Coherent Swing Under-Frequency Transient Stability for Renewable Sources Islanded Micro-Grid

Paul Muia Musyoka[1], Peter Moses Musau[2], Abraham Nyete[3]
Electrical and Information Engineering Department
University of Nairobi
pauilmuia80@gmail.com[1], pemosmusa@gmail.com[2], nsonorig@gmail.com[3]

***Abstract*---Renewable Energy Sources micro-grids experience operational challenges due the unpredictable weather patterns, requiring continuous demand control schemes, which are detrimental to both customers and the micro-grid operator. Optimal unit commitment plans coupled with a synthetic inertia system, that is, distributed renewable energy storage (DRES), are considered to lower power imbalances and thus contributing to frequency transient stability. This research models a renewable energy micro-grid with solar PV, wind turbine, hydro and a geothermal power plant. The transient stability study during times of severe power imbalances shows the micro-grid is unstable during such a time. Particle swarm optimization is developed to commit the units in an optimal scheme that considers load flow power losses and DRES in a multi-objective function. This improves the control and operation of the micro-grid, minimizing frequency fluctuations caused by power imbalance, at times of severe shortage of generation from intermittent renewable sources.**

***Index Terms*---coherent swing, rotor angle, transient stability, islanded micro-grid, renewable energy storage**

I. INTRODUCTION

Climate change campaign in different countries has led to development of numerous renewable energy micro-grids and thermal power plants shut down to lower carbon footprints and secure a clean environment for humanity. However, these developments come at a cost, since renewable energy grids depend on weather patterns that are intermittent and unpredictable. Frequency and voltage collapse in entirely renewable energy grids are therefore prevalent [1].

These challenges require compensation measures and beyond certain limits measures of last resort such as load shedding are deployed, hurting the economic benefit of both consumers and suppliers of the electricity. Optimal power harvesting, unit commitment schemes, least losses and distributed renewable energy storage systems, that closely assumes the load profiling, developed in this study, are necessary to ensure least amounts of loads are disconnected from micro-grid.

Intelligent techniques such as particle swarm optimization, genetic algorithm and artificial neural networks can be utilized to optimize dispatch and unit commitment, which reduces the amount of power imbalance, and hence sustaining loads that would otherwise have been disconnected from the network [2] [3] Advanced dynamic equivalency modeling techniques for coherent swing systems reduce the multi-objective function complexity and thus lowering computational time.

Primarily, this work involved a wide range of literature review, simulations in MATLAB code and results obtained indicate severe frequency collapse in the transient stability swing curve, which reduces with reduction of power imbalance on an optimized unit commitment, load flow and DRES micro-grid network. Key contributions addressed in this research include minimal power loss micro-grid modeling, power imbalance/ probable extra power outages reduction/ stabilization through DRES and recovery times thereof.

II. LITERATURE REVIEW

80% of the Kenyan national electricity demand is supplied by renewable energy generations such as hydro, geothermal, wind and solar making the power system vulnerable to unpredictable weather patterns. Reserve capacity at 35% ensures restoration within the specified time limits by the energy regulatory authority [4]. This setup informs selection of generation sources for the micro-grid model in this study.

[5] With interconnection to East Africa Power Pool and development of larger solar farms through the solar access project, the challenges are bound to soar higher even as the government stretches the high loss distribution network to last mile connections.

[6]Using scenario based method, Peter Moses Musau et al 2017, carried out simulations of multi-objective function with storage systems cost and frequency fluctuations as the key effects of power imbalances. This included a case study in which 180MW hyro-power generator tripping caused long hours of blackout before restoration of the network.

Rate of frequency changes and input frequency parameters were utilized for setting load shedding relays in [7], using particle swarm optimization for the computation of the parameters in the proposed model. Uncertainty in the setting of the system was solved by a fuzzy logic system model attaining least load disconnection for optimal operation at the standard frequency.

In [8] a model wind farm whose base load is carried on a diesel generator was investigated for under frequency collapse in which genetic algorithm in hierarchical forms were used to provide weighting factors, in largest peak loads and severe contingency, where an iterative process appending the fitness function, checking the problem constraints after population initialization, individual encoding, cross-over and mutation was simulated in the PSCAD software resulting in a more reliable solution, as compared to traditional methods.

Testing and validation of a hardware in the loop algorithm for predictive under-frequency instability was developed, providing a preventive measure to frequency collapse of micro-grids that are highly penetrated by the renewable energy sources [9]

In [10], fast-acting distributed energy storage system (DESS) to lower extra power outages in a case study of Guadeloupe electrical island in France is studied. The results show that DESS possess synthetic inertia that enhances frequency stability of the island, however, it failed to address voltage ride-through, forecast error and variability nature of renewable sources.

In [11], a multi-period load flows whose accuracy is higher and convergence time short, is studied by building a surrogate model using a combination of Latin hypercube sampling, Kriging and polynomial regression. The developed technique is more efficient when compared to voltage linearization or time sampling, with ten minutes power losses, bus currents and voltage profiles being computed within satisfactory time.

III. PROBLEM FORMULATION

a) Micro-Grid Model: Wind Turbines Generation

The output of wind turbine generation system is given in equation (1), explicitly defining MW output of the system as a function of velocity, turbine diameter and Euler/ power co-efficient

$$.P = \frac{1}{2}\pi\rho R^2 C_P\left(\frac{\omega R}{V}, \beta\right) V^3 \quad (1)$$

In this equation, β= pitch angle of the turbine blade, Cp= power coefficient, V= measured wind velocity, R= radius of rotor, ρ= density of air flow, ωR / v = tip velocity ratio with angular speed of rotor as ω.

b) Micro-Grid Model: Geo-Thermal Generation:

Equation (2) gives the specific work output for a geothermal generation system, where Whpt = turbine pressure upper limit, Wlpt= lower limit output power, w =turbine specific work output

$$w = \frac{W_{tatol}}{m_1} : \; W_{tatol} = W_{lpt} + W_{hpt} \quad (2)$$

c) Micro-Grid Model: Mini Hydro Power Plant

The real power output from a hydropower plant is characterized by equation (3), where f is a constant of conversion from ft pounds to kilowatts, Q is the volumetric flux release from all sources, θ is the elevation angle of the reservoir, H= net head, pi= power generated from the plant, γ = specific density of water and ε_I= efficiency.

$$P_i = \frac{H(Q,\theta)\varepsilon_I \gamma q_i}{f * 1000} \quad (3)$$

d) Micro-Grid Model: Solar PV Farm Generation

Solar PV system power generation is characterized by

$$P.R = \frac{\sum P_{PV}}{P_{nom}} * \frac{G_s}{G_{ag}} = \frac{E_{pv}}{P_{nom}} * \frac{G_s}{H_{AG}} \quad (4)$$

In which, Hag= solar irrandiance, Epv = Kwh output, Gag= gloabal radiation in per kW, Pnom= nameplate rating for nominal power, Rs= resistance in series arrangement, Ipv= output current, Vph= volltage at the termianl of the PV panel and Iph = solar panel current at output termianl

e) Objective Function

The underfrequency transient stability probem is formulated as shown in equation (5), in which NL= network losses, UCFF = Unit Commitment plan based Frequency Fluactions as a result of power imbalance and CRES is the cost of renewable energy storage. Each of these factors possess a weight φ_n, that is a range of a random value between 0 to 1, that is depended on extend to which the individual factor affects recovery of the system stability.Time sampling at intervals of 10 seconds is considered for evaluation of this function, to check for violations in frequency fluctuations.

$$Min\ F = \{\varphi_1 NL + \varphi_2 UCFF - \varphi_3 DRES\} \quad (5)$$

Network losses (NL) contribute to power imbalances, widening the gap between the generation and the demand, thus contributing to network instability. These losses are obtained from the multi-period load flow equation (6), in which the symbols carry their usual meaning in a load flow study

$$NL = \sum_{j=1}^{M}\sum_{i=1}^{M}\{V_j V_i (G_{ji}\cos\theta_{ji} + B_{ji}\sin\theta_{ji})\} \quad (6)$$

Unit Commitment Frequency Fluctuations are derived from swing equation, as shown in equation (7), considering RES commitment plan for the outputs of equations (1 to 4). A renewable energy sources commitment plan, whose $Pm_n \neq Pe_n$, contributes to network instability.

$$UCFF = \sum_{n=1}^{N_g} Pm_n - \sum_{n=1}^{N_g} Pe_n = \frac{2\sum_{n=1}^{N_g}\left\{H_n \frac{df_n}{dt}\right\}}{f_0} \quad (7)$$

Where LHS = power imbalance for commited N units, with mechanical power Pm_n and demand Pe_n. The RHS gives the frequency fluctuations resulting from the power imbalance, considering rate of change of frequency $\frac{df_n}{dt}$ and inertia constant H_n, in which f0 = standard frequency.

Distributed Renewable Energy Storage (DRES) formulation is illustrated in equation (8), considering charging time (T), storage system rating P_{gt} and total energy (E) available during positive power imbalance of the renewable energy source generation i.e. when available mechanical power is greater than demand ($Pm_n \geq Pe_n$)

$$DRES = \sum_{t=1}^{T}\Delta t P_{gt} \leq E \quad (8)$$

IV. METHODOLOGY: PARTICLE SWARM OPTIMIZATION ALGORITHM

a) Justification and Mapping of problem formulation to PSO algorithm

Selection of this method ensures minimum number of iterations is constituted to achieve the convergence criterion for the optimum under frequency commitment of the units, for minimal power loss, maximum renewable energy storage and least power imbalances that correspond to minimal frequency fluctuations. When applied to deficit contingencies and losses for medium, small and large systems, PSO adapts well with the system dynamics. Table 1.0 illustrates mapping of the problem formulation of equation 5, into the PSO algorithm.

Table 1.0 Problem –Method Mapping

No.	PSO Parameters	Prob. Formulation
1.	Fittness Function	Equation (5)
2.	inertia weight	0.4
3.	acceleration coefficient	0.2
4.	Population	1000 Particles
5.	No. of Iterations	200

6.	Constraints	E, Pm, Pe and $\frac{df_n}{dt}$

b) Optimization Algorithm Pseudo code

PSO algorithm in steps as utilized in optimization of the objective function given in equation (5) is outlined as follows;

1. Initialization of population (size of population, swarm and individual acceleration constants, number of partitions, partition variables and solutions etc.)
2. Fitness function evaluation for search agents
3. Application of PSO on the population
4. Partitioning of the whole population in Sub partitions/ sub-populations
5. Update the global best and individual best positions and iterate until the convergence criteria is met

V. RESULTS

a) Algorithm calculation time, Convergence and response times

Expected response time is highly dependent on the size of a disturbance/ power imbalance that micro-grid is recovering from. For extreme faults, causing frequency fluctuations such that f>51.50 or f<47.75, where f= operational frequency, frequency response is expected in 20 seconds or less [12]. Other bearable faults should have time response in 10 seconds or less. The developed simulation algorithm computes the fitness function using particle swarm optimization in 0.3575 seconds, converging within first 50 iterations on core i3 processor, 2.50GHz machine.

b) Output variables of the fuel constraint generation models

The renewable energy generation capacities are illustrated in table 2.0, where the wind turbine generation model has 3 input variable parameters/ data sets i.e. Wind Turbine Output Coefficient (WTOp), Wind Turbine diameter (WTd) and variable wind velocity (Wv) with a single output (WTG). Hydro-turbine model has 3 input variables i.e. hydraulic head (HTh), Volumetric Flux (HTQ) and Hydro-turbine efficiency (HTeff), with a single output (HTG). Solar PV Model has 3 input variables i.e. Solar Radiation (H), output co-efficient (OpCoef) and Area (A) with one output (PVG). The geothermal generation model carries the base load with a capacity of 175 MW. The four generation models give a total output variable (TotalGen) as shown in table 2.0.

Table 2.0 Output variables of the fuel constraint generation models

WTG	HTG	PVG	GTG	TotalGen
0.220	0.078	0.250	175	175.549
1.554	4.010	3.152	175	183.716
5.074	12.624	6.900	175	199.598
12.867	26.165	11.600	175	225.632
28.299	44.879	17.363	175	265.541
56.509	69.013	24.302	175	324.825
105.020	98.813	32.537	175	411.371
184.465	134.524	42.194	175	536.183
309.458	176.392	53.399	175	714.250
499.602	224.664	66.288	175	965.554
780.655	279.585	81.000	175	1316.239

c) A sample ideal load curve for load profiling

An ideal load curve that consists of loads from the Kenya national grid, (western region) as illustrated in fig. 1 is used to examine the difference between generation and demand.

d) Optimal generation commitment curve

From the optimization of unit commitment suitable for the load profile, the 2 optimal generation models shown in fig. 2 are used to examine the power flow. At the times of severe power deficiency, the generators can be dispatched optimally in 2 different models 1 and 2, in order to track the load curve closely, depending on available generation.

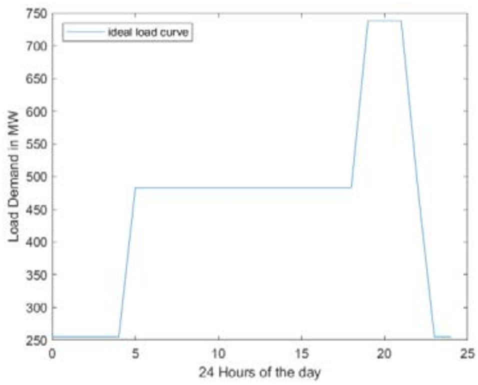

Fig. 1 Load profile curve for the model micro-grid

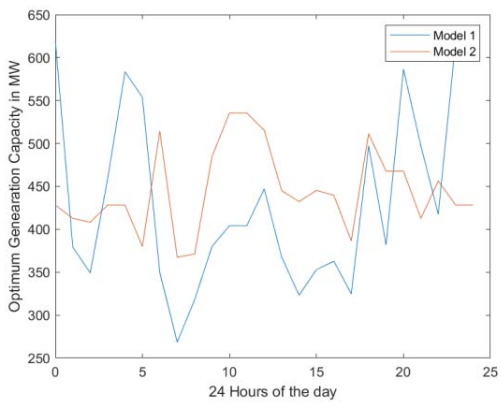

Fig. 2 Optimal generation commitment curve

e) Power imbalances for each of the optimal generation commitments

Power imbalances are derived, considering two models of generation reserves for power borrowing, resulting in a set of 4 similar power imbalance curves illustrated in fig. 3. A net power imbalance is eminent, as a result of unpredictable renewable energy source generation and probable load switching by consumers. The renewable energy micro-grid remains resilient for short periods of low net power imbalances, since the inertia constant of the wind, geothermal and hydro plants provides the self-restoration although with larger swings in the swing curve. A positive power imbalance is economically desirable since the operator will not incur the cost of energy not supplied.

For large negative net power imbalances, which occur majorly at the peak demand periods, it's necessary to take remedial measures of the last resort such as load shedding, by treating the loads as faults and disconnecting the feeders. This leads to economic losses on both sides of network i.e. to consumers and to operator in pursuit for a secure grid.

f) Transient Stability swing curve for the RE Micro-grid

The coherent transient swing curve for the highest power deficiency, investigated for a period of 1 hour (3600 seconds), at intervals of 10 seconds shows (in fig. 4), unstable system, requiring an under frequency load shedding for restoration of system stability. Investigation of the transient frequency stability is carried out, for the largest power imbalances, at intervals of 30 seconds which show that the system is unstable with swing curve increasing its swing amplitudes continuously

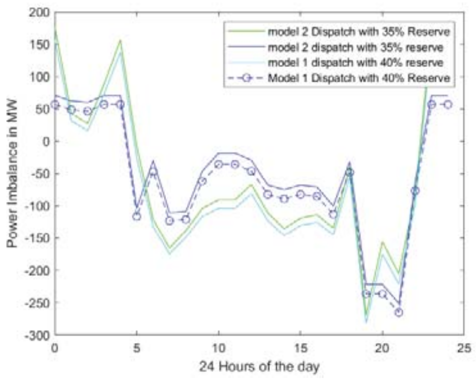

Fig. 3 Power imbalance curves considering generation reserves

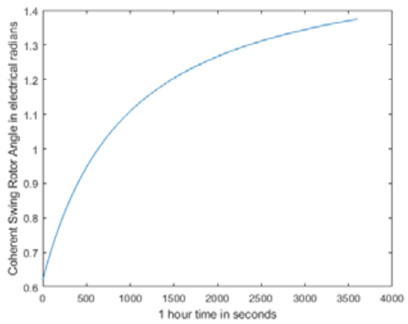

Fig. 4 Transient stability – coherent swing curve for the RES Micro-grid

c) CONCLUSION AND RECOMMENDATION

A highly penetrated RES islanded micro-grid exhibits both sessions of extra power potential generation and power deficiency. Optimization of the unit commitment using intelligent search PSO algorithm indicates improvements in net power imbalance and thus lower amounts of load will be affected by demand control measures. Connecting the micro-grid to national grid/ power pool solves these challenges in a smart metering power system. However, in the advent of climate change campaign, the national grids will be highly penetrated by renewable energy sources, multiplying the effect of instability. Although optimal unit commitment and dispatch lower the impact of demand control, an optimal under frequency load shedding (OUFLS) still necessary to restore the grid from frequency collapse. A localized OUFLS scheme at the islanded micro-grid levels would easily stabilize the overall network with consideration for primary feeder prioritization.

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