From Model-Driven to Model-Free: Comparisons using Real Smart Meter Data and Real Distribution Network from Australia Study

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Summary

The proliferation of residential distributed energy resources (DER), such as rooftop solar PV, batteries, and electric vehicles (EVs), is creating significant challenges for distribution companies. This is because the electricity distribution networks (i.e., the poles and wires connecting homes and businesses) have not been designed for the diverse behaviours of DER, leading to potential voltage rise issues from PV generation and voltage drop issues from EV charging. Given that ensuring voltage compliance is a key responsibility for distribution companies, the capability to accurately assess the effects of different DER scenarios on customer voltages (i.e., voltage calculations) is crucial.

This work proposes an innovative approach to carry out voltage calculations using smart meter data and artificial intelligence. Leveraging historical data and machine learning algorithms, it is possible to extract the physical relationships of a LV feeder with a tailored neutral network which, then, can be used to carry out voltage calculations. This is a stark contrast to the conventional approach where power flow analysis and electrical models are required.

Using real data and real LV feeders from Victoria, Australia, the performance of the model-free approach is quantified with the average deviation metric and visualised using a scatter plot technique. Furthermore, a first-of-its-kind comparison between the model-free and model-driven approaches is also presented leveraging the availability of fully validated electrical models for the considered LV feeders. The results show that the tailored neural network not only outperforms the conventional approach, but also offers significant cost savings for large-scale deployment by distribution companies.

Keywords

Distribution network, model-free voltage calculation, neural network, smart meter data

1. Introduction

The proliferation of residential distributed energy resources (DER), such as rooftop solar PV, batteries, and electric vehicles, is creating significant challenges for distribution companies. This is because the electricity distribution networks (i.e., the poles and wires connecting homes and businesses) have not been designed for the diverse behaviours of DER. For instance, high PV generation and low residential demand around noon can lead to excessive reverse power flows, and thus create voltage rise issues [1]. On the other hand, the coincidental charging from many electric vehicles in the evening can lead to substantial demand spikes, and thus exacerbate voltage drop issues [2]. Given that ensuring voltage compliance is a key responsibility for distribution companies [3, 4], the capability to accurately assess the effects of different DER scenarios on customer voltages (hereafter referred to as *voltage calculations*) is crucial.

Traditionally, voltage calculations entail running power flows, and thus require adequate electrical models (i.e., a complete set of information on customer phase groupings, feeder topology, and conductor impedances). While this concept (hereafter referred to as *model-driven* voltage calculations) is well-known to distribution companies, its application in low voltage (LV) residential feeders can be challenging as the required modelling data are often incomplete, erroneous or even non-existent [5, 6]. As a result, approximations and conservative limits are commonly adopted by industry today, and thus not fully utilizing the true capacity of the existing infrastructure [7].

One potential solution is to address the quality issues associated with existing LV feeder models. This approach has been investigated by the high-profile, government-funded trial “Energy Demand and Generation Exchange (EDGE)” in Australia [8]. As part of this project, historical smart meter data and advanced algorithms are utilised to produce validated electrical models for several real LV feeders in Victoria, Australia [9]. However, it has been found that the underlying process is extremely slow, costly and error prone due to the need for extensive data processing, manual cross checks, and physical site inspections. Therefore, a more cost-effective alternative is highly desirable to reduce the barriers to adoption at large-scale by industry.

Thanks to the growing deployment of smart meters and maturation of artificial intelligence techniques, an innovative approach that bypasses the need of electrical models has emerged. Leveraging historical data and machine learning algorithms, it is possible to extract the physical relationships of a LV feeder with a tailored neutral network [10, 11] which, then, can be used to carry out voltage calculations. This novel approach to voltage calculations using neural networks (hereafter referred to as *model-free* voltage calculations) has been successfully demonstrated using real smart meter data from hundreds of households in Victoria, Australia as part of the project “Model-Free Operating Envelopes at NMI-Level” [12].

Building on the authors’ prior work in [10, 11] that uses smart meter data only, this paper presents an adapted model-free voltage calculation approach that considers both smart meter data and head-of-feeder (i.e., at the secondary side of the distribution transformer) data [13]. Using real data and real LV feeders from Victoria, the performance of the model-free approach is quantified with the average deviation metric and visualised using a scatter plot technique. Furthermore, this paper presents a first-of-its-kind comparison between the model-free and model-driven approaches where fully validated electrical models are available for the considered LV feeders (which are produced as part of the Project EDGE trials). The results show that the model-free approach can accurately calculate customer voltages and even outperforms the model-driven approach (using validated electrical models).

2. Methodology

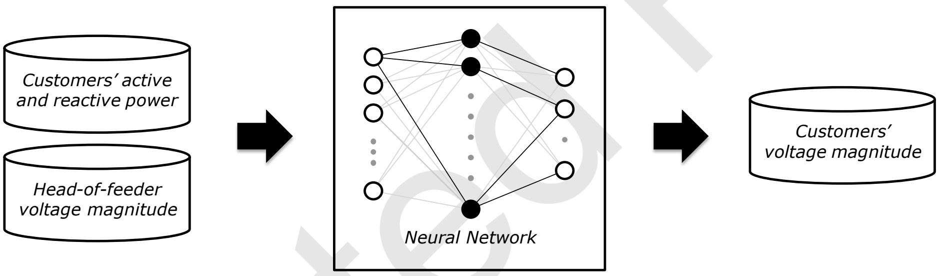
2.1 Model-Free Voltage Calculations

The purpose of voltage calculations is to determine the customer voltages for different scenarios which, then, allows distribution companies to assess customer voltage compliance (i.e., whether the customer voltages are within the statutory limits). The proposed model-free approach is illustrated in Figure 1 which consist of three key blocks: Input, Model-Free Engine and Output.

Input. The input corresponds to the scenario to be assessed which is shown on the left of in Figure 1. A scenario is comprised of the customer powers (the total active and reactive point at the point of connection of each customer) and head-of-feeder voltage (the voltage magnitude at the secondary side of the distribution transformer).

Model-Free Engine. The model-free engine to carry out voltage calculations is shown in the middle of Figure 1. Its purpose is to determine the effects of head-of-feeder voltage and customer powers on customer voltages. At the core of the model-free engine is a tailored neural network that has been trained with historical smart meter data and head-of-feeder data from the same LV feeder. The architecture of the neural network is adapted from the authors' prior work in [10, 11] which is shown inside model-free engine block in Figure 1. The input layer consists of the voltage magnitude at the head-of-feeder and the individual active and reactive power of customers. The hidden layer is a fully connected layer with the tanh activation function; the number of neurons is defined using the formula $8 \cdot C$ (per recipe proposed in [10]) where C is the number of customers in the corresponding LV feeder. The output layer consists of the individual voltage magnitude of each customer.

Output. The final output corresponds to the individual customer voltages for the given scenario which is shown on the right of Figure 1.



Inputs **Model-Free Engine** **Output**

Figure 1. Model-free voltage calculation architecture.

2.2 Performance Assessment

The overall performance of the proposed model-free voltage calculation approach is assessed using historical data. Firstly, the head-of-feeder voltage measurements and customer power measurements are used to produce calculated customer voltages using the proposed approach. Then, these calculated voltages are compared with the actual customer voltages measured by the smart meters. Particularly, two techniques are used analyse the performance: the average deviation metric and a scatter plot.

Average deviation. This metric quantifies the 'average error' of a given approach across all customers. The formula is shown in (1) where V^{AD} denotes the average deviation, $c \in C$ denotes the customer index, $t \in T$ denotes the time index (of all available data), $V_{c,t}^{Meas}$ denotes the voltage measured by the smart meter, and $V_{c,t}^{Calc}$ denotes the voltage calculated by the model.

$$V^{AD} = \frac{1}{|C||T|}\sum\nolimits_{c\in C}\sum\nolimits_{t\in T}\left|V_{c,t}^{Meas} - V_{c,t}^{Calc}\right| \quad (1)$$

Scatter plots. The scatter plot offers an immediate and visual way to interpret the performance of a voltage calculation approach. An illustration of a scatter plot is shown in Figure 2. The measured customer voltages are shown on the x-axis and the calculated customer voltages are shown on the y-axis. An adequate performance is illustrated by the green dots in Figure 2 where they are well-aligned with the grey line y=x. In contrast, a poor performance is illustrated by the red dots where they are significantly misaligned with y=x.

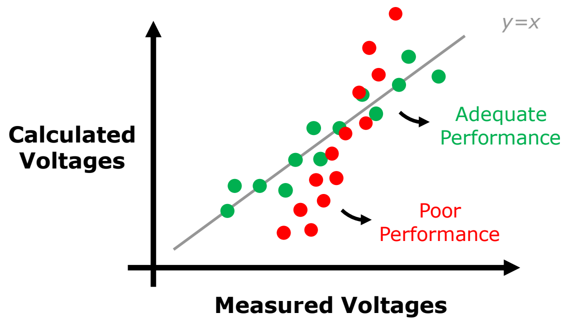


Figure 2. Illustration of a scatter plot.

3. Case Study

3.1 Real LV Feeders and Real Data

Two LV feeders (three-phase, unbalanced) from Victoria, Australia are used to assess the performance of the proposed model-free voltage calculation approach. These two feeders, namely Feeder A and B, are part of the trial sites in Project EDGE where extensive efforts were invested (over the course of several months) to produce fully validated electrical models [9]. Thanks to the prior efforts, these validated electrical models offer a unique opportunity as benchmarks for the proposed model-free approach.

The single line representation for both feeders are shown in Figure 3. Feeder A has 28 customers in total, of which 2 customers have three-phase connections. Feeder B has 8 customers in total, of which 3 customers have three-phase connections. Given that each phase of a three-phase customer is independently monitored by the smart meter, each of them is treated as 3 equivalent single-phase customers in this case study.

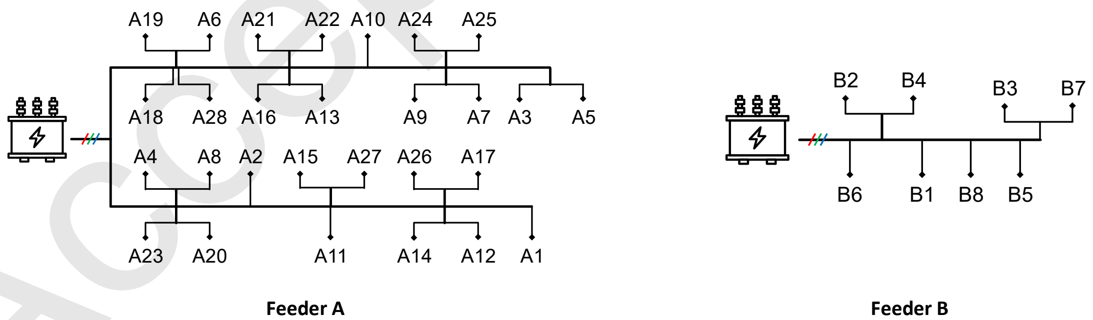


Figure 3. Single line representations of Feeder A (left) and Feeder B (right).

For each LV feeder, three weeks of historical smart meter data and head-of-feeder data are used. All data are collected as instantaneous readings with five-minute resolution. The corresponding measurements consist of the per phase active power, reactive power, and voltage magnitude for each customer (i.e., at the point of connection to the LV feeder) and at the head-of-feeder (i.e., the secondary side of the distribution transformer). It is worth highlighting that full smart meter penetration (for residential customers) is assumed, which is aligned with the state of smart meter deployment for the investigated feeders.

3.2 Implementation of Model-Free and Model-Driven Approaches

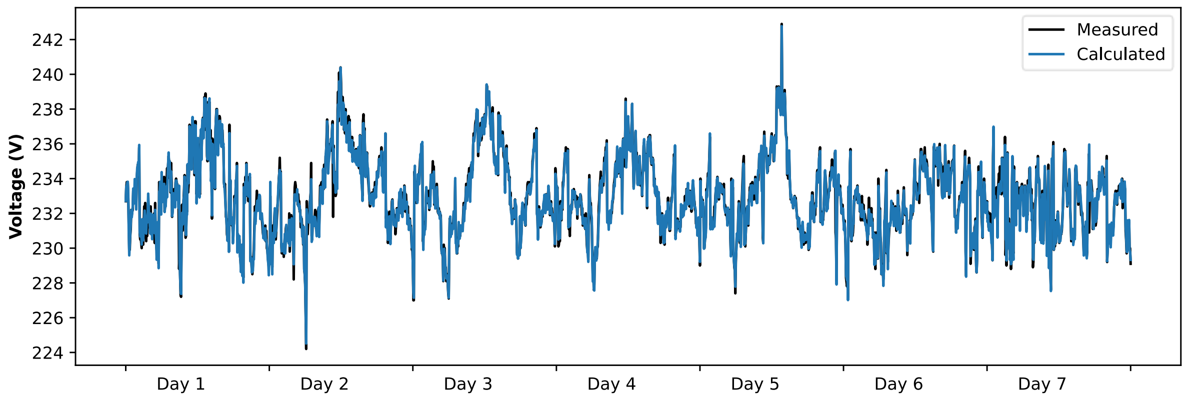
Model-Free Approach. The model-free voltage calculation approach is implemented in Python [14] using the Keras deep learning API [15] and the Tensorflow machine learning platform [16]. Out of the three weeks of data, the first two weeks are used to train the tailored neural network (for each feeder) and the final week is used to assess the voltage calculation performance. For both neural networks, the training time (using the first two weeks of historical data) is approximately 5 minutes using a single CPU core on a typical office laptop.

Model-Driven Approach. The model-driven approach is implemented in Python and uses OpenDSS [17] to carry out power flows.

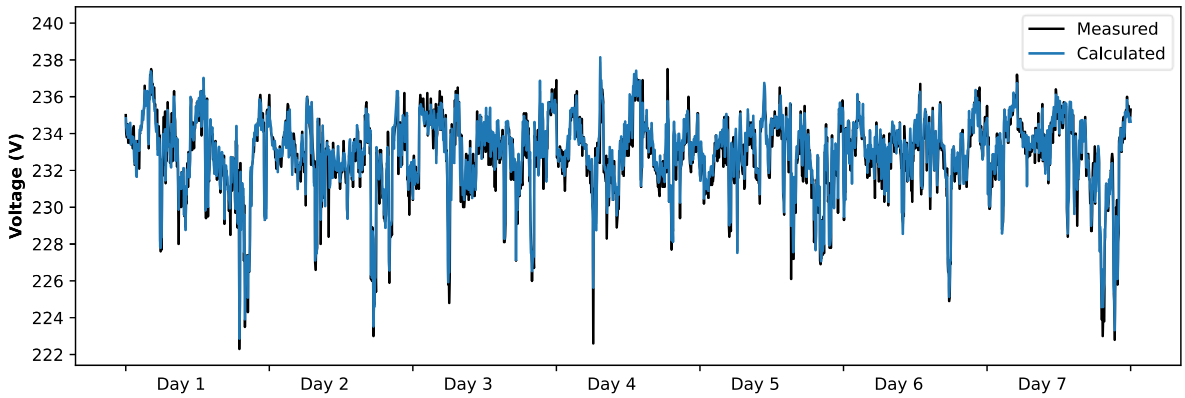
3.3 Results: Model-Free Voltage Calculations

The tailored neural network for each LV feeder is assessed using the data from the final week (i.e., unseen scenarios).

The voltage calculation performance is first demonstrated using time-series plots for two representative customers: A5 from Feeder A (as shown in Figure 4.a) and B8 from Feeder B (as shown in Figure 4.b). From the plots in Figure 4, it can be seen that the calculated voltages (in blue) mostly overlap with the measured voltages (in black), which means great accuracy is achieved with the proposed model-free approach.



(a) Customer A5, Feeder A

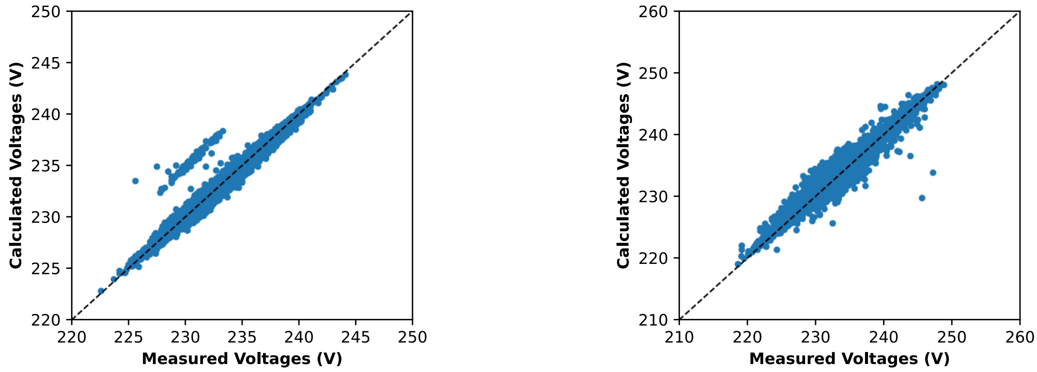


(b) Customer B8, Feeder B

Figure 4. Illustration of model-free voltage calculation using time-series plots.

Although the time-series plot is useful for individual customer analysis, it becomes cumbersome when dealing with many customers. Therefore, a scattered plot is utilised for more-effective visualisation and analysis of the overall performance. The scatter plots for all customers in Feeder A and B are shown in Figure 5.a and Figure 5.b, respectively. Here, it is clear that the model-free voltage calculation performance is able to accurately calculate voltages for both feeders as the dots in the scatter plot are well aligned with the line y=x.

Finally, the average deviation is found to be 0.23 V and 0.42 V, for Feeder A and B, respectively. This is close to negligible when compared to nominal line-to-neural voltage of 230V for these LV feeders.



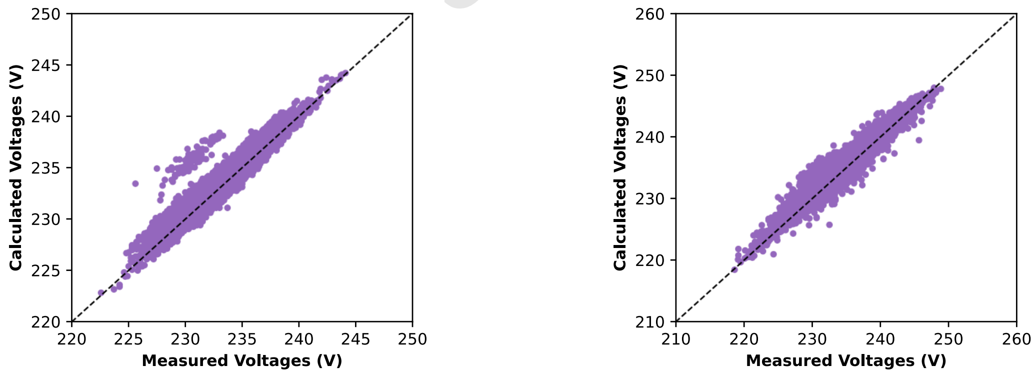
(a) Feeder A (b) Feeder B

Figure 5. Performance assessment of model-free voltage calculation using scatter plots.

3.4 Results: Model-Free vs Model-Driven

In addition to the performance assessment, the conventional model-driven approach (using the validated electrical models) is also considered as a benchmark for the proposed model-free voltage calculation approach.

Using the same testing data and the validated electrical models, the results for the model-driven voltage calculation approach is also produced. The scatter plots are shown in Figure 6; the average deviation for Feeder A and B are 0.40 V and 0.86 V, respectively.



(a) Feeder A (b) Feeder B

Figure 6. Performance assessment of model-driven voltage calculation using scatter plots.

While the validated electrical model also achieved comparable performance, it can be verified that the model-free approach still outperforms the model-driven approach. Particularly, the dots are closer to the line y=x in Figure 5 (i.e., model-free approach) and the average deviation is slightly lower.

The key differences between the two approaches can be illustrated using a representative customers A11 from Site A, which is highlighted further in Figure 7. As shown by Figure 7.b, while the calculated voltages by the model-driven approach are aligned with y=x, there is a noticeable offset from y=x that is fixed at all times. This is likely due to a degraded neutral conductor; something not being explicitly considered in the model-driven approach. Particularly, the neutral conductor is earthed at every meter in Australia (i.e., a multi-earthed system), and this is one of the assumptions used in the electrical model. However, this could change due to external factors such as equipment aging and poor connections. On the other hand, the model-free approach can successfully extract the physical relationships that is already embedded in the historical data without any explicit assumption about the neutral conductor (and potentially any other aspects). Thanks to this, the voltage offset issue seen in customer A11 for the model-driven approach is no longer present with the model-free approach, as shown by Figure 7.a.

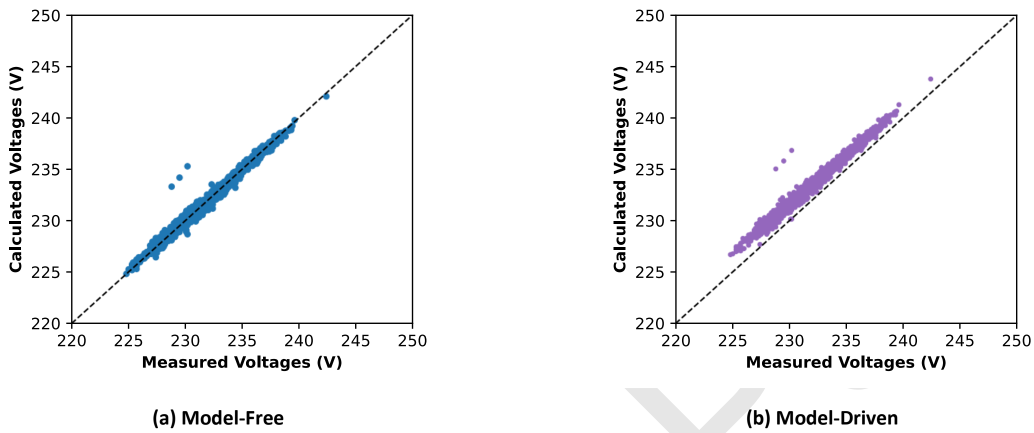


Figure 7. Comparison of model-free and model-driven approaches for customer A11.

3.5 Practical Insights, Learnings and Considerations

Limitations of model-driven approaches. As with any electrical model, there are inherent assumptions that may not be true in reality. This, in turn, introduces error that cannot be addressed without adapting the model which may require substantial efforts. One such example is the perfect earthing of the neutral conductor for every customer (as identified in this work). In contrast, the model-free eliminates this potential issue as it does not require such explicit assumptions. Given that the underlying physics is already being captured by the smart meter data, the model-free approach (i.e., the neural network in this work) will simply extract the physics as is from historical data.

Real data is imperfect. The use of real-world data introduces additional challenges due to the inherent noise/error within these data, which can be caused by factors such as synchronization issues, equipment's accuracy class, etc. Therefore, the key criteria when assess the scattered plot is to focus on the overall trend (i.e., whether the dots are aligned with the line y=x, rather than falling exactly on it). This also means that, the average deviation metric is also being influenced by imperfect data.

Data availability. This paper assumes the availability of both smart meter data from all customers and head-of-feeder data for the LV feeder. While both datasets are available in the context of Project EDGE [8] (whose feeders are used in the case study), it may not be applicable for other areas. While these datasets are pre-requisites for the model-driven approach, the model-free approach has been demonstrated to have adequate performance with partial smart meter data and/or without head-of-feeder data [13, 18].

Scalability. The proposed approach treats each LV feeder independently. This approach exploits the hierarchical nature of distribution networks and the inherent separation between the HV feeder and LV feeder through the distribution transformer. A key advantage is scalability as many LV feeders can be catered for in parallel. At the same time, this approach also assumes that meter-to-transformer mapping is correct and readily available.

4. Conclusion

Voltage calculations are essential to distribution companies. However, the lack of adequate electrical models for LV feeders can be extremely prohibitive for conventional model-driven approaches that requires running power flows. This work proposes a model-free voltage calculation approach where a tailored neural network is used to capture the physical relationships of the LV feeder from historical data. Once trained, the neural network can be used to carry out voltage calculations, eliminating the costly and time-consuming process of producing adequate electrical models.

The proposed model-free voltage calculation approach is successfully demonstrated using real LV feeders and read data from Victoria, Australia. Furthermore, the performance is also compared against the conventional approach where validated electrical models are produced (thanks to significant prior efforts).

While both approaches can calculate voltages accurately, the model-free approach has been shown to outperform the conventional approach. Furthermore, the model-free approach offers significant practical advantage due to its ease of implementation and cost-effective nature. This is because the neural network in a model-free approach can be produced in a matter of minutes which is a stark contrast to the costly and time-consuming process of producing electrical models in a model-driven approach. Ultimately, these advantages of a model-free approach can be a key enabler for its large-scale deployment by distribution companies.

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