# HYBRID INTELLIGENT OPTIMIZATION TECHNIQUE FOR OPERATING A SOLAR GENERATOR IN ELECTRIC DISTRIBUTION SYSTEM

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## ABSTRACT:

This paper presents a review study for hybrid intelligent optimization for operating solar generators in electric distribution system. A number of optimization techniques have been proposed in the literature review to solve optimization for solar generators in electric distribution system to meet the operational controls such as voltage drops, transmission limits, and voltage unbalance limits. This paper introduces the extensive of solar generators which are also called micro Fits. This paper has led to the development of optimization algorithm for minimizing phase unbalances in distribution systems by controlling the states of the existing system tools and resources. A decision making process has been developed in order to determine a single optimum solution from the Pareto front generated. Operational controls such as voltage drop, transmission limits and voltage unbalance limits, are taken in to consideration in this analysis. In the context of smart grids, the proposed algorithm will facilitate the deployment of small sized solar generators. The main motive deals with the minimization of current unbalance index and energy loss associated with the system during the specified period and by reducing the voltage unbalance and voltage profile is kept within acceptable limits.

***Index Terms***—Distributed generation, distribution system operation, energy loss, Pareto optimization, phase balancing, solar energy, CI.

## INTRODUCTION:

**I**n the context of smart grid implementation, many countries have introduced a feed-in tariff [1](FIT) program, which is considered a straightforward method of contracting for renewable energy generation. Such a program encourages the installation and implementation of renewable energy generation projects. Included under the umbrella of the FIT program is the micro FIT program [2], which was initiated for integrating very small renewable generators, rated at less than 10 kW, As a result of this program, a typical distribution system might include a large number of small renewable distributed generators.

Micro Fits are single phase generators, their extensive use will create an increase in voltage and current unbalance of the distribution system solar generators when connected to the Electric Distribution System pose two main problems to the system namely phase imbalance and increased energy losses. Unbalance in phase currents may lead to excessive levels of neutral currents, which may cause tripping of the distributed feeder. Phase balancing can enhance the capability of increasing the reliability and by reducing cost and improving voltage profile. Hence a multi-objective and decision making algorithm was developed that selects the optimal states of the distributed system. According to the control strategy the regulator taps, capacitor switching states and distribution system switches are altered to obtain the desired output. The algorithm involves, finding the current imbalance using the Current Unbalance Index (CUI), lower the values of more balance the system.

Unbalance in phase currents may lead to extortionate levels of neutral currents, which may then cause the tripping of the distribution feeders. Three phase unbalance additionally affects motors and other contrivances that depend on a well-balanced three phase voltage source. Phase balancing can enhance the competitive capability of a utility by incrementing reliability and quality, by reducing costs, and by amending the system voltage profile. Nonlinear effects, such as voltage drops and energy losses, make the unbalance quandary arduous to solve.

Non-dominant Sorting Genetic Algorithm (NSGA), also called an elitist algorithm which is simple and preserves diversity. Based on the hybrid intelligence optimization shows the significant reduction in current unbalance, energy loss, voltage profile is kept in certain limits. The Electric Distribution System follows a Stochastic Data Modeling involving the following namely historical data analysis; Data estimation using Markov chain and data forecasting using K-map clustering technique.

## II. PROBLEM FORMULATION

The following were the main objectives of this study:

1. Minimize the current unbalance in the main feeder of the electric distribution system under study.
2. Minimize the energy losses in the system studied during the study period.

These objectives were to be achieved on an operational planning basis (i.e., hourly or daily). On the whole, the proposed algorithm can minimize the current unbalance and the energy loss during a period specified by the operator.

The first objective is to minimize the current unbalance in the main feeder of the electric distribution system. The magnitude of the current at each phase of the main feeder $I_h^{\phi}$ is first determined. The current unbalance can then be calculated for each phase and at each hour of the specified period, as shown in (1):

$$\gamma_h^{\emptyset}=\frac{\left|\left|I_h^{\emptyset}\right|-I_{have}\right|}{I_{have}}\times 100, \qquad \forall\emptyset\in\{a,b,c\} \qquad (1)$$

$$I_{have}=\frac{\left|I_h^a\right|+\left|I_h^b\right|+\left|I_h^c\right|}{3}, \forall h\in\{1,2,3\ldots\ldots\ldots\ldots\ldots\ldots.h_{tot}\} \qquad (2)$$

where

The next step is the calculation of the current unbalance index (CUI) is based on the identification of the maximum value of the current unbalance for all the phases and for all the simulated hours during the specified period. The CUI is considered to be a measure of the upper bound of the current unbalance in the main feeder during the specified period. The reduction of the value of the CUI to below acceptable limits thus indicates that the distribution system is balanced.

The second objective is the minimization of the system energy loss during the study period. The total system energy loss can be calculated during the specified study period using the total number of hours , as in (3):

$$E_{loss}=0.5\times\sum_{h=1}^{h_{tot}}\sum_{i=1}^{n}\sum_{j=1}^{n}\begin{pmatrix} G_{ij}^h\times[(V_i^h)^2+(V_i^h)^2 \\ -2\times V_i^h\times V_j^h\times\cos(\delta_i^h-\delta_j^h)]\end{pmatrix} \qquad (3)$$

Where vi is the voltage at bus i;Gij is the conductance of the line connected between buses i and j ; $\delta_i$ is the power angle of the bus i voltage;n is the total number of buses in the system; h is the current hour under study; and $h_{tot}$ is the total number of hours during the study period.

The developed multi-objective problem can be described as follows:

***Objective function:***

Min (F) (4)

Where (5)

F=[$U_1$ ELI]

&

$U_I^h$=max× $\left\{U_I^1,U_I^2,U_I^3,\ldots..U_I^h,\ldots\ldots\ldots U_I^{h_{tot}}\right\}$

$\forall h=1,2,\ldots\ldots.h_{tot}$

ELI ; energy loss index

$$\text{ELI}=100\times\frac{E_{loss}}{h_{tot}\times\sum P_{genereated}} \qquad (6)$$

## III. A.MULTI-OBJECTIVE AND DECISION MAKING ALGORITHM

This section includes a discussion of the multi-objective algorithm, which forecasts the input and output power of the innate stochastic element (i.e.,microFITs, loads, etc.). Predicated on these factors, the multi-objective algorithm desires the optimal states of the distribution system voltage regulator taps, capacitor switches, and reconfiguration switches.

The states are culled predicated on their effect with deference to minimizing system unbalance and energy loss within the forecast study period.

The Algorithm is a multiple objective optimization problems, most of the researchers in the literature tackled the multi-objectives quandaries, in distribution systems, only by identifying objective priorities, which, consequently, will convert the problem into a single objective quandary with different weights for each objective [9], [12]. Weighted multi-objectives technique has a major arduousness with the cull of the congruous criterion that would be adopted for determining the weights values. Thus the quandary should be resolved with incipient weights. The second drawback with the weighted Sum approach is that it is infeasible to engender solutions on non-convex portions of the optimum feasible space boundaries [14]–[16].

For these reasons, solving a multi-objectives quandary requires the resoluteness of a set of points that all fit a predetermined definition of an optimum solution. For such a set of solutions, it cannot be verbalized that one solution is better than another.

For this research work, a genetic algorithm (GA) is utilized to formulate the Pareto non-dominated front. A GA is a heuristic search algorithm predicated on the mechanism of natural selection process [23]. A GA follows an evolutionary strategy and is an efficient implement for solving optimization quandaries. It can facilely determine a good solution for any objective function, even if it is discrete or even if its derivatives are not defined.

A GA is an efficient method of identifying the optimal non-dominated Pareto front. When GA is developed for multi-objective quandaries, the main questions are how to evaluate the fitness function and how to compose the Pareto optimality concept. The solution sets engendered after each generation are ranked into a set of non-dominated fronts according to a non-dominated sorting genetic algorithm II (NSGA-II) [24]. NSGA-II has a low caliber of computational intricacy but is an elitist algorithm and additionally preserves diversity in the final Pareto non-dominated front solutions [24].

**Decision making process:**

***Proposed algorithm summary:***

The following steps should be followed in the application of the proposed algorithm:

1. The data are estimated. An initial study period is specified by the operator: normally one day. The output power of the microFITs and the system load demand should be estimated for the period specified. The estimation is based on the proposed technique presented in Section III.

2. In this step, feasible random states for different decision variables are generated to form the initial GA population.

3. At this point, the current unbalance index (CUI) and the system energy losses are calculated during the study period. Parents are selected from the population generated, and the next population is generated using an NSGA-II[24].

4. Steps 2 and 3 are repeated until the non-dominated Pareto front is generated.

5. The proposed decision-making technique is utilized in order to generate the optimum states of the decision variables that will minimize the phase unbalance and energy loss in the distribution system.

**B.PROPOSED METHOD:**

This section introduces the proposed approach for the optimal planning problem. The optimization problem is based on the minimization of current unbalance index and to minimize the energy losses in the distribution system. In addition to modeling the current and energy loss, hybrid intelligent optimization method must be applied to find the optimization problem in the distribution feeders. Hence, heuristic methods have a special preference for solving this problem. The heuristic regression algorithm is mainly based on the non-dominated sorting procedure is that a ranking method is used to maintain stable sub population of good points. Since the algorithm is based on non dominated sorting procedure, we call this algorithm as the Non-Dominated Sorting Genetic Algorithm(NSGA).

**Non-Dominated Sorting Genetic Algorithm(NSGA):**

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\frac{d_{ij}}{\sigma_{\text{share}}}\right)^2, & \text{if } d_{ij} < \sigma_{\text{share}}; \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

**IV. STOCHASTIC DATA MODELING AND FORECASTING**

This section explains the generation process for the proposed modeling technique. In Ontario, the most economical micro Fits are solar-based generators [29]. Therefore, in this study, it is assumed that all installed micro FITs are 10 kW rated solar generators. This model is used as a means of estimating stochastic data (solar irradiance and load power), which are used in order to model the power output of the micro FITs and system loading power.

***A. Historical Data Analysis***

The proposed model was developed based on 15 years of historical data [30]. Each month is represented by one day. In other words, each year is divided into 12 d: the equivalent of 288 h (12 d x 24 h). Consequently, each daily hour in the model represents the same hour for the entire month. Given 15 years of historical data, each simulated day has 450 data points (30 d 15 yr).

### *B. Data Estimation*

For this research, a stochastic data model was developed based on discrete first order Markov chain analysis. Markov chain is used to imitate a Markov process, which has a discrete state-space [31]. A Markov process simulates system behavior using a set of transitional probabilities. The Markov process depends on three main assumptions:
The future state depends only on the current state of the system. The transitional probabilities are independent of time. Time can be discredited such that the system may change state only once per time

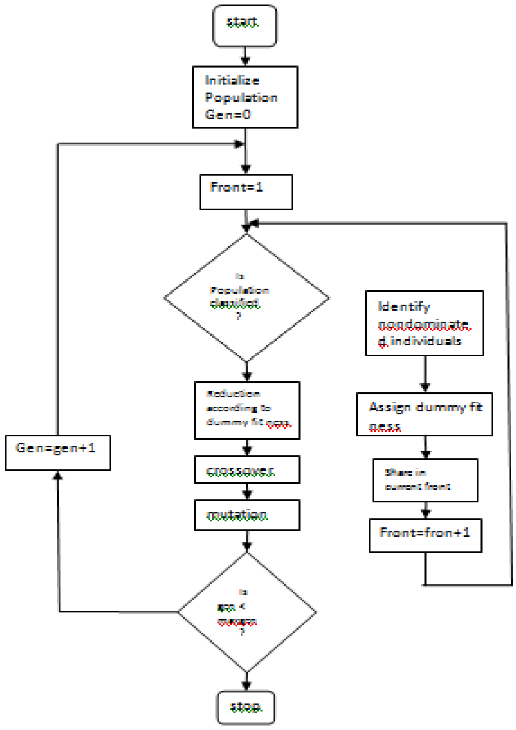



**Fig: 1:Flow chart for NSGA**

interval. Solar irradiance and load data are time-dependent data classified as non homogeneous Markov chain processes, so the proposed model therefore includes a technique that generates multiple transition matrices. The time dependency of the data is thus inherently included in the proposed model.

### *C. Data Forecasting Algorithm Procedures*

The proposed model includes the following steps:
1 First, each month's historical data are divided into fixed width states.
2 The data are clustered into clusters using a K-means clustering technique [32].
3 A set of daily groups is next created by assigning to the same group the data for each consecutive hour that corresponds to the same data cluster.
4 A probability transition matrix is then generated for each daily group of hours so that cumulative probability transition matrices can be constructed.
5 The next hour is estimated by utilizing the cumulative probability transition matrix of the corresponding group of hours. Given the value of the present hour, the estimation process begins with the generation of a random uniform number between zero and one. The value of the random number is then compared with the cumulative probability matrix row that corresponds to the state of the present hour. As an example, if the solar irradiance value for

the present hour is at state 1, then the random number is compared with the values of the first row in the cumulative probability transition matrix. The first column, which has a cumulative probability value equal to or greater than the value of the random number, represents the state of the irradiance for the next hour.
6 The estimated value of the next hour is then used in order to predict the value of the subsequent hour, as in step 5. This process is repeated until all the data for an entire day or the specified study period are estimated. Each hour is estimated using the cumulative transition matrix that corresponds to the predicted hour group. Steps 5 and 6 are considered to be a single scenario.
7 Scenarios are generated until the maximum value of the ratio of the standard deviation $\sigma(X)$ of the value of each hourly solar irradiance X to the expected value $\mathrm{E}(X)$ for the same hourly solar irradiance satisfies (24).

$$\sigma(X)/\mathrm{E}(\mathrm{X}) \qquad (8)$$

where is a selected small tolerance.

It is important to stress that the number of clusters and, accordingly, the number of transition matrices generated are based mainly on the accuracy required by the operator.

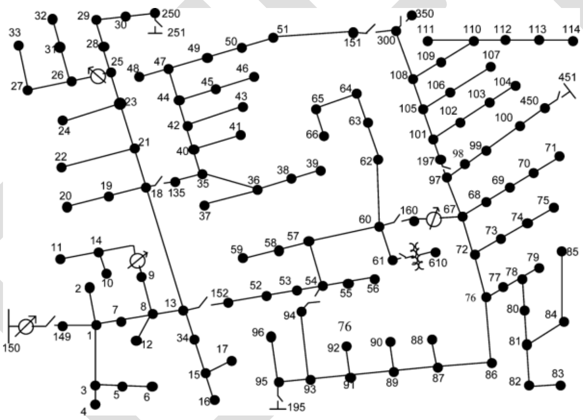



**Fig. 2. IEEE 123 bus test feeder.**

## V. MODELING OF SOLAR GENERATORS AND LOAD DATA

### *A. Load Modeling*

In this study, the load profile is assumed to follow the IEEE Reliability Test System (RTS) [33]. This system provides the weekly peak load as a percentage of the annual peak load, the daily peak load cycle as a percentage of the weekly peak load, and the hourly peak load as a percentage of the daily peak.

### *B. Solar Generators Modeling*

Once the hourly solar irradiance has been estimated, the output power of the photovoltaic (PV) array can be calculated using (25)–(29) [34]:

$$\mathrm{T}c = \mathrm{T}A + \mathrm{I}r(\frac{\mathrm{T}o-20}{0.8}) \quad (9)$$

$$\mathrm{I} = \mathrm{I}r\big(\mathrm{I}sc + \mathrm{K}i(\mathrm{T}c - 25)\big) \quad (10)$$

$$V = Voc - \mathrm{K}v * \mathrm{T}c \quad (11)$$

$$\mathrm{P}ir = \mathrm{N} * FF * V * \mathrm{I} \quad (12)$$

$$\mathrm{F}= \frac{Vmpp * Impp}{Voc * Isc} \quad (13)$$

where is the solar irradiance$\left(\mathrm{K}\omega/_{m^2}\right)$ , T$c$ is the cell temperature at Ir(℃),T$A$ is the ambient temperature , is the nominal cell operating temperature (℃), $\mathrm{K}_\vartheta$ is the current temperature coefficient ($V$|℃), $\mathrm{K}_v$ is the voltage temperature coefficient ($V$|℃), FF is the fill factor, $\mathrm{I}_{sc}$ is the short circuit current (A), $V_{oc}$ is the open circuit voltage (V), $\mathrm{I}_{Mpp}$ is the current at the maximum power point (A), $V_{Mpp}$ is the voltage at the maximum power point (V), and $\mathrm{P}_{Ir}$ is the output power of the PV array at $I_r$(kW).

To find multiple Pareto-optimal solutions in one single simulation run proposed evolutionary algorithms (EAs) work with a population of solutions, a simple EA can be extended to maintain a diverse set of solutions. With an emphasis for moving toward the true Pareto-optimal region, an EA can be used to find multiple Pareto-optimal solutions in one single simulation run, we address all of these issues and propose an improved version of NSGA, which we call NSGA-II. From the simulation results on a number of difficult test problems, we find that NSGA-II outperforms two other contemporary MOEAs: Pareto-archived evolution strategy (PAES) and strength- Pareto EA (SPEA) in terms of finding a diverse set of solutions and in converging near the true Pareto-optimal set.

In this paper we introduces Simulated Annealing **as** an effective method to solve a power distribution phase balancing problem with its non-linear effects. It is time-consuming method but it can provide a better solution than other heuristic methods (e.g. greedy algorithm, Quenching algorithm). It can solve the Phase swapping problems considering voltage drops and energy losses, which research interests include power system and balancing problems. This problem was solved for two case studies : one representing a typical day in both January and July.

**TABLE I: Base case values for both case studies**

| | January | July |
|---|---|---|
| CUI (%) | 11.58 | 12.47 |
| Energy Losses (%) | 3.3 | 3.43 |
| Voltage Profile (pu) | 0.9445-1.0559 | 0.9484-1.0551 |

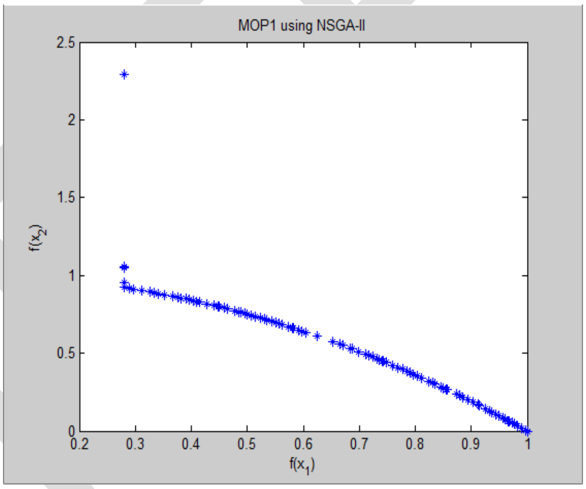
To determine a benchmark, a base case, initial capacitor states, and initial switch states were determined from the original IEEE 123 test feeder data given in [15]. For the base case, the voltage regulators were controlled automatically using line drop compensator (LDC) techniques, the settings for which are presented in [15]. Table I shows the base case values, which indicate a large CUI value and a more than 5% voltage deviation..

**TABLE II: Pareto front values for both system case studies**

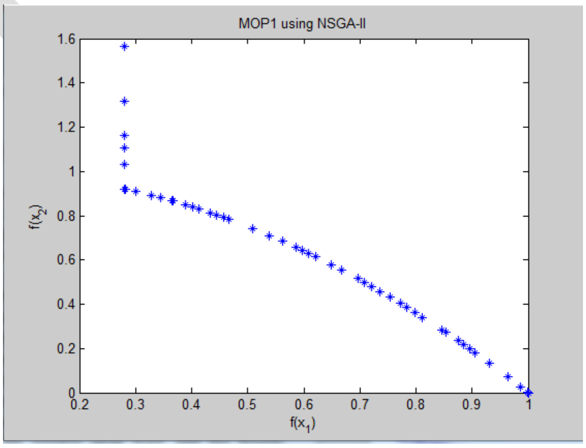
| Case Study (1) January | | Case Study (2) July | |
|---|---|---|---|
| Current Unbalance | Energy Loss | Current Unbalance | Energy Loss |
| 7.93 | 1.67 | 8.67 | 1.43 |
| 6.21 | 1.76 | 8.94 | 1.41 |
| 9.17 | 1.57 | 8.69 | 1.42 |
| 6.78 | 1.74 | 6.30 | 1.57 |
| 8.70 | 1.6 | 11.38 | 1.38 |
| 7.96 | 1.64 | 9.73 | 1.39 |
| 8.49 | 1.62 | 6.38 | 1.55 |
| 6.26 | 1.75 | 6.29 | 1.58 |
| 9.79 | 1.56 | 6.37 | 1.56 |
| 6.99 | 1.73 | 6.55 | 1.54 |
| 5.93 | 1.91 | 8.99 | 1.4 |
| 6.024 | 1.86 | | |
| 5.95 | 1.88 | | |

## A.RESULTS

**Existing output:**




**Proposed output :**



The simulated optimum results were compared with a variety of types of satisfaction criteria so that the final decisions generated by each criterion could be evaluated and the best decision determined based on which selection matches the largest number of criteria. System decisions were also compared with respect to two different types of ideal points. The system limits are assumed to be the base case values, which are dependent on the case study.

## V.CONCLUSION

With this we will conclude that this paper provides several evolutionary techniques for optimization as listed above, for minimizing the phase unbalance and energy loss in a distribution system with a large number of solar generators the Multi-objective optimization algorithm was applied. By using proposed-decision making algorithm and multi-objective algorithm, the pareto front for both the current unbalance index and energy loss are generated maximum .By using this algorithm the cost of installation is increased and the voltage profile is decreased. To overcome this problems an “Hybrid intelligent optimization algorithm” is used to show a significant reduction in current unbalance and energy loss can be decreased, the voltage profile, reliability, quality, competitive capability are increased and cost of installation is decreased. The codes are simulated on Matlab2013a. In future the paper may be implemented on high efficient simulated tools to achieve high optimized parameters.

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