

Estimation of Aggregate Reserve with Point-of-Load Voltage Control

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Abstract—Voltage dependent loads can collectively provide a certain amount of power reserve (by virtue of the ability to change their power consumption within the stipulated voltage tolerance) which could be exploited for grid frequency regulation through voltage control at the substation/feeder or at the point of load. The amount of such power reserve would vary with time of the day depending on the incidence of different types of voltage dependent loads and also the voltage profile across the feeders. It is important for the grid operators to know the aggregate power reserve from the voltage dependent loads during different times of the day in order to schedule other forms of reserves accordingly. This paper presents a methodology to estimate such power reserve from the measured power and voltage at the bulk supply points without knowing the actual distribution network topology and/or load profile of individual customers. The proposed method is applied to estimate the time variation of the aggregate reserve offered by the voltage dependent loads within the domestic sector in Great Britain (GB). Studies on a standard IEEE distribution network are presented to validate the estimated reserve margins under typical voltage profiles across the distribution feeders.

Index Terms—Artificial Neural Networks (ANN), Demand response, Electric Spring, Estimation, Frequency control, Load Disaggregation, Point-of-load Voltage control, Reserve.

I. INTRODUCTION

Reducing the voltage level of the electrical distribution system for peak demand reduction and energy savings is a common practice adopted by many utilities across the world. Such ‘Conservation Voltage Reduction’ (CVR) [1] is typically exercised through transformer tap changer control with appropriate line drop compensation. However, for feeders with large voltage drops (which would be the case during large PV power injection and/or EV charging) the depth of voltage reduction possible through a tap changer alone would be limited in order to maintain the voltages at the far end within the stipulated limits.

In such cases, an effective option is to deploy voltage regulators (such as electric springs [2], [3]) at the customer supply points to allow possible reduction of the load side

voltage down to the lowest permissible level (say 0.94 p.u. as in the UK) while maintaining the feeder side voltage within stipulated limits. Such point-of-load (PoL) voltage regulators offer greater flexibility and higher margin for voltage reduction (and increase, if required) compared to using substation and feeder level voltage control alone. The ability to control the power consumption of voltage dependent loads (within their stipulated voltage tolerance) collectively provides a certain amount of reserve which could be used by the grid operators for network services such as grid frequency control. It is important for the grid operators to know the aggregate power reserve offered by the voltage dependent loads across the system during different times of the day in order to schedule other forms of reserves accordingly.

In our previous work [4], we have shown that the available reserve using PoL voltage regulator within the industrial and service sector in GB could be comparable to the existing spinning reserve in GB (1.8 GW). However, the calculations were based on annual energy consumption data for different types of loads [5] without considering their daily variation of different types of loads. Since the amount and nature of voltage dependent loads connected to the system vary depending on the time of the day, the available reserve would also vary. Moreover, the reserve with PoL voltage control depends on the voltage profile across the feeders, which is volatile. Therefore, it is quite challenging but necessary for the grid operators to estimate the aggregate reserve available from voltage dependent loads in presence of PoL voltage control.

It is straightforward to estimate the reserve if the load profile for different voltage dependent load categories are known. This could be done through intrusive load monitoring where the customers are required to maintain record of the appliance operation [6] or energy and billing data [7] or through the use of smart meters [8]. For intrusive monitoring a device is generally connected between the socket and the appliance to record its operation. Such approach could be inconvenient and expensive considering large scale application in a variety of appliance types and buildings. For non-intrusive load monitoring based on load disaggregation there are many methods like high resolution measurement of device signatures (e.g. current) [9], power change in response to step changes in voltage [10], load monitoring using wavelet design [11], Support Vector Machine (SVM) based identification [12], harmonic signature based identification [13]. However, these methods are generally suitable for disaggregation of loads at the customer level (e.g. household). It is difficult to scale these up at the substation level (where monitoring is done

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The limitations of the proposed method are: (1) the accuracy of the estimated reserve amount is a trade off between the number of voltage dependent load categories considered and the error introduced by complicating the estimation algorithm, (2) the variability in voltage profile across the feeders. Nonetheless, it provides the grid operators an estimate of the reserve available at a given point in time with some confidence level so that they can schedule other forms of reserves accordingly.

The aggregated demand at a BSP can also be represented by a single ZIP model and the parameters of the model can be estimated using optimization techniques (e.g. Least

A two layer feed-forward ANN (FFANN), shown in Fig. 2 was used for load disaggregation due to its simple structure and the ability to map complex input-output relationships [18].

In Fig. 2 small bold non-italic letters (**a, p, b**) denote vectors of ANN output, input and bias, respectively while capital bold nonitalic letter (**W**) denotes the matrix of weights.

Selection of the optimal size of the hidden layer is not trivial and often involves some trial and error. An approach proposed in [19] was adopted here to approximate the size of the hidden layer by (3) for $\frac{N}{d} \gg 30$

$$n_h = \sqrt{\frac{N}{d \ln N}} \quad (3)$$

where n_h is the number of hidden layer neurons, N is the number of training sets (input matrix columns) and d is the number of inputs (input matrix rows).

The ANN Toolbox in Matlab was used wherein the transfer functions for the hidden layer and the output layer were chosen as *logsig* & *tansig*, respectively to limit the per unit share of each load category (i.e. ANN output) within [0,1].

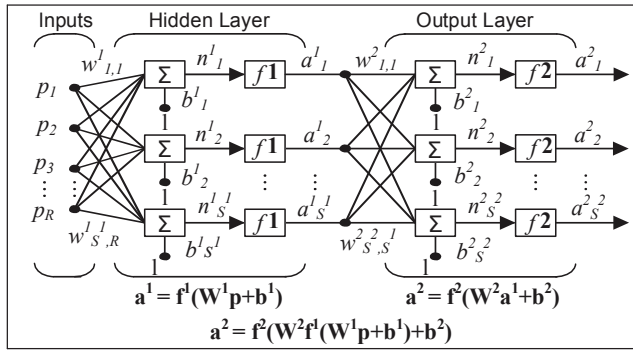


Figure 2. Structure of two layer feed-forward ANN

C. Training of Artificial Neural Network (ANN)

The ANN was trained using the Levenberg-Marquardt back-propagation (LMBP) technique [18], [20] to capture the relationship between the voltage (V) at the bulk supply point (BSP), aggregate active (P^{agg}) and reactive power (Q^{agg}) and the share of each load category at a given time under different scenarios. All possible combinations were considered for training of the ANN to capture the non-linear relationship. The steps involved in training of the ANN are as follows: (a) use (1) & (2) to define the models for each of the different load categories considered, (b) use Monte Carlo simulation to generate random samples of voltages and share of load categories within certain limits, (c) consider all possible combinations of voltages and share of load categories, (d) develop the input and target matrices (introduced later in Section II-C3) for ANN training using steps (a) & (c), (e) formulate a FFANN with hidden layer neurons as in (3) and train the ANN.

Training the ANN using a particular set of measurement data would not encompass all possible operating scenarios and also the trained ANN may not be generic enough to be used at other substations. Hence, the ANN was trained through Monte Carlo method using an exhaustive dataset (as done in [14]) with the objective of capturing the daily and the seasonal variations within a single estimation model. Once the ANN is trained offline, it can be used for load disaggregation in real-time and does not require re-training as long as the training

space (e.g. p.u. voltage limits of the substation) do not change. It is to be noted that the output of load disaggregation would be used in reserve scheduling, which is generally carried out at an interval of tens of minutes for which computation is not a problem.

1) *Voltage samples*: Under normal operation, voltage at the BSPs are generally maintained [21] within certain stipulated limits. Nevertheless, a voltage range of 0.94 to 1.1 p.u. was considered as per the standard BS EN 50160 [22]. Random voltage samples were selected from an uniform distribution to ensure equal probability for all sample points. The total number of voltage samples considered is denoted by N_v .

2) *Share of Load Category*: The number of load categories to be considered depends on the load mixture at the BSP. For instance, there could be 10 load categories, 5 of which represent static loads (e.g. lighting, heating, SMPS etc.) while the rest represent motor loads (e.g. constant torque induction motor, residential cold load). At a given time, the share of the static and motor load categories as seen from the BSP will vary between 0% to 100%. If the share of motor loads varies from 0% to 100% in steps of 5% (and the static loads changing accordingly to make up 100%) there could be 21 possibilities for such static-motor combinations. For each of these 21 possibilities, random weighting factors (w) have to be generated from uniform distribution to account for the share of each load category in P^{agg} & Q^{agg} at any t^{th} instant of time. As an example, for 40% dynamic load and 60% static load, the weighting factors for all dynamic load categories are generated between 0% and 40% with the summation being 40% and similarly, the weighting factors for all static load categories are generated between 0% and 60% with the summation being 60%. So for each of the 21 static-motor combinations N_w weighting factors (all positive) are required for each of the 10 load categories. The aggregate active power (P^{agg}) can be calculated using (4) for each voltage sample, one particular static-motor combination and one set of w for all the load categories. Q^{agg} can be calculated similarly.

$$P^{agg} = \sum_{i=1}^m w_i P_i \quad (4)$$

In (4) m stands for total number of load categories considered, w_i denotes weighting factor for i^{th} load category and P_i gives the active power of i^{th} load category from (1) and all the values are expressed in per unit. The per unit share of the i^{th} load category (p_i^{lc}) out of the total load at BSP can be calculated as:

$$p_i^{lc} = \frac{w_i P_i}{P^{agg}} \quad (5)$$

For developing the input and the target of ANN, all possible voltage-weighting factor combinations should be considered, i.e. $N_v \times 21 \times N_w$ combinations in total.

3) *Input and Target Matrices*: Using (4) the total active and reactive power at the BSPs can be calculated for all possible combinations of voltages and weighting factors. These values can be considered as the measurements available from the BSP. The input matrix for the ANN training thus includes P^{agg} , Q^{agg} and V and is given by (6).

$$I_{trn} = \begin{pmatrix} P_1^{agg} & P_2^{agg} & \cdots & P_{N_v \times 21 \times N_w}^{agg} \\ Q_1^{agg} & Q_2^{agg} & \cdots & Q_{N_v \times 21 \times N_w}^{agg} \\ V_1 & V_2 & \cdots & V_{N_v \times 21 \times N_w} \end{pmatrix} \quad (6)$$

The corresponding target matrix for ANN is formed using (5) and is given by (7).

$$T_{trn} = \begin{pmatrix} p_{1,1}^{lc} & p_{1,2}^{lc} & \cdots & p_{1,N_v \times 21 \times N_w}^{lc} \\ p_{2,1}^{lc} & p_{2,2}^{lc} & \cdots & p_{2,N_v \times 21 \times N_w}^{lc} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m,1}^{lc} & p_{m,2}^{lc} & \cdots & p_{m,N_v \times 21 \times N_w}^{lc} \end{pmatrix} \quad (7)$$

The dimension of T_{trn} matrix equals number of load categories along its row and number of possible combinations of voltages and load category percentages along its column.

D. Validation of Artificial Neural Network (ANN)

For validating the ANN, the input and target matrices could either be generated randomly following the same process for obtaining the training data or a specific load profile at the BSP could be used with known share of individual load categories. It is important to point out that validating a trained ANN using random set of data (having same seed as training data) may show very good conformity whereas, using a specific load profile pattern may result in relatively large error.

The steps for validation are: (a) generate an input matrix I_{val} and the corresponding target matrix T_{val} ; (b) input I_{val} to the trained ANN to get the output O_{val0} having the same dimensions as T_{val} ; (c) the sum of the elements (p_{i0}^{lc}) in each column of O_{val0} is not exactly one due to computational error hence, normalise as (8) and update the output matrix to O_{val} ; (d) the difference between the matrices O_{val} and T_{val} gives the load category percentage error (LCPE) matrix.

$$p_i^{lc} = \frac{p_{i0}^{lc}}{\sum_{i=1}^m p_{i0}^{lc}} \quad (8)$$

Since the validation data is a large set of randomly generated numbers, the LCPE can be expressed as either probability density function (PDF) or simple histogram plot to show the distribution of the errors. The type of PDF (e.g. Gaussian, Weibull) used to show the error distribution may vary for the different load categories.

E. Load Disaggregation

Once the ANN is trained and validated the P, Q, V measurements at the BSP can be used for load disaggregation. Since the ANN is trained in terms of per unit quantities the absolute measurements (rms) need to be converted using the base value or the rated demand (in kW/MW) at the BSP which varies with time depending on the amount of loads connected. As the rated demand is not known at any BSP, a Monte Carlo based probabilistic method could be used to estimate the rated demand [23]. A large set of per unit aggregate active power is calculated using (4) corresponding to each measured voltage value at the BSP. The value having highest probability density from the distribution of per unit active power is the most probable active power (in per unit) at that voltage. The

most probable rated demand at the BSP corresponding to this voltage will be the actual demand at that voltage divided by the most probable active power (in per unit). Validation of this load disaggregation method is shown later in Section III.

F. PoL Voltage Control

The point-of-load (PoL) voltage control is exercised by a new smart grid device called Electric Spring (ES) [2]. It is a power electronic compensator connected in series with the load (e.g. household) with only a fraction (say 5-10%) of the load rating. The compensator decouples the load from the feeder by injecting a controllable series voltage (V_{ES}). Based on the control objective, ES can either regulate the feeder side voltage (V_F) while allowing the voltage across the load (V_L) to vary within specified limits (voltage regulation [3]) or it can control the load side voltage at a desired value to vary the power consumption of the load for frequency regulation [24]. A typical arrangement is shown in Fig. 3.

The capability of an Electric Spring (ES) to control the load-side voltage depends on the rating of the power electronic converter and the load characteristic (type, power factor etc.). Generally, 5-10% voltage variation can be exercised with an ES rated at 5-10% of the load apparent power rating. For larger loads, the rating of the ES would have to increase proportionately.

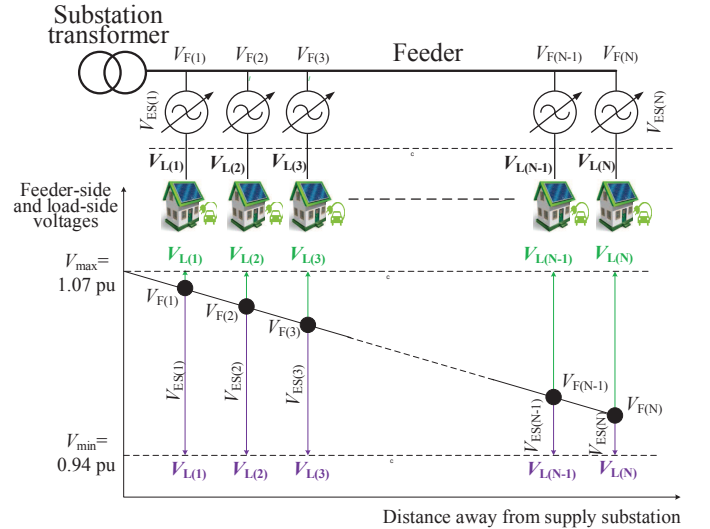


Figure 3. Typical voltage profile with point-of-load (PoL) voltage control

G. Per Unit Reserve Calculation

Alongside load disaggregation, another crucial factor in determining the reserve with PoL voltage control is the actual voltage profile across the length of the feeders which depends on many factors with a certain degree of variability. An effort has been made here to consider the uncertain parameters through Monte Carlo simulation so that the estimated reserve is realistic.

To illustrate the reserve calculation let us consider a set of k low voltage (LV) feeders each having n number of nodes. At each node the total connected load (group of households)

is divided into m load categories. The voltage at the start of the feeder is set by the secondary substation voltage which in Great Britain (GB) are 11/0.433 kV or 6.6/0.433 kV i.e. a natural boost of 8.2% compared to the nominal phase to phase voltage of 400V [25]. Survey on the use of off-load tap changers in GB [21] reveals that 52% of the secondary substations are maintained at tap position 3 (nominal), 38% are maintained below nominal and only 10% are maintained above nominal. The minimum tap position 1 provides a 5% reduction in nominal voltage. So the minimum voltage on the secondary side can be 1.03 p.u. (based on 400 V) considering nominal voltage at the primary side. Average voltage at the primary side of the secondary substation is about 0.99 p.u [25]. So the voltage at the start of the feeder for majority of the secondary substations will roughly range between 1.07 p.u. and 1.02 p.u. The voltage at the end of the feeder should be above 0.94 p.u. [22] and under light loading the customers often experience around 1 p.u. voltage. So the feeder end voltage is considered to vary between 1 p.u. to 0.94 p.u. A Monte Carlo simulation was performed to select sufficiently high (say 1000) number of points from a uniform distribution for feeder start voltage and feeder end voltage within the above limits. This provides 1000 different feeder profiles with n nodes along the feeder where, n can be a high value say 100.

For this study, it is considered that each residential customer (household) is decoupled from the distribution feeder through a power electronic voltage compensator (Electric Spring) which can reduce the load side voltage to 0.94 p.u. (v_{min}), if required. The feeder side voltages are automatically adjusted according to the current flow. The total per unit reserve available from each of the m load categories for a single feeder is given by (9) and for all the feeders together is given by (10), corresponding to one specific feeder voltage profile.

$$r_i^j = \frac{\sum_{ii=1}^n P_{0i} \left(pz_i \left(\frac{v_{ii}^2 - v_{min}^2}{v_{0ii}^2} \right) + pi_i \left(\frac{v_{ii} - v_{min}}{v_{0ii}} \right) + pp_i \right)}{n} \quad (9)$$

$$r_i = \frac{\sum_{j=1}^k r_i^j}{k} \quad (10)$$

In (9) & (10) $1 \leq i \leq m, 1 \leq ii \leq n, 1 \leq j \leq k$, P_{0i} is the nominal active power of i^{th} load category, v_{0ii} is the nominal voltage of ii^{th} node along the feeder, v_{ii} is the actual voltage of ii^{th} node along the feeder and pz_i, pi_i, pp_i are the coefficients of the ZIP model for i^{th} load category. Using (9) & (10) the per unit reserve at the secondary substation can be calculated for each load category and for all possible voltage profiles across the feeders. Using recorded measurements of P, Q, V over a year, the share of individual load categories (obtained from load disaggregation using ANN) is multiplied with the per unit reserve for each category to get the absolute reserve for each minute of a day throughout the year. This provides a reserve matrix with an order of 1000×365 for each minute and for each load category as shown in (11).

$$[R_i]_{1000 \times 365} = [r_i]_{1000 \times 1} \times [P^{agg} p_i^c]_{1 \times 365} \quad (11)$$

The reserve value with the highest density (i.e. the mode) from the probability distribution of R_i matrix is the most

probable reserve for the i^{th} load category at a given point in time. The summation of the most probable reserve values for all the considered load categories yields the total reserve, given by (12). This method when applied for each minute provides the most probable reserve profile at the BSP over 24 hours along with 90% confidence upper and lower bounds.

$$R = \sum_{i=1}^m Mo([R_i]_{1000 \times 365}) \quad (12)$$

In (12) Mo stands for the mode of the PDF. For reserve estimation in real-time a similar process can be followed by replacing the recorder measurements with the present values and thus forming a 1000×1 reserve matrix for every minute. Disaggregation using historical data recorded at a substation will provide the system operator with minimum and maximum reserve margins from that particular substation with certain confidence level. Reserve estimated using present measurements can be used to schedule other forms of reserve accordingly. For simplicity, similar load distribution was assumed at each node and the reverse power flow through the feeder was not considered in this study.

III. VALIDATION OF LOAD DISAGGREGATION METHOD

The load disaggregation method was validated using a stochastic high resolution domestic electricity demand model from the Centre for Renewable Energy Systems Technology (CREST) [16]. This model considers 35 commonly used household appliances in Great Britain and uses a combination of active occupancy pattern and daily activity profiles along with ambient lighting condition to develop a bottom-up model of household electricity consumption. It offers flexibility in terms of choosing the number of occupants, day of the week, month and stochastic allocation of appliances owned by individual households. Summation of the demand profile of individual appliances produces the overall household load profile. Repeated execution of the demand model provides different load profiles of each domestic customer which could be aggregated to produce typical load profile at the bulk supply point (BSP), such as the secondary substation.

The demand model was used to generate 500 customer load profiles, including all possible variations (occupancy level, month etc.), which provided the rated demand (actual load connected to the network) of each customer and the aggregated rated demand at the BSP considering the incidence of different appliances. In terms of the voltage dependence, the loads are classified into 5 categories as seen from the BSP. The classification is based on the following justification: (a) all the appliances with $pz = 1, pi = pp = 0$ and zero reactive power consumption ($qz = qi = qp = 0$) are grouped under Resistive type, (b) appliances having constant active power component ($pp = 1$) are grouped under constant power type or SMPS, (c) out of the motor type loads, constant torque appliances are grouped under one category (CTIM) and freezer type loads with quadratic torque characteristic are grouped under QTIM, (d) lighting loads are considered separately as they constitute 14.5% of the total electricity consumption in the domestic sector [5] (table 3.08).

The coefficients of ZIP load model [21] and the typical appliances under each load category are listed in Table I. For the purpose of load disaggregation, these 5 categories and the associated load models were considered. The parameters of each category were selected based on the appliances classified under that category. For load category 1 to 4 the ZIP parameters are the average of the respective individual appliance parameters. For load category 5, the parameters of all the freezer types were found to be the same from literature while that of the vacuum cleaner is different. Since the load factor of freezer type loads is much higher than vacuum cleaner, load category 5 is considered to have the same ZIP parameters as freezers.

Table I
LOAD CATEGORIES FOR DISAGGREGATION AT BULK SUPPLY POINT (BSP)

Load category	Load model	Appliances
LC1:Resistive	$p_z=1, p_i=0, p_p=0, q_z=0, q_i=0, q_p=0$	Iron, Hob, Oven, Kettle, Small cooking, DESWH(water heating), E-INST(water heating), Electric shower, Storage heaters, Other electric space heating
LC2:SMPS	$p_z=0, p_i=0, p_p=1, q_z=2.09, q_i=-5.76, q_p=4.67$	Answer machine, Cassette/CD player, Clock, Cordless telephone, Hi-Fi, Fax, PC, Printer, TV(type 1/2/3), VCR/DVD, TV receiver box
LC3:Lighting	$p_z=-0.01, p_i=0.96, p_p=0.05, q_z=-0.1, q_i=0.73, q_p=0.37$	Compact fluorescent lamp
LC4:Constant torque induction motor (CTIM)	$p_z=0.69, p_i=-0.47, p_p=0.78, q_z=10.76, q_i=-19.38, q_p=9.51$	Dish washer, Tumble dryer, Washing machine, Washer dryer, Microwave
LC5:Quadratic torque induction motor (QTIM)	$p_z=1.17, p_i=-1.83, p_p=1.66, q_z=7.07, q_i=-10.94, q_p=4.87$	Chest freezer, Fridge freezer, Refrigerator, Upright freezer, vacuum cleaner

The loads considered for this study are the typical UK household appliances as listed by the Department of Energy and Climate Change (DECC) in their 2016 update of Energy Consumption in the UK (ECUK) [26]. The ZIP model parameters of these appliances, as in [21], confirm that the proportion of voltage-dependent loads continue to be significant. This is further substantiated by the recent field study [27] which estimated that the aggregate domestic load real power exponent is about 1.3. Increasing interest in adopting Conservation Voltage Reduction (CVR) [28] for reducing power consumption through voltage control also confirms that reserve through voltage-controlled demand response would still be effective in future despite increasing proportion of power electronic interfaced constant power loads.

A. Rated Demand at Bulk Supply Point (BSP)

The variation of aggregate rated demand at the BSP for each of the five load categories is shown in Fig 4 in terms of their

mean values and upper/lower limits. These were obtained from the annual variations of 500 customer load profiles generated by the stochastic demand model from CREST. Resistive (LC1) and lighting (LC3) loads are seen to have the largest variation in terms of their rated demand. As expected, the peak demand at the BSP occurs around 6 pm.

Calculation of the per unit demand at the BSP (described in Section II-E) is validated here using the rated demand profile shown in Fig 4. A set of 1440 voltage samples (for each minute of the day) were generated randomly within the stipulated voltage limits in Great Britain (GB). The actual demand at the BSP was calculated using these voltages, rated demand profile (from Fig 4) and ZIP load model (from Table I). Following the steps outlined in Section II-E, the most probable (MP) values of aggregate active power at the BSP in per unit were obtained for each minute of the day. The most probable rated demand was determined by dividing the actual demand by the calculated most probable per unit active power for the corresponding minute. Fig. 5 (a) shows the most probable (estimated) and actual (from the demand model) values of rated demand at the BSP. Fig. 5 (b) presents the distribution of error between the actual and estimated rated demand confirming the reasonable accuracy of this method. The most probable rated demand of reactive power at the BSP can also be found in a similar way.

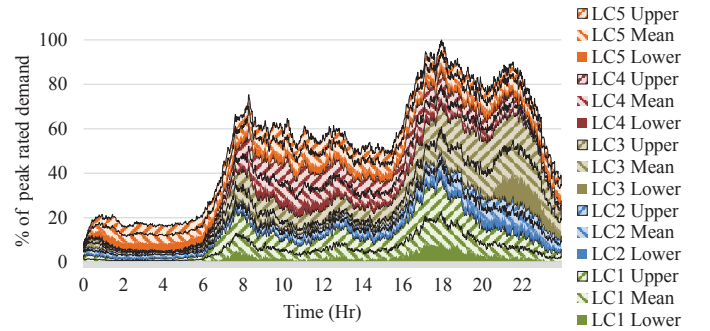


Figure 4. Variation of rated demand at the BSP during each minute for five load categories (LC1-LC5)

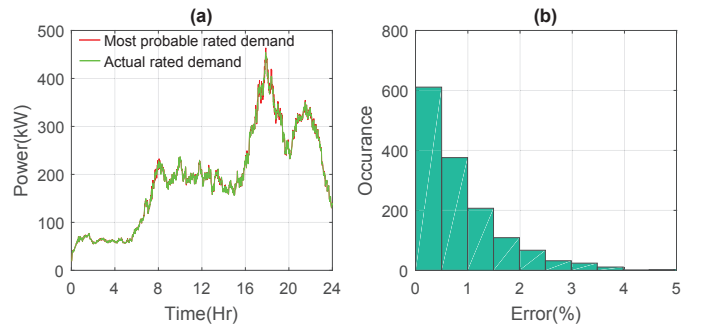


Figure 5. (a) Most probable (estimated) vs. actual (from demand model) rated demand at the BSP (b) Distribution of error between most probable and actual rated demand

This method for per unit demand calculation at BSP from known or estimated rated demand is used in the following subsections for ANN training and load disaggregation.

B. Load Disaggregation at Bulk Supply Point (BSP)

For load disaggregation, the aggregate active P and reactive Q power at the BSP were calculated using the CREST demand model (bottom-up approach) with 1 minute resolution. Together with randomly generated voltages V (within stipulated limits), such $P - Q - V$ profile mimics measured data from an actual substation. In this case, the actual share of each load category in the total demand is known beforehand and is shown in Fig. 6 (a). The $P - Q - V$ profile was used as input to the artificial neural network (ANN) to estimate the share (percentage) of each load category. It is then compared against the actual share (base case, Fig. 6 (a)) to assess the accuracy of load disaggregation for three forms of rated demand during ANN training.

1) *Known rated demand*: The artificial neural network (ANN) could be trained (as explained in Section II-C) using known values of rated demand at the BSP for each load category instead of using random values. So the uncertainty associated with the amount of each load type connected to the network at a given time is not considered but only the variability in voltage is included. This does not have practical application at present (availability of smart meter data in real-time may make it feasible in future) but provides an understanding of the inherent error associated with ANN training.

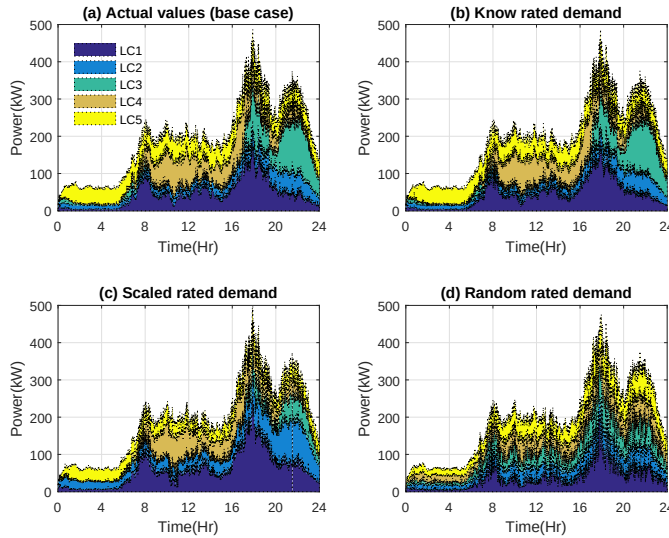


Figure 6. Share of each load category (a) Actual (base case); Disaggregated load shares using (b) known rated demand (c) scaled rated demand (d) random rated demand

The rated demand for each load category was taken from the base case and was used for P_0 & Q_0 in (1) & (2). A set of random voltage samples were used to calculate the actual demand at the BSP (and converted to per unit) and the percentage share of each load category to form the input (I_{trn}) and target (T_{trn}) matrices for the ANN training, respectively. The weighting factors (w_i) were no longer required for P_{agg} & Q_{agg} calculation. The disaggregated load profile for the same set of $P - Q - V$ values used in the base case is shown in Fig. 6 (b) which matches very closely with Fig. 6 (a). The distribution of error against the base case (shown in Fig. 7 (a)) points out that the most probable error lies around 2.5%

which is inherent to the ANN training process and is unlikely to be reduced any further.

2) *Scaled rated demand*: Training of ANN using known rated demand for each load category is accurate but not practical at present. It might be possible (although still difficult) to know the pattern of variation of rated demand for each load category instead of the actual amount. The accuracy of load disaggregation under such circumstances was compared against the base case.

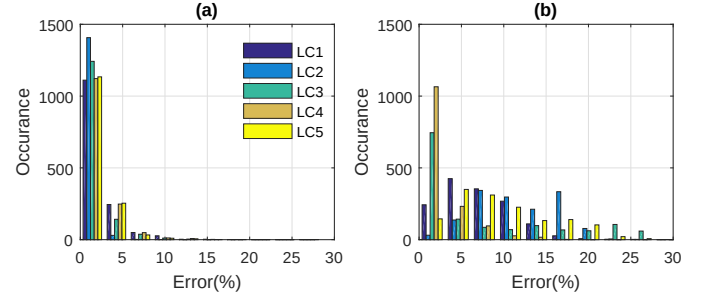


Figure 7. Distribution of error in load disaggregation based on (a) known rated demand (b) scaled rated demand

Fig. 8 (a) shows the percentage share of actual rated demand profiles obtained from CREST demand model. These profiles were scaled randomly to change the percentage share of each load category at every minute while preserving the pattern over 24 hours, as shown in Fig. 8 (b).

The ANN was trained with the scaled rated demand profile following the same procedure as in the case of known rated demand. The load at the BSP was disaggregated into the 5 load categories, as shown in Fig. 6 (c), using the same set of $P - Q - V$ values as in Fig. 6 (a). Comparison with the base case reveals some disparities especially, for SMPS-type loads (LC2) during the late evening hours. The distribution of error in Fig. 7 (b) confirms that it is mostly limited within 10% with the exception of LC2.

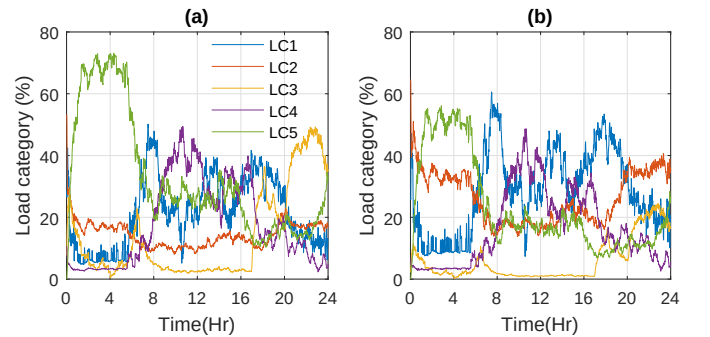


Figure 8. Percentage share of individual load category (a) before scaling (b) after scaling

3) *Random rated demand*: In practice, the rated demand for individual load categories will be unknown at the BSP. Hence, the load disaggregation would have to deal with the uncertainty associated with the number of loads connected and the corresponding voltages. As a result, the ANN should be trained extensively using the method discussed in Section II-C, considering a large set of data including all the possible combinations of $P - Q - V$. This would enable the trained

ANN to extrapolate values for load shares under different operating conditions.

For training the ANN, the number of random voltage samples and weighting factors considered were $N_v = 40$ & $N_w = 40$, respectively. As the share of motor-type load (LC4& LC5) is found to vary from 5% to 85% (and static-type load from 95% to 15%) based on the CREST demand profile, it was necessary to consider 17 static-motor type load combinations. This resulted in 27200 ($=40 \times 40 \times 17$) data sets for ANN training. The set of $P - Q - V$ values used in the base case were fed to the trained ANN to obtain the disaggregated load profiles shown in Fig. 6 (d). The error in load disaggregation (shown in Fig. 9 (b)) is mostly limited to 15% with the exception of LC3 and LC4. As expected, the accuracy of load disaggregation using random rated demand is poorer compared to using known or scaled rated demand. However, this amount of error is not reflected directly in the reserve estimation which also depends on voltage sensitivity of individual load category and the voltage profile across the feeders.

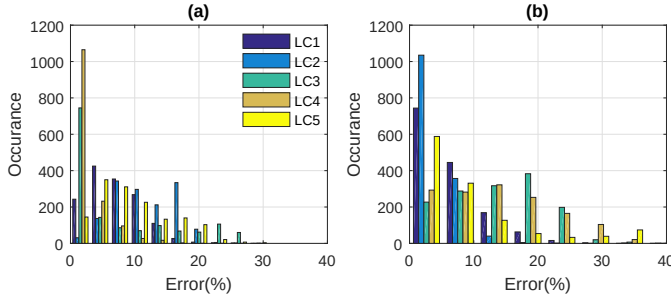


Figure 9. Distribution of error in load disaggregation based on (a) scaled rated demand (b) random rated demand

IV. CASE STUDY ON RESERVE ESTIMATION

The aggregate reserve estimation using the methodology in Section II is demonstrated here through a case study.

A. Reserve at Domestic Sector Bulk Supply Point (BSP)

The stochastic high resolution domestic electricity demand model from CREST [16] for 500 households was aggregated to synthesize the active and reactive power profile at the bulk supply point (BSP). This was done separately for the weekdays and weekends of each month of the year with 1 minute resolution and known share from each load category (listed in Table I). The reserve at the BSP was determined using the steps outlined in Section II-G and is shown in Fig. 10. The actual reserve from known share of each load category is marked with prefix “Ac” while the estimated reserve (load share from ANN) is marked with prefix “Es” in Fig. 10.

Fig. 10 (a) shows the most probable (MP) reserve available at the secondary substation with 90% upper/lower confidence bounds (UB/LB). The peak reserve is around 6 pm when the system experiences maximum demand. Fig. 10 (b) shows the empirical CDF of the percentage error between the actual and the estimated reserve. A negative error means the estimated reserve is less than the actual reserve. The CDF plots show

that the confidence level of the reserve estimation method is more than 95% in the confidence interval $[-1\%, +1\%]$.

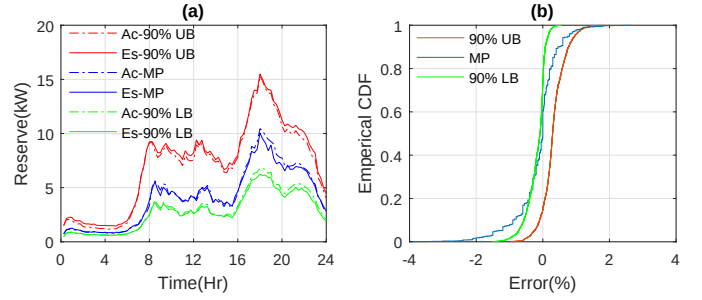


Figure 10. (a) Estimated and actual reserve from CREST (b) Empirical CDF of estimated reserve error

B. Reserve from Domestic Sector in Great Britain (GB)

The ‘typical’ domestic sector power profile at the BSP from the previous subsection was scaled up to obtain an estimate of the aggregate reserve available from the domestic sector loads in Great Britain (GB). The overall consumption of the GB system can be split into domestic, service, industry and transport sectors. The domestic sector has the largest share (37%) based on the annual energy consumption data [5]. The share of domestic sector loads varies between 20% around midnight and 40% at the peak hour (6pm) [21] with weekly as well as monthly variations [29].

For this study, half hourly domestic demand on weekdays for the month of February was used to scale up the estimated reserve based on the ‘typical’ aggregate domestic sector power profile at the BSP from Section IV-A. Fig 11 (a) shows the half hourly variation of GB domestic sector demand [29] and Fig 11 (b) shows the estimated reserve from the domestic sector in GB together with 90% upper/lower confidence bounds (UB/LB).

The most probable (MP) value of estimated reserve is found to be around 0.5 GW from midnight till 8 am while it reaches a peak value of almost 1.5 GW around 6 pm. The upper/lower bounds provide an envelope within which the estimated reserve at any day of a year should lie in 90% of the cases. Although the results are reported here only for the domestic sector, similar methodology can be applied to scale up the reserve figures using a stochastic high resolution electricity demand model for the industrial and service/commercial sectors. Moreover, actual substation recordings (which were not available for this study) could be used to refine the estimates. Nonetheless, these results show that use of PoL voltage control in the GB domestic sector alone could provide 500 MW (in low load condition) out of the 800-950 MW enhanced response (less than a second response time [30]) required under future low inertia scenarios [31].

C. Validation of Bounds on Estimated Reserve

The statistically estimated bounds on reserve, shown in Fig 11 (b), is validated here considering the actual voltage profiles across the feeders in IEEE 69 bus distribution network [32]. There is one main feeder and seven lateral feeders supplying 48 loads with a total capacity of 3802 kW.

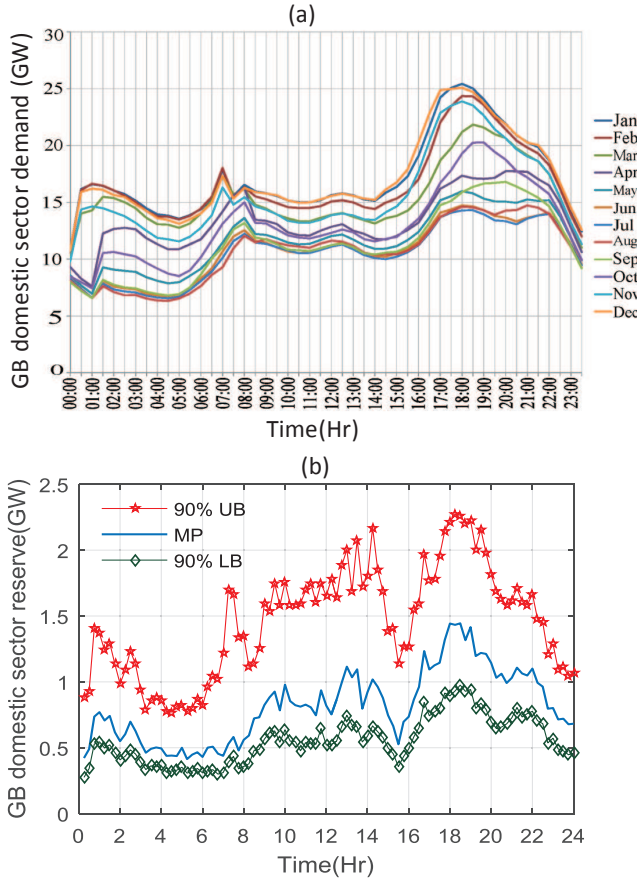


Figure 11. (a) Half hourly demand of GB domestic sector (b) Estimated reserve from GB domestic sector

Each load was considered to have a distinct 24 hour demand profile for a particular month which was generated using the stochastic high resolution electricity demand model (CREST). The substation voltage was maintained at 1.05 p.u. and feeder end voltages within the minimum permissible value of 0.94 p.u. The difference between the aggregated power at the substation under normal condition (P_{sub}^{NLL}) and in presence of PoL voltage regulators reducing all the load voltages to 0.94 p.u. (P_{sub}^{PoL}) provided the absolute value of reserve. This was obtained from power flow analysis which includes the network losses. The per unit reserve figure was determined using the known rated demand in this case and the calculations were repeated for each month. Using the domestic sector demand in GB for each month (shown in Fig 11 (a)), the absolute reserve was calculated for the GB system, which is shown in Fig. 12 together with the same 90% upper/lower confidence bounds (UB/LB) from Fig. 11. The monthly reserve profiles are found to lie within the statistically estimated upper and lower bounds.

V. CONCLUSION

In this paper, we have presented a methodology for the grid operators to estimate the aggregate reserve available with point-of-load (PoL) voltage control. This is based on load disaggregation at the bulk supply points (BSPs) and use of a probabilistic approach to capture the variability in various factors affecting the reserve. The method is generic and could

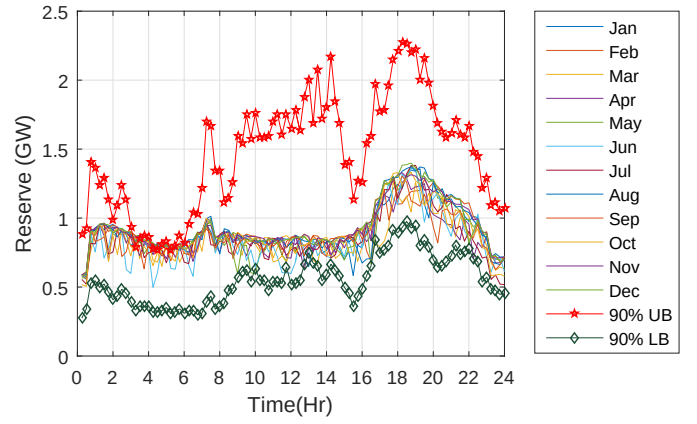


Figure 12. Estimated reserve from GB domestic sector based on case study in IEEE 69 bus distribution network

be applied at any BSP where power (active and reactive) and voltage measurements are available. Stochastic demand model for the domestic sector in Great Britain (GB) was used to validate the reserve estimation method and also to determine the overall reserve available with PoL voltage control in GB. The estimation could be done either offline or in real-time for use in time ahead reserve scheduling. Considering the variabilities involved, the actual reserve could differ from the estimated (most probable) values but are likely to lie within the corresponding upper/lower bounds 90% of the time. This would allow the grid operators to schedule other forms of reserve accordingly using for example, the conservative (lower bound) figures for the estimated reserve. The reserve estimation could be made more accurate if specific information at certain BSPs (e.g. trend of rated demand for different load categories etc.) are available. The results presented in this paper show that the use of PoL voltage control in the GB domestic sector alone could provide majority of the 800-950 MW enhanced response (act in less than a second) required under future low inertia scenarios.

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