A Closed-Loop State Estimation Tool for MV Network Monitoring and Operation

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***Abstract*—This paper discusses the design and simulation of an integrated load forecasting and state estimation tool for distribution system operations. A predictive database is created and applied to forecast future network states in order to allow short-term (e.g., hours/days ahead) planning to be carried out. The predictive database is based on adaptive nonlinear auto-regressive exogenous (NARX) load estimation and forecasting models, which are continuously updated using feedback from the state estimator. This creates a closed-loop information flow designed to continuously monitor and improve the system state estimation performance by updating and retraining models where appropriate. The aim of this methodology is to improve situational awareness and help to provide network operators with early warning of potential issues, in medium voltage (MV) networks where the number of on-line measurements is limited, and state estimation relies heavily on estimates of power injections. The applicability of the approach is demonstrated through simulation using supervisory control and data acquisition (SCADA) and smart meter measurements recorded from an actual MV distribution network.**

***Index Terms*—Distributed energy management systems, distributed energy resources (DER), load forecasting, state estimation.**

I. Introduction

RECENT YEARS have seen large increases in the penetration of distributed energy resources (DER) in medium voltage (MV) and low voltage (LV) networks, including distributed generation (DG), demand-responsive loads, and storage devices. This has resulted in a much higher level of variability and complexity in distribution system operation, and the need for better situational awareness and a more proactive system support [1], [2]. Recently, there has been considerable research interest in adapting a number of techniques, previously only used at the transmission level to distribution systems, including distribution system state estimation (DSSE) and short-term operational planning [3]–[6].

This paper describes an integrated load forecasting and state estimation tool for distribution system operations. Firstly, a predictive database is created using current and historical measurements from MV supervisory control and data acquisition (SCADA) and/or LV smart metering systems, along with information on local weather conditions. The predictive database allows forecasting of demand and DG profiles at each node in the network, and estimation of the future states of the distribution network using a robust DSSE solver. The predictive database is continuously updated and improved based on feedback from the DSSE. This results in a closed-loop information flow, which allows the user to estimate the network state accurately, even when measurement data are missing (e.g., due to metering communication errors), or in hours/days-ahead analysis of the system for short-term operational planning.

This paper presents several novel contributions in this context, including the proposal of a nonlinear auto-regressive exogenous (NARX) model for forecasting/estimation of disaggregated loads, and the comparison of this approach with other estimation methods, e.g., linear auto-regression and neural networks (NNs). In addition, a control chart-based methodology is presented to identify changes in the baseline performance of the load models over time, and retrain under-performing models accordingly.

The methodology presented in this paper is demonstrated through simulation, using a case study of a real MV distribution network. In this network, SCADA measurements of active and reactive flows are only available at the primary transformer (i.e., at the point of connection to the transmission system). In addition to this, detailed recordings of demand and local generation are available at the end-user (home/factory level) through smart metering, and these smart meter measurements have been aggregated at each MV node to provide historical consumption and production profiles. It is demonstrated that the integrated load forecasting and DSSE proposed in this paper can significantly reduce the load forecasting error, and improve the accuracy of the estimate of the MV network state (see results in Section IV).

This paper is structured as follows. Section II provides a brief literature review and discussion of the current state-of-the-art, putting the contribution of this paper into context. Section III deals with the methodology, including the development of the predictive database and DSSE, and the design of the closed-loop feedback system. Section IV gives the results, and finally, the conclusion is in Section V.

II. State-of-the-Art

Since its development for power system applications in the early 1970s, state estimation (SE) has become an integral

Manuscript received May 12, 2014; revised September 11, 2014; accepted November 30, 2014. This work was supported in part by the European Commission through the Marie Curie Researcher Mobility Action under Grant FP7-PEOPLE-2013-COFUND, and in part by the Smart HG Research Project under Grant FP7-ICT-2011-8. Paper no. TSG-00413-2014.

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Digital Object Identifier 10.1109/TSG.2014.2378035

part of the operation of transmission systems worldwide. SE is used to improve system observability, check for and detect errors in system measurements and network parameters, and mitigate against measurement and communication system noise. Comprehensive overviews of the main techniques and applications of SE are provided in [7] and [8].

Initial research into the area of DSSE, i.e., SEs designed specifically for use in distribution networks, followed in the 1990s [9]–[12]. DSSE presents a number of challenges, since the characteristics of distribution networks are fundamentally different from transmission networks, and hence many of the well-established techniques used in "conventional" transmission-level SE cannot be applied directly [13]. Distribution networks are typically characterized by high R/X ratios and radial configurations, which can cause computational issues for conventional SE techniques. Moreover, the quantity and quality of on-line measurements available to the network operator at the distribution level is much lower. Much of the research into DSSE has dealt with the development of solutions to these issues [14]–[17].

Recently, increased interest in active distribution networks and DER integration has led to a significant amount of work on advanced distribution management systems (DMSs). These are designed to optimize the energy management and operation of active distribution networks (see [2], [3], [18]–[21]). In all of these proposed DMS solutions, DSSE is an essential part of the methodology. Additionally, the incorporation of advanced metering infrastructure data as inputs to the DSSE has also been investigated, e.g., using phasor measurement units in [22] and [23], and LV smart meter measurements [24], [25].

An important aspect of DSSE is the provision of accurate pseudo-measurements, usually in the form of load estimates, which allow SE to be carried out even in under-determined networks with few measurement inputs, or when measurement data are missing/delayed due to metering or communication problems. In [26], NNs are used for load estimation, with the advantage that the NNs can be adapted, or retrained over time, in order to improve the load estimation, and hence, DSSE accuracy. In [27], a machine-learning technique is proposed in order to provide load estimates to the DSSE. This creates a closed-loop information flow, which allows the load estimation and DSSE performance to be improved over time, as more measurement data become available. The work presented in this paper builds upon such approaches, with the aim of developing an adaptive solution to the problem of DSSE load estimation, which is capable of automatically validating model performance and updating the load models, without requiring constant manual intervention from the network operator.

The approach in this paper is designed so that the DSSE can operate in either "real-time" mode, applying any real-time measurements available from the network along with load estimates, or in "forecasting mode" to forecast future network states for hours/days-ahead analysis of the system. In each case, measurements from the distribution network are used as feedback to the system, resulting in a closed-loop information flow. This is in contrast to most DSSEs in the literature, which have an open-loop configuration. The main contributions of this paper are as follows.

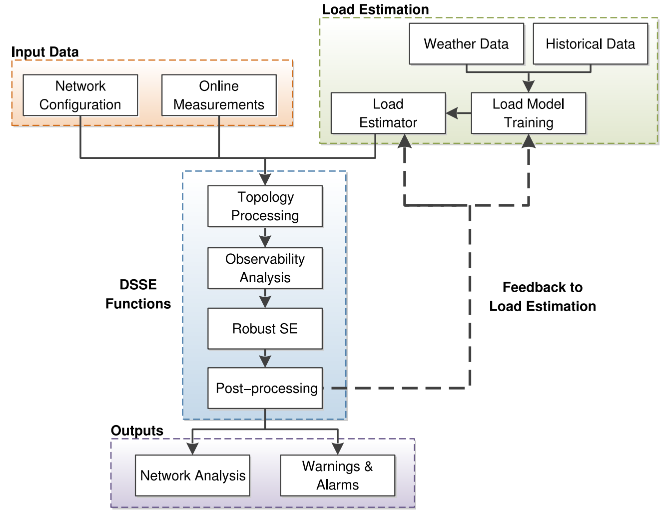

Fig. 1. Flowchart representation of methodology.

1) The design and implementation of an integrated load estimation/forecasting and DSSE service.
2) A demonstration of how the load estimation/forecasting services can be improved automatically using feedback from the DSSE.
3) A detailed study of the closed-loop DSSE responses to measurement errors, metering/communications failures.
4) Retraining and adaptation of load forecasting models.

Finally, there is a discussion on how the proposed approach can be integrated with existing DMSs, in order to improve network observability and optimize system performance.

III. Methodology

A. *Overview of Methodology*

Fig. 1 shows a flowchart of the overall methodology, illustrating the approach and how it could be integrated with the network monitoring and DSSE functions. The main inputs to the DSSE are the network configuration data (bus and branch information, switch statuses, etc.) and online measurements (telemetered measurements at various points in the network). First, a topology processor is normally applied to verify that the network configuration provided (e.g., line and switch statuses) is correct, ensuring that the network model is up-to-date. In the analysis presented in this paper, it has been assumed that the network topology is known *a priori*, and that the network parameters are correct. Network topology processing methods are outside the scope of this paper, these have been discussed in detail in previous papers, e.g., [28].

Next, the observability of the network is analyzed using the null space method outlined in [29]. If the network, or any parts of it, cannot be observed, estimates of demands and DER outputs from the load estimator are used to provide pseudo-measurements of power injections at each relevant network node. In real-time mode, load estimation is used to replace missing measurements in cases where the system is under-determined. In forecasting mode, all of the inputs to the system are pseudo-measurements, based on short-term forecasts of demand and DG outputs.

These data are fed to a robust DSSE, which identifies bad data, i.e., erroneous or missing values in the input measurements. In the post-processing phase, trending or out-of-control parameters are identified. The results of the SE are then used to carry out network analysis (e.g., power flows, contingencies, and setting initial conditions for transient studies), and also to provide warnings, alarms and recommendations to the network operator. One of the novel aspects of this approach is the use of feedback from the post-processing phase, which makes the DSSE a closed-loop system. This allows the predictive database and forecasting tools to be continually updated as more real-time data becomes available. The following sections of this paper outline the methodology used for the robust DSSE algorithm (Section III-B), the adaptive load forecasting tool (Section III-C), and the post-processing and feedback loop from the DSSE to the predictive database (Section III-D).

B. Robust DSSE

The DSSE uses various combinations of input data, comprising (in order of decreasing accuracy) of: 1) real-time measurements; 2) load pseudo-measurements; and 3) forecasts of future load/DER outputs. Each of these input data types potentially contains significant noise and gross errors. It was found that a least-squares estimator based on robust statistics [30] was required to produce acceptable performance in this application. Estimators based on robust statistics are particularly suited to dealing with gross errors and outlier values which can cause computational problems for conventional SEs. For the analysis in this paper, it has been assumed that the network of interest is an MV distribution network (i.e., nominal voltage 1 kV < V < 35 kV) with an European configuration, and that the level of imbalance across the three phases is not critical. The robust DSSE solution below would need to modified to include phase imbalances in order or to apply it to LV networks, or MV networks with single and two-phase laterals (see also the discussion in Section V).

Most DSSE algorithms operate by minimizing the conventional weighted least squares (WLS) objective function [13]

$$\min_x \quad \mathbf{J}(\mathbf{x}) = \sum_{i=1}^{N} w_{ii}(z_i - h_i(x))^2 \tag{1}$$

$$\min_x \quad (\mathbf{z} - \mathbf{h}(\mathbf{x}))^T\ \bar{\mathbf{W}}\ (\mathbf{z} - \mathbf{h}(\mathbf{x})) \tag{2}$$

$$\text{subject to} \quad \mathbf{z} = \mathbf{h}(\mathbf{x}) - \epsilon \tag{3}$$

where w_{ii} is the weight for measurement i, $\mathbf{z}$ is the input data vector, $\mathbf{h}(\mathbf{x})$ are the measurement functions, $\mathbf{x}$ is the state vector, N is the total number of measurements, ϵ is the measurement error, and $\bar{\mathbf{W}}$ is the measurement weight matrix

$$\bar{\mathbf{W}} = \begin{bmatrix} \frac{1}{\sigma_1^2} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_2^2} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & \frac{1}{\sigma_N^2} \end{bmatrix}. \tag{4}$$

The weights in the diagonal of $\bar{\mathbf{W}}$ are set according to the inverse of the variance σ_i^2, of each meter (in the case of real measurements), or the variance of each load estimate (in the case of pseudo-measurements, see Section III-D1). This is so that the SE solution gives more weight to input data points which are known to have greater accuracy. The measurement residuals are given by

$$\hat{\mathbf{r}} = \mathbf{z} - \mathbf{H}\ \hat{\mathbf{x}} \tag{5}$$

where $\hat{\mathbf{r}}$ is the vector of measurement residuals for the set of state estimates, $\hat{\mathbf{x}}$. The measurement residuals can be analyzed using statistical methods such as the Chi-squared test to identify bad data (i.e., input measurements that are grossly in error). Bad data analysis methods are described in detail in [8].

The minimization in (2) is solved iteratively as follows:

$$\Delta\mathbf{z_n} = \mathbf{z} - \mathbf{h}(\mathbf{x_n}) \tag{6}$$

$$\Delta\mathbf{x_n} = \left(\mathbf{H^T}\bar{\mathbf{W}}\mathbf{H}\right)^{-\mathbf{1}}\ \mathbf{H^T}\ \bar{\mathbf{W}}\ \Delta\mathbf{z_n} \tag{7}$$

$$\Delta\mathbf{x_{n+1}} = \mathbf{x_n} + \Delta\mathbf{x_n} \tag{8}$$

where n is number of SE iterations. However, it was found that in the presence of significant input data errors, the conventional WLS approach can have computational issues which result in the SE becoming insoluble. These problems are caused by poor conditioning of the network Jacobian matrix $\mathbf{H}$, which causes difficulties inverting $\mathbf{H}$ to form the gain matrix $(\mathbf{H^T}\bar{\mathbf{W}}\mathbf{H})^{-\mathbf{1}}$. These issues were overcome by applying the equivalent weight function proposed in [27]. The diagonal measurement weights matrix $\bar{\mathbf{W}}$ is modified as follows:

$$\bar{\mathbf{W}} = \text{diag}\ (\bar{w_1}, \bar{w_2}, \ldots, \bar{w_N}) \tag{9}$$

where the equivalent weights in (4) are recalculated at each SE iteration

$$\bar{w_i} = \left\{ \begin{matrix} w_i, & D'_i \le k_0 \\ w_i \frac{k_0}{D'_i}\left(\frac{k_0 - D'_i}{k_1 - k_0}\right)^2, & k_0 < D'_i \le k_1 \\ 0, & D'_i > k_1 \end{matrix} \right\} \tag{10}$$

$$D'_i = \frac{|r_i|}{\alpha(1 - z_i)\ \text{med}_j \left| r_j - \text{med}_i r_i \right|} \tag{11}$$

$$k_0 = \min(K_{t1}, K_{t2}), \qquad k_1 = \max(K_{t1}, K_{t2}) \tag{12}$$

$$K_{t1} = \alpha\ \text{med}\ (D'_i), \qquad K_{t2} = K_{t1} + \frac{\max(D'_i - K_{t1})}{3} \tag{13}$$

where $i, j = 1, 2, \ldots, N$, $\alpha = 1.438$, and med is the median. This iterative recalculation of the DSSE weights is based on the influence function from robust statistics theory [30]. The objective is to reduce the influence of input data points with extreme values which can cause the estimator to break down, by decreasing the weights $\bar{w_i}$ if D'_i approaches the upper threshold k_1. This inclusion of the equivalent weight function was crucial in making the DSSE robust to gross errors, particularly when a large number of load estimates and forecasts are applied.

C. Adaptive Load Estimation Tools for DSSE

The DSSE requires high-quality pseudo-measurements of demands and DER outputs in order to function properly, both in real-time mode, where pseudo-measurements are needed to replace bad or missing input data, and in forecasting mode where load forecasts are used as input. Several of the most common approaches for short-term load estimation/forecasting are applied below, using demand data from MV/LV substations in the test network.[1] The intention in this section is to introduce some of the most commonly-used methods for load estimation, in order to find a suitable approach for this particular application. This analysis is not, however, intended to be an exhaustive comparison of available load estimation techniques. A summary of the most commonly-used methods for load estimation is provided in [31]. Gross and Galiana [32] have applied auto-regressive models, while others have suggested machine learning approaches using NNs [33]. Most previous work in the area of load estimation applies to the estimation of much larger, more aggregated loads, e.g., prediction of regional or national demands [33], [34]. However, in this paper, the focus is on local-level load estimation [e.g., for few tens to hundreds of customers at the secondary (MV/LV) substation]. New techniques for load estimation at a much more localized level are required for the accurate assessment and management of voltages and flows in the MV distribution network [35].

In previous literature on short-term load forecasting [31], [34], [35], a "NAIVE" benchmark model has been used as a standard for assessing the performance of load estimation models. The NAIVE benchmark should be a credible forecast which captures the salient features of the load profiles of interest [31] e.g., assuming the demand at each hour will be equal to the demand at the same hour of the previous equivalent day. It provides a reference point which can be used to assess the forecasting skill of subsequent, more advanced models [31], [33]–[35]. A similar approach has been taken in this paper.

First, the variables which affect local demand and DER output in the case study MV distribution network were established through regression analysis (see Section IV-A for a full description of the case study network). The analysis identified if there was a clear trend (linear or nonlinear) between each variable and the demand measurements, and found that eight variables affected the demand: 1) two weather-related variables (temperature and dew point, both measured in °C); 2) three time-related (day, hour of day, and whether or not the day is a normal working day); and 3) three historical (previous hour demand, previous week equivalent hour demand, and previous 24 h average). In the case study network, there is also significant DER in the form of PV embedded in residential users' homes. Hence, solar irradiance in W/m^2 was also included as a variable in the model, in order to estimate the impact of PV on demand.

1) Selection of Load Estimation Model: The above data were used to estimate load and DG outputs using the following load estimation techniques.

1) *NAIVE:* A naive load forecast is made by simply taking the same hour, previous day demand value. For weekends, the same hour from the most recent weekend day is taken instead.
2) *ARX:* Linear auto-regressive exogenous (ARX) model.
3) *NN:* Nonlinear NN model.
4) *LMS:* Linear regressive model using the least mean squares (LMS) algorithm.
5) NARX: Non-linear auto-regressive exogenous model.

[1]The terms load estimation and load forecasting are used almost interchangeably in the literature on this subject. In the following text "load estimation" is used throughout to refer to short-term estimation, or forecasting of electrical power demand.

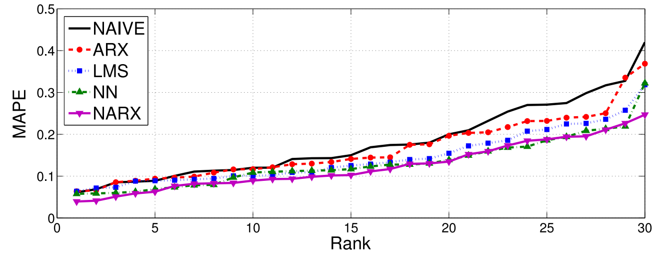

Fig. 2. Comparison of day-ahead forecasting accuracy at 30 individual MV distribution network demand points.

The five load models above were used to estimate the real power demand at 30 individual demand points selected from the test case distribution network. Note that a new model is trained and tested for each individual MV node. The available data from the test network comprised of 13 months of continuous recordings of consumption and production at each node, where each MV node had an average of approximately 40 customers, and peak demand of around 140 kWh (see also Section IV-A). This was split into model training data (70%), and model validation data (the remaining 30% of the recordings, equivalent to around four months of data). Fig. 2 compares the results for day-ahead load estimation at the system peak hour (assumed to be 19:00). The estimator performance in each case is expressed as the mean absolute percentage error (MAPE), averaged over the four months of validation data.

It can be seen from Fig. 2 that all load estimation models outperform the "NAIVE" model. In general, the nonlinear models have better performance than the linear models, with the "NARX" model demonstrating the best performance. In some previous studies on load estimation, it was noted that nonlinear methods, such as NN and NARX, did not offer any significant performance improvements compared to conventional linear methods [33]. However, for local-level load estimation, demands are much more variable and difficult to predict with accuracy. In this application, it was found that conventional forecasting techniques (e.g., ARX) did not perform well, and nonlinear methods provided better results. The NARX model was selected for all further analysis in this paper, and its structure is outlined below. Due to space limitations, the other models tested above (AR, NN, and LMS) are not described in detail, the reader is instead referred to the literature on load estimation in [31]–[36].

2) Description of NARX Model: NARX models are particularly useful for modeling load times series with nonlinearities [36]. The NARX model is expressed as

$$y_{t+1} = F\left(y_t, y_{t-1}, \ldots, y_{t-do}, \quad u_t, u_{t-1}, \ldots, u_{t-do}\right) \tag{14}$$

where the next value of the output signal (e.g., the kW load), y_{t+1}, is regressed using previous load measurement values y_t,

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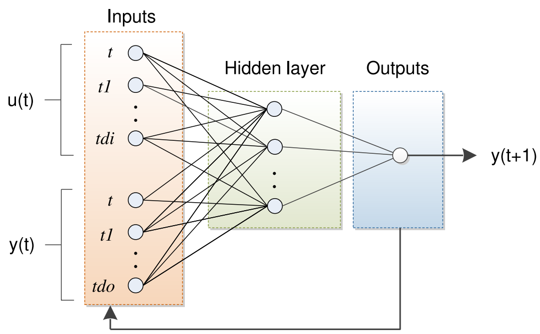

Fig. 3. Structure of the NARX model.

y_{t-1} and input signals u_t, u_{t-1}, (e.g., time-related, historical, and weather load variables). The number of time delays in the input and output layers are denoted *di* and *do*, respectively. These can be adjusted to allow for different forecasting horizons, e.g., hour-ahead, day-ahead, etc. The function F represents the NARX model illustrated in Fig. 3. The weights for each connection in the network were trained using MATLAB. The best results were obtained using a feed-forward NARX model, comprised of an input layer with nine neurons (one for each input variable), one hidden layer with ten neurons, and an output layer with one neuron. Samples of the results obtained from the proposed NARX model and discussion of the results are given in results (see Section IV-B).

D. Feedback Loop From DSSE to Predictive Database

Feedback from the DSSE described in Section III-B is used to update the predictive database for load estimation, with the aim of improving the performance, as more data become available. This creates a closed-loop information flow as shown in Fig. 1. Feedback is provided to the load estimator in several ways.

1) Adjustment of DSSE Measurement Weights: The diagonal values in the initial measurement weight matrix $\bar{\mathbf{W}}$ in (4), are generally set according to the accuracy of the corresponding input measurement. For instance, if the input i is a pseudo-measurement of the active power injection at a given node (i.e., a load estimate), the corresponding measurement weight in $\bar{\mathbf{W}}$ is set as follows. First, the variances of each load estimate, σ_i^2, are calculated, based on the recent performance of the load estimator at that node

$$\sigma_i^2 = \frac{1}{T_{SE}} \sum_{t=1}^{T_{SE}} (\hat{y}_t - y_t)^2 \tag{15}$$

where T_{SE} is the time period over which measurement data are sampled, $\hat{y}_t$ is the load estimate at time t, and y_t is the actual load values recorded at time t. For instance, if T_{SE} is set to 24 h, the measurement weights are updated based on the previous day average measurement accuracy. This approach is used in the subsequent analysis presented in this paper. The measurement weights are then calculated as

$$w_i = \frac{1}{\sigma_i^2} \tag{16}$$

where w_i is measurement weight for input i. Typically, load estimates have large variances, and hence low measurement weights in the DSSE function. If i is a real metered data point, the variability σ_i will be much lower, and the corresponding measurement weight in $\bar{\mathbf{W}}$ will be much larger.

2) Monitoring Load Model Performance and Retraining: Once a load estimation model has been developed for each node in the system, the performance of each load model is monitored continuously. Each model's performance is expressed as the MAPE of the predicted load demand versus the actual recorded value. The DSSE proposed in this paper is designed to detect if there are changes in the baseline MAPE over the medium-to-long-term (i.e., weeks to months), and retrain the model accordingly.

A widely-used approach for detecting a change in the baseline of a control variable is the cumulative sum, or CUSUM control chart method [37]. The cumulative sum, S, of the MAPE modeling error at each time step is calculated by

$$S_{t+1} = \max\,(0,\ S_t + x_t - k) \tag{17}$$

where S_{t+1} is the next cumulative sum to be calculated, S_t is the current values of S (the initial value $S_0 = 0$), x_t is the process sample (e.g., the calculated value of MAPE value at time t), and $k = 1\ \sigma$ is a weight applied to the process, so that only deviations from the mean greater than 1 σ are considered in the analysis. The control limit used in the CUSUM control chart method is denoted H, and is typically set as a multiple of σ, usually 4 or 5 σ [37]. It was found that using 4 σ as the CUSUM control limit resulted in too many false alarms (i.e., meaning that retraining would occur even when there was not a significant change in model performance baseline). Higher multiples (e.g., 6 σ) ran the risk of not detecting shifts in the baseline performance. The optimal value for any given network application depends on a number of factors, e.g., the inherent variability in the load data, the quality of the forecasting, and how many false positives/false negatives the user is willing to tolerate.

Fig. 4(a) shows the recorded and estimated daily peak demands at an individual MV network node. Fig. 4(b) shows the corresponding MAPEs. The mean MAPE, $\mu = 0.0734$, and standard deviation, $\sigma = 0.0591$. The cumulative sum, S_t, is then calculated over each time step, Fig. 4(c). It can be seen that individual high MAPE values do not cause an out-of-control (i.e., detection of a change in the baseline), but that the out-of-control occurs only when the cumulative sum exceeds the allowed threshold ($S_t > H$).

3) Application of Feedback to SE and Load Estimator: When implementing feedback to the SE and the load estimator, the time-scales used to apply adjustments to the SE measurement weights, and retraining of the NARX models should be considered. It is important to distinguish between short-term issues (e.g., temporary metering or communication system errors and bad data points), from longer-term issues (e.g., a change in baseline load estimation model performance). Therefore, the time-scales for the adjustment of measurement weights (Section III-D1) and for retraining of the load estimator (Section III-D2) are set as follows:

$$T_{\mathrm{LE}}\ >>\ T_{SE}\ >>\ t \tag{18}$$

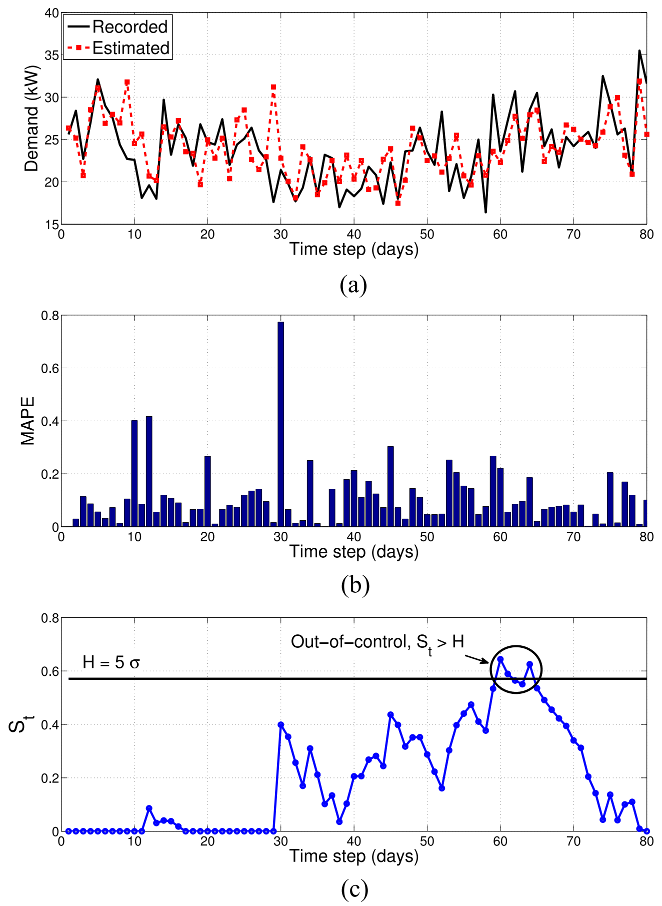

Fig. 4. Demonstration of use of CUSUM method to detect a change in baseline performance of load estimation model. (a) Daily peak kW demands. (b) MAPE at one selected node. (c) Corresponding cumulative sum of error, showing out-of-control.

where T_{LE} is the frequency at which the NARX load estimator at each node is retrained (if a change in baseline performance has been detected), T_{SE} is the frequency at which the SE weights in (4) are adjusted, and t is the time step, or sample frequency (1 h is used in the examples shown above). In this paper, T_{LE} is set to approximately 30 days (retraining is carried out if required at the end of each calendar month), and T_{SE} is set to 24 h. This approach ensures that the NARX load estimation models are not repeatedly retrained in response to temporary, short-term issues. However, if there is a significant change in performance at a particular node within the monthly cycle, the effects on overall DSSE performance are limited, since the corresponding SE measurement weights will be adjusted within 24 h. The network operator is notified if there are regular changes in the baseline performance of the load estimator model at a particular node, since this may indicate the presence of metering or communication issues. In addition to this, routines are set up to alert the operator to zero demand values at a particular system node, or individual values with very high standard deviations, since these may indicate the problems with the monitoring system.

It was found that using the time-scales indicated above in (18) resulted in a stable system, i.e., DSSE performance gradually converged over time, as weight adjustment and retraining were applied. However, the quantity of measurement data that were available from the test distribution network was quite limited (around four months of continuous data, after the recordings had been separated into model training and model validation data). This meant that it was not possible to simulate the proposed approach over longer time scales, e.g., to examine the effects of seasonal changes on load estimation accuracy, and the evolution of system performance over months and years. This will be addressed in future work as more data becomes available from the test network (see Section V).

IV. Results

This section demonstrates the main functions of the proposed closed-loop DSSE using recorded data from an existing MV distribution network. First, the characteristics of the case study network are described. Next, the response of the DSSE to issues with the monitoring system is demonstrated by example. The response of the adaptive load estimator to a change in the demand pattern at an individual node is then discussed. Finally, the overall performance of the closed-loop DSSE in the test case network is assessed.

A. Description of MV Network Case Study and Measurement Data

The data used in this paper are taken from the case study network used in the European Commission Smart HG Project [38]. The test network is a 48-bus, suburban/rural 10 kV system with a weakly-meshed structure. This network has a peak demand of 3.2 MW, which is made up primarily of suburban/rural residential customers, which make up 77% of the total annual demand. The remainder of the network demand is comprised of factories, and some district heating and street lighting loads. There are around 1600 customers located at 46 MV nodes (where each MV node corresponds to a secondary transformer 10:0.4 kV), with an average peak demand at each MV node of 140 kWh. There is also approximately 0.4 MW capacity of embedded photovoltaic (PV) generation installed at the LV residential user level.

On-line measurements of active and reactive power consumption on an hourly basis were available at the primary 50:10 kV transformer. At the MV demand nodes, there are no direct, on-line measurements of voltage, or active/reactive power measurements available (this is typical of most real MV distribution networks, where measurement redundancies are very low due to economic and technical reasons). However, in the case study network, smart meters are installed at all consumers in the LV network, and the hourly consumption/production data for each MV node were available in the form of aggregated smart meter measurements. The above data were available from September 2012 to October 2013 (13 months). This data set received from the network operator was generally of a high quality, with only some minor issues with missing/zero values at certain nodes due to occasional metering/communication errors. These missing values were replaced with estimated demands where appropriate (see example shown in Fig. 7 below).

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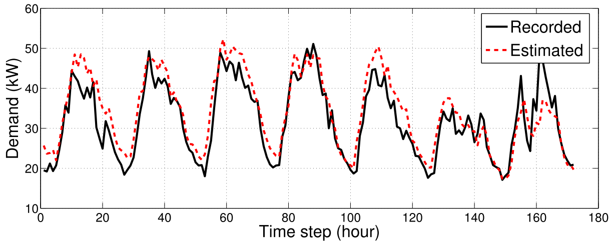

Fig. 5. Sample of day-ahead NARX load estimation results at individual MV node.

It is assumed in the analysis in this paper that the aggregated smart meter kWh measurements are not available to the network operator on-line, but were available for the previous day, i.e., with a time delay of 24 h. Since no recorded data were available for the reactive power at each MV node, the measured reactive power demand at the primary transformer was used to scale reactive power demands at each MV node so that the total reactive power demand matches the recorded value at the primary. As would be expected for an MV network serving mainly residential load, power factors are generally very close to unity, but there was some variation between 0.8 and 1.0, particularly during the early morning hours.

B. Load Estimation Model Results

The following results show output from the NARX load estimation model described in Section III for day-ahead estimation at an individual MV node. A sample time series is shown in Fig. 5, comparing the recorded kW demand at an MV node, to the NARX estimation, where the "estimated" values are calculated the day before, i.e., an estimate is made at 00:00 h for the 24 h ahead. The example shown by Fig. 5 is typical of the day-ahead NARX estimation error in the case study network. The day-ahead MAPE at the MV nodes in the network varied between 4% and 20%, with an average of approximately 10% obtained across the 46 MV nodes.

The load estimation model errors are represented in (15) by a unimodular variance, σ_i^2. However, it should be noted that the probability distribution functions (PDFs) of the actual MV distribution loads are not unimodular, and are typically multimodal and irregular [see Fig. 6(a), which shows the recorded PDF from the same individual MV node as above]. The proposed NARX model is able to reproduce the characteristics of the distribution load PDFs with a good degree of accuracy [Fig. 6(b)]. The resulting NARX estimation error can be represented by a unimodular variance, which justifies the use of σ_i^2 to calculate the DSSE measurement weights in (15). It is possible that a closer fit to the estimation errors could be obtained using an alternative distribution, e.g., a Gaussian mixture model (GMM) as proposed in [17]. The GMM is perhaps a more general solution, since it could be used to model any estimation error, and is independent of the load estimation method used. However, GMM fitting adds to the complexity and computation time required at each time instance in the SE, and was not found to be necessary when the NARX estimation model was applied.

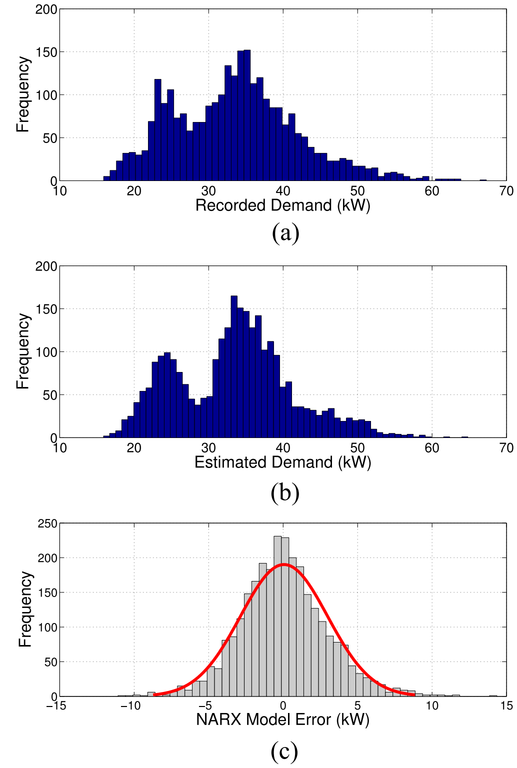

Fig. 6. NARX estimation results at individual MV node. (a) Recorded demand PDF. (b) Estimated demand PDF. (c) Load error PDF.

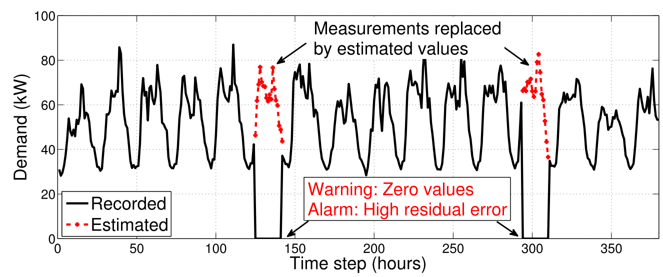

Fig. 7. Example showing DSSE response to intermittent monitoring issue.

C. Detection of Errors and Changes in Load Estimator Performance

1) Metering and Communication Errors: The following results show the response of the closed-loop DSSE to a monitoring issue which occurred in the test network at one individual MV node. Fig. 7 shows a sample of the active power demand measurement at one MV node, where there is an intermittent issue with the monitoring system that results in the input measurements equalling zero at certain times. It is likely that such an issue was caused by a temporary metering or communication system failure at this node. This analysis provides a means for highlighting suspect or erroneous values, but establishing the root cause of anomalous values in the data with certainty would require further analysis offline.

When the monitoring error occurs, the DSSE issues a "warning" to the network operator, notifying that zero values have occurred in the input measurement data, and also an "alarm" for high residual error values at this node, indicating a gross error in the input data [i.e., a statistically significant

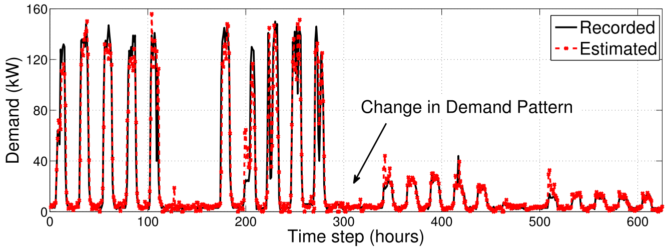

Fig. 8. Example showing load estimator response to change in demand pattern at an individual bus.

large value of $\hat{\mathbf{r}}$ in (5), Section III-B]. The bad input data are detected by the DSSE, and replaced with estimated values from the load estimator, Fig. 7. This ensures that gross input data errors do not have a significant impact on the DSSE calculation.

2) Load Estimation Model Response to Changes in Demand: The NARX load estimation model developed in Section III is designed to adapt to changes in the pattern of network demands. This ability to adapt to changing demand patterns is illustrated below, using an example from an individual node in the test network. The recorded demand for a node which is made up entirely of industrial load, and the corresponding hour-ahead estimated load is shown below in Fig. 8. The characteristics of the demand change suddenly, in this case due to a reduction in the output of the factory located at this node. It can be seen that the load estimator adapts quickly to the changes in the pattern of the load in the short-term (i.e., over the course of several hours). In the longer-term (e.g., weeks to months), changes in the baseline performance of the load estimator are detected, and the NARX model retrained, as discussed in Section III-D2.

This ability to respond to short-term and long-term changes in demand patterns at each node is particularly important in active distribution networks with DER. Demand profiles in these networks are highly-variable, since they are affected by changes in DG outputs, demand-response schemes, building management system settings, etc.

D. Simulation of Closed-Loop DSSE Tool

The overall performance of the presented closed-loop DSSE tool is assessed by carrying out a simulation of the MV case study network. The results are compared below for two simulation cases.

1) *Case (i):* The network state (e.g., voltages and active/reactive power flows) is estimated using power injections calculated from the NAIVE model described in Section III-C1, where the DSSE load estimates are based on the corresponding hour of the previous day. No feedback loop is applied in this case.
2) *Case (ii):* The network state is calculated using load estimates from the proposed NARX model, applying the feedback to the DSSE described in Section III-D.

In each case, the performance of the tool is measured by comparing the accuracy of the estimated day-ahead network voltages and active/reactive power flows, with the "actual" values for the network state, once the measurements at all MV

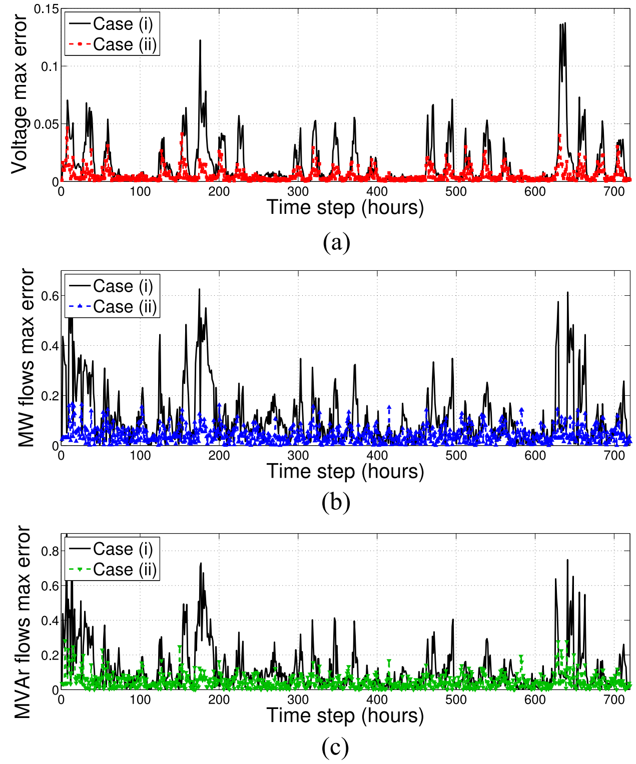

Fig. 9. Sample showing maximum absolute percentage errors from DSSE. (a) System voltages. (b) System active power flows. (c) System reactive power flows.

TABLE I
SUMMARY OF RESULTS FROM CLOSED-LOOP DSSE TOOL SIMULATION

	Case (i) mean error (%)	**Case (i) max error (%)**	**Case (ii) mean error (%)**	**Case (ii) max error (%)**
Voltages	0.9	14.6	0.3	6.6
MW flows	7.0	62.9	3.1	16.7
MVAr flows	6.9	89.5	3.4	28.3

nodes throughout the network have become available from the smart metering system. The simulation was run over a time period of approximately four months. Fig. 9 shows some samples of time series of the output obtained from the simulation, illustrating the maximum absolute percentage errors for per unit voltages and MV/MVar flows (considering all buses and lines in the MV network).

The mean and maximum absolute percentage errors obtained over the entire simulation period are summarized in Table I. The results illustrate the importance of providing accurate load estimates to the DSSE. The absolute percentage errors in case (i) are significantly larger, with mean voltage errors around 1% and mean MW/MVar flow errors of 7%. However, it is shown that the maximum errors which occurred in case (i) can reach 60–90% (column 3, Table I), which is clearly unacceptable for any practical application. In case (ii), the mean errors are relatively low (0.3% for voltage and 3–3.5% for MW/MVar flows), and the maximum errors obtained are in a more acceptable range (6–28%, column 5, Table I).

E. Computational Requirements and Practical Considerations

Most of the computational effort in the proposed approach is required in the initial model development stage, where the NARX estimation models for each network node are created. The NARX model training time (which includes validation check of the trained model) averaged 1.3 s for each MV network node. For the entire MV network considered (approximately 1600 customers in total, located at 46 MV nodes) the total NARX training time required was 59.8 s. However, it is expected that this model training can be carried out off-line. Once the NARX models at each MV node have been trained, they are only retrained/updated when there is a significant change in the baseline performance of the load estimation model. In the presented analysis in this paper, the retraining frequency is limited by $T_{\mathrm{LE}} = 30$ days. In practice, most MV nodes will have a lower retraining frequency (e.g., 1 or 2 retrains per year).

The other parts of the methodology are much less computationally expensive than the NARX model training. The calculation and readjustment of DSSE weights (Section III-D1) across the entire network required 0.10 s, running the CUSUM calculation (Section III-D2) required 0.16 s per MV node every 30 days, and the robust DSSE takes on average 0.15 s to complete for the entire network. All of these computation times are based on running MATLAB on a standard PC with a 2.6 GHz dual-core processor and 4 GB RAM. It is expected that all computation times could be reduced significantly if more efficient code implementation and/or more powerful computers are applied. In summary, while the computational effort required to actually implement the proposed approach certainly cannot be neglected, it is expected to be within the capabilities of practical distribution utilities, even for much larger networks than the example presented in this paper.

V. CONCLUSION

This paper presented an integrated load forecasting and state estimation tool for monitoring and operation of MV distribution networks. A predictive database is created in order to forecast future network states, which allows short-term (e.g., hours/days-ahead) planning to be carried out. The predictive database allows forecasting of demand and DG profiles at each node in the network, and estimation of the future states of the distribution network using a robust DSSE solver. The predictive database is continuously updated and improved based on feedback from the DSSE, creating a closed-loop information flow.

This paper presented several novel contributions in this context. One contribution was the proposal of a NARX model for forecasting/estimation of disaggregated loads. The NARX load estimation models can be trained at any network node without *a priori* knowledge of the load structure, and can adapt according to observed changes/trends in load behavior. This has the advantage that the load estimation and DSSE services can run automatically, with minimal intervention from the user. The load estimation approach described in Section III is flexible, in that new variables can be added or removed as required, e.g., if there is embedded wind DG present in the network, wind speed can easily be included as a variable in the model. In addition, this paper proposed a new control chart-based methodology for identifying changes in the baseline performance of the load estimation models over time, which allows retraining of under-performing models. The approach is demonstrated by a simulation using SCADA and smart meter measurements recorded from an actual MV distribution network.

However, there are some limitations in the analysis presented in this paper. It has been assumed that the MV network of interest is balanced in the three phases, or at least that the level of imbalance is not critical. This assumption is valid for the case study network, since it is a mainly residential MV distribution system with an European configuration, where the entire MV system is in three phases, and the LV laterals are well-balanced across the phases. However, it is recognized that this assumption may be unacceptable in some cases. For instance, in North American MV distribution systems single-phase MV laterals are used extensively, making the system inherently unbalanced. Clearly, three-phase system models are required if the approach is to be applied in MV networks with significant phase imbalances, or in LV networks. Future work will extend the methodology accordingly, and will also demonstrate the approach on larger distribution networks, with different characteristics and configurations to the case study presented. In addition to this, work is ongoing to carry out the analysis using a larger measurement data set, in order to examine the ability of the DSSE to improve its performance and respond to changes in the characteristics of the demand patterns over longer time periods (i.e., seasons and years). The most effective way to test the presented approach would be to implement it real-time in a small section of distribution network, for an extended trial period. This possibility was not available at the time of writing, but it is expected that by demonstrating the approach through simulation, that a strong case for implementing a full-scale network trial in the future could be developed.

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