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REAL TIME MONITORING OF RADIAL DISTRIBUTION SYSTEM THROUGH OPTIMAL PSO METER LOCATION

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ABSTRACT
Proper meter placement is necessary to accurately measure the values of electrical parameters which is important for automatic management and control of complex power distribution networks. This paper presents a new algorithm of optimal meter placement for power system state estimation, (SE) which would minimize the total investment cost subject to a constraint of state estimation accuracy. The problem solution is based on Particle Swarm Optimization (PSO) algorithm and reflects the cost of individual meter installation and its contribution to the state estimation accuracy in the probabilistic sense. The next stage of the work is monitoring the distribution system by proper placement of meter at specified location. The algorithm is tested with IEEE 37 node system and Tamil Nadu Electricity Board (TNEB) 12 node distribution system.

KEY WORDS
Distribution System, meter placement, particle swarm optimization, automatic management and control, state estimation accuracy

1. Introduction

The health of the distribution system depends on accurate monitoring of network parameters. Power distribution system state estimation is the process of estimating, real time measurement data, the network power flows and busbar voltages. The voltage magnitudes and angles are called state variables of the network. The accuracy of state estimation not only depends on the methods used but is also related to measurement redundancy, locations, arrangements and types of measurements. Redundancy ratio is defined as the ratio of the total number of measurements to the total number of state variables, normally, the greater the redundancy ratio, the more reliable is the estimated variable. These measurements are collected by RTU's (Remote Terminal Units) and transmitted to the control computer system through telemeter lines. The measurements data are usually contaminated by measuring device errors and telemeter noise. An Occurrence of some failure on a meter or a RTU may make the system state unobservable. Thus, the measurement system must be designed to be observable for any failure with considerable occurrence probability. Consequently the optimal meter placement should be performed under the following considerations, Securing the sufficient -accuracy of state, Enhancing the reliability of state estimator and Reducing the investment cost. The optimal meter placement problem requires a unified performance criterion which reflects all the above considerations, and the solution algorithm should be established to minimize the performance criterion.

Y.M.Park *et al.* initiated [1] meter placement for the power system state estimation using addition and elimination algorithm, which minimizes the total investment cost subject to a constraint of state estimation accuracy .The authors in their paper [2] provide comprehensive survey on meter placement for monitoring power system where various algorithms (GA, SA, ANN, IP, LP, TS, STF) were discussed in detail. Later in 1996 M.E.Baran *et al.* [3] identifies the data requirements for real-time monitoring and control of distribution systems through rule based meter placement algorithm with less accuracy and system performance, where forecasted load data needs to be added as pseudo-measurements. J.C.S.Souza *et al.* presented [4] GA based optimal meter placement methodology for real-time power distribution systems monitoring is capable of obtaining optimal metering systems that attend constraints such as network observability and absence of critical measurements. The switch position, accuracy and time computation was not considered for execution where pseudo measurements are assumed randomly. S.Naka et al. [5] proposed a distribution state estimation method using a Hybrid PSO algorithm which can estimate load and distributed generation output values at each node by minimizing the difference between measured and calculated voltages and currents. The optimal meter placement position is not considered for estimation. H.Wang et al. [6] developed a revised branch-current-based three-phase distribution system state estimation algorithm. The goal of this work was to get the snapshot of the state of the distribution systems as accurate as possible, using all the available information on the system where real time measurement value was not taken for estimation. A.Shafiu et al. [7] developed a heuristic approach to identify potential points for location of voltage measurements for SE as part of a proposed distribution management system controller. B. Das [8] enumerated, a technique employing ANN for estimating the bus voltage magnitudes in radial distribution feeders. To determine the meter locations and the number of ANNs required for achieving a given estimation accuracy, simple rule based algorithms are proposed in this article where real time measurement not considered for estimation. V. Cecchi et al. [9] presented an outline of the measurement and control system for the Drexel University general laboratory and then focuses on the capabilities purposely added for the meter placement and network reconfiguration studies. A. Moradi et al. [10] developed a novel multistage version of a discrete PSO algorithm to determine the Optimum number and locations of CBs and sectionalizes in a distribution system. Authors in their previous paper [11] proposed PSO algorithm to minimize the number of necessary measurements and required Remote Terminal Units, subject to the system observability requirements. The method based on particle swarm optimization (PSO) algorithm is proposed to solve the problem of optimal placement of meters for distribution system. The algorithm predicts the cost and location of meters for identification and collection of measurements from the system. The algorithm has been tested with IEEE and TNEB systems where the position of switches not considered.

C.Muscas et al. [12] proposed an optimization algorithm that is suitable for choosing the optimal number and position of the measurement devices in distribution state estimation (DSE). The algorithm is based on the techniques of dynamic programming, and its goal is to guarantee both the minimum cost and the accuracy required for the measured data needed to operate management and control issues. R.Singh et al. [13] adopted a probabilistic approach to meter placement, based on Monte Carlo simulations for the purpose of improving the quality of voltage and angle estimates across a network. The objective is to bring down the relative errors in the voltage and angle estimates, at all buses, below some predefined thresholds in more than 95% of the simulated cases. The idea is to identify measurement locations that reduce the "area" of the associated error ellipses. A.Hamlyn et al. [14] proposes a new network-enabled, real-time monitoring strategy for tracking the operating states of the distribution system, with a focus on monitoring the dynamic operations of DGs. The design of a new network monitoring architecture is presented in this paper. This architecture is fault tolerant and has features from classical cascading, star, and ring architectures.

In the literatures [4] [6] [8] [11] authors identify the RTU/Meter location by different algorithms without considering the position of switching devices and real time transformer parameters. The authors in this paper try to rectify the above said constraints by considering minimum network switch location. The procedure is based on two consecutive steps 1) a Particle Swarm Optimization (PSO) optimization technique to find the location of RTU/Meter location subjected to minimum investment cost considering minimum switch position 2) PSCAD real time monitoring of the system with identified meter location . The IEEE 37 node and TNEB benchmark systems are considered for executing the result.

2. Meter Placement Strategy

In distribution system planning, optimal metering is formulated as an optimization problem where, the investment costs are to be minimized subject to some constraints in order to guarantee a good performance of state estimation (SE). The formulated problem is given below:

$$Min\sum_{i}^{n} w_i * x_i$$

$$subject\ to: f(x) \geq \hat{1}$$

where,

Wi = the cost of meter including RTU

$\hat{1}$ = a vector whose entries are all ones.

X = a binary decision variable vector, whose entries are defined below:

$$x_i = \begin{cases} 1 \rightarrow if\ a\,meter\,is\,installed\ at\,bus\,i \\ 0 \rightarrow otherwise \end{cases}$$

f(x) = a vector function whose entries are non-zero if the corresponding bus voltage is solvable using the given measurement set and zero otherwise.

The product of the binary decision variable vector and the cost vector represents the total installation cost of the selected meters. Constraint functions ensure full network observability while minimizing the total installation cost of the meters. The procedure for building the constraint equations is described in the paper by considering a system with no conventional measurements or zero injections. In this case, the flow measurement and the zero injection are ignored. The aim of the RTU is to perform wide area monitoring protection and control (WAMPAC) for electric power distribution system. Here the power system is managed by Supervisory Control and Data Acquisition/Energy Management System (SCADA/EMS) including a RTU. The RTU is likely to be located at the substation of the power distribution system and at the nodes of the system where the RTU comprises first level of data acquisition. This means acquiring measurement data which is to be evaluated by the SCADA/EMS system.

The formulated problem for cost of meter to be installed is in (1):

W i = Min (Crtu+ Cm) (1)
subject to performance requirements
where:
Cm = cost of meters that will be installed
Crtu = cost of RTUs

To calculate the cost of metering this system, the following method is adopted. The cost of RTU would be Crtu=1 unit. One unit is equal to 100 US $. The cost of meter at each node is 0.2 units.

3. PSO Meter Placement Scheme

The authors consider the Binary PSO algorithm by Kennedy and Eberhart [15] [16] for the optimization of pseudo-Boolean function f: {0, 1} n → R. Generally, the Binary PSO algorithm maintains μ triples (x (i), x*(i), v(i)), 1 ≤ i ≤ μ, denoted as particles. Each particle i consists of its current position x(i) in {0, 1}n, its own best position x*(i) in {0, 1}n and its velocity v(i) in R^n. It must be note that the velocity is from a continuous domain. In PSO terminology, the three components of a particle are called vectors. In optimization terminology, particle positions x(i), x*(i), and x* are synonymously referred to as solutions. The movement for each particle is influenced by the best particle in its neighbourhood. Hence, depending on the neighbourhood structure, different particles may be guided by different good solutions. In this work, however, the authors only use the trivial neighbourhood consisting of the whole swarm. This means that all particles are influenced by a single global best particle, denoted as x*. The velocities are updates as follows: (a) The velocity vector is changed towards the particle's own best solution and towards the global best solution x*; (b)using the language of social-psychology, the first component is often called cognitive component and the latter is often called social component; (c)the impacts of these two components are determined by learning factors c1 and c2 representing the parameters of the system. The factor c1 is the learning factor for the cognitive component and c2 for the social component. It is usual to to set c1 = c2 = 2. This gives a precise definition for the Binary PSO algorithm with a swarm size of μ and learning factors c1, c2. By lower indices the authors address the n components of the three parts of the particle.

The algorithm starts with an initialization step

Step 1) All velocities are set to all-zeros vectors and all solutions, including own best and global best solutions, are undefined, represented by the symbol .

Step 2) The subsequent loop (Steps 2–5) chooses random scalars r1 and r2 anew in each iteration. These values are then used as weights for the cognitive and the social component, respectively. The iterations synonymously referred to as generations.

Step 3) The velocity is probabilistically translated into a new position for the particle, i.e., a new solution. As proposed in the original formulation, the authors use the sigmoid function $S(v)=\frac{1}{1+e^{-v}}$. Hence, positive velocity components bias the corresponding bit towards 1-values while negative velocities towards 0-values. At velocity 0n, each bit is completely random, hence the first created solution is uniformly distributed over $\{0,1\}^n$. Afterwards, the own best and global best solutions are exchanged if the newly constructed solution is better. The selection is strict, i.e., a best solution is only exchanged in case the new solution has strictly larger fitness.

Step 4) The Binary PSO performs some vector arithmetic to update the velocity vectors probabilistically in the direction to the particle's own best solution and the global best solution.

To ensure convergence of the heuristic, every velocity vector is bounded component wise by minimum and maximum values. This reflects the common choice of a maximum velocity as studied by Shi and Eberhart [17]. For practical purposes, often velocities in the interval [−4, 4] are proposed. Since the authors are conducting an asymptotic analysis, they allow the maximum velocity to grow with the problem dimension n and confine the components to logarithmic values by setting
Vmax = ln(n−1).

Throughout this paper, the authors deal with different implementations of the Binary PSO, differing in the swarm size μ and the learning factors c1 and c2. In this context, the algorithm mentioned above is not used because of the level of randomness present in it. Due to this randomness it becomes difficult to satisfy the constraint equations when the program is executed.

To deal with this difficulty, the original PSO algorithm is used for solving the continuous optimization problems, with some modifications in the algorithm. Firstly, the range of the particles is restricted to [0,1]. Then the velocity is calculated in the normal procedure using equation, but while updating the position of the particles it is rounded off to either 0 or 1. Figure 1 represents the flowchart of proposed PSO meter placement algorithm.

3.1 PSO Meter Placement Flowchart

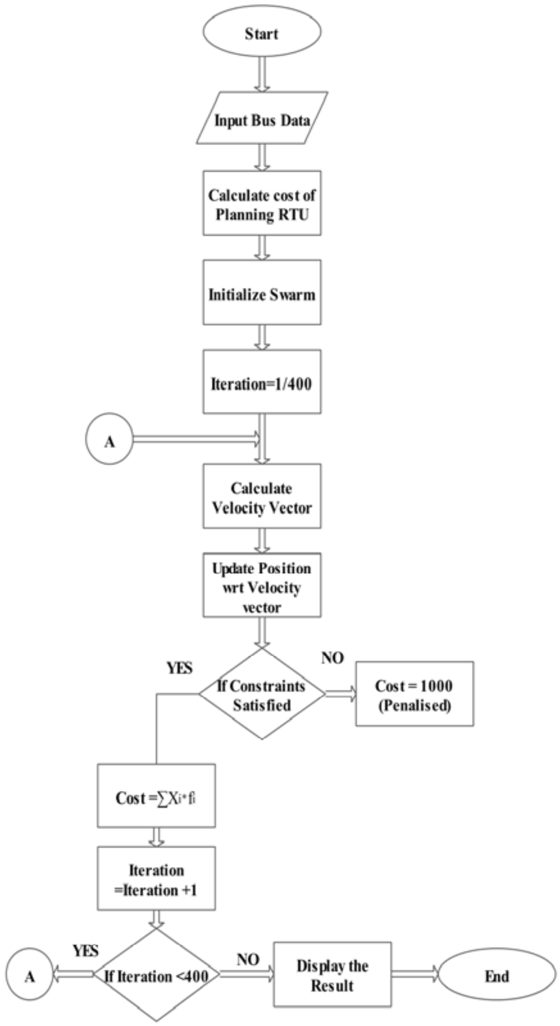


Figure 1: PSO Meter Placement Flowchart

4. Simulated Output

The proposed work is two stage of process, planning optimal metering for distribution state estimation is formulated as first stage, real time monitoring of state parameters with meter located at specified placement. The PSO algorithm and monitoring tested with IEEE 37 node system and TNEB 12 node bench mark system. The PSO algorithm is written in Matlab 6.2 and distribution networks are simulated using PSCAD 4.2.

4.1 PSO Meter Placement

The PSO algorithm is tested with IEEE 37 node and TNEB 12 node distribution system. The algorithm simulated with the following PSO parameters.

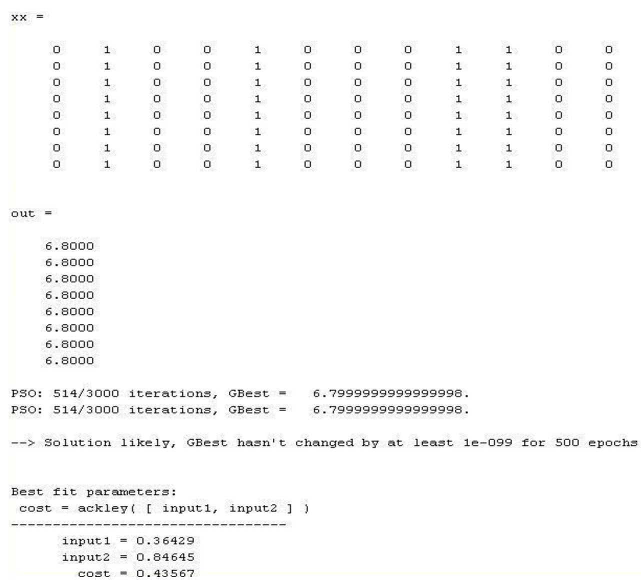
Number of Particles = 34; Maximum Velocity Divisor =2; PSO Model = Common PSO with Inertia; Iteration = 500.

Test result of IEEE 37 node system indicates that 12 RTUs at location 1,3,6,10,13,14,19,21,24,28,31,35 are to be placed at the following buses to make the system observable with minimum cost of 20.4 units. The respective meters must be placed at branches with respect to these RTU locations.

The alternate back up system for placing meter is 1, 3, 4, 9, 13, and 14,19,23,27,29,30,35 with total cost of 20.6 units.

Test result of TNEB 12 bus system indicates that 4 RTUs has to be placed at the following buses to make the system observable with minimum cost of 6.8 units. The respective meters must be placed at branches w.r.t. these RTU locations.
RTU Location Bus number: 2, 5,9,10.

The alternate back system for placing meter at position 1, 4, and 5,9,10 with total cost of 8 units.


```
xx =

     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0
     0     1     0     0     1     0     0     0     1     1     0     0


out =

    6.8000
    6.8000
    6.8000
    6.8000
    6.8000
    6.8000
    6.8000
    6.8000

PSO: 514/3000 iterations, GBest =   6.7999999999999998.
PSO: 514/3000 iterations, GBest =   6.7999999999999998.

--> Solution likely, GBest hasn't changed by at least 1e-099 for 500 epochs.


Best fit parameters:
 cost = ackley( [ input1, input2 ] )
---------------------------------
      input1 = 0.36429
      input2 = 0.84645
        cost = 0.43567
```

Figure 2: Screen shot of TNEB 12 node PSO output

The screen shot of executed output of PSO TNEB 12 node system shown in Figure 2.

4.2 Branch and Bound Meter Placement

Branch and bound algorithms [18] are methods for global optimization in non convex problems. They are non heuristic, in the sense that they maintain a provable upper and lower bound on the (globally) optimal objective value; they terminate with a certificate proving that the suboptimal point found is suboptimal. Branch and bound algorithms can be (and often are) slow, however.

Algorithm tested for IEEE 37 and TNEB 12 standard systems to make the system observable with total meter cost total number of meters.

Test result of IEEE 37 node system indicates that 14 RTUs at location 2,4,7,10,13,14,19,21,22,23,26,30,34,35 are to be placed at the following buses to make the system observable with maximum cost of 22 units. The respective meters must be placed at branches with respect to these RTU locations. Test result of TNEB 12 node system indicates that 5 RTU at location 1, 4, 5,9,10 are to place at above bus to make the system observable with maximum cost of 8 units. Through figure 3 we conclude that optimal meter placement executed through PSO meter placement algorithm when compared with numerical algorithm.

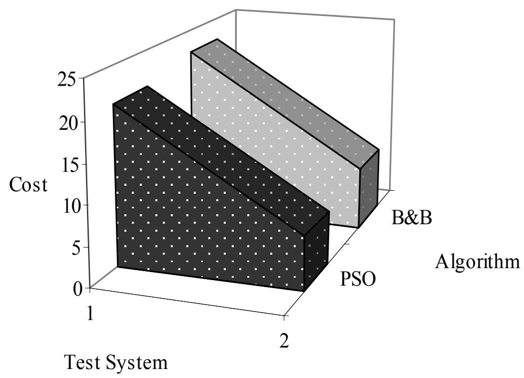


Figure 3: Comparison of Meter Placement algorithm

4.3 PSCAD Monitoring Output

Tamil Nadu Electricity Board (TNEB) 12 node system and IEEE 37 node system are modeled in PSCAD [19][20]. The designed input parameters are described below. The 11kV S.A Colony feeder from Sembium sub station has connected load of 8000 kVA and the 5 distribution transformers. The measured length of this feeder from sub station breaker to tail end is 5750m (other than spur line). Feeder type consists of underground 3x300 sqmm XLPE cable and 3x120 sqmm XLPE cable. Individual peak reached for this feeder is 6.75MVA (diversity factor = 1.67). Simulated TNEB system is shown in Figure 1, where all the parameters are selected as per the TNEB guideline. As per the result of meter placement, meters are placed at bus nos. 2, 5, 9 and 10. Figure 4(a) and 2(b) show PSCAD simulation and the real time monitored graphical voltage and current output respectively of the TNEB system. These measured values are used for estimating state of the system where pseudo-measurement values s taken for unmeasured buses.

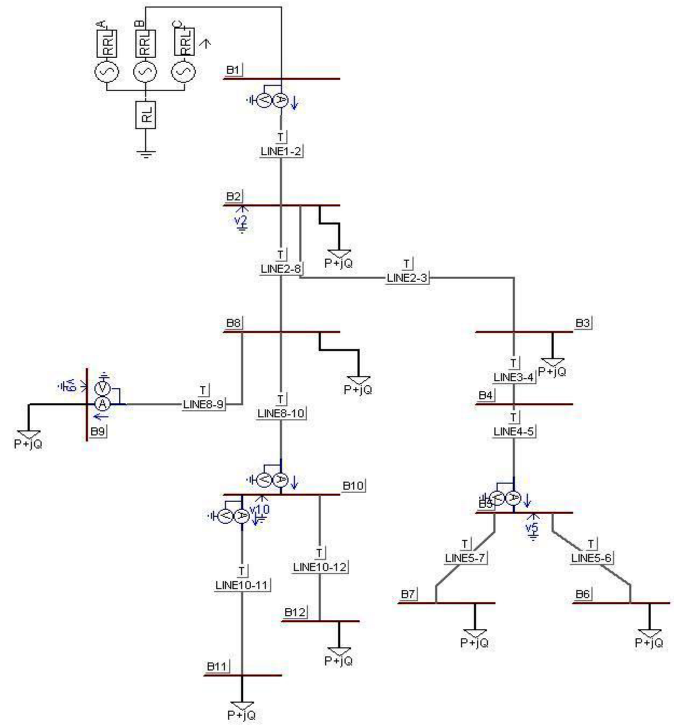


Figure 4(a) : TNEB 12 node system PSCAD simulated layout

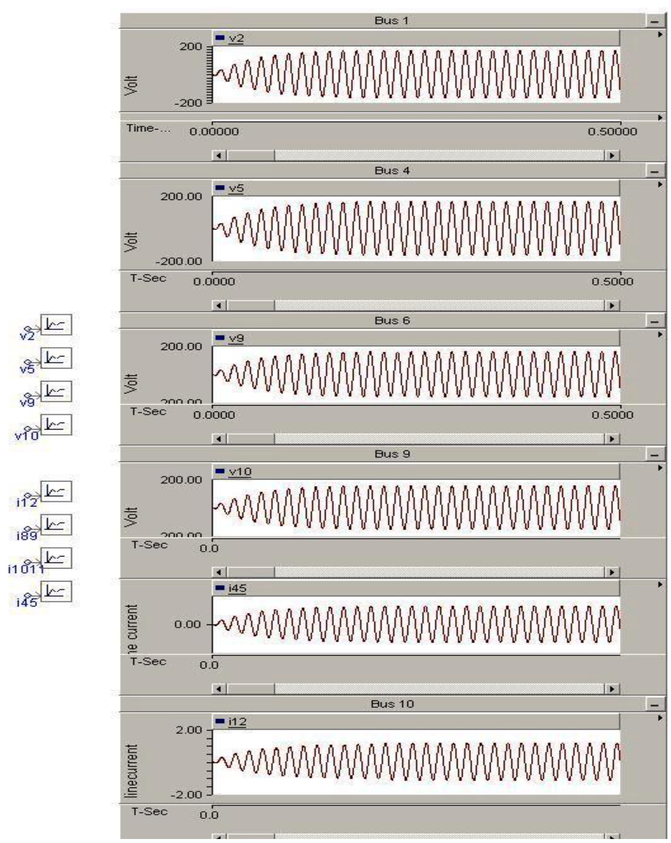


Figure 4(b) : Monitored output of meter placement buses

The IEEE 37 node system designed with following parameters. The transmission line designed with Frequency Dependent (Mode) model is basically a distributed RLC traveling wave model, which incorporates the frequency dependence of all parameters. Out of the two frequency dependent models available, the frequency dependent phase model is the most accurate as it represents the frequency dependence of internal transformation matrices, whereas this model assumes a constant transformation. The curve fitting starting frequency is 0.5 HZ and end frequency is 1.0E6 [Hz] .The maximum fitting error for surge impedance is 2% and propagation function is 2%.The designed transmission tower for analysis shown in Figure 5. Figure 6 represents the output of node voltage as per the meter placement scheme. This measured value will be used for estimating state of the system where pseudo-measurements value is taken for unmeasured buses. Figure 7 represents the monitored value of node voltage and line current under random variation of load between 10-50%. The PSCAD layout of IEEE 37 node system is shown in Figure 8.

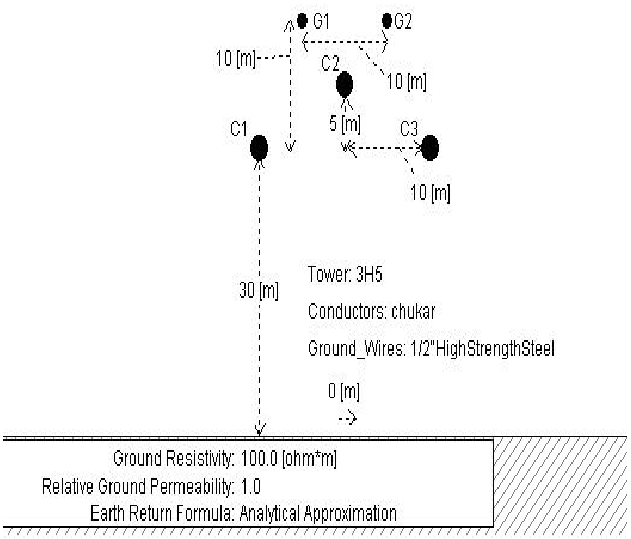


Figure 5: Transmission line tower design layout

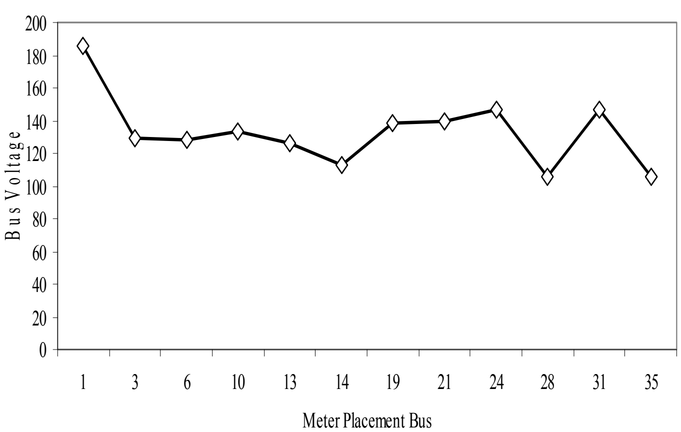


Figure 6: IEEE 37 node monitored meter placed bus voltage

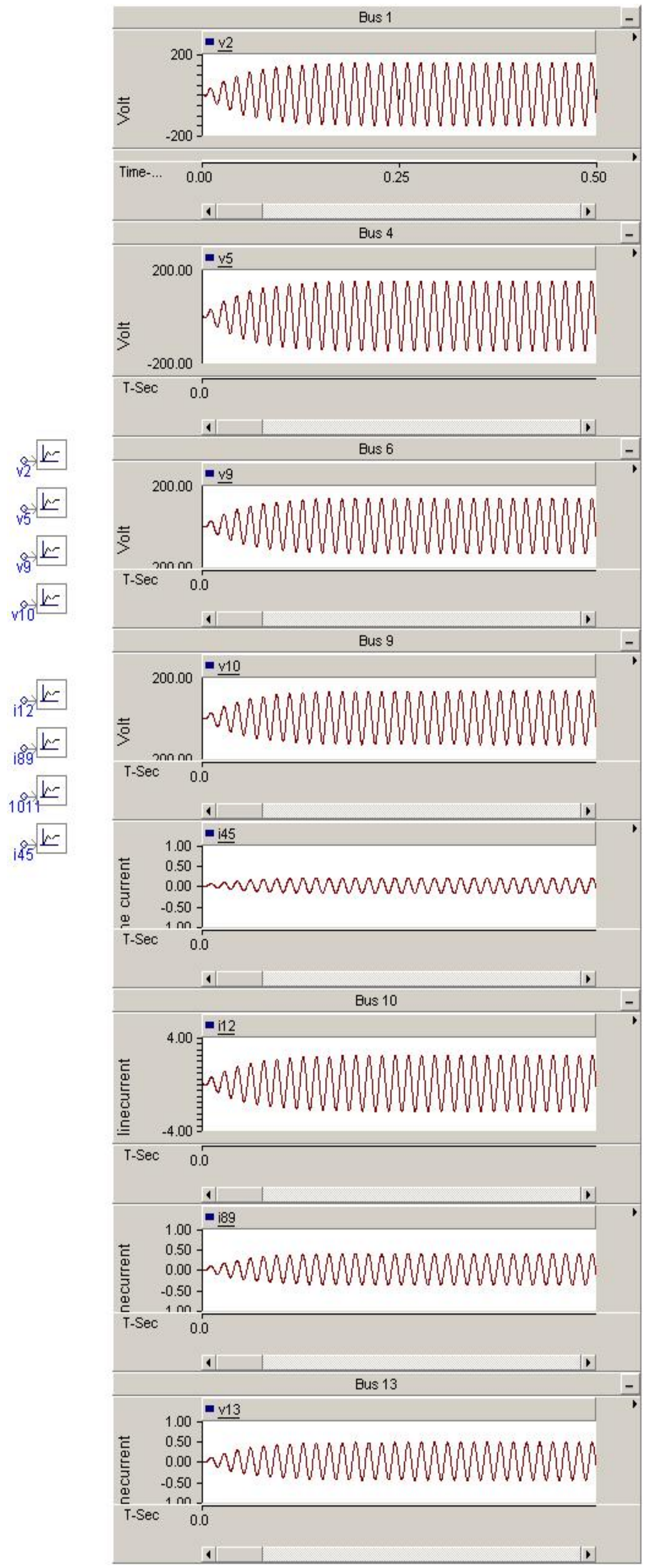


Figure 7: IEEE 37 node monitored value under variable load

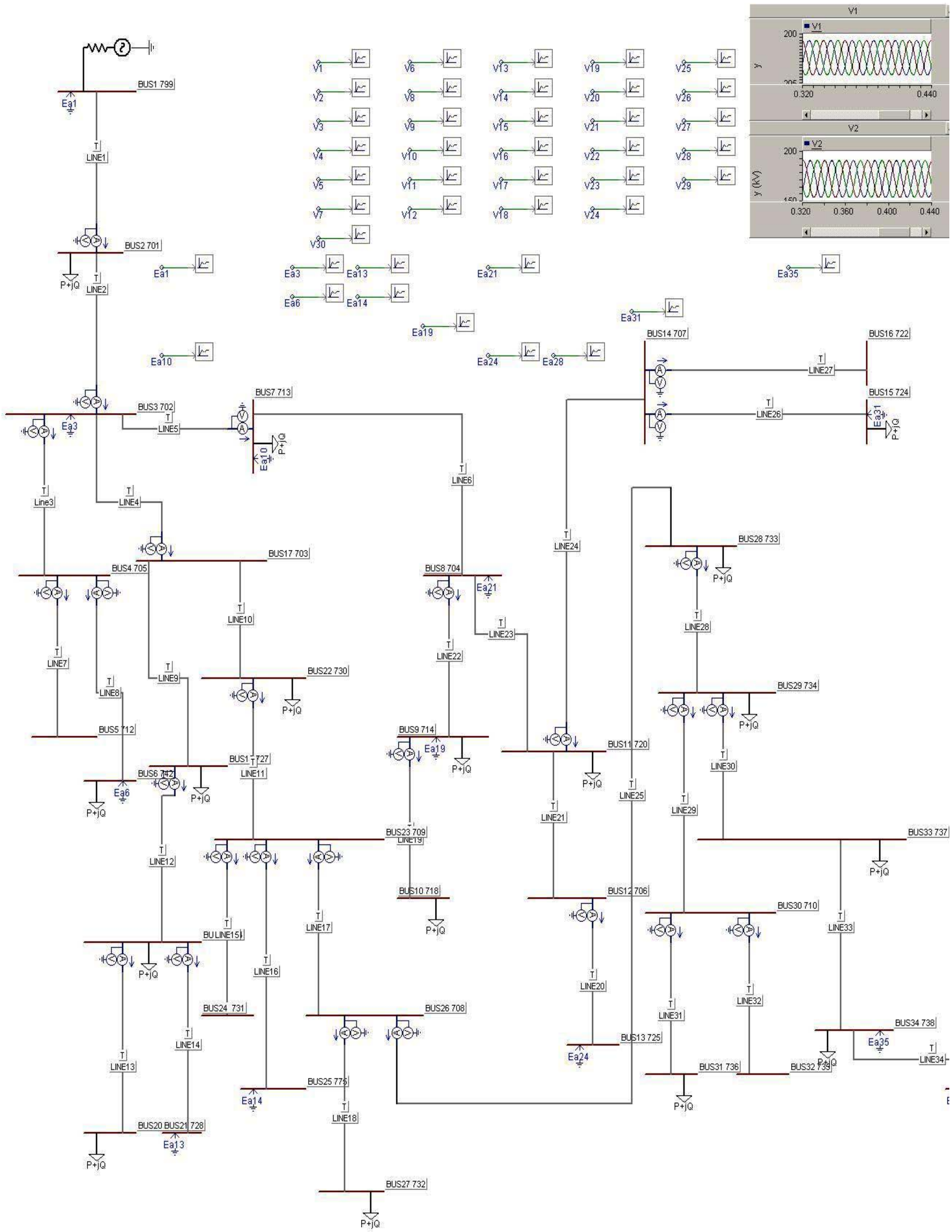


Figure 8: IEEE 37 node PSCAD simulated layout

5. Conclusion

The real time monitoring of power distribution system is simulated by placing meter at specified location located by PSO optimization algorithm. The PSO planning metering system is cost effective when compared with the previous author's papers. The measured value from the PSCAD can be used for estimating the state of the system. The future development of this paper is to design suitable estimator for the proposed system considering pseudo-measurement for unmetered buses.

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