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Performance Improvement of Preventive Security Constraint OPF Using Different Approaches

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ABSTRACT: Preventive security-constrained optimal power flow (PSCOPF) dispatches controllable generators at minimum cost while ensuring that the system adheres to all operating constraints. All the transmission and generation limits are respected during both the pre- and post-contingency states without relying on post-contingency redispatch. Therefore, all credible generation contingencies should be modeled in PSCOPF and the system wide automatic primary response should be allocated accordingly among synchronized generators by adjusting their droop coefficients. This paper proposes a new PSCOPF model that optimizes the droop coefficients of the synchronized generators. The cost savings attained with the proposed approach and its computational performance is evaluated. Different wind penetration levels and reserve policies are tested using annual simulations on the one- and three-area IEEE Reliability Test System.

I. INTRODUCTION

Optimal Power Flow, OPF, is a set of computations to solve the power flow in a way that one or several objectives are optimized. The OPF, given an initial state of the system and a set of constraints, determines the best possible values for the control variables that simultaneously fulfil the constraints and optimize the objective function. Both the formulation and interpretation of the results of the OPF differ from the traditional general purpose optimization problems. The particularities of the power flow problem shall be accounted for and caution exerted when formulating the OPF and when analyzing the results, including the feasibility of the formulation, as pointed out by:

- The OPF must reflect and account for the characteristics of the power flow problem. The first and most important step is the formulation of the problem. Special caution is necessary in order to avoid poorly formulated problems, resulting from inadequate selection of controls to achieve a particular objective function.
- The OPF should include the mechanisms to deal with non-feasible solutions, instead of just declaring a solution as non-feasible and aborting the execution.

The classical formulation and solution methods of the OPF require that the target function be convex. The nature of the OPF and the different methods used to solve it are beyond the scope of this report. Power conventional flow has been the analysis tool routinely executed in control centres to assess the system steady state operating condition. The ideology of optimal power flow, has gained great attention since its application to power systems analysis. From systems planning viewpoint the OPF model solution provides the optimal settings for the variables of a power network. From the power system operation and control viewpoints, an OPF solution gives an answer to adjust. The optimal power flow algorithms solve a nonlinear problem of the following form:

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1.1 OPF FORMULATION

The classic formulation of the OPF using the compact notation introduced is as follows:

Optimize f(x, u) (1)

Subject to:

G (x, u) = 0 (2)

H (x, u) < 0 (3)

$u_{min} \leq u \leq u_{max}$ (4)

1.2 CONTROLS

Control parameters in OPF correspond to the variables that are specified and depend on the type of bus. They can be voltage magnitudes in PU buses, transformer tap ratios, dispatchable real power, etc. The most important step in OPF is the formulation where the objective functions are matched with appropriate control variables. The classical target function of cost minimization is associated to the generator's active power production, whereas minimization of losses is normally associated with voltage/VAR scheduling. The list of typical controls for different approaches is summarized as follows,

- Active power
  - Generator MW outputs
  - phase-shifting taps
  - MW interchange transactions
  - HVDC link MW transfers

- Reactive power
  - Generator voltages or reactive powers
  - in-phase transformer taps
  - shunt reactors and capacitors

- Active and reactive power
  - transformers with varying complex turn ratios
  - generating unit start-up/shut-down
  - load reduction or shedding
  - line switching.

1.3 CONSTRAINTS

Equality constraints, correspond to the power flow equations, in AC. These constraints account basically for the Kirchhoff laws. Inequality constraints, correspond to different limits in the states of the system. Some typical constraints for different approaches are summarized

- Active power
  - o spinning MW reserves
  - o area MW interchanges
  - o branch group MW transfer
  - o Bus voltage angle separations.

- Reactive power
  - o Bus voltage
  - o branch VAR flows
  - o spinning MVAR reserves
  - o area MVAR interchanges

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o Branch-group MVAR transfers.

- Active and reactive power

  o Branch current and MVA flows
  o Branch-group MVA flows.

An optimization problem is said to be feasible, if and only if it has a feasibility region associated with it. This region corresponds to the geometrical space where the controls are free to change while the solution is kept optimal. Depending on the nature of the problem, the constraints can be "soft" meaning they can be relaxed, or "hard", meaning they are rigid and must be enforced. Upper and lower limits of control variables are usually "hard", corresponding to physical limitations. When an optimization problem cannot simultaneously meet all the constraints, it is pronounced as non-feasible. However, as stated before, an important aspect of the OPF is how it deals with such situations. The OPF solver should provide the "best possible" solution without interactive guidance. When the problem is found to be non-feasible it can be altered and resolved in two alternative ways that can be combined:

1. Modifying OPF controls or constraints
   – switching in additional controls (freeing previously fixed controls, connecting Extra generators, etc.)
   – switching operating limits to more expanded values, for instance switching from Long-term to medium term values.
   – network topology change
   – load reduction or shedding
2. The objective function is augmented in a way that operating limits causing infeasibility are minimally affected. Augmentation is done with a series of weighted minimum-deviation functions, in a similar way as the additional constraints are incorporated in the method developed. It is better to find a solution where some limits are violated than not finding any solution at all.

1.4 LOAD FLOW

Load flows are used to ensure that electrical power transfer from generators to consumers through the grid system is stable, reliable and economic. Conventional techniques for solving the load flow problem are iterative, using the Newton-Raphson or the Gauss-Seidel methods. However, there has been much interest in the application of stochastic search methods, such as Genetic Algorithms to solving power system problems. Distributed alternative energy sources increase in geographically remote locations, complicates load flow studies and has triggered a resurgence of interest in the topic

II. LITERATURE REVIEW

SECURITY-constrained optimal power flow (SCOPF) optimizes the operating cost in the pre-contingency state and ensures that operating limits would be satisfied in the post contingency steady state. The preventive SCOPF (PSCOPF), which assumes that the post-contingency steady-state conditions can be met without redispatching, dominates among 1932-8184.

Personal use is permitted, but republication/re- distribution requires permission for more information. This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination. IEEE SYSTEMS JOURNAL real-life SCOPF applications. Indeed, following any single contingency, power flows and voltages need to remain within operating limits. Even short-term transmission line overloads increase the likelihood of blackouts, because over current and distance relays can trip protected elements in a few seconds. While some corrective SCOPF (CSCOPF) models account for both the generation and transmission contingencies, it is not the case with the existing PSCOPF models. These typically consider only transmission contingencies and do not explicitly model generator failures, although the latter ones have been shown to increase the pre-contingency operating cost. Additionally, the discussions in point out that generators respond differently to line and

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generator outages and that the issue of generator contingencies should be accounted for in the PSCOPF. This paper argues that generator contingencies must be considered in the PSCOPF.

It proposes an optimization model that ensures the allocation of primary response in a way that keeps power flows through transmission elements within the allowed limits immediately after any single generator contingency. This proposition is consistent with computationally effective solving strategies. In the following, the primary response is defined as the automatic speed-governor-operated response of synchronized generators intended to compensate the energy imbalance caused by the sudden failure of a generator. Generator outages are normally considered to be part of the set of credible contingencies. The need for the system to continue operating satisfactorily through these contingencies determines its primary response requirement, which depends on the size and generation mix of the system as well as the economic considerations.

The most common requirement is that the primary reserve should be sufficient for the system to sustain the sudden outage of the largest synchronized generator; however, some system operators enforce more stringent requirements. For example, in ERCOT, the primary response requirement is 2300 MW, which prevents load shedding upon the simultaneous loss of the two largest generation resources. In ERCOT, NYISO, WECC, and PJM, all synchronized and eligible generators must contribute to the provision of primary response by having their turbine governors in service and unblocked.

The contribution of a generator to primary response is determined by its droop coefficient, which is usually set at the same value for all generators. Restrepo account for the primary response at the day-ahead unit commitment stage using an MIP model of the turbine speed governor and assume that all generators have the same droop coefficient. These authors co-optimize primary response and tertiary reserve but ignore transmission constraints, which may result in violations of network constraints when primary response is deployed in real time. Doherty amend the model of the turbine speed governor in by formulating a day-ahead UC model with rate of change of frequency constraints.

The standard droop coefficients differ between interconnections but typically range from 2% to 6%. In some power systems, droop coefficients are required to be adjustable in a larger range: from 2% to 8% in Saudi Arabia and even from 2% to 12% in Norway. Drop parameters are usually set at the commissioning of the generators and not modified after. However, modern control devices make it possible to change the droop coefficient of a generator in real time. The compulsory provision of primary reserve with constant droop coefficients is not necessarily cost effective and does not provide an incentive to generating units to provide primary response.

This raises some reliability concerns. For instance, some turbine control systems may override the turbine speed governor control loop, which may seriously affect the system-wide primary response. The large generation outages that occurred from 1994 to 2004 and observed that the primary response in the US Eastern Interconnection reduced from 37.5 MW/mHz in 1994 to 30.7 MW/mHz in 2004. PMU measurements obtained during large generation contingencies in the WECC system and concluded that the primary response of generators has reduced due to more renewable generation. Since renewable generation replaces base-load controllable generators which provide most of primary response, high levels of wind generation may affect a power system's operational reliability. This problem can be somewhat alleviated if each balancing authority is required to provide its own primary response. However, a case study on a relatively small isolated system showed that, under some conditions, available wind generation must be curtailed to ensure the provision of an adequate amount of primary response. Observations in, suggest that the compulsory provision of primary response is likely to limit the ability of power systems to accommodate wind power injections. In line it concludes that methods that will indicate the contribution of each generator to primary response should be investigated. This paper argues that the contribution of each generator to the overall system primary response must be determined by co-optimizing the droop coefficients with the rest of the PSCOPF decisions. This approach takes into account the characteristics of the synchronized generators and the network constraints in the allocation of the responsibilities for primary response.

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III. METHODOLOGY

Particle swarm optimization (PSO) is an effective computation technique developed. Particle swarm optimization is a population based search algorithm and initialized by random solutions referred to as particles. Unlike the other computation techniques, each particle in PSO has a velocity. With this velocity each particle moves with in the search space and dynamically adjusts its velocity, according to its previous behaviors. Therefore, particles tend to move towards better points within the search space. Since the method is easy to implement and has various application areas, many researchers have conducted studies about PSO. Studies about the method can be categorized as particle swarm optimization algorithms, neighborhood topologies used in the particle swarm optimization, parameter adjustment of particle swarm optimization algorithms, hybrid particle swarm optimization algorithms, stability analysis of the particle swarm optimization, and applications of particle swarm optimization method.

3.1 Particle Swarm Optimization Algorithm

The basic particle swarm optimization algorithm is developed exploiting social model simulations. The method is developed with inspiration from flocking of birds and schooling of fish. The PSO method was first designed to simulate behavior of birds searching for food in a bounded area. A single bird would find food through social cooperation with other birds in the flock, i.e., with its neighbors. Later, the method was extended for multi-dimensional search, and neighborhood topologies are considered to determine the relationship between particles in a swarm. The particle swarm optimization algorithm with dynamic neighborhood topology for every particle (i = 1, . . . , N) can be described as

$$v^i(t+1) = \chi[v^i(t) + \varphi_1^i(t)(p^i(t) - x^i(t)) + \varphi_2^i(t)(g^i(t) - x^i(t))], \qquad x^i(t+1) = x^i(t) + v^i(t+1), \tag{5}$$

Where $x^i(t) \in R^n$ is the position of i^{th} particle at time t, $p^i(t) \in R^n$ is the position achieved by i^{th} particle at time until time t, $g^i(t) \in R^n$ is the best position achieved by i^{th} particle and its neighbors until time t, $v^i(t) \in R^n$ is the rate of position change (velocity) of the i^{th} particle at time t , and N is the number of particles in the swarm. The coefficients $\phi_1^i(t) \in [0, \bar{\phi}_1]^n$ and $\Phi_2^i(t) \in [0, \bar{\phi}_2]^n$ are n- dimensional uniform vectors with random distribution referred to as social and cognitive learning coefficients, respectively. They determine the relative significance of social and cognitive components.

The first equation in (4.1) shows how particles update their velocities dynamically during search, while the second equation shows how particles adjust their positions according to their updated velocities. The first equation in (4.1) has three components. The first component is the momentum component, which shows an adjustment of updated velocity according to current velocity prevents a rapid change in velocity and updates the velocity according to the current velocity. The second component is the cognitive component, which shows that particles have memory and are able to use their previous experiences while determining their velocity in search space. The last component is referred to as the social component, which shows social cooperation of particles in swarm ability, i.e., particles ability to exploit their neighbor's experiences while determining their velocity in search space.

The sum of the three components designated in (4.1) could result in large velocity values. In such cases the algorithm is said to be in "explosion" behavior, where high values of the updated velocity prevent the particles from converging and they scatter through the search space. V max is the most significant parameter in the basic PSO algorithm affecting its performance, and it is the only parameter that needs to be adjusted in order to use the basic PSO algorithm. A large value of V max causes the particles to search in a larger area and to move far from the areas having good solutions, while a small value causes the particles to search within a smaller area and to possibly get trapped in local minima. In order to prevent such cases, each particle's velocity could be limited to a range $[-V_{max}, V_{max}]$.

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Particle swarm optimization algorithms have a simple structure, are easy to implement and have a high computational efficiency. In the basic particle swarm optimization algorithm, each particle in n - dimensional search space is assigned randomly generated position and velocity vectors. A fitness value according to the chosen fitness function is assigned to each particle according to their initial positions in the search space. During search, each particle's fitness value is compared with the best fitness value achieved until that instant (pbest); the better value is assigned as the best fitness value achieved until that instant, and its position is recorded as $p^i(t)$. If all the particles are connected it is global best, otherwise it is neighborhood best. A better value is assigned as the global best fitness value and the corresponding position is $g^i(t)$. After determining the best and neighborhood global best position vectors using (4.1), each particle updates its position and velocity vectors. This situation continues iteratively until it reaches a predefined stopping criterion, which determines the desired performance aspects of the algorithm.

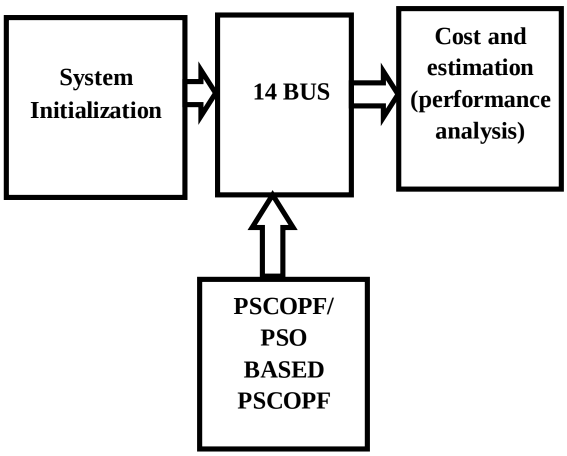

Fig. 1 Block Diagram of methodology

As mentioned before, equation (4.1) determines the particle's velocity within the search space and is divided into a momentum part, a cognitive part and a social part. Balance between these three parts determines the method's global and local search capabilities. The uniform n -dimensional random vectors ϕ_1 and ϕ_2 , which are referred to as cognitive and social learning coefficients, respectively, greatly influence the particles' local and global search capabilities. Increasing the value of cognitive learning coefficient (ϕ_1) results in an increase of the local search capability, while an increase of the social learning coefficient (ϕ_2) results in an increase of the global search capability . The most significant disadvantage of these random coefficients is that the method could exhibit "explosive" behavior. Even though the randomness increases the method's search capability, it is possible that these particles can attain undesired velocity values due to this randomness. As a result of the above situation, the particles could move in the search space with high velocities and this may not let the particles converge to a common point in the search space. Due to this fact, a constant velocity bound V_{max} value is dynamically changing could result in better performance.

3.1.1 System initialization

Different Probability Distributions like Exponential and Gaussian have already been used for the fine tuning of PSO parameters. But for initializing the swarm most of the approaches use uniformly distributed random numbers investigated the possibility of having a different probability distribution (Gaussian, Exponential, Lognormal) for the generation of random number other than the uniform distribution. Empirical results showed that distributions other than uniform distribution are equally competent and in most of the cases are better than uniform distribution. The algorithms GPSO, EPSO and LNPSO use Gaussian, exponential and lognormal distributions respectively.

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3.1.1.1 Initializing the Swarm using low-discrepancy sequences

Theoretically, it has been proved that low discrepancy sequences are much better than the pseudo random sequences because they are able to cover the search space more evenly in comparison to pseudo random sequences (please see Figures 4.2(a) and 4.2(b)). Some previous instances where low discrepancy sequences have been used to improve the performance of optimization algorithms include. The performance of PSO using Van der Corput sequence called VCPSO along with PSO with Sobol sequence called SOPSO (which is said be superior than other low discrepancy sequences according to the previous studies) for swarm initialization is scrutinized and tested them for solving global optimization problems in large dimension search spaces.

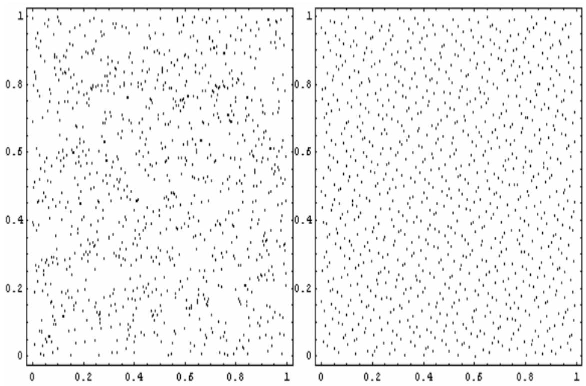

Fig. 2 (a) Sample points generated using a pseudo random sequence. (b) Sample points generated using a quasi random sequence

3.1.1.1.1 VAN DER CORPUT SEQUENCE

A Van der Corput sequence is a low-discrepancy sequence over the unit interval first published in 1935 by the Dutch mathematician J. G. Van der Corput. It is a digital (0, 1)-sequence, which exists for all bases b ≥2. It is defined by the radical inverse function φb: $N_0 \rightarrow [0, 1)$. If n ∈N0has the b-adic expansion Particle Swarm Optimization: Performance Tuning and Empirical Analysis

$$n = \sum_{j=0}^{T} a_j b^{j-1} \tag{6}$$

With $a_j \in \{0,\ldots, b-1\}$, and $T= [\log_b n]$ then φ_b is defined as

$$\varphi_b(n) = \sum_{j=0}^{T} \frac{a_j}{b^j} \tag{7}$$

In other words, the j^{th} b-adic digit of n becomes the j^{th} b-adic digit of $\varphi_b(n)$ behind the decimal point. The Van der Corput sequence in base bis then defined as $(\varphi_b(n))_n \geq 0$.

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The elements of the Van der Corput sequence (in any base) form a dense set in the unit interval: for any real number in [0, 1] there exists a sub sequence of the Van der Corput sequence that converges towards that number. They are also uniformly distributed over the unit interval.

3.1.1.1.2 SOBOL sequence

The construction of the Sobol sequence uses linear recurrence relations over the finite field, F2, where F2 = {0, 1}.

Let the binary expansion of the nonnegative integer n be given by $n = n_1 2^0 + n_2 2^1 + \ldots n_W 2^{W-1}$. Then the n^{th} element of the j th dimension of the Sobol Sequence, $X_n^{(j)}$, can be generated by

$$X_n^{(j)} = n_1 v_1^{(j)} (+)\ n_2 v_2^{(j)} (+) \ \ldots (+) n_w v_w^{(j)} \tag{8}$$

Where (v_i^j) is a binary fraction called the i th direction number in the j th dimension. These direction numbers are generated by the following q-term recurrence relation:

$$v_i^{(j)} = a_1 v_{i-1}^{(j)} \oplus a_2 v_{i-2}^{(j)} \oplus \ldots \oplus a_q v_{i-q+1}^{(j)} \oplus v_{i-q}^{(j)} \oplus (v_{i-q}^{(j)} / 2^q) \quad i > q, \tag{9}$$

and the bit , a_i, comes from the coefficients of a degree – q polynomial over F2.

3.1.2 14 BUS

Electrical energy is the vital ingredient for the day to day functioning of modern societies. It is required for functioning of the various sectors of society like information and communication technology, transportation, lighting, food processing and wide variety of industrial processes. To meet the future energy demand we need more generation sources with adequate capacity. Renewable energy sources are better solution for the future energy demand. Many countries are placing enormous pressure on entire energy industry to reduce carbon emission and thereby reducing greenhouse effect. Combustion of fossil fuels, coal, oils is the main cause of greenhouse gases.

All these effects can be avoided using renewable energy sources. Wind, Solar Photovoltaic, Fuel cells are examples of renewable energy sources. Among these wind and solar photovoltaic are most commonly used, wind energy is the most promising source of clean and cheap energy. According to the wind energy council report the total worldwide installation of wind farm is 31% in 2009 i.e., 157.9GW. It is predicted that by the end of 2020 the total wind energy generation will be 1261GW. The increasing environmental challenges forces the electric power utilities to modify their system operation routine to reduce carbon emission. Due to the intermittent nature of renewable energy, they bring a great challenge to power system optimization problems. However the integration and high penetration of distributed generations into the power system poses many issues that need to be addressed carefully. The variations in wind speed and unpredictable solar radiation causes the output powers from wind and photo voltaic systems to fluctuate considerably. With increased size and complexity of modern power system, there are chances of cascaded effect of oscillations from a small disturbance leading to complete system black out. In this paper an extended Optimal Power Flow (OPF) is presented to research the effect of renewable energy sources on system load ability of power system.

The IEEE 14 bus system is used to analyze the effect of connected wind farm on the power system operation and verify the effectiveness of model and the validity of proposed algorithm . Integrating wind sources to the grid is a major problem in power sector facing today .

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3.1.3 PSO BASED PSCOPF

An Equivalent Current Injection (ECI) based Preventive Security- Constrained Optimal Power Flow [PSCOPF] is presented in this paper and a particle swarm optimization (PSO) algorithm is developed for solving non-convex Optimal Power Flow (OPF) problems. This thesis integrated Simulated Annealing Particle Swarm Optimization [SAPSO] and Multiple Particle Swarm Optimization [MPSO], enabling a fast algorithm to find the global optimum. Optimal power flow is solved based on Equivalent- Current Injection [ECIOPF]algorithm. This OPF deals with both continuous and discrete control variables and is a mixed-integer optimal power flow [MIOPF]. The continuous control variables modeled are the active power output and generator-bus voltage magnitudes, while the discrete ones are the shunt capacitor devices. The feasibility of the proposed method is exhibited for a standard IEEE 30 bus system, and it is compared with other stochastic methods for the solution quality. Security Analysis is also conducted. Ranking method is used to highlight the most severe event caused by a specific fault. A preventive algorithm will make use of the contingency information, and keep the system secure to avoid violations when fault occurs. Generators will be used to adjust the line flow to the point that the trip of the most severe line would not cause a major problem.

3.1.4 Cost and Estimation (Performance analysis) of PSO

Accurate cost estimation helps to complete project within time and budget. Many estimation models have been proposed over the last 30 years. This paper provides a detail overview of existing software cost estimation models and techniques. Cost estimation models are basically of two types: algorithmic and non-algorithmic. It also includes the recent developed techniques for software cost estimation field. This paper presents the strength and weakness of various software cost estimation methods. It also focuses on some of the relevant reasons that cause inaccurate estimation. In this paper a comparative analysis among existing popular models are performed and the performance is analysed and compared in terms MMRE (Mean Magnitude of Relative Error) and PRED (Prediction).

The importance of software cost estimation has been increasing gradually over last three decades. Software cost estimation is related to how long and how many people are required to complete a software project. Software cost estimation starts at the proposal state and continues throughout the life time of a project. The estimation process includes size estimation, effort estimation, developing initial project schedules and finally estimating overall cost of the project. Software development has become an essential question because many projects are still not completed on schedule, with under or over estimation of efforts leading to their own particular problems. Therefore, in order to manage budget and schedule of software projects, various software cost estimation models have been developed . Accurate software cost estimates are critical to both developers and customers. They can be used for generating request for proposals, contract negotiations, scheduling, monitoring and control. Accurate cost estimation is important because of the following reasons

- It can help to classify and prioritize development projects with respect to an overall business plan.
- It can be used to determine what resources to commit to the project and how well these resources will be used.
- It can be used to assess the impact of changes and support preplanning.
- Projects can be easier to manage and control when resources are better matched to real needs.
- Customers expect actual development costs to be in line with estimated costs.

Software cost estimation historically has been a major difficulty in software development. Several reasons have been identified that affects the estimation process such as:

- It is very difficult to estimate the cost of software development. One of the first steps in any estimate is to understand and define the system to be estimated.
- A software cost estimate done early in the project life cycle is generally based on less precise inputs and less detailed design specifications.

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- Software development involving many interrelated factors, which affect development effort and productivity, and whose relationships are not well understood.
- Lack of a historical database of cost measurement that means historical data is sometimes incomplete, inconsistent, or inaccurate.
- Lack of trained estimators and estimators with the necessary expertise. However, Software is intangible, invisible, and intractable so it is more difficult to understand and estimate a product or process that cannot be seen and touched.
- While too low effort estimates may lead to project management problems, delayed deliveries, budget overruns and low software quality, too high effort estimates may lead to lost business opportunities and inefficient use of resources. Other factors that affect the cost are programmer ability, experience of the developer‘s area, complexity of the project and reliability requirements etc.

The primary cost driver is assumed to be the software requirements. It is the primary input to the estimation process. The estimator is then adjusted according to a number of cost drivers (such as experience of personnel & complexity of system) to arrive at the finale state. Financial constraints limit the amount of money that can be budgeted for the project. Calendar constraints specify a delivery date that must be met and manpower constraints limit the number of people that can be allocated to the project. Loading is the number of engineering and management personnel allocated to the project as a function of time. Effort is defined as the engineering and management effort required to complete a project. It is usually measured in person-months. Duration is the amount of time required to complete the project. The estimator can also quantify a set of cost drivers.

3.2 Particle Swarm Optimization with Constriction Factor

Constriction factor is proposed in some works for convergence of the particle swarm optimization method. For the new parameter the method’s dynamic equations are changed as

$$v^i(t+1) = \chi[v^i(t) + \varphi_1^i(t)(p^i(t) - x^i(t))$$

$$+\varphi_2^i(t)(g^i(t) - x^i(t))], \qquad x^i(t+1) = x^i(t) + v^i(t+1), \tag{10}$$

Where X is the constriction factor. The constriction factor is defined as a function of the cognitive and social learning coefficients φ_1 and φ_2 as

$$\chi = \begin{cases} \frac{2\kappa}{\varphi-2+\sqrt{\varphi^2-4\varphi}} & \text{if } \varphi > 4, \\ \sqrt{\kappa} & \text{otherwise}, \end{cases} \tag{11}$$

Where $\varphi = \varphi_1 + \varphi_2$ and k .

In (4.2), if the inertia weight parameter is equal to the constriction factor and if the learning coefficients φ1 and φ2 are chosen such that φ1 + φ2 = φ, and if φ> 4 is satisfied, the method with inertia weight parameter is equivalent to the method with the constriction factor. In the authors compared the method with inertial weight parameter and constriction factor and provided some guidelines to select the parameters in order to increase the method’s performance. Carlisle and Dozier considered (7) and determined the factors that affect the method’s performance, such as the size of the swarm, the size of the neighborhood, the ratio of the cognitive and social learning coefficients and the velocity bound V max. They considered that these factors are in different ranges for different

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fitness functions. They showed that certain values of the parameters may be advantageous in some problems. The constriction factor considered. It is usually calculated by taking the upper limit of the learning coefficient (ϕ) as 6. The cognitive and social learning coefficients are taken as uniform n -dimensional random vectors such as $\phi_1^i(t)\in [0, 2.05]^nand\phi_2^i$ $(t)\in [0, 2.05]^n$. After considering the above values and talking $\kappa = 1$, the constriction factor (χ) could be calculated as 0.7298.

The particle swarm optimization algorithm is a nonlinear algorithm. For this reason it is thought that dynamic change of the algorithm's parameters could increase the performance. The studies mentioned above focus on determining which parameters would increase the performance of the particle swarm optimization method and present some guidelines for the parameter adjustment. According to the problem and function to be optimized, different adjustments for parameters are considered. On the other hand, a generalization cannot be made and it is noted that for different problems the values of the parameters yield optimum performance, and so the parameter adjustments are left to the user.

3.3 Hybrid Particle swarm optimization algorithms

Hybrid particle swarm are studied, where the particle swarm optimization algorithms are incorporated with other computational techniques. The hypothesis was a hybrid PSO has the potential to reach a better optimal solution than the standard PSO. The operators used in the computation methods such as selection, crossover and mutation are widely used with the method. With the selection operator only the particles having the best fitness value are passed to the next generation to increase the chance of finding global optimum points. The crossover operator could be considered as the communication among the particles, where the particles share their information with each other, so that the particles could search different regions in the search space. The most widely used operator is the mutation operator, since it is easy to incorporate with the method. Also this operator increases the diversity of the particles in the search space, which could prevent the particles from getting trapped into local minima. The mutation operator is used for mutating method's parameters, like the constriction factor (χ), the cognitive and social learning coefficients ($\varphi1$ and $\varphi2$) and the inertia weight parameter (w) in some studies.

In the authors used the mutation operator to mutate the inertia weight parameter, in order to prevent the particles from clustering in the search space (collision of the particles) and distribute them in the search space. A similar philosophy was used , where the authors have proposed a method to increase the particle diversity, but without using the mutation operator. They compare the difference between the particle's current fitness value and the best fitness value achieved until that instant, and determine a relocation condition for the particle. With this relocation condition the objective is to prevent the particles converging to local minima points in the search space. There are also other studies where various methods are proposed to prevent particle collisions (the particles whose search regions are close to each other). The studies show that in some cases the mutation operator increases the performance of the method drastically. Esquivel and Coello have proposed a nonlinear mutation operator used for mutating the particle's position information.

They noted that with the mutation operator the particle diversity is increased, thus the performance of the method is increased. Higashi and I_{ba} used a Gaussian mutation operator to update the equations where the particles update their position and velocity. They concluded that the proposed method performs better than the nominal PSO method and genetic algorithms. The particle swarm optimization method is also incorporated with other computation methods. Løvbjerg studied the idea of applying particle swarm optimization, genetic algorithm or hill climbing algorithm to every sub-swarm in the search space and proposed a stochastic search method. The change among the applied algorithms is performed considering the fitness value achieved by a sub-swarm. If a certain algorithm at certain number of iterations could not reach a better fitness value, then the sub-swarm is switched to the next algorithm. Since particle swarm optimization has greater global search capability than the other two algorithms, the PSO is used first. Hendtlass and Randall have used the ant colony optimization algorithm along with the particle swarm optimization method. Some studies have also proposed that the hybrid particle swarm optimization algorithms use non-evolutionary methods. Van den Berg and Engelbrecht developed a cooperative particle swarm optimizer. The philosophy of cooperation among the individuals is adopted, instead of competition among them. In "re-hope" and "no-hope" conditions in order to increase the method's performance. A global neighborhood topology is used and the particles are desired to converge

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to an optimum point in the search space. If the desired case does not happen, “re hope” is invoked and the particles are re-initialized, close to the neighborhood’s best position. However, if the number of re-initializations exceeds a predefined number and the particles are still searching in a small region far away from an optimum point, the “no-hope”condition is invoked and the particles are not re-initialized for that instant. In contrast to the above approach, An “Attractive-Repulsive PSO” method.

In order to increase the diversity in the swarm, threshold values for low and high diversity conditions are determined. If the threshold values are exceeded, the particles are either attracted to or repulsed from the best fitness value (pbest) in the search space. For attraction, the velocity update equation of the basic particle swarm optimization algorithm is used, while for the repulsion the sign of velocity update equation is changed and used in this way. With a similar philosophy, Parsopoulos and Vrahatis developed deflection, the stretching and repulsion methods, in order to prevent the particles from converging to local minima and to continue to search for the global minimum. In this way, the method’s capability to find the global minima is increased. In [22], the authors present particles in the swarm as a dynamic hierarchy in a uniform tree structure. The particles move vertically in the hierarchy according to their best fitness values so that the particles having the best fitness values are located at the top of the hierarchy, and these particles are more influential to velocity updates of particles in the swarm. Monson and Seppi incorporated Kalman filtering with PSO method in their study. They used Kalman filtering for determining the velocity vector of the particles, instead of using the dynamic update equations of the method. They claim that with this method the particles can perform a detailed search in a specific area, and the method’s fast convergence property to better points in the search space can be preserved as well. The studies mentioned above deal with the problem of premature convergence (converging to local minima points) by considering hybrid algorithms and different forms of the PSO method. In order to minimize this problem, it is noted that the diversity of the swarm can be increased. However, increasing the diversity may lead to more search time and not necessarily better results.

On the other hand, there is no generalization made, such that the PSO method displays better or worse performance than the genetic algorithms etc. In the particle swarm optimization method and genetic algorithm by testing on different benchmark functions. For some functions the particle swarm optimization and differential evolution algorithm show better performance, but the genetic algorithm has better performance in the functions that added noise.

III. RESULTS AND DISCUSSION

In order to validate is performance improvement of preventive security constraint OPF using different approaches designed with the source modeling in MATLAB /Simulink and the experimental waveforms are obtained. The performance of the PSO is studied under steady state condition .The performance of the PSO based PSCOPF (Preventive security-constrained optimal power flow) are validated with the models to their efficiency conditions.

In the below Figure 3 shown in the PSO method. This method is used to find the velocity of the system. In this method we method to above calculate the maximum iteration in this parameter of PSO.

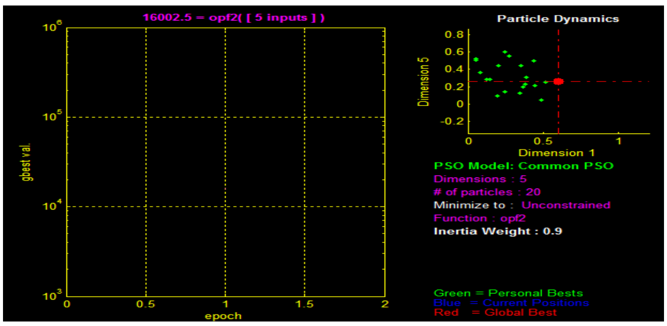

Figure 3 PSO

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The green point represents the personal best values. The red point represent the global best value and the blue point represents the current position. Now this method presents the highest personal best values was obtained.

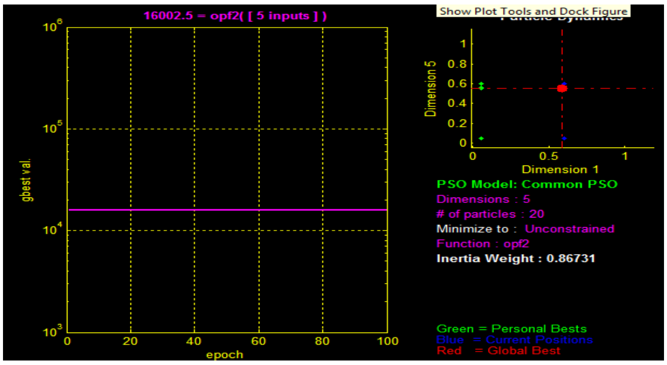

Figure 4 PSO Based PS-OPF2

In the above Figure 4 shown in the PSO based Optimal Power Flow method. This method is used to find the velocity of the system. In this method we method to above calculate the maximum iteration in this parameter of PSO. Now this method in the current position was global best values so this method was obtained maximum iteration per velocity.

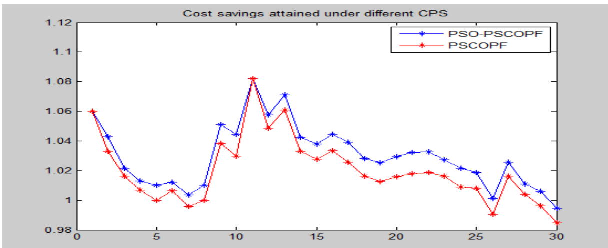

Fig. 5 Cost saving different stages

The cost saving different stages. If we compare with the PSCOPF and PSO-PSCOPF method cost saving analysis as shown in the Figure 5. Finally the PSO-PSCOPF method cost saving efficiently increased so the cost was reduced.

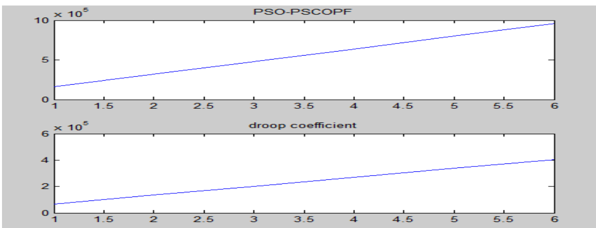

Fig. 6 Droop Co-efficient

We determined the droop step provides sufficient accuracy of the model without significant increase in computing time. However, in general, a finer resolution of this discretization may lead to more cost-effective decisions at the expense of increasing computing times in the PSO-PSCOPF method as it shown in Figure 6.

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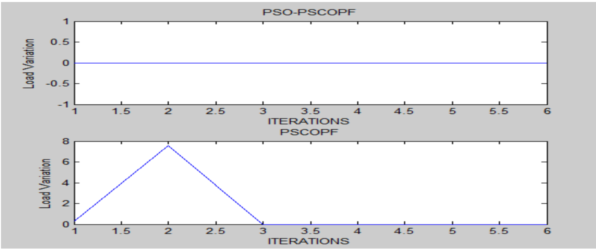

Fig. 7 Load variation vs iterations

The load variations are due to each change in the iterations. The load variation are less in the PSCOPF methodology compared to the PSO- PSCOPF.

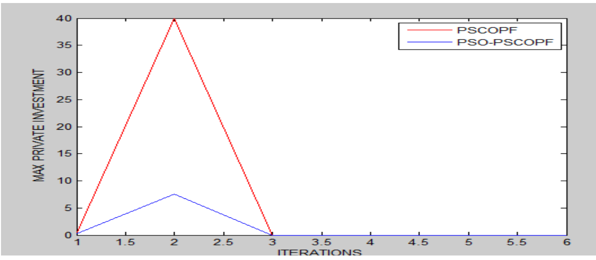

Fig. 8 Maximum private investment vs iterations

The maximum private investment are due to each change in the iterations. The maximum private investments are less in the PSCOPF methodology compared to the PSO- PSCOPF.

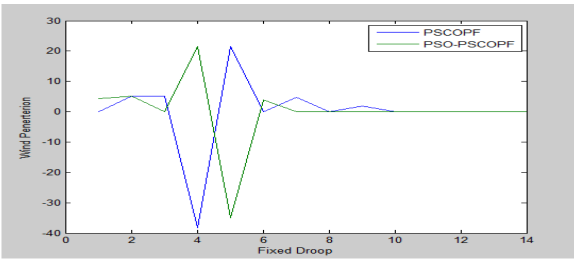

Fig. 9 Wind penetration vs Fixed droop

Wind energy penetration is the fraction of energy produced by wind compared with the total generation. The wind penetrations are due to each change in the fixed droop. The wind penetration are high in the PSCOPF methodology compared to the PSO- PSCOPF. Finally generation wind energy was efficiently high in this PSO-PSCOPF method.

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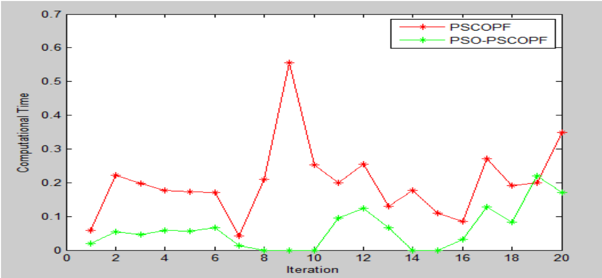

Fig. 10 Iteration vs computational complexity

The computational times are due to each change in the iterations. The computational time are less in the PSCOPF methodology compared to the PSO- PSCOPF. Finally the computational complexity was reduced in the PSO-PSCOPF method.

Finally we describe that results are very efficient in the PSCOPF method compared to the PSO-PSCOPF.

IV. CONCLUSION

It formulates a PSCOPF model that explicitly models generator contingencies in a vertically integrated environment, thus leaving out market implications of the primary response provision. The proposed PSCOPF model optimally allocates primary response among synchronized generators to respect network constraints by adjusting the droop coefficients of individual generators. These coefficients can be optimize on an hourly or daily basis. A Benders-type decomposition is implemented to reduce computing times. The near-optimality of the results obtained with this approximation is demonstrated by comparing them with those obtained using the full formulation of the PSCOPF model on the IEEE Reliability Test System (RTS). The proposed method is then used to assess reserve policies for primary response for large wind penetrations.

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