An Analytical Approach of Integrating Automated Load Scheduling to a Smart Energy Meter using Differential Evolution Algorithm

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Abstract. Leading-edge power systems which are employed in present-day scenario are significantly complex, extensively distributed and populous. Rising costs of generating power, ever-increasing demand for electricity and shortage of resources have led to introduction of applications of optimal power systems. Hence Smart Energy Meters (SEMs) and highly efficient algorithms are required to facilitate Automated Load Scheduling (ALS). The latest optimization methods for ALS which works on the principle of genetics and natural selection has been presented in the paper. Differential Evolution (DE) is a simple numerical optimization approach that is easy to implement and significantly faster and robust. This article presents a novel mathematical modelling approach for the minimization of the energy consumption. The paper proposes an in depth modelling approach for ALS considering numerous aspects of the DE: initialization, mutation, crossover and selection. Case-studies have been made which include multiple aspects of non-linearities like prohibited zones of operation and transmission losses. The performance of DE based ALS algorithm was implemented using Python and evaluated at the test site in New Delhi which integrates a local renewable energy source (Local PV Grid) with an SEM. The Peak-to-Average (PAR) Ratio was used as a measure of evaluation. The proposed algorithm saved up to 19.42% power in the best-case scenario.

1. Introduction

Smart Energy Meter (SEM) technologies have led to a worldwide change in the aspect of power grid management. The Energy Management (EM) in SEMs is eminently complicated process which needs to be discussed so as to maximise the capability to generate income while minimizing the power consumption of the unit. Over the years, the power grid and SEMs have changed into an advanced system of networks with the purpose of integration of large number of Local Energy Resource (LER) under suitable conditions of the market. [1]. However, one of the major challenges we currently face is the inability of LERs to compete in the present-day market due to their irregularities in energy generation capabilities which puts a limit of their use in grid contribution operations. [2]-[3]. The perfect known solution to this problem is the accumulation of LERs through Smart Grids (SG) and Storage units (Virtual Power Plants (VPP)) providing functionalities like controlling ability, data monitoring and capability to compete in market with the conventional sources of energy. [4].

This paper focuses on the above-mentioned problems of Energy Management so as to provide effective support in the operation of SGs and VPPs. The role of the VPP is the effective control of LERs with the aim to reduce power generation and costs while maximising profits. In a real-time
scenario to successfully achieve this goal the EM should incorporate a massive assortment of resources like different types of Storage Units and Distributed Generation System. [5]. Furthermore, factors like supplier involvement, bids in market, balance restrictions of AC power, along with a proper Demand Response Management (DRM) programs turn the EM problem into a Floating Decimal Non-Linear Problem (FDNLP). [6]-[7]. It is quite known that an FDNLP is complex and hard to solve using classical and basic approaches, but are quite apt to be solved via Evolutionary Algorithm (EA). [8]-[9]. This paper recommends the application of DE to find an optimized solution for the EM problem in the SEM and SG. Differential Evolution provides a simple algorithm for optimization, yet it is effective for global optimization. In the classical form, Differential Evolution is loaded with a set of solutions and it then follows analogous set of computational procedures (like crossover, selection and mutation) after each iteration. The application of the DE was implemented with the help of the scipy library for Python and used for integration at the test site (Energy Utilisation Laboratory, DTU, Delhi, India) between the Local Solar PV grid and the Smart Energy Meter (SEM). The algorithm contains the mathematical model for each operation of the DE Algorithm specifically tailored to the optimization problem. The objective of the minimization of energy consumption along with increment in the amount of energy generation is proposed to be achieved by this use of DE Optimization Algorithm. An exhaustive analytical and successful practical application of DE is provided in this paper and various other applications of DE in various disciplines of science can be found in [10].

2. Differential Evolution

Developed in 1997 by Price and Storn, Differential Evolution (DE), is an optimization technique that is easy to implement as well as quite robust and considerably faster. One of the unique features of operators for evolution in DE entails various components of the present generation adapting to a specified scaled step-size. At the time, numerous variations were introduced that can help differentiate between the process and make the evolutionary process more dynamic e.g. population size of the sample etc. Use of Differential Evolution has been done numerous optimization problems of the power system such as the problem on planning of generation expansion (by Kannan, 2005) and problem of scheduling of hydrothermal scheduling (Subramanian and Lakshminarasimman, 2006). [11]. The focus of this paper is on the implementation of the DE algorithms to the optimization problem of minimization of energy consumption and increment in the energy generation. Differential Evolution determines the unit of optimum operation with the prediction of the demand load in a scheduled time period.

3. Mathematical Model

The DE optimization technique disseminates the total generation requirement among the operation units to minimize the energy consumption and transmission losses thereby increasing the amount of energy generated over a recommended load schedule. The mathematical model determines the five core models for the operation of the DE Algorithm in regards to the optimization problems. The five core models are of objective function for minimization, equation for initialization of the DE Algorithm, mutation, crossover and selection processes.

3.1 Objective Function

The objective function for the problem of minimization of consumption energy can be represented as the minimizing the following function:

\[
\text{Optimize } P = \sum_{i=1}^{N_g} PC(i)
\]

where \(N_g\) is the number of operation units and \(P\) is the energy consumption. The power consumption, \(PC\) equation is represented in terms of decision variables as follows

\[
PC(i) = \sqrt{3}V_{il}I_{il}PF_i
\]

where \(V_{il}\) is the parameter of line voltage, \(I_{il}\) is the parameter of line current and \(PF_i\) is the parameter of power factor of the \(i^{th}\) unit of operation.
3.2 Initialization

An arbitrary selection of \( N_p \) individual entities is made on the basis of uniform distribution for the initial population so that all the present variables can encompass the complete search space in a uniform manner. The expression of power generation by the \( i \)th PV module is as follows

\[
P_i = P_i^{\min} + \rho (P_i^{\max} - P_i^{\min})
\]

where \( \rho \) is a random number of uniform distribution and it belongs to the set of \([0,1]\).

The concept of penalty function is used to tackle to issue of constraint of power balance. This approach decreases the vector fitness in accordance to the parameter of constraint infraction. The corrected expression for objective function to be used for minimization problem is

\[
\varphi = \sum_{i=1}^{N_g} \sqrt{3} V_i l_i P_{Fl} + \sum_{z=1}^{N_c} \lambda_c |VIOL_z|
\]

where \( \lambda_c \) is known as the penalty factor, \( N_c \) represents the number of constraints and \( VIOL_z \) is the expression for constraint violation.

3.3 Mutation

Generation of new vector in DE is done by summation of the weighted difference between two members to the third member. A new vector is generated along the lines of parent vector in the process of mutation governed by the following model

\[
Z_{i}^{G+1} = Z_p^G + F \times (Z_m^G - Z_n^G)
\]

where \( m \) and \( n \) are random selection and \( F \) represents the scaling factor. The value of \( F \in [0,1] \) and it assures the possibility of quickest convergence and \( G \) is the expression for generation number.

3.4 Crossover

The process of crossover produces the upcoming generation from the new vector and the present vector on basis of binomial distribution. The expression of crossover is determined as

\[
\hat{Z}_{i}^{G+1} = \begin{cases} Z_j^G & \text{if random no.} > C_R \\ Z_{ji}^{G+1} & \text{if random no.} \leq C_R \end{cases}
\]

where \( C_R \) is the crossover factor which is user assigned and \( C_R \in [0,1] \) and \( i = 1,2 \ldots N_p, j = 1,2 \ldots n \).

3.5 Selection

The process of selection is a competition of the parent and the successor one-on-one. If the fitness of the successor is surpassing that of the corresponding parent then the successor replaces the parent. Otherwise, if the fitness of the parent is surpassing that of the corresponding offspring then the retention of the parent takes place.

The expression of choosing between the fitness of the parent and its successor is defined as

\[
Z_{i}^{G+1} = \arg \min \{ \varphi(Z_i^G), \varphi(\hat{Z}_i^{G+1}) \}
\]

\[
Z_{p}^{G+1} = \arg \min \{ \varphi(Z_i^{G+1}), i = 1,2,3 \ldots N_p \}
\]

where \( \arg \min \) is the minimum argument and \( i = 1,2 \ldots N_p \).

4. Results and Discussion

In this paper, the performance of the DE Optimization Algorithm for energy consumption is carried out in Python (scipy library) code on a Core i7 PC while the simulations are carried out on the MATLAB platform. This data is over a scheduled evaluation time period of 15 days from mid-December to starting of January. The related energy consumption, generation and convergence
characteristics are thereby represented in the Fig 1, Fig 2 and Fig 3 respectively. The laboratory setup is also shown in Fig 4. The SEM are further connected to automated data loggers. The results quite evidently express that the proposed DE Algorithm for the optimization of energy consumption is better than the solution that is expressed in the literature overview. The best DE parameter were observed at $F = 1$, $C = 0.71$ and $N_p = 38$ while the optimized results were procured in 20 seconds.

5. Conclusion

In this paper, the integration of Smart Energy Meter and Smart Grids is done with a Differential Evolution Optimization Algorithm for the purpose of optimization of energy consumption and generation via the load present in the at the test site in New Delhi and local renewable energy source (Solar PV) for generation. The results clearly express that the objective of smart energy consumption, reduced transmission losses due to the smart energy consumption and increase in energy generation is successfully achieved. The proposed DE optimization algorithm saved up to 19.42% power in the best-case scenario. The Peak-to-Average (PAR) ratio was used as a parameter for evaluation over the scheduled evaluation period of 15 days. According to the results the best DE parameter was observed at $F=1$, $C = 0.71$ and $N_p = 38$ while the optimized results were procured in 20 seconds. This
arrangement is financially sound not only for the electricity consumer (in terms of cost and energy saved) but also to the producer (in terms of higher energy generation). Additionally, the reduced value in power consumption from the convergence characteristics and increased generation is an indication to minimized transmission losses which inhibits the hampering of the Transmission and Distribution (T&D) channels. Further implementation in industrial scale controllers and customized software (scipy Python library) is recommended.

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