Author/s:
de Hoog, J;Muenzel, V;Jayasuriya, DC;Alpcan, T;Brazil, M;Thomas, DA;Mareels, I;Dahlenburg, G;Jegatheesan, R

Title:
The importance of spatial distribution when analysing the impact of electric vehicles on voltage stability in distribution networks

Date:
2015-03-01

Citation:
de Hoog, J., Muenzel, V., Jayasuriya, D. C., Alpcan, T., Brazil, M., Thomas, D. A., Mareels, I., Dahlenburg, G. & Jegatheesan, R. (2015). The importance of spatial distribution when analysing the impact of electric vehicles on voltage stability in distribution networks. Energy Systems, 6 (1), pp.63-84. https://doi.org/10.1007/s12667-014-0122-8.

Persistent Link:
https://hdl.handle.net/11343/282622

Energy Systems manuscript No.
(will be inserted by the editor)

The Importance of Spatial Distribution when Analysing the Impact of Electric Vehicles on Voltage Stability in Distribution Networks

Julian de Hoog · Valentin Muenzel · Derek Chanaka Jayasuriya · Tansu Alpcan · Marcus Brazil · Doreen Anne Thomas · Iven Mareels · Glenn Dahlenburg · Raman Jegatheesan

Received: date / Accepted: date

Abstract The recent emergence of distributed generation, smart meters, and electric vehicles means that much attention is now being given to network modelling and analysis at the distribution, rather than transmission, level. Many optimisation studies, both regarding technical and economic questions, aim to satisfy the constraints posed by grid infrastructure. We explore in detail

J. de Hoog and D. A. Thomas
Department of Mechanical Engineering
University of Melbourne, Australia
Tel.: +61-3-9035 8961, E-mail: julian.dehoog@unimelb.edu.au

V. Muenzel, D. C. Jayasuriya, T. Alpcan, M. Brazil, and I. Mareels
Department of Electrical and Electronic Engineering
University of Melbourne, Australia

G. Dahlenburg
Ergon Energy
Queensland, Australia

R. Jegatheesan
United Energy
Victoria, Australia

one of these network constraints, minimum required voltage, at the distribution level and demonstrate that the physical locations of individual loads in the network play a significant role in determining whether voltages throughout the network remain within required limits or not. Our simulations use real distribution network data and are run on models of two real neighbourhoods. We show that the addition of a single load at a weak point of the network can have the same impact as considerably greater numbers of loads at stronger locations of the network. This has important implications for applications such as electric vehicle charging, and suggests that spatial distribution of loads should be taken into account when analysing network stability.

Keywords Voltage Stability · Electric Vehicles · Distribution Networks · Simulation · Optimisation · Spatial Distribution

1 Introduction

Traditionally, low voltage distribution networks were seen as the last step in the power distribution chain, and most utilities had no need to model and analyse the distribution level in great detail. However, in recent years this has changed due to a number of strong trends: increasing installation of distributed generation [1]; an increased emphasis on demand management and decentralized intelligence [2]; and the emergence of large new controllable loads such as electric vehicles [3]. In short, the electricity industry is undergoing an upheaval that is leading to much research on voltage control, fault analysis, and general stability at the *distribution* level, rather than at the transmission level.

Electric vehicles (EVs) will likely play a large role in distribution network analysis and control. Not only are they among the largest loads in distribution networks – with charge rates of 3.5 kW in current models and charge rates greater than 6kW expected in the next generation of models – but they can be *controllable* loads that may be charged at off-peak times to make maximum use of network capacity. Many studies are pursuing such smart charging strategies [4–7], and several further suggest the use of vehicles as distributed storage units [3, 8].

A typical approach to solving the electric vehicle charging problem, and indeed many similar control problems at the distribution level, is to find an optimal solution that respects the various constraints in the network. There are many such constraints, for example: transformers have power ratings that should not be exceeded; lines have current ratings that should not be exceeded; voltage at each point of connection must be kept within specific lower and upper limits; harmonic distortion may not exceed a particular limit; and phase unbalance should not exceed a certain percentage.

Many studies on the impact of new grid technologies – both technical and economic – consider these constraints under average load profiles, average penetration rates, or (in the case of electric vehicles), average charging behaviour. However, in distribution networks, the size, timing and in particular location of *individual* loads can have a very strong impact on network performance. In this paper we explore how extensive this impact can be, and point out the importance of taking spatial distribution of loads like electric vehicles into account when conducting such studies.

1.1 Impact of Electric Vehicles

Over the last decade there have been many case studies regarding the potential impacts of electric vehicles, both in real trials and in extensive simulation studies. In a study based on typical network types found in British Columbia, Canada, it is found that electric vehicles could lead to significant increases in peak demand, overloading of the secondary transformer (particularly in suburban networks), and voltage drop (particularly in rural networks) [9]. A study using a Danish distribution network model finds that voltage levels drop below required levels already at 10% vehicle uptake, with a peak demand increase of 31% when there is a vehicle uptake of 50% [10]. A study in Belgium shows a significant increase in power losses and voltage deviations when vehicle charging is uncontrolled [4]. A study coming out of Spain finds that 60% electric vehicle uptake leads to a 40% increase in energy losses [11]. A 10% electric vehicle uptake rate was found to lead to violation of grid constraints in a network model based in Portugal [3]. The limiting factor in an uncontrolled charging scenario in a study in Ireland was found to be voltage drop [6].

In the Australian networks we have previously studied, the first point of failure in electric vehicle charging applications has typically also been voltage dropping below required levels [7]. Voltages drop from one house to the next along a distribution system feeder since the feeder has an impedance of its own. As the amount of current in the feeder increases, so do the drops in voltage from one house to the next. With distribution networks often stretching for several hundred metres (or more in rural areas), voltage supplied to customers at the far end of the network will often have dropped considerably from its original level at the distribution transformer.

Large loads like electric vehicles draw additional current, leading to additional drops in voltage. The problem is compounded by phase unbalance: unbalanced phases will lead to increasing current in the neutral line, which will further contribute to lowering voltages due to neutral line impedance. Distribution service operators are required by distribution codes to maintain voltages at point of supply within specific limits[1]; when thresholds are exceeded, appliances may have shorter lifetimes or fail, and the distribution companies may face heavy fines. Many networks were built 10, 20, or even 30 years ago and did not take the emergence of electric vehicles into account, so there is concern that new large loads like electric vehicles will significantly increase the risk of voltage dropping below required minimum levels in many networks.

1.2 Voltage Stability

Voltage stability is defined as "the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition" [13]. In this paper we focus on *small-disturbance voltage stability*, which refers to "the system's ability to maintain steady voltages when subjected to small perturbations such as incremental changes in system load" [13].

Voltage stability first began to receive notable attention in the 1970s, and has since been extensively studied [14], with popular approaches including continuation power flow [15], sensitivity analysis [16], and modal analysis [17]. However, most work has focussed on the transmission system, and only the last decade has seen a greater interest in voltage stability at the distribution level. As with transmission networks, in distribution networks a typical approach is to predict the weakest bus in the system. Early attempts reduced the network to a single line equivalent [18, 19]; more recently this has been done using

[1] Australian standard 60038 sets voltage limits at customers' point of connection to be 230V +10% / -6%, in other words within (216V, 253V) [12].

voltage stability indices [20, 21], which have been extended to unbalanced multi-phase networks [22]. Voltage stability indices provide an insight into which nodes in the network are the weakest; a good review of different types of indices and their relative advantages can be found in [23].

In this paper we use a voltage stability index almost identical to the one recently proposed in [22], since we are studying 3-phase, unbalanced distribution networks. Since distribution networks are mainly resistive (in the data set provided by our utility partner, 99% of data points have a power factor greater than 0.95), this index uses only the magnitude of the positive sequence voltages at each bus:

$$L_i = \frac{V^+_{i,limit}}{V^+_{i,noload}} \tag{1}$$

where i is the number of the bus, $V^+_{i,limit}$ is the voltage at bus i when voltage at any bus in the network drops below the required limit, and $V^+_{i,noload}$ is the voltage at bus i when all loads are zero. $V^+_{i,limit}$ is found by iteratively increasing the load at all buses in the network and performing load flow analyses on the network model, until the low voltage limit at any of the buses is reached. Determining voltage stability indices in this way is common practice when load flow analyses are available, since it is a fast and easy way to find the weakest buses in the system [23], and a similar method has previously been used to evaluate potential locations of electric vehicle charging stations in a network [24].

1.3 Contributions

Using our in-house simulator, POSSIM (POwer Systems SIMulator), we study the impact of electric vehicle charging on voltage levels in two different distribution networks. The first is based on a real network containing 114 houses in Melbourne, Australia, in a scenario typical for a suburb of a major city; the second is based on a real network containing 30 houses near Townsville, Australia, in a scenario typical for a semi-rural township. All simulations use real network specifications and data, as provided by two different utility companies. A validation exercise demonstrates that our simulator outputs closely match real measurements.

Using these models, we calculate voltage stability indices for each house in the network to determine which ones are most sensitive to addition of load in the network. We then iteratively add electric vehicles to the network. In a first step, we add them in order from the house having the highest stability index to the lowest; in a second step we add them in the opposite order. These experiments are performed both for charging rates of today's electric vehicles (3.45kW) and for likely charging rates of the next generation of electric vehicles (6.9kW). For each scenario, 20 different simulations are performed to take into account a large variety of electric vehicle charging profiles.

We find that the *locations* and *phase allocations* of the vehicles in the network have a very significant impact on network stability. Although each simulation uses different vehicle charging profiles, we find that at certain vehicle penetrations the network always fails when vehicles are added to the weakest nodes, whereas the network never fails when vehicles are added to the more robust nodes. In other words, the spatial distribution of vehicles has a very strong impact on network performance. These results are important for network planners: both the location and phase allocation of electric vehicles in distribution networks should be of great concern when determining the likely stability of a network.

We acknowledge that voltage stability is certainly not the only concern regarding large loads in distribution networks; e.g. thermal constraints of lines and transformer are very important as well. However, we have found voltage drop to be the first point of failure in our previous work [7], which is consistent with data gathered in real trials by our utility partners, and so we make this the main focus of our investigations in this paper.

This paper is organised as follows: Section 2 describes our simulator and data sources, while Section 3 shows our simulator validation results. In Section 4 we present the outcomes of the simulations we conducted to determine the impact of electric vehicles on voltage stability; Section 5 discusses the results, and finally Section 6 concludes.

2 Simulator and Data

Our simulator, POSSIM (**PO**wer **S**ystems **SIM**ulator) was built in-house in C++, and is available free and open-source to the community[2]. Simulations are conducted as a time series, simulating the full system at each interval, taking into account any events that occurred during that interval. An interval size of 30 minutes was considered suitable to simulate the many household and vehicle load variations occurring over a 24-hour period. Fig. 1 presents the simulation loop; for each interval EV arrival/departure, battery charging/discharging, household and vehicle loads are simulated, and a steady-state load flow analysis is conducted to determine voltages and currents at all nodes in the network. We use an interface to MATLAB SimPowerSystems to build our distribution networks and conduct our load flow calculations; all other calculations, logging and data input/output are performed in POSSIM. We describe each step in the simulation process individually below.

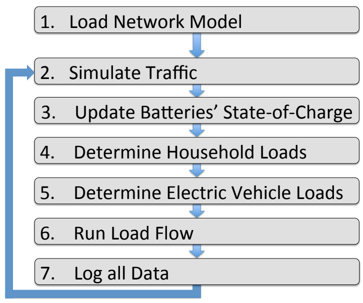


Fig. 1: Simulator loop

2.1 Network Models

We created models of two distribution networks:

[2] http://www.possim.org

- **Suburban network**: The first, based on a real suburban residential neighbourhood in Melbourne, Australia, contains 114 houses. A diagram of the network and key network specifications are presented in Figs. 2a and 2b. This model represents a typical suburban neighbourhood of a major city, with small distances between houses, overhead cables, and multiple houses connected at each pole. Individual phase connections were not provided; to determine the number of houses on each phase we used distribution transformer data gathered over several months and estimated phase load ratios using total current measured on each phase over the whole data gathering period. This led to us assigning 50 houses to phase A, 43 houses to phase B, and 21 houses to phase C. As can be seen, the network is heavily unbalanced.
- **Semi-rural network**: The second, based on a real semi-rural residential neighbourhood near Townsville in Queensland, Australia, contains only 30 houses. A diagram of the network and key network specifications are presented in Figs. 3a and 3b. This model is representative of neighbourhoods that are farther out from main metropolitan areas, or of neighbourhoods in rural townships. Properties are large, cables are overhead, and individual houses may have service line extensions to reach their houses from the main poles. In this case individual household phase connections were provided, with 12 on phase A, 12 on phase B, and 6 on phase C – also a fairly unbalanced network.

In the models for these two networks, phases, neutral and earth are modelled individually, as are piecewise sections of the distribution network backbone, laterals, and individual service lines. All houses are connected single phase to neutral, and electric vehicles assigned to a given household connect on the same phase as that house, in parallel to the household load. At each simulation interval, voltages and currents for each phase and neutral at the transformer are computed, as well as voltages at each household's point of connection.

Of note is that the low voltage limit differs between the two networks. Victoria has adopted Australian standard AS60038 [12], which sets voltage limits at 230V +10% / -6%, but Queensland still maintains limits of 240V ±6%.

2.2 Vehicle Traffic

Simulating traffic is important towards knowing *when* EVs will be at home and charging, and *how long* they will need to charge for (i.e., how far they have driven). To model EV traffic, we use travel survey data provided by the Victorian Department of Transport, which undertakes regular detailed surveys of travel activity across the state [25]. The 2009 dataset contains 11,435 records of private vehicle trips for the city of Melbourne; reducing this to only those trips having a total distance less than 160km per day (our assumed maximum EV range), leaves us with 11,135 individual 24-hour vehicle use records.

For the suburban network we further reduce this set to weekday travel profiles created by people living in the municipality that this network is located in. This left us with 324 records, having an average daily travel distance of 37.7 km. Fig. 2c presents a histogram of travel distances, while Fig. 2d shows aggregated numbers of arrivals at home, which is a good indicator of when vehicles are likely to plug in and begin charging.

For the semi-rural network, located in a part of the country for which travel survey data is not available, we used Victorian travel survey data for local government areas classified as “Middle Suburban”. We believe these profiles have roughly the same daily travel distances as people in our semi-rural network, with the distance to the central business district from Middle Suburban neighbourhoods being almost the same as the distance between our network and its nearest metropolitan centre. This left us with 2492 weekday records, having an average daily travel distance of 53.6 km. Fig. 3c presents a histogram of travel distances; Fig. 3d shows aggregated numbers of arrivals at home.

2.3 Battery

We assume the vehicles use lithium-ion batteries. Our vehicle battery pack consists of 96 blocks in series, with each block having two battery cells in parallel. Each cell has a nominal voltage of 3.75V and a capacity of 33Ah, for a total battery capacity of 24kWh. This is the same configuration used by one of the commercially available electric vehicles today.

For the charging process, we model the batteries on a cell-by-cell level using a simple battery circuit that takes the cell's internal resistance (we use 0.01Ω) into account (Fig. 4). Batteries are naturally more complex than this, but we aim to find the right balance between having a reasonably realistic model while being able to determine state of charge in a manner that is easy to compute and scales well to large numbers of cells and many vehicles.

Using the model in Fig. 4, we find that the battery draws power $P_{Battery}$:

$$\begin{aligned} P_{Battery} &= V_{Battery} * I_{Battery} \\ &= (V_{OpenCircuit} + V_{Internal}) * I_{Battery} \\ &= (V_{OpenCircuit} + I_{Internal} * R_{Internal}) * I_{Battery} \end{aligned}$$

But $I_{Internal} = I_{Battery}$, we know both $P_{Battery}$ and $R_{Internal}$, and we can find $V_{OpenCircuit}$ from the known voltage-SOC relationship (we use standard Li-ion values similar to those reported elsewhere [26]). We can therefore determine the current through the cell using the quadratic formula:

$$I_{Battery} = \frac{-V_{OpenCircuit} + \sqrt{V_{OpenCircuit}^2 + 4 * R_{Internal} * P_{Battery}}}{2 * R_{Internal}} \tag{2}$$

However, Li-ion batteries have an upper voltage limit that must be respected to ensure safe charging (we use 4.2V). Therefore, when this limit is reached, the current through the battery is reduced to ensure that voltage stays within limits. In other words, our charging algorithm follows a constant power, constant voltage process.

Additional losses in the charging process are known to occur due to energy loss in converters, the cooling system, and monitoring/control systems. To take this into account we apply an additional loss factor of 10% between the power drawn from the grid and the power received by the battery.

Li-ion batteries age faster if charged or discharged to the extremes of their capacity – typically the top and bottom 10% are avoided. We therefore scale the battery charging process to an operating region that avoids these limits. State of charge is therefore defined by

$$SOC = \frac{C_{Battery} - C_{min}}{C_{max} - C_{min}} \tag{3}$$

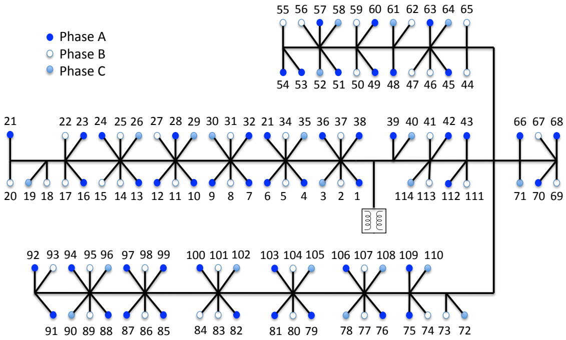
where $C_{Battery}$ is the present capacity of the battery (in Ah) and C_{min} and C_{max} are the lower and upper limits of the operating region, respectively.

The full charging process of an individual cell using our charging model is described in Algorithm 1, and the resulting behaviour is shown in Fig. 5.

Battery discharge is highly dependent on factors that are difficult to simulate, such as driving style, which we considered beyond the scope of this study. Instead, we assume a typical range of 160km (a common range for several commercial electric vehicles today), and assume that battery discharge is proportional to distance driven for each trip in our traffic model. In other words, if a vehicle is found to have driven 80km when it returns home, we assume the battery to have discharged 50% of its capacity.

2.4 Household Loads

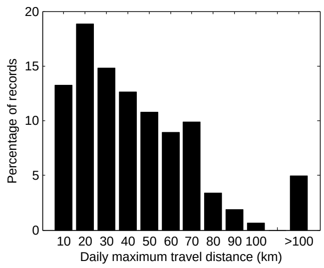
Household demand is simulated using real demand data provided by the two utility companies managing the networks we studied. Individual household load data was not available, so we used phase voltage and current data as measured at the transformer to estimate average household load. This was done by calculating total phase impedance for each phase, subtracting impedance due to lines, and determining an average household impedance individually for each phase. Then, using an average voltage of 230V, a constant impedance load was determined for each household, which was fed into our network model.



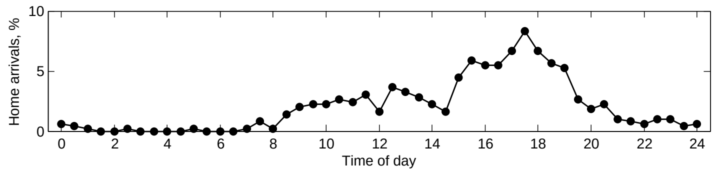
(a) Network diagram

Suburban network specifications	
Backbone	Aerial 66mm^2 Cu
⊢ pole to pole	30-40 m
⊢ resistance	0.497 Ω/km
⊢ reactance	0.378 Ω/km
Service Lines	Aerial 2x16mm^2 Cu
⊢ pole to pole	20-25m
⊢ resistance	2.33 Ω/km
⊢ reactance	0.089 Ω/km
Transformer (Tx)	300 kVA
Distance, Tx to farthest customer	421.5 m
Low voltage limit	216 V

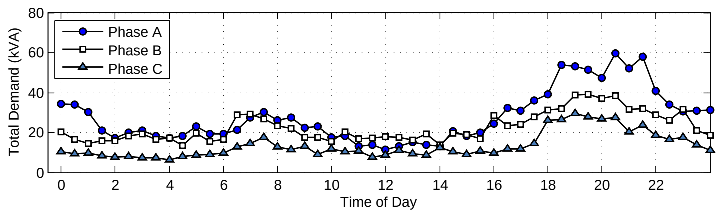
(b) Network specifications



(c) Histogram of daily vehicle travel distances (likely charging needs)

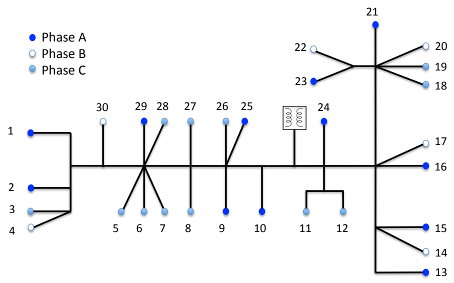


(d) Frequency of home arrivals (likely start of charging)



(e) Household demand for a weekday in August

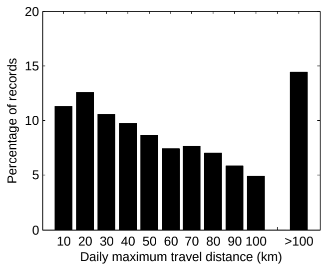
Fig. 2: Suburban network



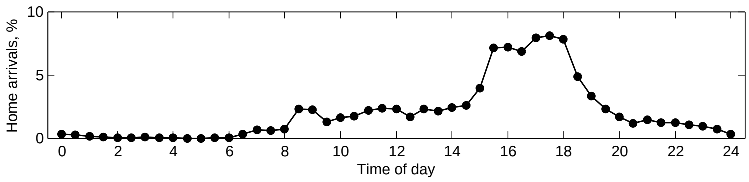
(a) Network diagram

Semi-rural network specifications	
Backbone	Aerial 4x95mm^2 Al
⊢ pole to pole	50-80 m
⊢ resistance	0.398 Ω/km
⊢ reactance	0.087 Ω/km
Service Lines	Aerial 2x10mm^2 Cu
⊢ pole to pole	20-50m
⊢ resistance	2.31 Ω/km
⊢ reactance	0.098 Ω/km
Transformer (Tx)	200 kVA
Distance, Tx to farthest customer	399 m
Low voltage limit	226 V

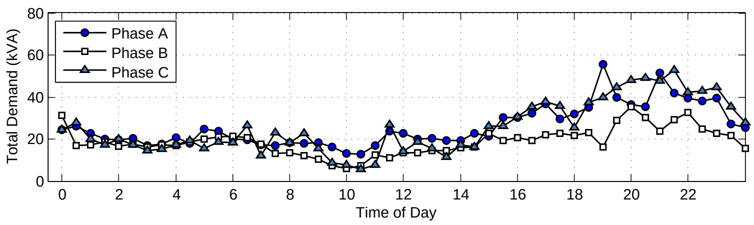
(b) Network specifications



(c) Histogram of daily vehicle travel distances (likely charging needs)



(d) Frequency of home arrivals (likely start of charging)



(e) Household demand for a weekday in February

Fig. 3: Semi-rural network

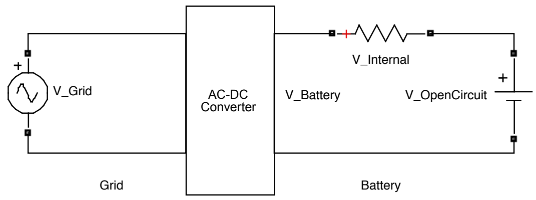


Fig. 4: Simple circuit model for one cell in the battery. $V_{Internal}$ is the voltage drop due to internal resistance of the cell, $V_{OpenCircuit}$ is the battery's open circuit voltage, and $V_{Battery}$ is the sum of the two.

Input: initial capacity (C_{init}), initial state of charge (SOC_{init}), power drawn (P_{in}), internal resistance (R_{int}), interval length (Δt)

Output: updated capacity (C_{new}), updated state of charge (SOC_{new})

$P_{charge} = P_{in} * LossFactor$; `// Apply loss due to AC/DC conversion, etc.`

$V_{oc} = \text{findVoltage}(SOC_{init})$; `// Find SOC-dependent open circuit voltage`

$I_{cell} = \frac{-V_{oc}+\sqrt{V_{oc}^2+4*R_{int}*P_{charge}}}{2*R_{int}}$; `// Determine current through cell`

if $V_{oc} + I_{cell} * R_{int} > V_{max}$ **then** `// If maximum cell voltage is reached`

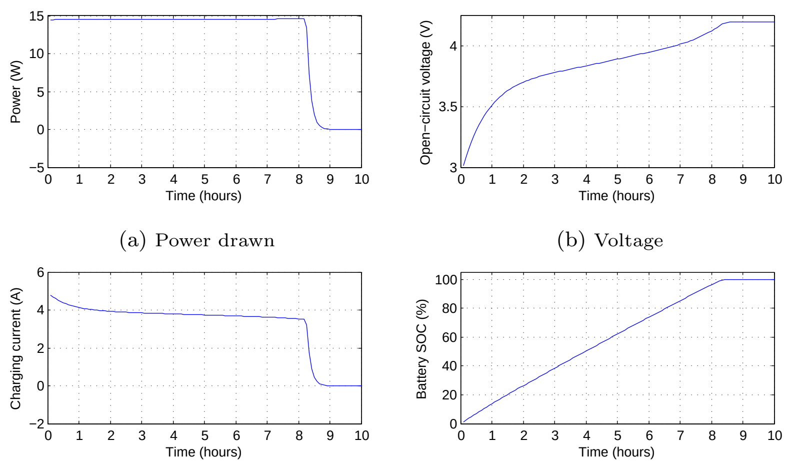
$\quad I_{cell} = \frac{V_{max}-V_{oc}}{R_{int}}$; `// Limit current to avoid maximum voltage`

end

$C_{new} = C_{init} + I_{cell} * \Delta t$; `// Update cell capacity`

$SOC_{new} = \frac{C_{new}-C_{min}}{C_{max}-C_{min}}$; `// Calculate new state of charge`

Algorithm 1: Simulated charging process of one battery cell



(a) Power drawn (b) Voltage

(c) Current (d) SOC

Fig. 5: Charging of a single cell from empty to full in our battery model

Estimating individual household loads in this manner allowed us to simulate network voltages and currents to within less than 2V and 6A of real measurements, respectively, as discussed further in Section 3. Daily load profiles for each phase are presented in Fig. 2e (suburban) and Fig. 3e (semi-rural).

Residential households will have a mix of different load types. Common practice is to model household loads as a combination of constant power and constant impedance loads [27]. Summer peak loads are often estimated as a 60%/40% mix of constant power/constant impedance, while winter peak loads can be estimated using a 40%/60% mix. Different types of residential areas will have different types of mixes [6, 27]. This mix of load types is important when analysing the impact on voltage stability: systems with high percentages of constant power loads can present higher voltage drops along a feeder than systems with high percentages of constant impedance loads [28].

In this paper we model household loads as constant impedance loads. This means that our simulations may slightly underestimate the impact of electric vehicles on voltage drop; in reality most houses will have a constant power component as well and the voltage drops discussed in this paper could be even larger. However, as the validation exercise suggests (Section 3), the network and load models present reasonably accurate results.

2.5 Electric Vehicle Loads

In our first set of simulations (see Section 4), we assumed vehicles charge at rates similar to several commercially available models today: at 15A, 230V outlets, these draw up to 3.45kW of power. In our second set of simulations we assumed charge rates that are expected for the next generation of electric vehicles: at a 30A outlet up to 6.9kW of power can be drawn. We further assumed that vehicles were plugged in at all times that they were home for more than 2 consecutive hours, and that when plugged in they charged until the battery reached a state of charge greater than 98% (within our scaled operating region, see Section 2.3). There were no attempts in this study to

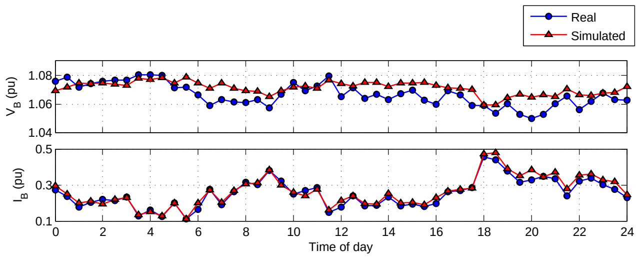


Fig. 6: Validating the model of the suburban network: V and I as measured at transformer, phase B

apply smart charging techniques that have been discussed elsewhere [4–7] as this was not the focus of our research in this case.

3 Validation

To ensure that our simulations provide realistic results, we conducted a validation cycle of the model that compared our simulated outputs to real measured values. Loads were assigned to individual houses via the process described in Section 2.4. Applying such loads to our network, and running load flows in Matlab SimPowerSystems, we received voltage and current outputs for each phase and the neutral as measured at the transformer, as well as voltages at individual houses throughout the network. These were then compared to available measurements provided by the utilities. We validated our model for data across several different days, at different times of the year. Here we present only a 24-hour period for each network, but the results were consistent across all validation tests.

Avg. Error	V_A	V_B	V_C	I_A	I_B	I_C	I_N
Absolute	1.28	1.42	1.59	5.37	6.04	4.04	9.75
Percentage	0.52	0.58	0.64	5.97	7.18	7.54	21.67

Table 1: Errors, suburban network validation, at transformer

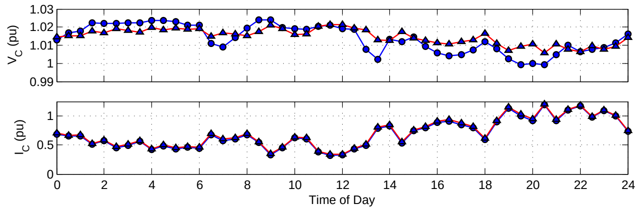


Fig. 7: Validating the model of the semi-rural network: V and I as measured at transformer, phase C

Avg. Error	V_A	V_B	V_C	I_A	I_B	I_C	I_N
Absolute	1.17	1.09	0.90	2.58	2.07	2.33	15.93
Percentage	0.48	0.45	0.37	3.68	3.22	2.80	36.51

Table 2: Errors, semi-rural network validation, at transformer

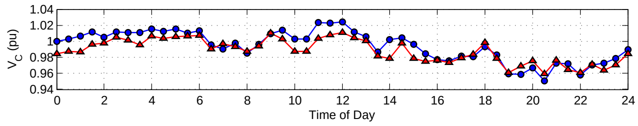


Fig. 8: Validating the model of the semi-rural network: V as measured at end-of-line, phase C

Avg. Error	V_A	V_B	V_C
Absolute	2.99	2.59	1.99
Percentage	1.25	1.06	0.83

Table 3: Errors, semi-rural network validation, at end-of-line

Fig. 6 presents a comparison between simulated and real phase voltages and currents for the suburban network, and Table 1 shows percentage and absolute errors. Differences in voltage measurements are within 1.5 V on average (0.6 %); differences in current measurements are within 6A on average (7 %). Errors in neutral current are greater (10A, 22%), but this is to be expected since the errors in each phase contribute to the error in the neutral.

Fig. 7 presents a comparison between simulated and real phase voltages and currents for the semi-rural network, and Table 2 shows percentage and absolute errors. Differences in voltage measurements are typically within 1V on average (0.5%); differences in current are within 3A on average (4%). Again, the neutral current is not as accurate, being within 16A (37%). For the semi-rural network, voltage measurements at end-of-line were also available. Comparison of simulated voltages at end-of-line to real measurements is important for determining whether voltage drop is modelled accurately in our network (in other words, whether lines are modelled accurately). Fig. 8 presents a comparison of phase voltages at end-of-line, and Table 3 presents average absolute and percentage errors: on average voltages were within 2-3V (1.5%).

Overall, the simulated results match real measurements reasonably well in both networks. There are several factors that may have contributed to the simulation errors. First, it was not known whether there were any tap changes at the distribution transformer (or at a substation) during any of these experiments, and if yes these were not taken into account. Second, individual houses were assigned a demand profile that was based on an average demand as measured at the transformer. In reality there would have been much deviation from one house to another, which as we show in the next section can have a big impact. However, with the close correlation between simulations and real data, we consider the simulator a useful tool for evaluation of further scenarios in these networks.

4 Simulations: Determining the Impact of Spatial Load Distribution on Voltage Stability

4.1 Voltage Stability Indices

In a first test, we determined the voltage stability indices of all houses in both networks using the voltage stability index described in Section 1.2. Table 4 shows the indices for the suburban network, and Table 5 shows the indices for the semi-rural network. In both cases, the house numbers refer to the network diagrams shown earlier in Figs. 2a and 3a.

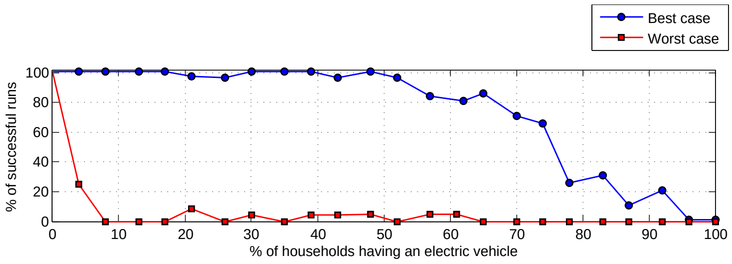
In the suburban network, the weakest bus (lowest stability index) is found at house 91. This is to be expected, since this is the farthest house from the transformer on the most heavily loaded phase. In the semi-rural network, the weakest bus is found at house 7. This house is also on the most heavily loaded phase, but it is not the farthest from the transformer (house 3 is on the same phase and farther away). However, house 7 has a longer service line which is of poorer quality (copper) than the backbone (aluminium). Therefore, due to the higher impedance of its service line, it is more exposed to drops in voltage.

4.2 Addition of Vehicles: Methodology

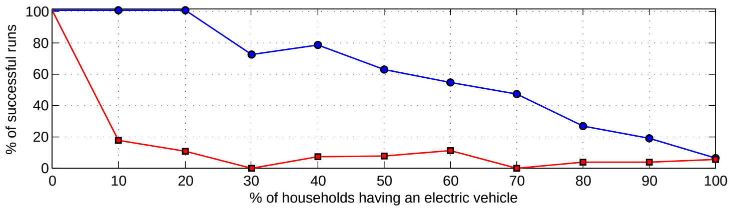
To examine in more detail how individual loads – and their locations – impact voltage stability, we evaluated different possible levels of EV penetration in the two networks.

– In the **Worst Case** scenarios, we added electric vehicles to houses, one at a time, in order from lowest stability index to highest stability index.
– In the **Best Case** scenarios, we added electric vehicles to houses, one at a time, in order from highest stability index to lowest stability index.

As described in Section 2, we use average load profiles on a per phase basis for households, without addition of any noise. Vehicle travel profiles, however, are chosen at random, which means that outcomes of our runs may be different from one run to the next. For example, a vehicle charging at peak demand time is more likely to lead to network failure than a vehicle charging in the middle of the night. To take into account the different effects resulting from randomly chosen travel profiles, we conducted at least 20 simulation runs for each level of EV penetration, for each of the worst and best case scenarios. Each run involved simulation of a full 24-hour day – 21 August 2012 in the case of the suburban network, and 2 February 2012 for the semi-rural network. Household



(a) Suburban network



(b) Semi-rural network

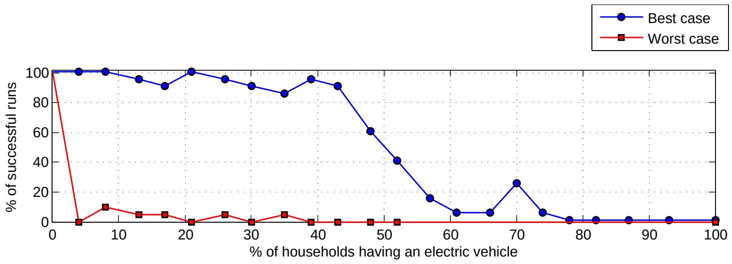
Fig. 9: Comparing best and worst case scenarios for charge rates of **3.45kW**. In the best case, vehicles are added in order from those houses having the highest voltage stability index to those having the lowest. In the worst case, they are added in the opposite order.

and vehicle loads were simulated in 30-minute intervals, and a full load flow analysis was conducted in each interval.

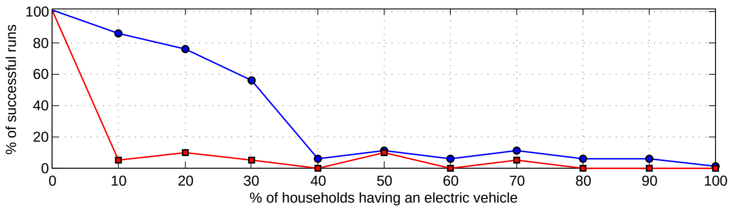
A **successful** run was any simulation in which voltage did not drop below distribution code specified low voltage thresholds (216V for the suburban network in Melbourne; 226V for the semi-rural network in Queensland) at any house, during any of the 48 simulation intervals; any runs in which this did occur were considered **unsuccessful**.

4.3 Results – Charging at 3.45kW

In our first set of simulations, all vehicles charged at a rate of 3.45kW (equivalent to the maximum rate possible using a 15A outlet at 230V).



(a) Suburban network



(b) Semi-rural network

Fig. 10: Comparing best and worst case scenarios for charge rates of **6.9kW**.

In the suburban network, the difference between the numbers of successful runs for worst case and best case scenarios is very significant. Fig. 9a shows the percentage of simulations succeeding for a given EV penetration in the suburban network. As an example, for an EV penetration of 35%, in the best case scenario all simulation runs succeed; in the worst case not a single one does. Best case addition of vehicles to the network allows up to 50% vehicle penetration with a high likelihood of voltage levels staying at adequate levels. Worst case addition of vehicles to the network means that just a single vehicle added to the network already causes excessive voltage drop in some cases.

In the semi-rural network, the differences between best case and worst case are not as strong, but still significant (Fig. 9b). The success rate of best case placement tails off faster than in the suburban network, likely due to higher impedance in the longer service lines. At 20% EV penetration, however, in the best case all runs succeed, while in the worst case only one in ten runs succeed.

4.4 Results – Charging at 6.9kW

In our second set of simulations, all vehicles charged at a rate of 6.9kW (equivalent to the maximum rate possible using a 30A outlet at 230V).

In the suburban network, the differences between best and worst case scenario are again very large (Fig. 10a). At an EV penetration of 22%, all runs succeeded in the best case scenario; none of the runs succeeded in the worst case. An EV penetration up to 40% allows for high likelihood of adequate voltage levels in the best case. Only a single vehicle at the worst location in the network already leads to high likelihood of low voltage in the worst case.

In the semi-rural network, the differences between best case and worst case are again not as strong, but still considerable (Fig. 10b). While both lead to similarly poor success rates from 40% penetration levels onwards, there is a marked difference in the early levels of EV penetration. At an EV penetration level of 10%, for example, best case vehicle placement allows success rates of 85% while worst case only allows 5%. Even in the best case, the network already fails in some cases at 10% vehicle penetration.

4.5 Importance of the Weakest Bus

To further examine the importance of the weakest bus in the network (in other words, the house having the lowest stability index), we conducted one further set of tests:

- First, we applied an average peak demand to all houses in our networks (using demand data at peak time), conducted a load flow, and examined the voltage at the weakest bus (the red triangle in Figs. 11 and 12).
- Next, we added a single EV load (of 3.45kW) at the weakest bus, keeping all other loads the same, and ran another load flow, again measuring voltage at the weakest bus.
- Finally, we removed the EV load from the weakest bus, and added EV loads to the network one at a time, in order from highest stability index to

lowest stability index, measuring the voltage at the weakest bus following the addition of each vehicle.

The voltage comparisons are presented in Tables 6 and 7 and placement of these loads is shown in Figs. 11 and 12.

The result was that a single vehicle connected at the weakest bus of the network has the same impact on voltage drop as large numbers of vehicles connected at buses having high voltage stability indices. In the suburban network, a single vehicle at the weakest bus led to almost the same voltage levels as the addition of 45 vehicles at the strongest buses in the network. In the semi-rural network, it was possible to add vehicle loads to 27 of the network's 30 houses, and still maintain the same minimum voltage as in the situation with only one vehicle at the weakest bus. In percentage terms, this means that one vehicle at the weakest bus can have the same impact as equivalent loads at 39% of the network's houses in the suburban network (or 90% in the semi-rural network).

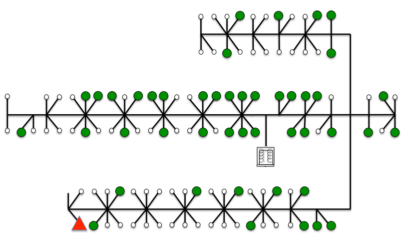


Fig. 11: Suburban network: adding a single vehicle at the weakest bus of the network (red triangle) has the same impact on lowest voltage measured in the network as adding 45 vehicles at stronger locations in the network (green circles)

	Voltage, weakest bus
An average load profile for all houses, no additional loads	225.7
A single additional EV (3.45kW) at weakest bus	218.1
No EV at weakest bus, but EVs at 45 strongest locations	218.5

Table 6: Suburban network: Voltages at the weakest bus of the suburban network

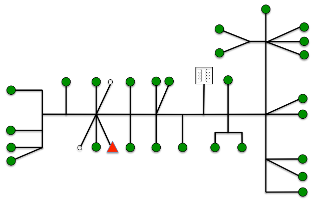


Fig. 12: Semi-rural network: adding a single vehicle at the weakest bus of the network (red triangle) has the same impact on lowest voltage measured in the network as adding 27 vehicles at stronger locations in the network (green circles)

	Voltage, weakest bus
An average load profile for all houses, no additional loads	232.5
A single additional EV (3.45kW) at weakest bus	225.7
No EV at weakest bus, but EVs at 27 strongest locations	226.0

Table 7: Semi-rural network: Voltages at the weakest bus of the suburban network

5 Discussion

Clearly, the addition of electric vehicles to the network can have vastly different impacts depending on where exactly the vehicle is added. Vehicles added at weaker locations in the network will have a much greater impact and are more likely to lead to network failure. Vehicles added at stronger locations can actually *increase* voltage stability levels in the network. This is due to the fact the electric vehicle loads can *rebalance* networks that are inherently unbalanced. By adding load to the least loaded phase, current in the neutral line is decreased, leading to an overall decrease in lowest voltage. This is evident in our case studies if the addition of vehicles in Fig. 11 is compared to phase allocation as shown in Fig. 2a: adding vehicles to phases B and C leads to a more stable network than adding vehicles to the already highly loaded phase A.

These results are significant for any studies involving the impact of loads on distribution networks. In our suburban network in particular, the placement of vehicles could lead to 100% success rates in one set of vehicle assignments, and 0% success rates in another set of vehicle assignments, *for the same number of vehicles*. Thus for many studies it is not sufficient to say for example, “Network Y can sustain Z electric vehicles”. Spatial distribution of vehicles has an enormous impact on voltage stability, and studies of distribution networks should quantify such statements by indicating whether it applies to the worst case, the best case, or in X% of cases having randomly assigned vehicles.

An interesting outcome in both sets of simulations was that the curves for vehicle penetration percentage vs. success rate percentage were not smooth, despite each data point representing at least 20 simulations. We believe this is due to the impact of randomly chosen vehicle travel profiles: those simulations in which vehicles needed to charge during peak time were more likely to fail than those in which vehicles arrived home outside of peak hours.

Another important observation, both in real world trials and in the simulations presented here, was that end-of-line measurements are not necessarily reliable indicators of network voltage stability. The most sensitive location in the network will not necessarily be near the end of the line, even in radial systems having no distributed generation, because of either high impedance in service lines or phase unbalance. This is evident also in the stability indices calculated for our semi-rural network.

There are several ways in which voltage drop in distribution networks could be addressed. Distributed generation will alleviate the impact of large loads like EVs and raise voltage (although matching timing of generation to demand remains a challenge). Our networks are highly unbalanced, and a rebalancing of the networks could lead to much improved performance since less current in the neutral line would lead to a reduction in voltage drop. Loads that are connected 3-phase, rather than single phase, would also help in reducing this unbalance (as is the case in many countries in Europe). Shifting of EV load to off-peak times could certainly lead to a decreased impact. Addition of small step-up transformers or static VAR compensators along network feeders could be a solution, but may be costly to install across large networks.

An additional question that these results raise is the notion of *fairness*. Should an EV owner at the weakest bus of the network have the same right to charge his or her vehicle as owners living at more stable locations? The general consensus appears to be that all EV owners should have equal charging rights, but when a single load can have the same impact as 45 equivalent loads elsewhere in the network, this is an issue that may need to be revisited.

Finally, these studies support the case for controlled charging of electric vehicles. It is already known that shifting of vehicle load to off-peak times will be important towards managing increasing penetration levels of electric vehicles; however the results presented here suggest further that vehicle charging can actually be used as a tool in the management of networks. Adding additional electric vehicle load in some cases *improves* network stability when it leads to a rebalancing of the phases.

6 Conclusion

Distribution networks are receiving considerable attention these days due to the emergence of new smart grid technologies, and many studies aim to optimise a particular set of variables taking into account the constraints in the grid. One of these constraints, minimum voltage level, is a serious concern, particularly with the increasing penetration of large loads like electric vehicles, and we have found it to be the first point of failure in the distribution networks we have previously studied [7].

In this paper we examined in detail the impact of electric vehicles on voltage stability in two networks: the first is a suburban residential network in Melbourne, Australia, and the second is a semi-rural residential network near Townsville, Australia. All of our simulations used real demand data as provided by two different utility companies, and government travel survey data to simulate vehicle demand.

For each network we examined a worst case scenario (in which vehicles are added in order from the weakest bus to the strongest) and a best case scenario (in which vehicles are added in order from the strongest bus to the weakest). The gulf between worst case and best case scenarios is enormous: in some cases a given level of electric vehicle penetration will always lead to excessive voltage drop in one set of vehicle assignments, and never in another set of vehicle assignments, for the same number of vehicles.

The implications of these experiments are significant for studies of distribution networks: voltage stability indices and physical placement of loads have a significant impact on whether the network's voltages will stay within required limits or not. In one of our networks, addition of an electric vehicle at the weakest bus of the network had the same impact as the addition of 45 equivalent loads near the transformer. Adding vehicles at the strongest nodes can in fact lead to improved voltage levels, by rebalancing the phases. Such results also raise questions regarding fairness in EV charging: should the customer at the weakest bus have the same right to charge as customers at less sensitive locations?

In future work we aim to find an optimal charging algorithm that takes the constraint of voltage drop into account, and we aim to explore the issues surrounding fairness of EV charging in greater detail.

Acknowledgements This work has been funded by a Linkage Grant supported by the Australian Research Council, Better Place Australia, and Senergy Australia. We are grateful to United Energy and Ergon Energy for providing data and assistance.

References

1. J.M. Carrasco, L.G. Franquelo, J.T. Bialasiewicz, E. Galvan, R.C.P. Guisado, Ma.A.M. Prats, J.I. Leon, and N. Moreno-Alfonso. Power-electronic systems for the grid integration of renewable energy sources: A survey. *IEEE Transactions on Industrial Electronics*, 53(4):1002–1016, 2006. ISSN 0278-0046.
2. A. Weidlich, H. Vogt, W. Krauss, P. Spiess, M. Jawurek, M. Johns, and S. Karnouskos. Decentralized intelligence in energy efficient power sys-

tems. In A. Sorokin, S. Rebennack, P. M. Pardalos, N. A. Iliadis, and M. V. F. Pereira, editors, *Handbook of Networks in Power Systems I*, Energy Systems, pages 467–486. Springer, 2012. ISBN 978-3-642-23193-3.

3. J.A.P. Lopes, F.J. Soares, and P.M.R. Almeida. Integration of electric vehicles in the electric power system. *Proceedings of the IEEE*, 99(1):168 –183, Jan. 2011. ISSN 0018-9219. doi: 10.1109/JPROC.2010.2066250.
4. K. Clement-Nyns, E. Haesen, and J. Driesen. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems*, 25(1):371–380, Feb. 2010. ISSN 0885-8950.
5. A.G. Boulanger, A.C. Chu, S. Maxx, and D.L. Waltz. Vehicle electrification: Status and issues. *Proceedings of the IEEE*, 99(6):1116–1138, Jun. 2011. ISSN 0018-9219. doi: 10.1109/JPROC.2011.2112750.
6. P. Richardson, D. Flynn, and A. Keane. Optimal charging of electric vehicles in low-voltage distribution systems. *IEEE Transactions on Power Systems*, 27(1):268–279, Feb. 2012. ISSN 0885-8950. doi: 10.1109/TPWRS.2011.2158247.
7. J.de Hoog, D. A. Thomas, V. Muenzel, D. C. Jayasuriya, T. Alpcan, M. Brazil, and I. Mareels. Electric vehicle charging and grid constraints: Comparing distributed and centralized approaches. In *Proceedings of the IEEE Power and Energy Society General Meeting*, 2013.
8. A. Ipakchi and F. Albuyeh. Grid of the future. *IEEE Power and Energy Magazine*, 7(2):52–62, March-April 2009. ISSN 1540-7977.
9. L. Kelly, A. Rowe, and P. Wild. Analyzing the impacts of plug-in electric vehicles on distribution networks in British Columbia. In *Transactions of the IEEE Electrical Power Energy Conference*, 2009.
10. J. R. Pillai and B. Bak-Jensen. Impacts of electric vehicle loads on power distribution systems. In *Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2010.
11. L. Pieltain Fernndez, T.G.S. Romn, R. Cossent, C.M. Domingo, and P. Fras. Assessment of the impact of plug-in electric vehicles on distri-

bution networks. *Power Systems, IEEE Transactions on*, 26(1):206–213, 2010. ISSN 0885-8950. doi: 10.1109/TPWRS.2010.2049133.

12. Australian Standard 60038: Standard Voltages. Available at http://www.standards.org.au., Accessed Mar 2013 .
13. P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, T. Van Cutsem, and V. Vittal. Definition and classification of power system stability: IEEE/CIGRE joint task force on stability terms and definitions. *IEEE Transactions on Power Systems*, 19(3):1387–1401, 2004. ISSN 0885-8950.
14. V. Ajjarapu and B. Lee. Bibliography on voltage stability. *IEEE Transactions on Power Systems*, 13(1):115–125, 1998. ISSN 0885-8950.
15. V. Ajjarapu and C. Christy. The continuation power flow: a tool for steady state voltage stability analysis. *IEEE Transactions on Power Systems*, 7 (1):416–423, 1992. ISSN 0885-8950.
16. N. Flatabo, R. Ognedal, and T. Carlsen. Voltage stability condition in a power transmission system calculated by sensitivity methods. *IEEE Transactions on Power Systems*, 5(4):1286–1293, 1990. ISSN 0885-8950.
17. B. Gao, G. K. Morison, and P. Kundur. Voltage stability evaluation using modal analysis. *IEEE Transactions on Power Systems*, 7(4):1529–1542, 1992. ISSN 0885-8950.
18. G. B. Jasmon and L. H. C. C. Lee. Distribution network reduction for voltage stability analysis and loadflow calculations. *International Journal of Electrical Power and Energy Systems*, 13(1):9–13, 1991.
19. F. Gubina and B. Strmcnik. A simple approach to voltage stability assessment in radial networks. *IEEE Transactions on Power Systems*, 12 (3):1121–1128, 1997. ISSN 0885-8950.
20. M Chakravorty and D Das. Voltage stability analysis of radial distribution networks. *International Journal of Electrical Power & Energy Systems*, 23(2):129 – 135, 2001. ISSN 0142-0615.
21. U. Eminoglu and M.H. Hocaoglu. A voltage stability index for radial distribution networks. In *Transactions of the Universities Power Engineering*

Conference, pages 408–413, 2007.

22. P. Juanuwattanakul and M. A S Masoum. Voltage stability enhancement for unbalanced multiphase distribution networks. In *Transactions of the IEEE Power and Energy Society General Meeting*, 2011.
23. C. Reis and F. P. Maciel Barbosa. A comparison of voltage stability indices. In *Proceedings of IEEE MELECON*, Benalmadena, Spain, May 2006.
24. P. Juanuwattanakul and M. A S Masoum. Identification of the weakest buses in unbalanced multiphase smart grids with plug-in electric vehicle charging stations. In *Innovative Smart Grid Technologies Asia (ISGT), 2011 IEEE PES*, pages 1–5, Nov 2011. doi: 10.1109/ISGT-Asia.2011.6167155.
25. Victorian Integrated Survey of Travel and Activity. Online: http://www.transport.vic.gov.au/research/statistics/victorian-integrated-survey-of-travel-and-activity, 2009.
26. B.T. Kuhn, G.E. Pitel, and P.T. Krein. Electrical properties and equalization of lithium-ion cells in automotive applications. In *Transactions of the IEEE Vehicle Power and Propulsion Conference*, Sep. 2005.
27. H. Lee Willis. *Spatial Electric Load Forecasting*. CRC Press, 2002.
28. N. Mithulananthan, M. M. A. Salama, C. A. Canizares, and J. Reeve. Distribution system voltage regulation and var compensation for different static load models. *International Journal of Electrical Engineering Education*, 37(4):384–395, 2000.

House	Index	House	Index	House	Index	House	Index
1	0.9418	30	0.9953	59	0.9280	88	0.8533
2	0.9595	31	0.9446	60	0.8850	89	0.9135
3	0.9918	32	0.9153	61	0.9887	90	0.9895
4	0.9268	33	0.9268	62	0.9290	**91**	**0.8498**
5	0.9518	34	0.9518	63	0.8956	92	0.8510
6	0.9275	35	0.9936	64	0.9895	93	0.9116
7	0.9153	36	0.9418	65	0.9339	94	0.8533
8	0.9446	37	0.9595	66	0.9033	95	0.9135
9	0.9153	38	0.9418	67	0.9346	96	0.9895
10	0.9071	39	0.9559	68	0.9012	97	0.8563
11	0.9381	40	0.9905	69	0.9353	98	0.9153
12	0.9071	41	0.9531	70	0.9005	99	0.8563
13	0.9020	42	0.9358	71	0.9898	100	0.8641
14	0.9322	43	0.9164	72	0.9898	101	0.9171
15	0.9316	44	0.9332	73	0.9359	102	0.9899
16	0.8989	45	0.8950	74	0.9318	103	0.8736
17	0.9290	46	0.9305	75	0.8955	104	0.9217
18	0.9276	47	0.9305	76	0.8860	105	0.9889
19	1.0000	48	0.8884	77	0.9271	106	0.8860
20	0.9272	49	0.8844	78	0.9880	107	0.9271
21	0.8983	50	0.9274	79	0.8736	108	0.9880
22	0.9290	51	0.8821	80	0.9217	109	0.8949
23	0.8989	52	0.9870	81	0.8736	110	0.9883
24	0.9020	53	0.8796	82	0.8641	111	0.9426
25	0.9322	54	0.8796	83	0.9171	112	0.9164
26	0.9989	55	0.9280	84	0.9164	113	0.9531
27	0.9374	56	0.9272	85	0.8563	114	0.9901
28	0.9077	57	0.8827	86	0.9153		
29	0.9971	58	0.9870	87	0.8563		

Table 4: Stability indices, suburban network, using the index defined in Section 1.2. House numbers refer to the numbers shown in the diagram of Fig. 2a.

House	Index	House	Index	House	Index	House	Index
1	0.9363	9	0.9508	17	0.9664	25	0.9653
2	0.9447	10	0.9500	18	0.9584	26	0.9419
3	0.9038	11	0.9316	19	0.9620	27	0.9288
4	0.9695	12	0.9294	20	0.9541	28	0.9026
5	0.8936	13	0.9116	21	0.9262	29	0.9577
6	0.9043	14	0.9690	22	0.9548	30	0.9789
7	**0.8855**	15	0.9351	23	0.9369		
8	0.9219	16	0.9461	24	0.9509		

Table 5: Stability indices, semi-rural network, using the index defined in Section 1.2. House numbers refer to the numbers shown in the diagram of Fig. 3a.