



AN NSGA-II BASED MULTI-OBJECTIVE APPROACH FOR DISTRIBUTION SYSTEM VOLTAGE CONTROL

Vijayanarasimha H. PAKKA
De Montfort University – UK
vpakka@dmu.ac.uk

R. Mark RYLATT
De Montfort University – UK
rylatt@dmu.ac.uk

ABSTRACT

The aim of this work is to offer a voltage control strategy for distribution networks that experience voltage unbalance due to single phase and unbalanced loads and voltage rise due to high penetration of Distributed Generation units. The objectives are minimization of voltage imbalance on each node and total power losses on the entire network. The control of node voltages by Distributed Generation units has potential to clash with the more traditional method of voltage control adopted by Distribution Network Operators namely, tap changing voltage regulators and shunt capacitors. We look at a coordinated method of voltage control that solves the multi-objective optimization problem of voltage profile improvement and power loss reduction using a Pareto optimal and elitist evolutionary optimization algorithm called Non-dominated Sorting Genetic Algorithm II (NSGA-II). The study system is the IEEE 123 bus distribution test feeder which is highly unbalanced and includes most of the elements of a real network.

INTRODUCTION

Distribution systems worldwide have been undergoing rapid changes in the way they are operated and managed on a minute-by-minute basis. Distribution Network Operators (DNOs) are responsible for delivering power to the consumer doorstep in an efficient, cost effective and reliable manner. The quality of power delivered should also adhere to strict efficiency measures such as voltage being within a prescribed range of the rated value and the power factor being as close as possible to unity. Any sustained deviations in the voltage levels at the customer point would not only be detrimental for various appliances but would also have undesired effects for the network in the long-term.

Active management of distribution systems involves maintaining a good voltage profile across the network, while simultaneously minimizing the losses in the network. Additionally, the power factor at each node should be kept as close to unity as possible. This is done by supplying reactive power closer to the load, which is done by DGs and capacitors [1]. Reactive power and voltage are closely related, as are real power and frequency. Hence by injecting reactive power into the system, especially at the point of consumption, voltage can be maintained.

While a reduction in voltage would reduce the current consumed by constant impedance loads such as lighting and heating elements and in turn reduce the losses on the network, a persistent low voltage could increase the effort on heating coils to heat water and thereby increase the effective load for longer durations of the day. Constant power devices such as motors would draw more current and may even stall resulting in an exponential increase in load current and thereby damaging the motor. Hence Conservative Voltage Reduction (CVR) needs to be carefully employed for achieving load reduction only in peak times and for a short duration. On the other hand, high voltages at the consumer end could have adverse impact on the operation of loads such as motors and could cause permanent damage. Furthermore, the voltage unbalance across the phases results in high neutral currents and could cause further damage to equipments. Therefore a constant, optimal and balanced voltage profile is needed. The presence of varying loads, long feeders, and Distributed Generation (DG) units make this a challenge. Phase balancing is employed to alleviate this issue [2]. However, such tools rarely operate in isolation. One of the other tools is capacitor switching, which is mainly to bring the voltage at the load end to the required standards. To achieve unity p.f. at the load end, DNOs employ either fixed or switched capacitors that are centrally controlled via a master program or locally through voltage, VAR sensors.

The ways in which the DNO controls the voltages across the network is via

- Substation Transformer Tap Changing (OLTC)
- Voltage regulator tap changes across the feeders
- Shunt capacitor switching
- Reactive power control at DG nodes
- Network reconfiguration
- Phase-shifting and shedding of loads

A combination of some of the above approaches is used to alleviate voltage issues. They depend on the cost of employing that strategy in terms of time, effort and money. For example, an effective strategy is to employ tap changing along with capacitor switching to get the desired voltage profiles. On the other hand, reactive control via DG units could put a significant stress on the tap changing units leading to a fall in the generator bus voltage [3]. Therefore there is a need for a coordinated approach to solving the voltage control problem.

MULTI-OBJECTIVE FORMULATION

The objectives are to minimize the voltage unbalance on each node and to simultaneously reduce the total power losses on the entire network. The quality of voltage can be measured using various indices. For example, in [2] a voltage deviation index was used that measured the deviation both from the minimum and maximum specified values, weighted by power injections at the nodes. In [4], voltage unbalance was tackled as a constraint set within the limits of $\leq 3\%$. Some of the optimization problems also consider the voltage unbalance indices over 48 half-hourly periods. In this study our primary focus is the total of maximum phase unbalance across all the nodes at a specific half-hour time period. The voltage limits are tackled as constraints. This allows the objective function to be precise and simple. The other constraints are the power limits of the DG units and power balance equations of injected power at each node. The decision variables are the tap positions of Voltage Regulators (VR), status of Capacitors (CP), and the optimal reactive power generated by the DG units.

The optimal reactive schedule is such that the voltage rise caused by the active generated power is minimised and is applicable over a range of load values [5]. On the other hand the optimal set of solutions for the tap positions and capacitor status also contribute to the optimization process. This solution set is derived half-hourly and is extendible for the entire load profile over 48 half hours. The outcome of this method is that the system operator is provided with an optimal set of tap positions of voltage regulators, status and switchable capacities for shunt capacitors in conjunction with a control strategy for the reactive power generated through DG sources. The result is a combination of traditional DNO voltage control and reactive power control strategy for mitigating voltage rise.

Objectives:

The Multi-objective Optimization Problem (MOP) to be solved is:

$$\min(F) \\ F = [VUI, P_{loss}]$$

where
and

$$VUI = \sum [VUI_1, VUI_2, \dots, VUI_i, \dots, VUI_N] \quad (1)$$

which is the total Voltage Unbalance Index of the system. The unbalance at each node is given by:

$$VUI_i = \max(V_{un}^a, V_{un}^b, V_{un}^c) \quad \forall i \in \{1, 2, \dots, N\}$$

$$V_{unbalance}^\emptyset = \frac{|V^\emptyset - V_{avg}|}{V_{avg}} \times 100, \quad \forall \emptyset \in \{a, b, c\}$$

$$V_{avg} = \frac{|V^a| + |V^b| + |V^c|}{3}$$

The total Power Loss across the system is:

$$P_{loss} = \text{Real} \left\{ \sum_{i=1}^N \sum_{\substack{j \in \\ \text{child} \\ \text{Nodes}}} [V_i I_{inj} - V_j I_{j inj}] \right\} \quad (2)$$

where,

V_i is the voltage and I_{inj} is the current injected at node i

Decision Variables:

Voltage Regulators:

$$T_i^\emptyset = \frac{V_{set} - |V_j^\emptyset|}{V_{step}} = \frac{V_{set} - |V_i^\emptyset - Z_{comp}^\emptyset \times I_{comp}^\emptyset|}{V_{step}} \\ T_{i_{min}}^\emptyset \leq T_i^\emptyset \leq T_{i_{max}}^\emptyset \quad \forall i \in \{1, 2, \dots, N\}$$

Capacitors:

$$Q_j^\emptyset = X_j^\emptyset Q_{j_{max}}^\emptyset \\ 0 \leq X_j^\emptyset \leq 1 \quad \forall j \in \text{Capacitors}$$

DG Reactive Power: $Q_{G_k} = -P_{G_k} [\tan(\cos^{-1} X_k)]$

$$0.95 \leq X_j^\emptyset \leq 1 \quad \forall k \in \text{DG nodes}$$

Constraints:

Voltage Limits:

$$V_{i_{min}}^\emptyset \leq V_i^\emptyset \leq V_{i_{max}}^\emptyset \quad \forall i \in \{1, 2, \dots, N\}$$

DG Reactive Power Limits:

$$Q_{i_{min}} \leq Q_i \leq Q_{i_{max}} \quad \forall i \in \text{DG nodes}$$

Power Balance:

$$S_i^\emptyset = V_i^\emptyset \left[\frac{S_{G_i}^\emptyset}{V_i^\emptyset} - \frac{S_{L_i}^\emptyset}{V_i^\emptyset} + \sum_{\substack{j \in \\ \text{Parent} \\ \text{Nodes}}} \frac{(V_j^\emptyset - V_i^\emptyset)}{Z_{ji}^\emptyset} - \sum_{\substack{k \in \\ \text{Child} \\ \text{Nodes}}} \frac{(V_i^\emptyset - V_k^\emptyset)}{Z_{ik}^\emptyset} \right]$$

where, $S_{G_i}^\emptyset$ and $S_{L_i}^\emptyset$ are the total generated and load powers at node i , and Z_{ji}^\emptyset is the impedance of the line $j-i$. This constraint is automatically satisfied on running the power flow algorithm.

METHODOLOGY

Multi-objective Optimization Evolutionary Algorithms (MOEAs) offer tools for solving such highly non-linear and complex optimization problems in order to arrive at a set of optimal solutions. MOEAs are population based and hence consider all possible solutions simultaneously. The solution evolves in a sense that the information from the parent solutions is mixed and passed on to the offspring. The aim in solving a MOP is to obtain a set of alternate solutions that are Pareto optimal. A general methodology for genetic algorithms is shown in Fig. 1. Pareto optimality refers to the condition reached where a better solution in the solution set to a MOP cannot be achieved without detriment to at least one of the other solutions in the set. Non-dominated Sorting Genetic Algorithm II (NSGA-II) is one such elitist approach that provides the Pareto

optimal solution front [6]. Such a methodology is quite relevant when a solution (such as tap positions on a voltage regulator) is to be chosen amongst a set of non-dominant solutions based on the experience and expert judgement of the network operator [4].

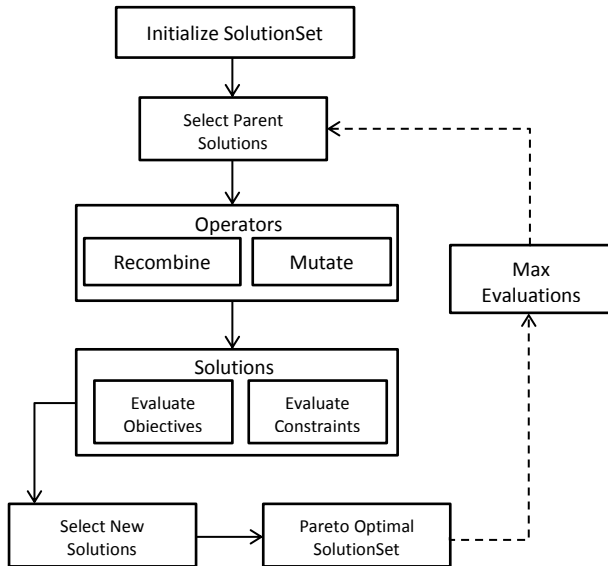


Figure 1: General methodology of Pareto-optimal seeking Genetic Algorithms.

Non-dominated Sorting Genetic Algorithm-II

NSGA-II is a Pareto optimal based elitist algorithm [6] that sorts the solution set for Pareto optimality and all the objectives simultaneously. It is made up of two steps: a fast non-dominated sorting approach and a method to preserve the diversity amongst the solutions in the Pareto optimal front. The second step is further divided into estimation of the crowding distance around a solution and a crowded-comparison operator. An offspring population is generated using a binary tournament selection procedure, and then the recombination and mutation operators are applied. Elitism is then introduced through comparison of the current population with previously found best non-dominant solutions. The resulting population is then used to generate a new set of solutions using selection, crossover and mutation as operators. At the end of each generation (run), the generated solution set are ranked into a set of non-dominated fronts.

Power flow solver and MOP framework

DNetPower (Distribution Network Power Flow Algorithms) is a Java based power flow solver developed by the authors [7] specifically for highly unbalanced distribution networks in the context of the developing CASCADE framework [8], with detailed models of loads, transformers, voltage regulators, distribution lines, capacitors, etc. The power flow

algorithm is based on the simple forward/backward sweep technique or better known as the ladder technique applicable for radial or weakly-meshed networks.

jMetal (Metaheuristic Algorithms in Java) is a framework for solving MOPs with metaheuristic techniques [9]. It is made up of abstract classes for *Algorithms*, *Operators*, *Problems* and *SolutionType*, etc. The variables are either binary or real coded. There are several implementations of classes *Selection*, *Mutation* and *Crossover*. The developers of *jMetal* have included several MOPs and MOEAs for testing purposes.

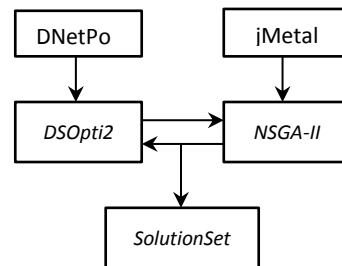


Figure 2: Overview of model framework. The *SolutionSet* represents the set of variables such as Tap positions, capacitor status & Reactive power of DGs.

The abstract class *Problem* describes the objectives and constraints in an analytical form. However, in our case, since such an analytical relation between the decision variables and the objective functions is difficult to derive, we use equations (1), (2) where voltages act as the secondary decision variables. The abstract class *Problem* is implemented as a power flow algorithm “*DSOpti2*” that is run for different values of the decision variables. The voltages obtained are used to evaluate the objective functions. Once the constraints are evaluated, each *solution* is added to the *solutionSet* and crossover, mutation and selection applied to obtain the Pareto optimal set (Fig. 2). The Pareto front consists of values for the decision variables (Table. 1), that when used in *DNetPower* gives a balanced voltage profile (Fig. 4) with minimal power loss.

RESULTS

The proposed methodology is applied to the IEEE 123 bus radial distribution test feeder [10]. The test system is highly unbalanced having a wide variety of loads dispersed on three-phase, two-phase and single-phase laterals. The loads are of constant impedance, constant power and constant current type. There are four voltage regulators on the feeders and laterals at a voltage level of 4.16 kV. While the test system has no generation, we introduce DG units at specific locations on the network. The DGs at nodes 8 and 44 are of 1000 kVA capacity each, while the DG at node 81 is of 3000 kVA capacity. The system also has a three phase and three single-phase shunt capacitors that can be switched on remotely or through local actuators.

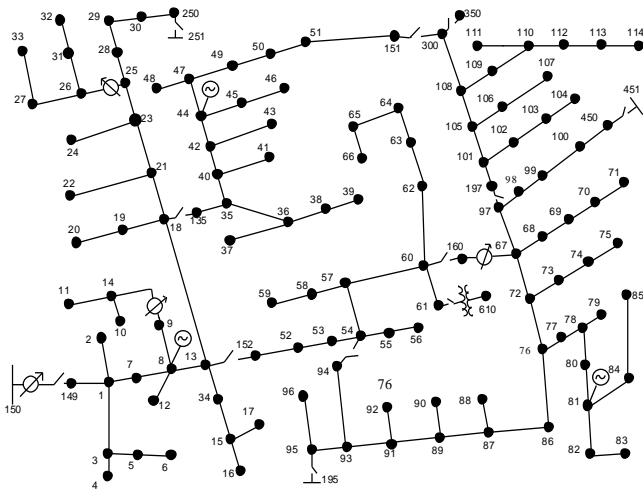


Figure 3: IEEE 123-bus test feeder. Position of switches is known a-priori and set for a radial configuration.

Base case (no regulation):

This refers to a case where there is no voltage control. The network is passive and the voltage profile is dictated solely by the loads. Node voltages steadily decrease as we move away from the substation located at node 150. For example, $V_{114}^a = 0.9277 \text{ p.u.}$ (Fig. 4a). The total voltage unbalance index is around 124 and the real power loss is around 99 kW (Fig. 5).

VR-Auto:

This refers to the case where the voltage regulators are set to compensate for drop in the feeder voltage and keep the target-node voltages at a particular Set level. We call this as the VR-automatic mode. From Fig. 4 and Table. 1 we see that the tap positions are set such that the end nodes are effectively raised to above 1.03 p.u. The VUI reduces significantly to 72.54 (Fig. 5).

MOP [VR]:

This is the case where the MOP is solved with the tap positions being the decision variables (7 in total). The shunt capacitors are switched 'on' to fixed maximum ratings. From Table. 1 we see that the optimal solution to the MOP throws up a different set of tap positions such that the voltage is phase-balanced (Fig. 5) and the profile across all the three phases tends towards 1.0 p.u (Fig. 4). For example, the taps on VR at nodes 160-67 tend to reduce the voltage (Table. 1) on all the three phases as compared to the case where the VRs operate automatically. From Fig. 5 we also notice that the values of the objective functions VUI and P_Loss reduce further as compared to the previous two cases.

MOP [VR, CP]:

Here, we enable the shunt capacitors to be switched 'on' in steps and in tandem with VR tap changers. We now have a total of 7+6 decision variables. The optimized

KVAR values for the capacitors at node 83 (phase-b) and at node 90 (phase-a) are less than previous cases. The effect of this reduction in KVAR injected is that the voltage on phase 'b' further approaches 1.0 p.u in the lateral nodes emanating from node 67. This effect is further amplified by a reduction in tap changing of VR at nodes 160-67. The total VUI is further reduced to 59.66 and the total power losses to 87.03 kW (Fig. 5).

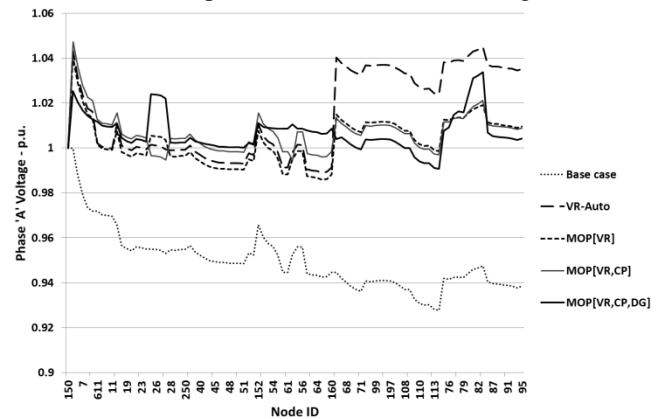


Figure 4(a): Node voltages on phase 'a' of IEEE 123-bus test feeder for different cases of voltage control.

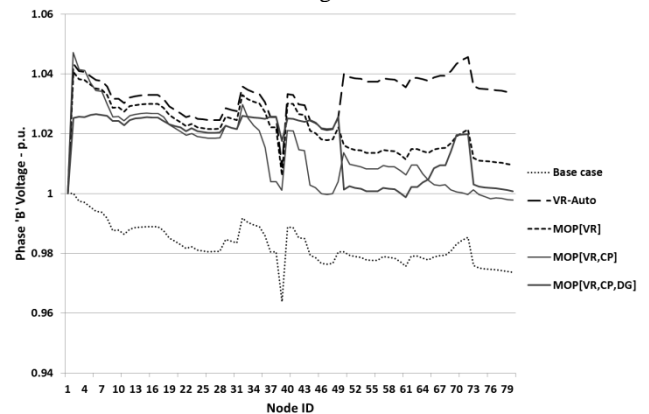


Figure 4(b): Node voltages on phase 'b' of IEEE 123-bus test feeder for different cases of voltage control.

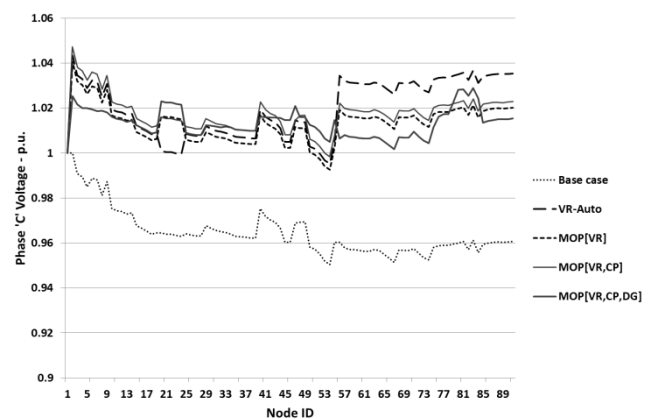


Figure 4(c): Node voltages on phase 'c' of IEEE 123-bus test feeder for different cases of voltage control.

MOP [VR, CP, DG]:

This is the case where the DG units are installed at nodes 8, 44 and 81 and their ability to absorb reactive power is controlled such that any increase in the node voltages due to power injection by these units is effectively compensated. The units initially work at unity pf and are switched to Q-control mode when the voltage is sufficiently high for a significant amount of time. This strategy works in coordination with the VR tap changers and the shunt capacitors such that the latter get the initial preference for voltage regulation. This is reflected in the fact that the tap positions for the VRs are significantly lower (as compared to other cases) due to an increase in voltage through load compensation by DG units. In addition, the DG units absorb reactive power at around 0.95 lag (Table. 1) to pull the voltages towards 1.0 p.u and further reduce VUI and P_Losses (Fig. 5). The optimal solutions and the Pareto optimal front across both the objectives are shown in Fig. 6.

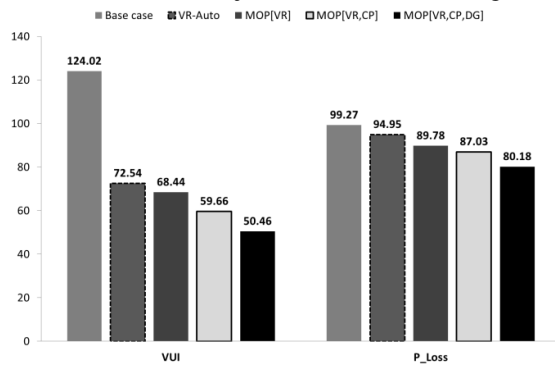


Figure 5: Values of objective functions of Pareto optimal solutions for each case of voltage control.

	VR-Auto	[VR]	[VR,CP]	[VR,CP,DG]
Taps ₁₅₀₋₁₄₉	[7,7,7]	[6,6,6]	[7,7,7]	[4,4,4]
Taps ₉₋₁₄	[-2,0,0]	[-1,0,0]	[4,0,2]	[0,0,0]
Taps ₂₅₋₂₆	[0,0,-1]	[4,0,2]	[-1,0,1]	[3,0,2]
Taps ₁₆₀₋₆₇	[8,2,5]	[4,-1,3]	[2,2,2]	[-1,-4,-1]
CP ₈₅ (kvar)	200,200,200	200,200,200	170,10,170	190,70,130
CP ₈₈ (kvar)	50,0,0	50,0,0	30,0,0	0,0,0
CP ₉₀ (kvar)	0,50,0	0,50,0	0,0,0	0,50,0
CP ₉₂ (kvar)	0,0,50	0,0,50	0,0,40	0,0,50
DG ₈ (kvar)	-	-	-	90
DG ₄₄ (kvar)	-	-	-	270
DG ₈₁ (kvar)	-	-	-	920

Table 1: Pareto solutions (values of the decision variables across all three phases) for different cases of voltage control.

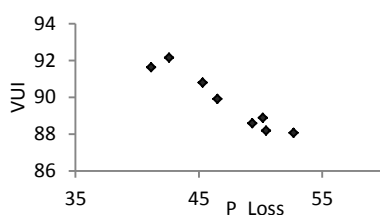


Figure 6: Pareto front for the case of [VR, CP, and DG] control. The points represent the values of objective functions, which are the total voltage unbalance and total real power loss.

CONCLUSIONS

Voltage control in distribution systems is one of the core operational issues for present day utilities due to the nature of loads and high penetration of DGs. We have presented here a coordinated strategy for regulating voltage by means of tap changing VRs, switching capacitors and reactive control by DG units themselves. The two-fold objective of balancing the voltages and reducing power losses is solved via a genetic based non-dominated sorting approach (NSGA-II) and a power flow solver. The results show that a very good balanced voltage profile and a high degree of control over each phase is possible through coordination of different variables.

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REFERENCES

- [1] J. Zhang, et. al., 2009, "Technical and economic impacts of active management on distribution network", *Electrical Power & Energy Systems*, vol. 31, 130-138.
- [2] R. Hooshmand, and S.H. Soltani, 2012, "Simultaneous optimization of phase balancing and reconfiguration in distribution networks using BF-NM algorithm", *Electrical Power and Energy Systems*, vol. 41, 76-86.
- [3] P.M.S. Carvalho, P.F. Correia, and L.A.F.M. Ferreira, 2008, "Distributed reactive power generation control for voltage rise mitigation in distribution networks", *IEEE Trans. On Power Systems*, vol. 23(2), 786-772.
- [4] H.A. Mostafa, R. El-Shatshat, and M.M.A. Salama, 2013, "Multi-Objective Optimization for the Operation of an Electric Distribution System with a large number of Single Phase Solar Generators", *IEEE Trans. On Smart Grid*, vol. 4(2), 1038-1047.
- [5] T. Sansawatt, L.F. Ochoa, and G.P. Harrison, 2010, "Integrating Distributed Generation Using Decentralised Voltage Regulation", *IEEE Power and Energy Society General Meeting*.
- [6] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, 2002, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II", *IEEE Trans. On Evolutionary Computation*, vol. 6(2), 182-197.
- [7] V. H. Pakka, and R. M. Rylatt, "An object-oriented framework for analysis of MV/LV distribution systems", July 2013, *13th Spanish-Portuguese Conference on Electrical Engineering*, (XIIIICHLIE), Valencia, Spain.
- [8] R.M. Rylatt, et al., 2013 CASCADE: "An Agent Based Framework For Modeling The Dynamics Of Smart Electricity Systems", *Emergence: Complexity & Organization (E:CO)*, vol. 15(2), 1-13.
- [9] J.J. Durillo, A.J. Nebro, 2011, "jMetal: A Java framework for multi-objective optimization", *Advances in Engg Software*, vol. 42, 760-771.
- [10] IEEE Distribution Test Feeders – <http://www.ewh.ieee.org/soc/pes/dsacom/testfeeders/>