A Data-Upload Strategy of Measurements for Lean Management in Distribution Network Under Certain Communication Cost

He Kaiyuan, Ye Xueshun
China Electric Research Institute Co., Ltd.

***Abstract*—Distribution system lean management (DSLM) is becoming an essential element of many distribution applications, the distribution network measurements are serving as the core data foundation of numerous DSLM. Considering the communication cost, the most valuable measurement data should be selected and uploaded. This paper proposes a data-upload strategy (DUS) based on distribution system state estimation (DSSE), which considers both the network observability and the mesurements' contribution. The measurements are first sorted, and then the most valuable data set is selected by using a particle swarm optimization (PSO) and a greedy algorithm. The method is tested on IEEE 4 node test feeder, different data sets are studied under several given communication cost constraints, its results are always in the top 5% group, and the DUS' result is also used on a period of time containing multipy time points, and is shown to have good stability. The proposed method is also applied to a IEEE 123 test system and works well.**

***Index Terms*—data-upload strategy, lean management, distribution network, state estimation, communication cost, particle swarm optimization**

I. Introduction

THE coverage of measurement equipment in the medium voltage distribution network and the low voltage distribution network has reached a high degree to support DSLM. However, limited to the cost of data communication, the uploaded data only accounts for a small part of the measurement data. The development of communication technology has made the cost of data communication reduced, which lays the foundation for the data support of DSLM, and the DSLM becomes more feasible and more important. However, the development of communication technology is a long-term process, and the cost of data communication will only be reduced gradually. The cost constraints of data communication must be considered in the future for a long period of time. It is of great practical significance to maximize the DSLM effect under given data communication cost constraints. There are many factors that affect the s DSLM effect, including data source and state estimation algorithm, but as the base of DSLM, data source determines the highest level of calculation results, which is the key factor.

Based on the data sources, the DSSE produces a data foundation for DSLM. The current DSSE depends on the data sources. The measurement equipment of the distribution network has different measuring precision, the measurement data have different types and the acquisition points have different positions, so the different measurement data have different influence on the DSSE. Therefore, it is necessary to study the data uploading strategy of DSSE for DSLM under given cost of data communication.

Now it still lacks of direct research on the DUS of measurement data for DSSE. Fortunately, the placement of measurment devices such as PMUs could be used for reference [1]-[8]. Firstly, the observability of the grid should be guaranteed so that the runtime state can be solved [9]-[14]. There are mainly two kinds of methods. One enforces the algebraic invertibility of the linearized load-flow models [9]-[11], while the other treats the grid as a graph and analyzes its topological observability [12]-[15], depending on the measurements support for the devices with uncertain state. To improve DSLM effect, the DSSE performance should also be considered [16]-[17]. Based on a given accuracy target, the problem could be solved by various methods as an optimization model.

This paper joinly considers observability and accuracy. The measurements are first sorted, and then the most valuable data set is selected by using a particle swarm optimization (PSO) and a greedy algorithm combine. The contributions of this paper are: 1) the derivation of the observability and performance metric to evaluate the numerical property for a given DUS and 2) the PSO and and the greedy algorithm solution method.

Manuscript received July 15, 2018.
He Kaiyuan is with China Electric Research Institute Co., Ltd., Beijing, China (e-mail: hekaiyuan@epri.sgcc.com.cn).
Ye Xueshun is with China Electric Research Institute Co., Ltd., Beijing, China (e-mail: yexueshun@epri.sgcc.com.cn).

II. MEASURMENT MODEL FOR STATE ESTIMATION

A. General Formulation

Based on the commonly used weighted least squares (WLS) approach, the model of DSSE can be described as follows [18]:

$$\min \mathrm{J}(\mathbf{x}) = [\mathbf{z} - \mathbf{h}(\mathbf{x})]^{\mathrm{T}} \mathbf{R}^{-1} [\mathbf{z} - \mathbf{h}(\mathbf{x})] \tag{1}$$

Where $\mathbf{x}$ is the state variables vector, focusing on some special devices, the dimension of $\mathbf{x}$ is usually bigger than the distribution network state variables number; $\mathrm{J}(\mathbf{x})$ is the WLS object function, $\mathbf{z}$ is the known measurements vector, $\mathbf{h}(\mathbf{x})$ is the state dependent measurement function, $\mathbf{R}$ is the diagonal covariance matrix.

B. Observability Model

The numerical observability is used in the paper. The numerical observability is typically based on the WLS model of DSSE, the observability constraints [1] can be written as follows.

$$O(\mathbf{x}) = \lambda_{\min}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}) > 0 \tag{2}$$

Where $\mathbf{H}$ is the Jacobian matrix of measurements, and $\lambda_{\min}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H})$ calculates the minimum eigenvalues of matrix $\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}$.

C. *Accuracy* Model

According to the WLS state estimation theory, the accuracy model [1] can be defined by the mean square error and measured like

$$\max\ \alpha(\mathbf{x}) = \mathrm{trace}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}) \tag{3}$$

Where $\mathrm{trace}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H})$ calculates the trace of matrix $\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}$.

III. THE DUS OPTIMIZATION MODEL

The DUS target can be modeled as an optimization problem, the PSO searches an observability solution, and the greedy algorithm focuses on the accuracy and carries out the final solution.

A. *Optimization* Model

According to section II, considering the communication limits the optimization model can be formulated:

$$\begin{aligned} &\max\ f(\mathbf{x}) = \mathrm{trace}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}) \\ &\mathrm{s.t.}\ O(\mathbf{x}) > 0 \\ &\qquad n_s \le N \end{aligned} \tag{4}$$

Where n_s is the number of basic measurements sets (BMS), each BMS contains several measurement datas, the communication of each subset of BMS has the same cost, and the BMS should be defined to have the maxmium number of measurement datas to reduce the communiation cost; N is a constant number which reflects the cost limit.

B. PSO Algorithm

The PSO algorithm [19] is a effective method for optimization model, which uses the globe best position and the local best position to generate the new vector and then position. Each particle is refreshed iteratively as below:

$$\begin{cases} \mathbf{v}_{t+1} = \omega \mathbf{v}_t + c_1 \mathrm{rand}()(\mathbf{s}_p - \mathbf{s}_t) + \\ \qquad\qquad c_2 \mathrm{rand}()(\mathbf{s}_g - \mathbf{s}_t) \\ \mathbf{s}_{t+1} = \mathbf{s}_t + \mathbf{v}_{t+1} \end{cases} \tag{5}$$

Where t is the iteration times; $\mathbf{s}$ is the state variables vector as above; $\mathbf{v}$ is the particle vector; ω, c_1 and c_2 are the inertia, memory, social factor, respectively; $\mathbf{s}_p$ and $\mathbf{s}_g$ are the local best an global best position, respectively; and rand() generates random numbers vector which has the same size with $\mathbf{x}_t$.

The solving object of PSO is:

$$\begin{aligned} &\min\ fit(\mathbf{x}) = -\mathrm{trace}(\mathbf{H}^{\mathrm{T}} * \mathbf{R} * \mathbf{H}) + f_1 * o_x \\ &o_x = \begin{cases} 0, O(\mathbf{x}) > 0 \\ 1, else \end{cases} \end{aligned} \tag{6}$$

Where f_1 is the penalty factor.

C. *Greedy* Algorithm

For each iteration, a new BMS is selected to join in an exsiting solution to maxminum $f(\mathbf{x})$. Repeating the iteration until $n_s = N$.

IV. IMPLEMENTATION

The steps of the proposed algorithm are described here.

1) Import data and establish DSSE data base.

2) Determine the BMS.

3) Compute $f(\mathbf{x})$ for each BMS, using (4). And sort the BMS based on $f(\mathbf{x})$ value.

4) For each n_s value from n_m to N, using the PSO algorithm to search a solution under a certain n_s, if $O(\mathbf{x}) > 0$, turn to step 5). Where n_m is the mininum number of BMS whose total elements number is more than the $\mathbf{x}$ dimension. It is worth noting that no solution will be found for an unobservable network.

5) Using the greedy algorithm to find out the solution.

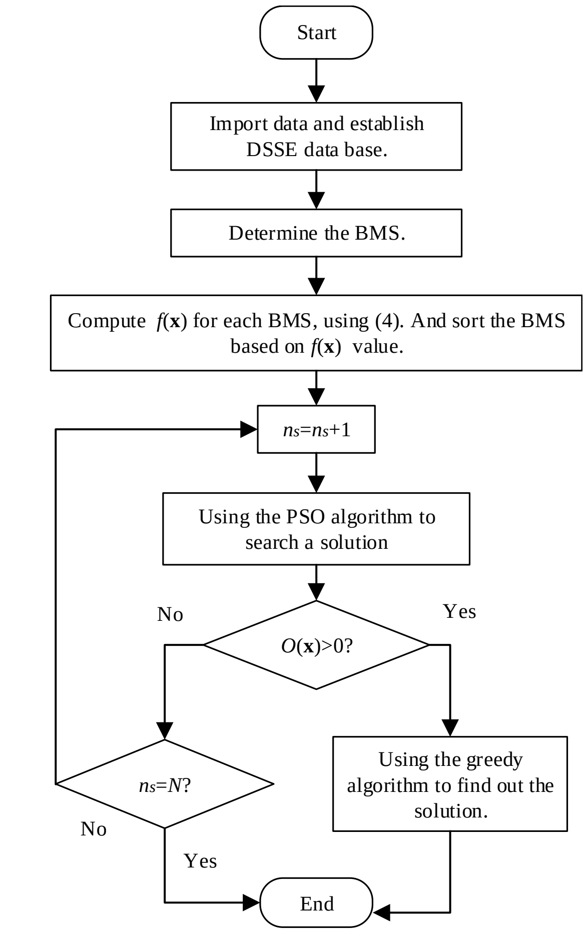

Fig. 1. The flow chart of proposed algorithm.

V. CASE STUDY

The algorithm has been implemented for verification. Two test feeder systems are used. For both networks, a reference solution is obtained from a power flow solution. Next, random noise following a normal distribution is added to the power flow reference solution for simulation.

A. IEEE 4 Node Test Feeder

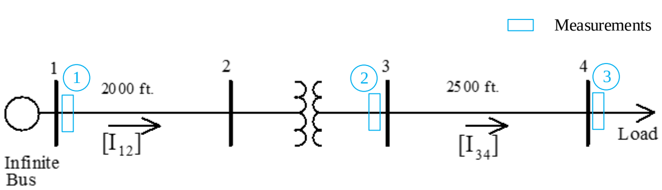

Fig. 2. The measurements configuration for IEEE 4 Node Test Feeder.

The first system is the IEEE 4 Node Test Feeder [20]. Combined with the actual situation, three measurements are configured to the system as shown in Fig.2. Voltage amplitude, current amplitude, active power and reactive power all are collected for three phases.

While n_s=1, the datas of the measurement with the highest precision are selected; if all measurements have the same precision, the datas of each measurement are possible to be selected in a single experiment. While n_s=2, the datas of the measurements with the top two precision are selected. The results are the same as the results of the exhaustion method. To shown the DSSE performance, a set of experimental datas is listed as follows. The maxmium relative is 0.1113%.

TABLE I

THE COUFIGURATION AND THE DUS RESULT

n_s	Precision [①, ②, ③]	Result [①,②,③]
2	[1%,1%,1%]	[1,1,0]

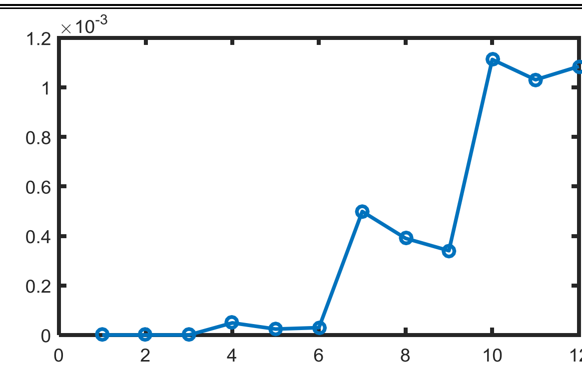

Fig. 3. The relative error of voltage amplitude between power flow and DSSE.

B. IEEE 123 Node Test Feeder

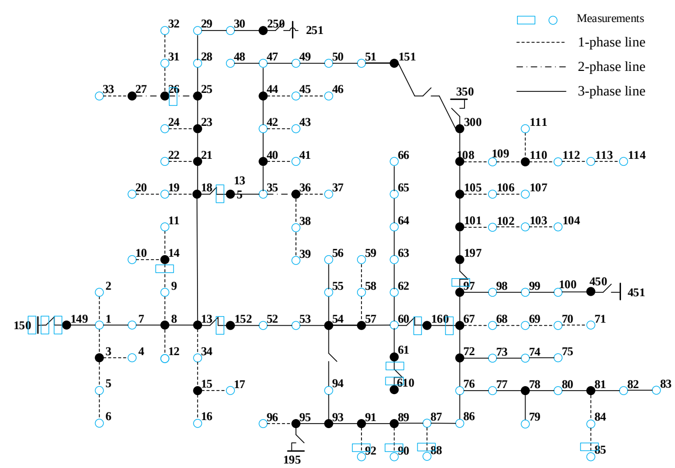

Fig. 4. The measurements configuration for IEEE 123 Node Test Feeder.

The IEEE 123 Node Test Feeder [20] is considered next. The measurements are configured on the loads, source, switches, transformer, regulators and capacitors. As shown in Fig.4, there are total 101 measurements; some measurements seem at the same position, but they locate on different devices in fact; taking node 150 for example, the three measurements configure on the source, regulator and switch respectively. Voltage amplitude, current amplitude, active power and reactive power all are collected for exsiting phases. To simplify the configuration, all devices has the same maximum error of 1.0%, and each device is treated as a BMS.

Set n_s=50, the system observability can be satisfied while n_s=38, the data upload strategy is shown in Fig.5; and the last result is shown in Fig.6.

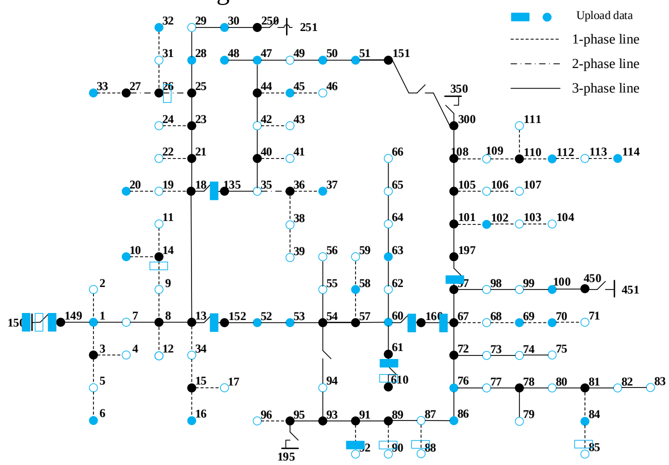

Fig. 5. The measurements upload while n_s=38.

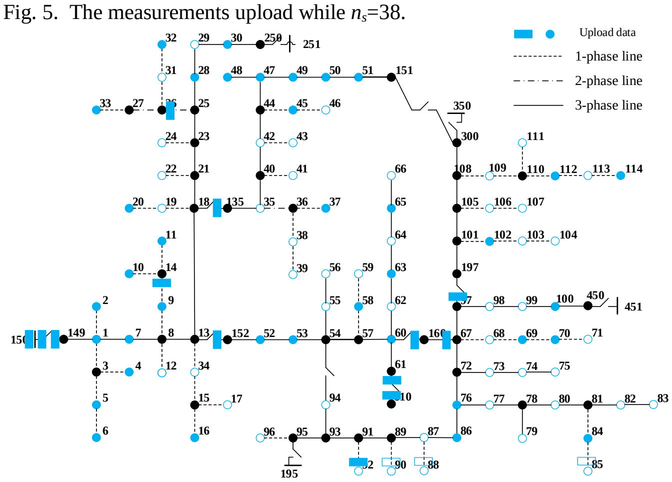

Fig. 6. The measurements upload for n_s=50.

VI. CONCLUSIONS

This paper presents a data-upload strategy of measurements for lean management in distribution network under certain communication cost. The proposed approach is based on DSSE, both observability and performance are considered. It is also shown in this paper how to use PSO and greedy algorithm collaboratively to search solution. In the first study, the proposed algorithm is shown to find the optimal solution stably. The second study, executed on a larger scale distribution network, highlights robust of the proposed approach.

REFERENCES

[1] Xiao Li, Anna Scaglione, and Tsung-Hui, “ A framework for phasor measurement placement in hybrid state estimation via Gauss-Newton”, *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 824-832, March, 2014.

[2] Seyed Mahdi Mazhari, Hassan Monsef, Hamid Lesani, and Alireza Fereidunian., “A multi-objective PMU placement method considering measurement redundancy and observability value under contingencies”, *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2136-2146, August, 2013.

[3] Nikolaos M., Manousakis, N. Korres, “ A weighted least squares algorithm for optimal PMU placement”, *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3499-3500, August, 2013.

[4] Vassilis Kekatos, Georgios B. Giannakis, and Bruce Wollenberg, “Optimal placement of phasor measurement units via convex relaxation”, *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1521-1530, August, 2012.

[5] Farrokh Aminifar, Mahmud Fotuhi-Firuzabad, and Amir Safdarian, “ Optimal PMU placement based on probabilistic cost/benefit analysis”, *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 566-567, Feb., 2013.

[6] Junjian Qi, Kai Sun, and Wei Kang, “Optimal PMU placement for power system dynamic state estimation by using empirical obervability Gramian”, *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 2041-2054, July, 2015.

[7] Masoud Esmaili, Kiarash Gharani, and Heidar Ali Shayanfar, “Redundant observability PMU placement in the presence of flow measurements considering contingencies”, *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3765-3773, Nov., 2013.

[8] Bei Gou, and Rajesh G. Kavasseri, “Unified PMU placement for observabilty and bad data detection in state estimation”, *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2573-2580, Nov., 2014.

[9] B. Gou, “Optimal placement of PMUs by integer linear programming,”*IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1525–1526, Aug. 2008.

[10] C. Madtharad, S. Premrudeepreechacharn, N.Watson, and D. Saenrak, “Measurement placement method for power system state estimation: Part I,” in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Jul. 13-17, 2003, vol. 3, p. 1632.

[11] B. Gou and A. Abur, “An improved measurement placement algorithm for network observability,” *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 819–824, Nov. 2001.

[12] X. Bei, Y. Yoon, and A. Abur, “Optimal placement and utilization of phasor measurements for state estimation,” *PSERC Pub. 05–20*, 2005.

[13] T. Baldwin, L. Mili, M. Boisen, Jr, and R. Adapa, “Power system observability with minimal phasor measurement placement,” *IEEE Trans. Power Syst.*, vol. 8, no. 2, pp. 707–715, May 1993.

[14] R. Emami and A. Abur, “Robust measurement design by placing synchronized phasor measurements on network branches,” *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 38–43, Feb. 2010.

[15] K. Clements, “Observability methods and optimal meter placement,” *Int. J. Electr. Power Energy Syst.*, vol. 12, no. 2, pp. 88–93, 1990.

[16] N. Manousakis, G. Korres, and P. Georgilakis, “Taxonomy of PMU placement methodologies,” *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 1070–1077, May 2012.

[17] Q. Li, T. Cui, Y. Weng, R. Negi, F. Franchetti, and M. Ilic, “An information-theoretic approach to PMU placement in electric power systems,” *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 445–456, Mar. 2013.

[18] Francis Therrien, Ilhan Kocar, and Juri Jatskevich, “A unifed distribution system state estimator using the concept of augmented matrices”, *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3390-3400, August, 2013.

[19] Kennedy J., and Eberhart R., “Particle swarm optimization”, presented at the IEEE International Conference on Proceedings, Perth, WA, Nov. 27–Dec. 1, 1995, pp. 1942-1948.

[20] “Distribution test feeders” IEEE PES DSAS Test Feeder Working Group. [Online]. Available: http://sites.ieee.org/pes-testfeeders/.

He Kaiyuan (S’09–M’12–SM’15) received the B.S. and M.S. degrees in mechanical engineering from University of Science and Technology Beijing, Beijing, China, in 2009 and 2012 respectively. He is currently a research engineer at China Electric Power Research Institute Co., Ltd.. His research interests include the application of AI, OPF and SE in distribution network.