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A Statistical Method to Establish Voltage Dependency Load Parameters Based on Field Measurements

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***Abstract*—Voltage dependency static load models are commonly applied to simulation studies on low voltage network. However, there is generally a lack of established key parameters for voltage dependency static load models to represent loads commonly used in residential premises. This paper presents a statistical approach to determine key parameters in voltage dependency static load models. Eleven (11) individual single- phase types of loads were investigated based on field measurements corresponding to on-load tap-changer operations at 33 kV upstream. Changes in active and reactive power of the individual loads due to changes in input voltages were recorded and analyzed statistically to determine the parameters used for the voltage dependency static load model. The results were validated through laboratory measurements of the individual loads and found to be consistent and in close agreement with results obtained from the statistical analysis. A simulation case study performed on a low voltage network with solar photovoltaic penetration indicates significant deviation in peak power demand, power losses, reverse power flow and energy consumption in the network between constant power load model and LTV model in particular when source voltage is set at above 1.0 per unit.**

***Index Terms*—voltage dependency load modelling, exponential load model, power system study, low voltage distribution network.**

I. INTRODUCTION

Distribution networks at both medium and low voltage levels are evolving from the traditional passive type to active network as distributed generation, electric vehicle charging facilities, volt-var optimized (VVO) operation, storage devices and other smart grid technologies are being added to the system. Consequently there is a need to represent loads even at low voltage (LV) network more accurately using voltage dependency models for simulation studies. A number of research and pilot projects were launched to study the LV network in detailed. For example, voltage measurements at LV busbars, LV voltage network solutions, LV integrated automation, LV protection and communications were carried out by Electricity North West Limited in the UK, while LV network modelling and analysis environment were conducted by Scottish energy, and smart urban LV network by UK power network.

With the introduction of active distribution network, it becomes necessary to perform power flow simulations using quasi dynamic loads as input in order to obtain a more meaningful and strategic solution. One of the main challenges for network modeling is in choosing the appropriate load models for the simulation studies. Numerous efforts have been put at the medium voltage load modelling [1]–[4] to accurately represent different types of loads. At the LV distribution network level, electrical characteristics of consumer's appliances with time-varying models of residential loads suitable for the analysis of smart grid applications and LV demand-side management were developed and reported in [5].

The importances of using appropriate load model in the power system study are mentioned in [6]. Dynamic load models are required for stability studies whereas static load models are applied to load flow studies. A survey was conducted in [7] to study the industry practices in load modelling. Majority of the utilities (around 84% in the world) are still using the simplest load model, which is the constant power model for load flow studies, which do not accurately reflect the actual systems behavior in terms of voltage fluctuations throughout the day. Hence, load to voltage (LTV) dependency models are required for power flow simulations in order to obtain results which truly reflects the network capability and behavior. Generally, they are three common types of LTV dependency model; namely ZIP which is also known as polynomial model [8], exponential model [4] and composite model [9].

Most of the load modelling techniques proposed in the literatures are based on actual measurements [1], [3], [8], [10]. These measurements are typically based on expensive fault recorders installed at primary substations which capture the load response during disturbance events and then uses the data to model the LTV loads [9], [10]. However, this approach has a limitation as it requires fault events to generate sample data, and fault events are usually infrequent. For LV power flow simulations, it is usually sufficient to assess the impact of voltage changes to power flow in the network.

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This paper proposes a statistical approach using on load tap changer (OLTC) operations at 33 kV upstream to determine key parameters of voltage dependency static loads in representing single phase loads commonly found in residential premises. Laboratory experiments were carried out to validate the mean value of the parameters obtained from the statistical analysis of the field measurements data. A LV network with solar photovoltaic (PV) penetration is used as a case study to determine the impact on peak power demand, peak power losses, reverse power flow and energy consumption in the network using LTV model to represent consumer loads.

The organization of this paper is as follows. Section II discusses the methodology to establish the key parameters and power coefficients of the LTV model. Section III presents the results from statistical analysis of field measurement data and comparing them with laboratory experiment results. Section IV discusses the application of the LTV model for a case study on a LV network with solar PV penetration. Section V concludes the findings of this paper.

II. STUDY METHODOLOGY

A. Voltage Dependency Load Model

Previous researchers have developed three types of voltage dependent load models, namely the polynomial, exponential and composite models.

The polynomial model comprises of mixed constant impedance, constant current and constant power loads. The equations representing active and reactive power of the polynomial model are as shown in (1) and (2) respectively.

$$P = P_o\left(\alpha_1\left(\frac{V}{V_0}\right)^2 + \alpha_2\left(\frac{V}{V_0}\right) + \alpha_3\right) \quad (1)$$

$$Q = Q_o\left(\beta_1\left(\frac{V}{V_0}\right)^2 + \beta_2\left(\frac{V}{V_0}\right) + \beta_3\right) \quad (2)$$

where α_1, α_2, and α_3 are the active power composition of constant impedance, constant current and constant power respectively, and β_1, β_2, β_3 are the reactive power composition of constant impedance, constant current and constant power respectively, with $\alpha_1+\alpha_2+\alpha_3 = 1.0$, and $\beta_1+\beta_2+\beta_3 = 1.0$.

V_0 is the nominal voltage and V is the supply voltage. P_0, P and Q_0, Q are the active and reactive power at the nominal and supply voltage respectively.

The exponential load model equations are shown in (3) and (4).

$$P = P_0\left(\frac{V}{V_0}\right)^{Zp} \quad (3)$$

$$Q = Q_0\left(\frac{V}{V_0}\right)^{Zq} \quad (4)$$

where z_p and z_q are the load coefficients for the active and reactive power component respectively and could be determined from α_1, α_2, α_3 and β_1, β_2, β_3 [7].

B. Field Measurment Set Up

In Malaysia, OLTC operation is at the 33/11 kV transformers with each step tap change at 1.67%. 11/0.4 kV distribution transformers are equipped with no load tap changer and therefore do not contribute to dynamic voltage regulations. Additionally, voltage variations are due to switching ON/OFF loads.

Supply voltage from the utility fluctuates throughout the day due to load change and OLTC operations. High resolutions energy loggers with one second time interval were used to record supply voltage (V), active power (P), and reactive power (Q) consumption of individual appliances in a residential home for two consecutive days so as to capture sufficient data samples for the load model.

Power and voltage measurements were performed on home appliances which includes fluorescent lamp, compact fluorescent light (CFL), LED light, computer workstation, portable laptop, table fan, tablet, conventional air-conditioner, inverter type air-conditioner, inverter type refrigerator and LCD television using power recorders. See Fig. 1.

A 24-hour voltage profile as shown in Fig. 2 indicates the changes in supply voltage to the home appliances due to OLTC operations and load switching.

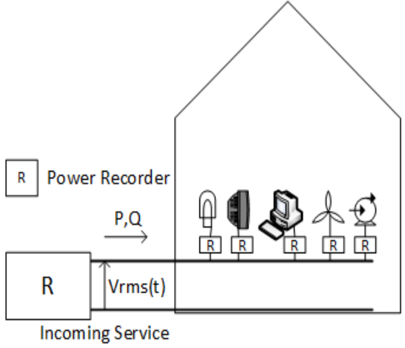

Figure 1. Field measurement set up.

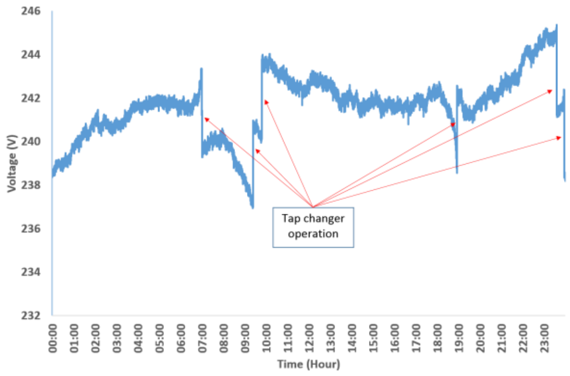

Figure 2. Changes in OLTC operation in a 24 hour period.

C. Data Processing

The recorded data of each individual loads were processed according to the steps described below corresponding to the flow chart shown in Fig. 3.

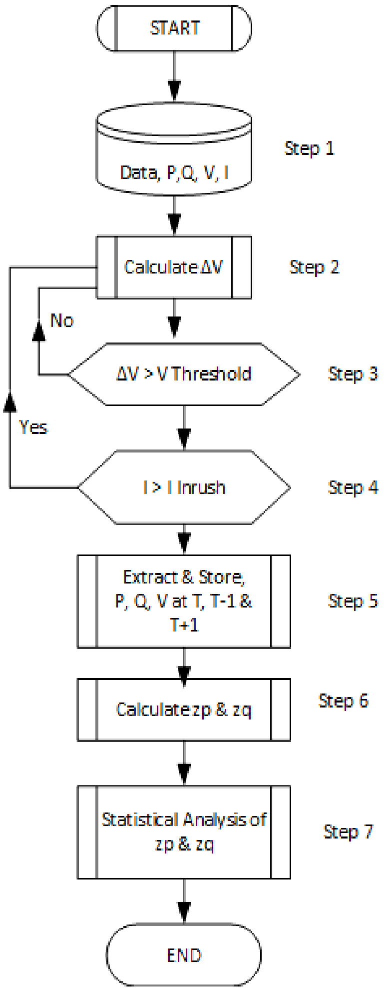

Figure 3. Data process flow chart.

Step 1: Import data from power recorder; one second resolution voltage (V), current (I), active power (P) and reactive power (Q). Operation time of OLTC is within one second.

Step 2: Calculate change in voltage, ΔV which is the difference in voltage before and after each OLTC operation or due to a transient voltage resulting from switching in the network.

Step 3: A threshold voltage, ΔV_{TH} of 0.2% is selected and used to filter insignificant changes in voltages. Voltage variations due to OLTC operation is between 0.5 to 2.5% [6]. A 0.2% is selected so as to include minor changes in voltage due to load/equipment switching in the network.

Step 4: Changes in current before and after voltage change are used to filter events related to inrush current of the load under investigation. For example, voltage drop due to inrush current of a water heater is considered as an invalid data for the water heater load itself but are valid for other loads.

Step 5: Data extraction in the form of V, P, and Q that corresponds to each time T, T-1 and T+1 as in (5) and (6).

Step 6: Calculate active and reactive power coefficient, z_p and z_q from the data extracted in Step 5 using (5) and (6).

Step 7: Perform statistical analysis on z_p and z_q.

$$P_T = P_{T-1}\left(\left[\frac{V_T}{V_{T-1}}\right]^{zp}\right) \tag{5}$$

$$Q_T = Q_{T-1}\left(\left[\frac{V_T}{V_{T-1}}\right]^{zq}\right) \tag{6}$$

The statistical output of the active and reactive power coefficients of a CFL load are shown in Fig. 4 and Fig. 5. Both coefficients shown normal Gaussian distribution curve. The mean and standard deviation for both coefficients are calculated.

D. Laboratory Measurement

Experiments to determine the relationship between changes in voltage and power in each of the loads were carried out in laboratory and the results compared with those obtained from field measurements. The experimental set up is as shown in Fig. 6.

In the experiment, a voltage stabilizer is used to regulate the AC voltage at a constant level. Input voltage to the load under test is varied with a variable transformer from 215V to 250V. Voltage, current, active, and reactive power of the load under test are recorded by the power recorder.

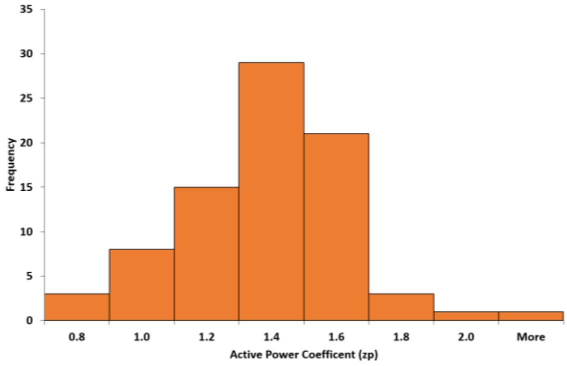

Figure 4. Distribution of calculated active power coefficient, z_p.

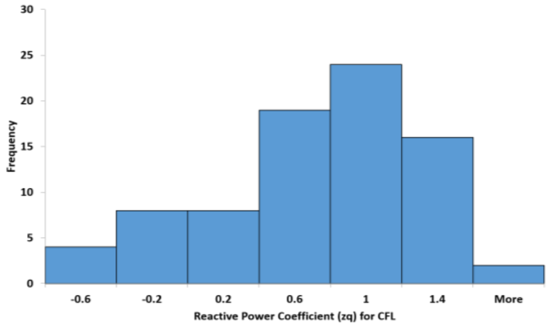

Figure 5. Distribution of calculated reactive power coefficient, z_q.

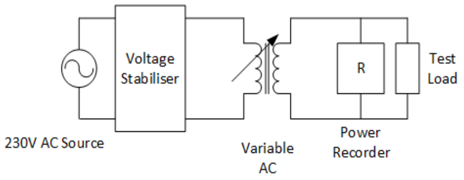

Figure 6. Laboratory measurement.

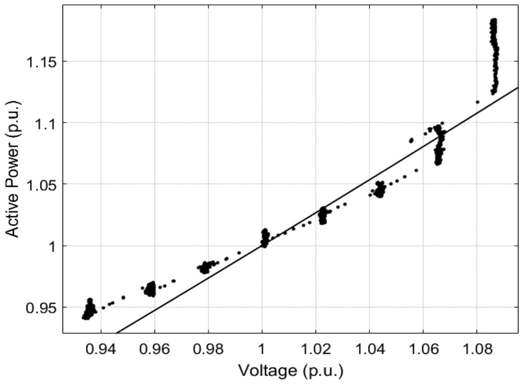

Figure 7. Active power curve fitting for CFL.

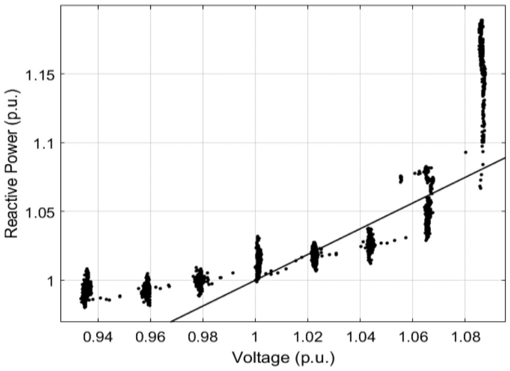

Figure 8. Reactive power curve fitting for CFL.

TABLE I: GOODNESS OF CURVE FITTING

Coefficient	SSE	R-square	Adjusted R-square	RMSE
Z_p	1.868	0.8651	0.8651	0.02458
z_q	4.493	0.4598	0.4598	0.03812

The data measured from the experiment is then processed using curve fitting technique. The active and reactive power coefficient are tuned with 95% confidence bounds. Fig. 7 and Fig. 8 show the curve fitting for CFL with goodness of fit shown in Table I.

III. RESULTS

Statistical analysis of the data based on field measurements shows that the power coefficient z_p and z_q obtained for the eleven (11) types of loads are distributed with mean and standard deviations as shown in Table II.

Additionally, the power coefficients obtained from laboratory measurements were compared against field measurement results and found to be in close agreement as shown in Table II.

Among the eleven (11) types of loads measured, it is found that the fluorescent lamp is the most sensitive to voltage changes with the highest LTV power coefficients.

The power coefficients, z_p and z_q for typical home appliance varies between 0.07 to 2.44, and -0.67 to 21.49 respectively. Positive coefficients indicate that any voltage reduction would likely reduce power consumption while negative coefficients imply that any voltage reduction would increase power consumption.

IV. CASE STUDY

The voltage dependency aggregate load model based on field measurements of a LV residential network was developed and used in this case study. The measurement was carried out at one residential house in Malaysia. The aggregated load coefficient was calculated using the proposed method. The load coefficients, z_p and z_q are time varying as the voltage and power varies at different periods of the day as shown in Fig. 9. In this case study, the aggregate load model is used to study the impact of solar PV system on a residential LV distribution network.

TABLE II: ACTIVE AND REACTIVE POWER COEFFICIENT

Appliances	LTV Power Coefficients							
	z_p				z_q			
	Field Measurement		Laboratory Experiment		Field Measurement		Laboratory Experiment	
	Mean Value	Standard Deviation	Best Fit Value	Difference (%)	Mean Value	Standard Deviation	Best Fit Value	Difference (%)
Compact Fluorescent Light	1.24	0.36	1.33	-6.64	0.73	1.29	0.94	-21.92
LED Light	0.24	0.16	0.27	-2.20	-0.67	1.95	-0.68	+1.41
Personal Computer	0.24	1.64	0.23	+6.12	1.69	0.56	1.89	-10.11
Laptop	1.48	1.56	1.56	-5.15	1.68	1.13	1.40	+20.12
Fan	1.99	0.15	1.90	+4.43	3.04	1.86	2.90	+4.84
Fluorescent	2.44	0.14	2.30	+6.26	2.90	0.09	3.46	-16.01
Tablet	0.07	1.77	0.08	-7.58	-1.93	12.77	-1.90	+1.48
Conventional Air Cond.	0.98	0.59	0.89	+4.40	5.30	1.46	5.44	-2.55
Inverter Air Cond.	0.77	0.13	0.53	+2.41	21.49	7.47	15.97	+10.27
Refrigerator	0.12	0.40	0.82	-2.85	3.82	2.89	2.20	+14.38
Television	0.04	0.93	0.05	-3.47	1.81	4.92	1.69	+7.25

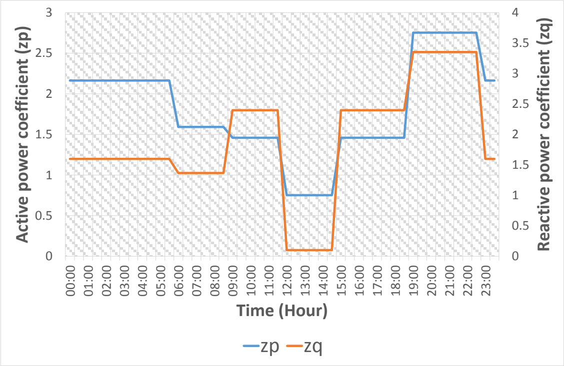

Figure 9. Time varying power coefficient.

TABLE III: CASE INVESTIGATED

Case	Source voltage (per unit)	Load model
I	0.94, 1.00, 1.10	Constant power
II	0.94, 1.00, 1.10	LTV

Two (2) cases as shown in Table III were investigated to determine the impact of different load models on power losses, reverse power as well as energy consumption in the low voltage distribution network with solar PV system.

A. LV Reference Network

The reference network developed in [13] is used in this case study. The network is modified to include the active and reactive power coefficient of various home appliances. The home appliance is modelled in details using DIgSILENT PowerFactory software. The single line diagram of the LV network is as shown in Fig. 10.

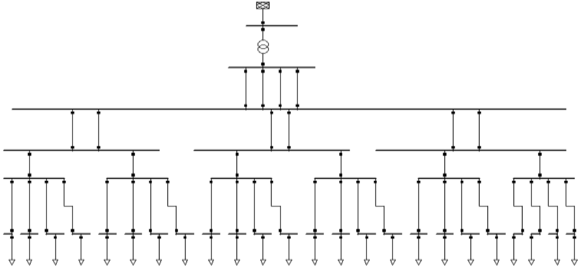

Figure 10. Single line diagram for residential network with fully underground system.

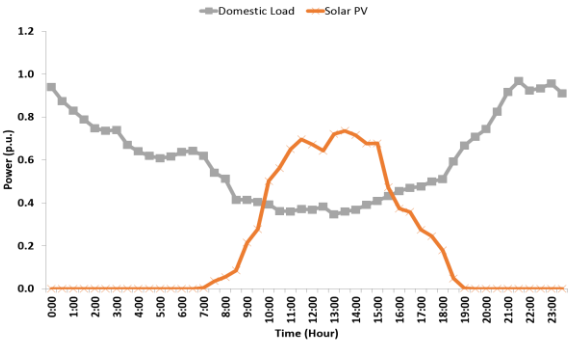

Figure 11. Load demand and PV generation profile.

Fig. 11 shows the load profile and PV generation profile. The load profile is generated by using the actual aggregated load profile recorded at Malaysian utility as well as PV generation profile.

B. Peak Power Demand and Network Losses

Peak power demand at the distribution substation is influenced by the type of load model used in the simulation. For source voltage less than 1.0 p.u, LTV model results in lower peak power demand compared to the constant power model as shown in Table IV.

Consequently, peak power losses is also lower in the case of LTV model is used as shown in Table V.

However, when the source voltage is raised to above 1.0 p.u, the LTV model shows a higher peak power demand, and higher power losses than the constant power model.

The effect of LTV model on reverse power flow which is consistent with the changes in peak power demand is shown in Table VI. With source voltage above 1.0 p.u, LTV model indicates higher consumption of power and therefore a smaller amount of reverse power flow.

TABLE IV: LOAD MODEL EFFECT ON PEAK POWER DEMAND

Source Voltage (p.u.)	Maximum demand (kW)		Difference (%)
	Constant power model	LTV load model	
0.94	244.54	208.00	-14.94
1.00	244.30	235.64	-3.54
1.10	244.08	285.53	16.98

TABLE V: LOAD MODEL EFFECT ON PEAK POWER LOSSES

Source Voltage (p.u.)	Peak power losses (kW)		Difference (%)
	Constant power model	LTV load model	
0.94	4.54	3.76	-17.18
1.00	4.31	4.13	-4.17
1.10	4.08	4.82	+18.14

TABLE VI. LOAD MODEL EFFECT ON REVERSE POWER FLOW DUE TO SOLAR PV

Source Voltage (p.u.)	Maximum reverse power (kW)		Difference (%)
	Constant power model	LTV load model	
0.94	124.18	133.28	+7.33
1.00	124.10	123.87	-0.19
1.10	123.91	106.80	-13.81

C. Energy

LTV model shows lower energy consumption in consumer loads as indicated in Table VII.

TABLE VII: ENERGY CONSUMPTION CALCULATED FROM THE SIMULATION

Source Voltage (p.u.)	Load Model	Grid (kWh)	PV (kWh)	Consumer Energy Consumption (kWh)
0.94	Constant Power	2131	1423	3495
	LTV	1653	1423	3022
1.00	Constant Power	2132	1423	3495
	LTV	2057	1423	3421
1.10	Constant Power	2134	1423	3495
	LTV	2787	1423	4141

V. CONCLUSION

Voltage dependency load parameters established from field measurements were used as LTV model to perform case studies to determine the effect of LTV model on network simulation studies. The results shows that LTV model gives a more conservative outcome in terms of substation peak power demand, network peak power losses and energy consumption of loads when the source voltage is set at less than or equal to 1.0 p.u. This gives an indication that energy conservation could be realized when voltage is set conservatively at the grid source and optimally controlled in the distribution network.

Further improvement in establishing the power coefficients will be addressed in the next part of our research through advanced noise and bad data filtering process. In addition, the proposed methodology will be used to quantify the potential benefits of implementing conservative voltage reduction (CVR) schemes power utility network.

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