Capacity (MW)	Current Output (MW)	R (pu)	X (pu)	Qmax(MVAr)
Hydro					
Kindaruma	72.0	70.5	0	0.14	-10
Sondu	60.0	60	0	0.14	-4.6
Gitaru	226.0	216	0	0.13	7.3
Kamburu	94.0	63	0	0.17	33.9
Masinga	40.0	26	0	0.17	10.8
Kiambere	164.0	164	0	0.17	-8.8
Turkwel	106.0	105	0	0.18	11.5
Sangoro	21.0	20	0	0.12	45.9
Tana	20.0	20	0	0.13	7.3
Geothermal					
Olkaria I	206.0	247	0	0.18	177.2
Olkaria II	105.0	97	0	0.18	80.5
Olkaria IV	140.0	140	0	0.18	90.2
Olkaria V	316.0	305	0	0.18	195.7
Gas					
Muhoroni gas	55.0	28	0	0.11	27.2
Wind					
Ngong wind	25.5	15	0	0.16	0
Lake Turkana	310.0	200	0	0.16	0
Solar					
Garissa	50.0	40	0	0.13	15.9
Baggass					
Mumias	38.0	26	0	0.06	28.1
Diesel					
Kipevu I	75.0	54	0	0.17	71.5
Tsavo	74.1	74	0	0.16	65.9
Iberafrica	52.5	52.5	0	0.18	52
Rabai Power	90.0	90	0	0.18	19.5
Thika Power	87.0	87	0	0.18	34.4
Gulf	80.0	80	0	0.18	32.5
Triumph	83.4	83	0	0.18	44.1

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