energies

Article

A Novel Virtual Power Plant Uncertainty Modeling Framework Using Unscented Transform

Lucas Feksa Ramos [1,*], Luciane Neves Canha [2], Josue Campos do Prado [3] and Leonardo Rodrigues Araujo Xavier de Menezes [4]

1 Department of Electrical Engineering, Federal University of Rondônia, Porto Velho 76801-059, Brazil
2 Graduate Program in Electrical Engineering, Federal University of Santa Maria, Santa Maria 97105-900, Brazil; lucianecanha@ufsm.br
3 School of Engineering and Computer Science, Washington State University, Vancouver, WA 98686, USA; josue.camposdoprado@wsu.edu
4 Department of Electrical Engineering, University of Brasilia, Brasilia 70910-900, Brazil; leonardo@ene.unb.br
* Correspondence: lucasfeksaramos@gmail.com

Abstract: This paper proposes a new strategy for modeling predictability uncertainty in a stochastic context for decision making within a Virtual Power Plant (VPP). Modeling variable renewable energy generation is an essential step for effective VPP planning and operation. However, it is also a challenging task due to the uncertain nature of its sources. Therefore, developing tools to effectively predict these uncertainties is essential for the optimal participation of VPPs in the electricity market. The purpose of this paper is to present a novel method to model the uncertainties associated with energy dispatching in a VPP using the Unscented Transform (UT) method. The proposed algorithm minimizes the risks associated with the VPP operation in a computationally efficient and simple manner, and can be used in real-time on a power system. The proposed framework was evaluated based on an Electric Power System (EPS) model with historical data. Case studies have been performed to demonstrate the effectiveness of the proposed framework in minimizing power demand and renewable-energy-forecasting uncertainty for a VPP.

Keywords: forecast uncertainty; virtual power plant; unscented transform

check for updates

Citation: Ramos, L.F.; Canha, L.N.; Prado, J.C.d.; de Menezes, L.R.A.X. A Novel Virtual Power Plant Uncertainty Modeling Framework Using Unscented Transform. *Energies* **2022**, *15*, 3716. https://doi.org/10.3390/en15103716

Academic Editor: Georgios Christoforidis

Received: 15 April 2022
Accepted: 17 May 2022
Published: 19 May 2022

1. Introduction

There have been concerns throughout many countries and regions about the rational consumption of electricity, which is increasing every day, along with concern for the environment. This has sparked a quest for new ways to improve energy efficiency, and has been a motivation for the development of more efficient and cleaner technologies.

This increasing energy demand, along with higher penetration of variable renewable energy, is posing many challenges for the electricity sector due to the need to balance generation and load in real-time and meet energy-efficiency and sustainability goals. In addition, the number of inverter-based distribution generation (DG) and other distributed-energy resources (DERs) has been increasing continuously, and has created additional complexities for power-system operation, thus highlighting the need for innovative methods to model various uncertainties and reduce overall operational complexity.

Distributed-Energy Resources (DERs) are smaller energy sources that can be aggregated to provide the amount of energy needed to meet demand. However, their small installed capacities, intermittences, and uncertain generation make it difficult for these plants to enter and directly participate in the electricity market.

Innovative technologies must be harnessed to make the most of DERs. Because of this, a paradigm for the operation of modern power-distribution and transmission systems is being presented through a Virtual Power Plant (VPP) [1]. Important solutions for the reliable supply of electricity in a power system are coming to light, establishing an efficient and effective mechanism [2]. The literature and studies regarding this technology already indicate the direction of this new tool as a promising solution [3,4].

VPPs demonstrate their relevance as an integral part of predictability research on power-generation variability and demand. However, various uncertainties are present due to the intermittent nature of renewable production units, market prices, and power demand. Therefore, it is necessary to consider and know the degree of uncertainty during the operation of a VPP, since this information is crucial for efficient operational planning [5]. In this paper, the Unscented Transform (UT) method is used to improve the daily predictability of a VPP system with minimal aggregation error [6].

Typically, this problem could be solved by electrical engineering using the Monte Carlo (MC) model, as it is one of the most widespread techniques for modeling uncertainty in a short-term forecast. However, the need for real-time usage makes the MC model impractical [7]; the method uses millions of iterations to obtain a satisfactory result in terms of confidence intervals. This makes its use computationally impracticable in several cases [8].

The UT method, however, presents a new approach for solving this problem, which requires less computational effort when compared to the Monte Carlo method [9]. In the next chapter, we will present the UT method for individual forecasting of each VPP user in order for the aggregator to have prior knowledge of the data and be able to make relevant decisions.

2. Virtual Power Plant (VPP)

VPPs aim to achieve better use of normally spatially dispersed energy resources, and to coordinate their joint operation to meet energy demand requirements [1]. They present a set of generation units, controllable loads, and network-dispersed energy storage systems and aggregates [10] to operate as a single plant [11] for the system operator, as shown in Figure 1.

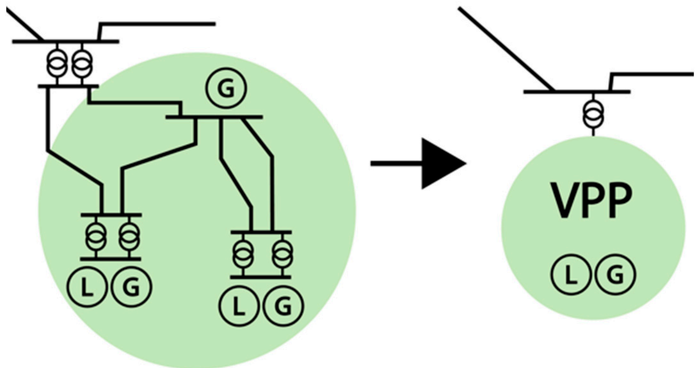

Figure 1. Concept representation of a VPP (adapted fenix-project [12]).

The representation in the known literature of a VPP connected to the system presents Distributed Generators (DG). These have different generations (G) and different load profiles (L), and are controlled by a VPP that presents a system operator through an aggregator [13] with a single operational profile of a parameter composed of the whole system, which characterizes each DER and each load. These make it possible to act directly on market scenarios through energy supply and demand, improving reliability and price fluctuations in daily or real-time markets.

Some key components of a VPP's topology include the establishment of information connections and the changing of energy resources along with the energy market. Figure 2 represents the sets of different non-renewable and renewable storage generators and storage devices that can be integrated. Some perform commercial roles, such as bringing together the energy production of several local units and marketing them as a single entity. Others perform more technical operations, such as being able to adjust the production profile of their generator components or even providing ancillary services to the system.

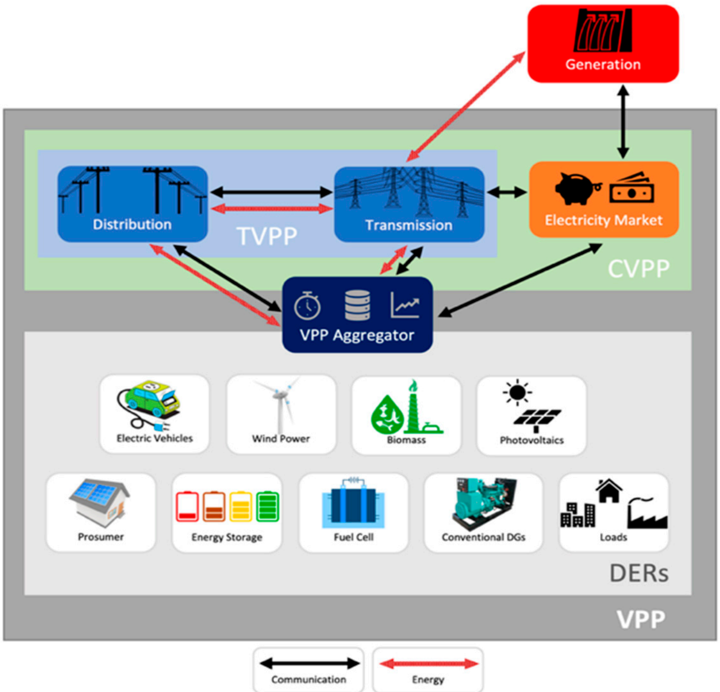

Figure 2. Illustration of the Virtual Power Plant.

2.1. Technical Virtual Power Plant (TVPP)

The VPP essentially depends on a TVPP for its existence and operation. It works and communicates mainly at the distribution-and-transmission-network level of the same geographical placement, as represented in green in Figure 2 [14].

The generation capacity of DERs is aggregated in the distribution network, where the VPP can participate in a competitive electricity market, and may require detailed knowledge of the local grid to provide technical services to the system operator, such as ancillary services and balancing services [15], similar to a system operator, especially in energy-balance performance [16].

The TVPP is involved in managing and easing grid constraints, as well as in aggregating DERs with appropriate parameters for distribution [17]. It may dispatch controllable resources and decide whether to buy from, or sell energy to, the electricity market, while considering various sources of uncertainty [18,19].

2.2. Commercial Virtual Power Plant (CVPP)

CVPPs allow DERs to gain visibility in energy markets, which would be very difficult, if not impossible, if the same DERs were operated as single entities. Moreover, aggregation allows them to participate in wholesale markets as if they were conventional generators [18]. Aggregation can also be facilitated through long-term contracts, potentially lowering transaction costs and reducing price uncertainties.

CVPPs are considered to be commercial entities in that they report the price and amount of energy they can provide through production and consumption forecasting, based on weather forecasting and demand profiles, thereby optimizing the economic use of the VPP portfolio and schedule. Aggregate units of DERs for the electricity market are based on anticipated needs and cannot be limited to a defined electrical area, meaning VPPs are not limited geographically [19]. Trading in the wholesale energy market is one of the main services provided by CVPPs.

2.3. Aggregator

The aggregator is responsible for market operations that deal with portfolio aggregations [10]. The VPP aggregator communicates directly in real-time with the CVPP and TVPP to provide a profile and forecast of energy production from diverse and geographically distributed sources between distribution and transmission networks [13]. The process includes many details internally, such as prediction algorithms. Its main feature is error reduction through the knowledge of uncertainties, since for a trader interested in selling energy, this experience allows accurate energy forecasts to be traded within the stipulated trading period. It can group numbers of small or large generators to generate economies of scale in market access. It is also responsible for balancing a VPP's entire system as a power supplier and buyer of locally generated electricity [20].

2.4. Distributed-Energy Resources (DERs)

One of the most significant changes in electricity systems worldwide has been the rapid expansion of DERs, which provide an energy-generation solution that has great potential in the global energy sector, and are directly connected to local distribution systems or to aggregated VPPs within those systems, and have the potential to offer substantial benefits to a power system.

DERs may include electric vehicles (EVs), wind energy, biomass and biogas, photovoltaic production, prosumers, energy storage, fuel cell, flexible consumption (controllable/dispatched loads), and small plants (gas turbines, diesel, etc.), among others. Discussions on how to better integrate and manage these features are under intense development and this should contribute to an increase in the potential benefits gained from adding more DERs.

3. Unscented Transform (UT)

Power-grid uncertainties are gradually increasing, making safe and stable operation a challenge and constraining accurate estimates of variables during VPP operation. Therefore, it is necessary to recognize the sources of these uncertainties and to select the appropriate means of description.

It is important to have accurate forecasts of demands and generations with the unpredictability of their uncertainties, so that the forecasting-error impact on system operating performance is minimized [21,22].

The integration of VPPs in the market occurs with the need to consider uncertainties without being overlooked. One solution for managing renewable energy uncertainties and demands is using the Unscented Transform (UT), in which the uncertainties can be modeled by one or more random variables for multiple sources of uncertainty.

The UT consists of a discrete approximation method of the continuous probability-density function (PDF), ensuring that the two distributions have statistically the same properties, being even easier to implement and using the same order of calculations as linearization [23]. For the realization of the transform, one of the prerequisites is that the discrete distribution has the same moments as the continuous distribution.

The UT can effectively model uncertainties and decision-making risks. It was developed with the intuition that it is easier to approximate a probability of distribution than to approximate a function or transformation of an arbitrary nonlinear function. The basic principle of the UT is the approximation of the PDF by a set of selected points, called sigma points, and their associated weights. The statistics of mean, variance, and other moments of the mapping will be available from a weighting of these sigma points [23,24].

As such, the UT is a powerful tool for obtaining statistics from a distribution that has undergone a linear or nonlinear process [25]. It can be viewed either as a nonlinear mapping expansion, a discrete approximation of the continuous probability-density function by a discrete distribution, or even with Gauss-quadrature integration.

To use the UT, it is necessary to know the sigma points and the weights of the equivalent discrete distribution. These are obtained by equality between the moments of discrete distribution and continuous distribution:

$$\sum_{i=1}^{m} w_i x_i^n = \int p(x) x^n dx \tag{1}$$

Ideally, the two distributions (discrete and continuous) will be equivalent if the equality described in (1) holds for all moments (i.e., any value of n). However, for practical reasons, it is considered sufficient to satisfy the system of (1) to a desired value of n. The higher this value, the greater the number of equal moments, and the more faithful the approximation. Therefore, sigma points and weights are not chosen randomly, they are calculated deterministically to have specific properties such as mean, variance or any other previously known moments [26]. The resolution of (1) can be performed using a mathematical transformation, where the nonlinear system becomes a nonlinear equation plus a linear system.

The formulation for the choice of sigma points and weights uses an approximation of the ideal solution of the quadrature problem, so the choice of sigma points and weights extrapolates the weights and sigma points from a uniform distribution to the others.

The weight function is a fundamental element for the following calculations. Let $w(x)$ be a function defined in an interval $I = [a,\ b]$. Furthermore, $w(x)$ is a weight function in I if $w(x) \geq 0, \forall x \in I$ and satisfy the following equation:

$$\int_a^b w(x) dx = 1 \tag{2}$$

As the interval may even be unlimited, Equation (2) is akin to the probability distribution integral in the whole support if $w(x) = f(x)$, Therefore, given a function $f(x)$ defined in I, the integral can be calculated.

$$S = \int_a^b w(x) f(x) dx \tag{3}$$

The integral in (3) has the same properties of the expected value $E\{f(x)\}$. Since the quadrature consists of determining a finite set of abscissae x_i and weights w_i such that the integral S can be approximated by the sum of the areas of the base rectangles w_i and height $f(x_i)$.

$$\int_a^b w(x) f(x) dx \approx \sum_{i=1}^{m} w_i f(x_i) \tag{4}$$

Equation (4) is an approximation, where the quadrature has an associated error, given by the difference between the integral value and the approximation value. The quadrature will have an accuracy of at least m if the error is at least zero for $f(x) = x^n$ with $n = 0,\ 1,\ \ldots,\ m-1$. By defining M_n as the moment of $w(x)$ in I, we have:

$$M_n = \int_a^b x^n w(x) dx \tag{5}$$

Equation (5) is equivalent to calculating the raw statistical moments $E\{x^n\} = M_n$. We can determine the weights $w_1,\ w_2,\ \ldots,\ w_m$ by the linear system of m equations through the following equation:

$$\sum_{i=1}^{m} w_i x_i^r = M_r \tag{6}$$

with n = 0, 1, . . . , $m-1$.

This quadrature is said to be generalized Gaussian because there are no quadrature constraints in either range I or function. The target accuracy depends on at least $2m-1$ in an interval I. This gives the weights, which are important for finding the associated sigma points.

The sigma points S_i are determined by calculating the roots of the polynomial $\pi_m(x)$, with the values of w_i found by determining the roots $x_1, x_2, \ldots x_m$, of the polynomial by the following equation:

$$\pi_m(x) = \sum_{i=0}^{m} w_i x^{m-1} \tag{7}$$

With this nonlinear transformation defined by the UT, it is possible to obtain an approximation of the moments of $w(\hat{u})$ from the moments of w_i. The UT makes the discrete distribution have the same moments as the continuous distribution after nonlinear transformation or mapping, according to the following equation [25]:

$$E_d\{\hat{u}^k\} = \int_{-\infty}^{+\infty} \hat{u}^k w(\hat{u}) d\hat{u} = \sum_i w_i S_i^k \tag{8}$$

where:

E_d—expected value of the discrete distribution;
$\hat{u}$—the set of random variables with known probability distribution;
$\int_{-\infty}^{+\infty} \hat{u}^k w(\hat{u}) d\hat{u}$—the expected value of the continuous distribution;
S_i—UT sigma points;
k—desired approach;
w_i—defined as UT weights, besides being the discrete probability density function.

The use of the simple moving average method where the forecast is the average of the most recent N observations of the X series, as can be observed in Equation (9), is necessary.

$$X_t = \frac{1}{N} \sum_{i=1}^{N} X_{t-1} \tag{9}$$

4. Problem Definition

The proposed case study considers a VPP aggregator that aims to make profit and avoid losses in the electricity market by properly forecasting short-term generation and demand. Two days of historical data are considered, and the UT method is applied so that the third day is predicted by the proposed methodology and compared with the Persistence Method [24].

Figure 3 illustrates the VPP considered. It comprises three solar photovoltaic (PV) generators, three load sets (i.e., EV charging stations, a residential condominium, and a shopping mall, respectively) connected to a 13.8 kV bus, and three load sets (i.e., four households without EV, one household with EV, and one street light) connected to a 0.22 kV bus.

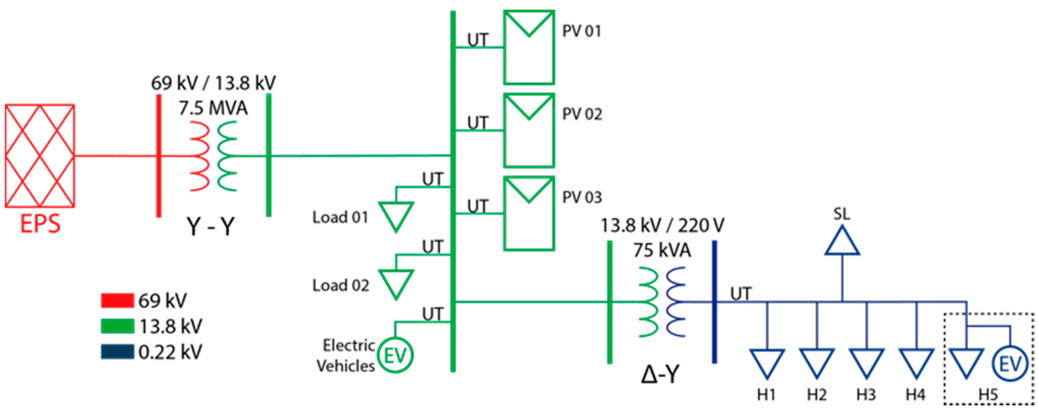

Figure 3. Electrical Region with VPP.

The main challenge for this VPP is to obtain, for the next day, a forecast interval mapped with the smallest possible generation error, and individual demand, minute-by-minute. By accurately predicting generation and load, the VPP aggregator can reduce its risks when purchasing and selling power in the electricity market.

Figure 4 shows the energy production of the three photovoltaic generators, connected to the 13.8 kV bar during three consecutive days. Data from the first two days are used to train the model. Two days are used in the model to buy, with the last day containing the error of the proposed model.

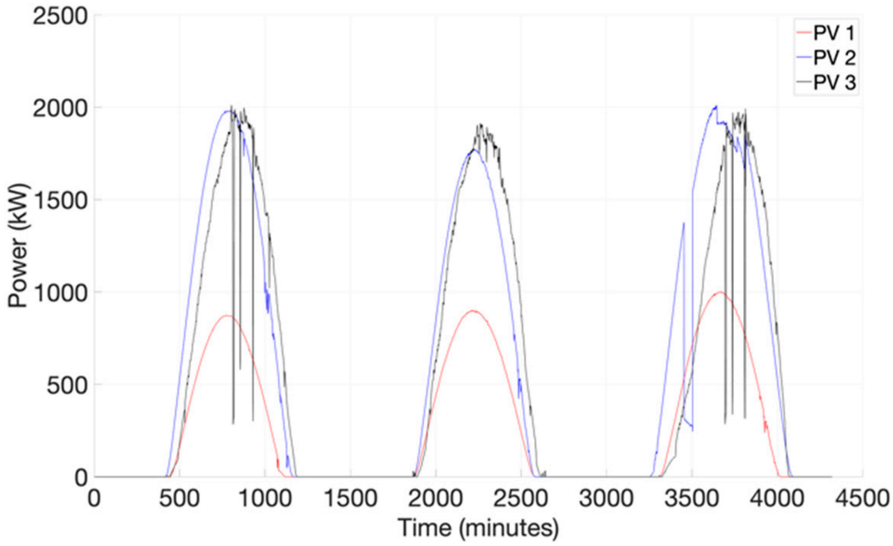

Figure 4. Photovoltaic power generation.

Figure 5 shows the 3 days of demand data connected to the 13.8 kV bus.

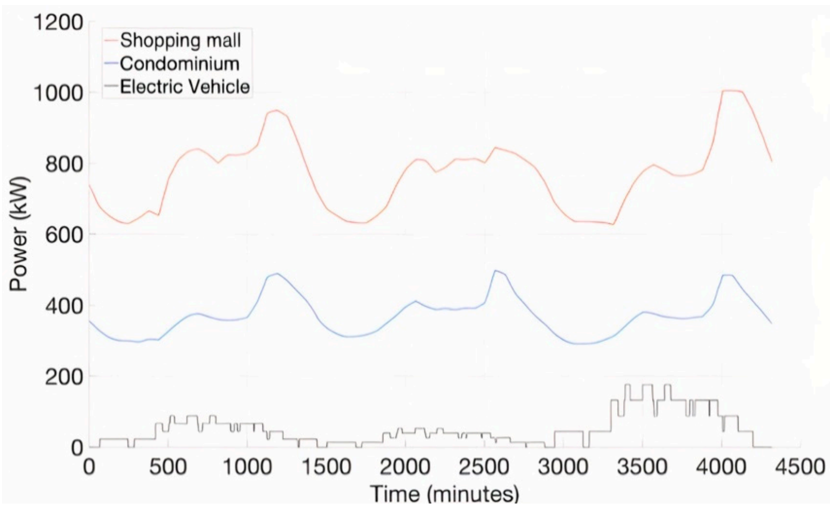

Figure 5. Electricity demand (13.8 kV).

Finally, in Figure 6, the demands connected to the low voltage are shown.

Figure 7 shows the total aggregated generation and load data for the VPP considered in this study.

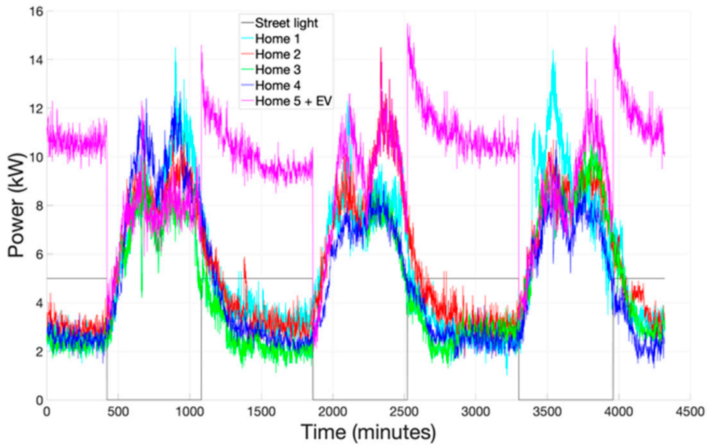

Figure 6. Electricity demand (low voltage).

Figure 7. Total Generation and Total Electricity Demand.

5. Methodology

In this paper, the UT is used to manage the uncertainties related to variable renewable energy production and intermittent power demands. The UT is applied to create a forecasting method for power generation and demand minute-by-minute, allowing both current and forecasted energy to be treated as random variables in a 1-day future.

In order to verify the effectiveness of the model, the very simple and effective persistence method is used. Equation (9) defines the persistence forecast in which the index is assumed to remain constant, relative to the previous step. This technique tends to perform better on small time scales (e.g., minutes) than larger time scales (e.g., hourly and daily). Persistence assumes that conditions will remain constant, relative to the previous stage of the forecast.

$$P(t + \Delta t) = kt(t)\ P_o(t + \Delta t) \tag{10}$$

The UT method and the persistence of two days of input data are used. The methodology is applied to all VPP users, after which, the result with the errors is compared with the third day of reference data for the model. The third day is for comparison and analysis of the model between the two methodologies.

To further illustrate the methodology, we randomly choose a load to present, and then all are similarly solved. The findings are presented in Table 1, below, with their proper comparisons. In Figure 8, the proposed methodology uses the UT. It applies to the minute historical data over the 2 days. The answer is a forecast that contains an interval range of UT+ and UT−, which is the predictability gap where the demand will be inserted.

Table 1. Daily Forecast Errors.

0.22 kV	UT	Persistence
Home 1	2.3%	7.3%
Home 2	0.4%	4.5%
Home 3	0.5%	7.5%
Home 4	1.9%	4.1%
Home 5 + EV	0.23%	3.3%
PV 1	2.8%	3.5%
PV 2	5.9%	11.3%
PV 3	0.7%	8.8%
Condominium	0%	1.8%
Shopping Mall	0.6%	2.1%
Electric Vehicle	25.2%	39.3%

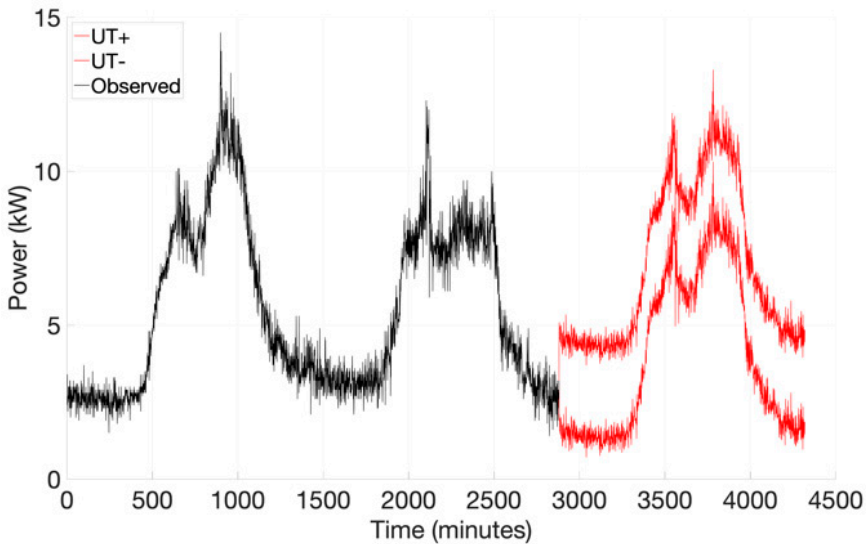

Figure 8. UT applied in home 1 demand.

The available historical data are data from loads and generations that were chosen arbitrarily, from an observational point of view. The three midweek days are considered for use in the simulation. All data are separated into independent days, day 1 has data from 1 to 1440, day 2 has data from 1441 to 2880 and day 3 has data from 2881 to 4320, in such a way that to simulate the chunk UT and persistence uses only 2 days, the first and second, respectively, which, after running their algorithms, will generate the third day as results that will be compared with the real data.

After applying the UT methodology, the historical reference data of the three days are used to compare and verify the prediction error in the UT interval, as shown in Figure 9.

Figure 10 shows the persistence of the third day using 2 days of historical data.

After persistence is applied, the three-day historical data are compared and verified for the error, as shown in Figure 11.

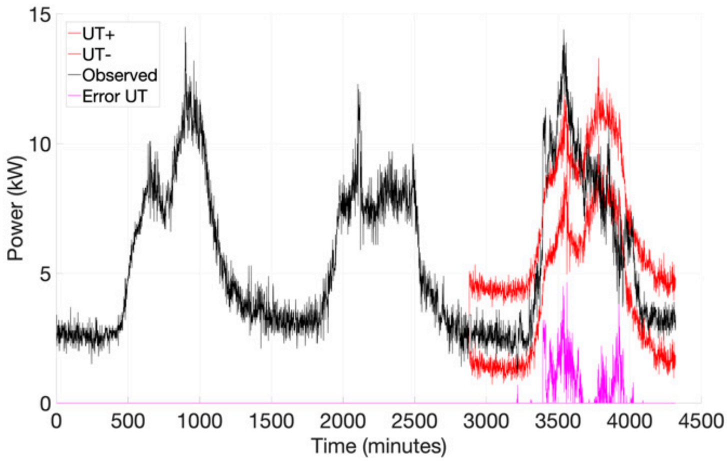

Figure 9. UT applied on demand house 1 plus error.

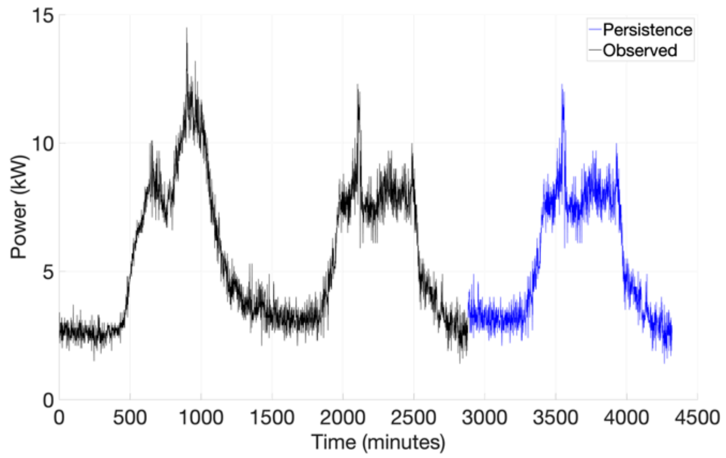

Figure 10. Persistence applied in home 1 forecasting.

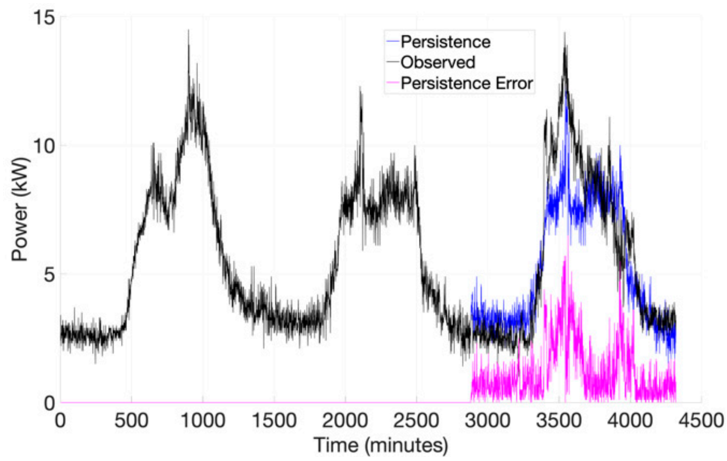

Figure 11. Persistence applied on demand forecasting plus error.

Finally, Figure 12 shows the comparison of prediction errors in the UT and persistence.

In Figure 12, one can visibly verify the low proportion of error of the UT method in relation to persistence. The errors presented in this specific case for house 1 connected to the 220 V system were 2.3% for the UT and 7.3% for persistence.

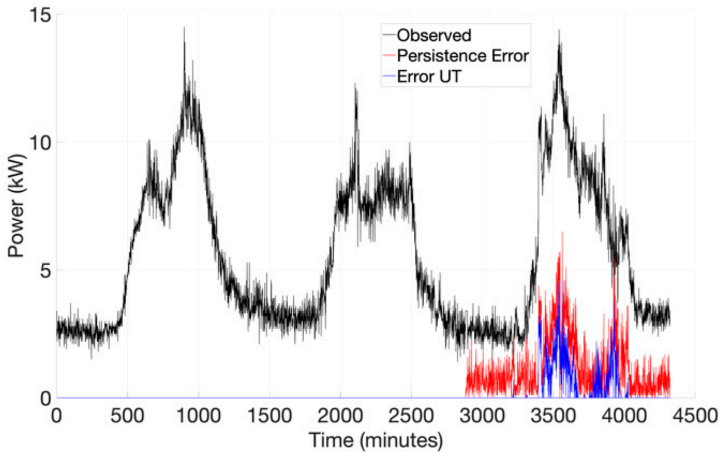

Figure 12. Persistence applied on demand forecasting plus error UT.

6. Results and Analysis

This section presents the results of the applicability of the UT method in a VPP. Comparisons were made with the persistence method, using all system users.

The simulations were sufficient to obtain statistically significant results. The actual data from the third day were compared with the UT and the persistence to verify the error of each VPP user.

Table 1 below shows the sum of the third-day forecast errors for each user logged into the VPP system, compared to actual observed data. The UT data and persistence of the entire connected VPP system are presented to the VPP aggregator from minute to minute.

The values in Table 1 present a clear comparison of the errors. The predictability gain that the UT implies in a VPP system is noticeable.

The software performed the prediction using the UT in 3 s for the 24 h horizon. Therefore, when the UT is executed within the VPP at a one-minute step ahead, the computational time is much smaller than the desired step, and there is a solution before the next event, which is considered real forecast time.

A highly variable and unpredictable example that injects a high degree of error into the VPP is the entry of electric vehicles into the system. With the UT, the error was 25.2%, and with persistence, the error was 39.3%. Furthermore, for PV2, the UT resulted in a prediction error of 5.9%, whereas persistence resulted in a prediction error of 11.3%. These results show that predicting uncertainties using the UT can be beneficial to VPPs with uncertainties in variable renewable generation and intermittent power demand.

7. Conclusions

This paper presents an innovative methodology for reducing the risks associated with operation and decision-making in a VPP. The UT method accurately predicts the generation and demand uncertainties of a VPP.

The UT is an alternative application for this forecasting, presenting a response very close to the desired response, while presenting a higher computational efficiency compared to other existing techniques. It has adequate performance for real-time operations and error reduction compared to the traditional forecasting method. The UT was used to estimate predictions from the stochastic model of generations and demands of a VPP. The results of the UT confirmed the expected benefits in terms of performance, the possibility of real-time applications, and risk-reduction for new business models.

The validation of the method was performed by simulations and comparisons of its results with actual measurements from a real-world VPP. Compared with the persistence method, the UT method presented similar accuracy to the actual data, and the smallest errors for all generators and loads. This proves the applicability and quality of the proposed methodology. Furthermore, this paper shows the fundamental importance of considering and knowing the variability of future generation and demand for a VPP aggregator from an economic point of view.

An important fact that can be verified is that all simulation models introduce some kind of intrinsic prediction error. Such error cannot yet be adequately modeled using the UT. However, future works can be conducted to address this issue. Another direction for future work includes the integration of energy storage systems.

Author Contributions: Conceptualization, L.F.R. and L.R.A.X.d.M.; methodology, L.F.R., L.R.A.X.d.M. and J.C.d.P.; software, L.F.R.; validation, L.F.R., L.N.C., J.C.d.P. and L.R.A.X.d.M.; formal analysis, L.F.R.; investigation, L.F.R.; resources, L.F.R. and L.N.C.; data curation, L.F.R. and J.C.d.P.; writing—original draft preparation, L.F.R., L.N.C., J.C.d.P. and L.R.A.X.d.M.; writing—review and editing, L.F.R. and J.C.d.P.; visualization, L.F.R. and J.C.d.P.; supervision, L.F.R. and L.N.C.; project administration, L.F.R. and L.N.C.; funding acquisition, L.N.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank the Federal University of Rondônia and support from Federal University of Santa Maria, Santa Maria—RS, Brazil, funding from CNPq PQ 1-D 310761/2018-2, CNPq process 465640/2014-1, CAPES process no. 23038.000776/2017-54 and FAPERGS 17/2551-0000517-1, support from CNPq, Brazilian National Council for Scientific and Technological Development—Brazil. This study was also financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES/PROEX)—Finance Code 001.

Conflicts of Interest: The authors declare no conflict of interest and the funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. Pudjianto, D.; Pudjianto, D.; Ramsay, C.; Ramsay, C.; Strbac, G.; Strbac, G. Virtual Power Plant and System Integration of Distributed Energy Resources. *IET Renew. Power Gener.* **2007**, *1*, 10–16. [CrossRef]
2. Maceas Henao, M.; Espinosa Oviedo, J.J. Bidding Strategy for VPP and Economic Feasibility Study of the Optimal Sizing of Storage Systems to Face the Uncertainty of Solar Generation Modelled with IGDT. *Energies* **2022**, *15*, 953. [CrossRef]
3. Sarmiento-Vintimilla, J.C.; Torres, E.; Larruskain, D.M.; Pérez-Molina, M.J. Applications, Operational Architectures and Develoment of Virtual Power Plants as a Strategy to Facilitate the Integration of Distributed Energy Resources. *Energies* **2022**, *15*, 775. [CrossRef]
4. Podder, A.K.; Islam, S.; Kumar, N.M.; Chand, A.A.; Rao, P.N.; Prasad, K.A.; Logeswaran, T.; Mamun, K.A. Systematic Categorization of Optimization Strategies for Virtual Power Plants. *Energies* **2020**, *13*, 6251. [CrossRef]
5. Yu, S.; Fang, F.; Liu, Y.; Liu, J. Uncertainties of Virtual Power Plant: Problems and Countermeasures. *Appl. Energy* **2019**, *239*, 454–470. [CrossRef]
6. Julier, S.J. The Scaled Unscented Transformation. In Proceedings of the American Control Conference, Anchorage, AK, USA, 8–10 May 2002; Volume 6, pp. 4555–4559. [CrossRef]
7. Fernandes, L.C.; De Menezes, L.R.A.X. Using Unscented Transform in Interference Studies. *IEEE Antennas Propag. Mag.* **2017**, *59*, 131–138. [CrossRef]
8. Drezner, Z. Operational Research Society Is Collaborating with JSTOR to Digitize, Preserve, and Extend Access to Journal of the Operational Research Society. *J. Oper. Res. Soc.* **1987**, *38*, 509–514. [CrossRef]
9. Ishihara, J.Y.; Silva, L.M.; Soares, A.J.M.; de Menezes, L.R.A.X. Using Unscented Transform as Alternative to Monte Carlo in Bit Error Rate Calculations. *Electron. Lett.* **2013**, *49*, 675–677. [CrossRef]
10. Yi, Z.; Xu, Y.; Gu, W.; Wu, W. A Multi-Time-Scale Economic Scheduling Strategy for Virtual Power Plant Based on Deferrable Loads Aggregation and Disaggregation. *IEEE Trans. Sustain. Energy* **2020**, *11*, 1332–1346. [CrossRef]
11. Vesey, A. *The Virtual Utility*; Awerbuch, S., Preston, A., Eds.; Springer: Boston, MA, USA, 2011; ISBN 978-1-4613-7827-3.
12. FENIX—Future Business Models for the Efficient Recovery of Natural and Industrial Secondary Resources in eXtended Supply Chains Context. Available online: www.fenix-project.eu (accessed on 20 February 2022).
13. Correa-Florez, C.A.; Michiorri, A.; Kariniotakis, G. Optimal Participation of Residential Aggregators in Energy and Local Flexibility Markets. *IEEE Trans. Smart Grid* **2020**, *11*, 1644–1656. [CrossRef]

14. Kolenc, M.; Nemček, P.; Gutschi, C.; Suljanović, N.; Zajc, M. Performance Evaluation of a Virtual Power Plant Communication System Providing Ancillary Services. *Electr. Power Syst. Res.* **2017**, *149*, 46–54. [CrossRef]
15. Palizban, O.; Kauhaniemi, K.; Guerrero, J.M. Microgrids in Active Network Management—Part I: Hierarchical Control, Energy Storage, Virtual Power Plants, and Market Participation. *Renew. Sustain. Energy Rev.* **2014**, *36*, 428–439. [CrossRef]
16. Hooshmand, R.A.; Nosratabadi, S.M.; Gholipour, E. Event-Based Scheduling of Industrial Technical Virtual Power Plant Considering Wind and Market Prices Stochastic Behaviors—A Case Study in Iran. *J. Clean. Prod.* **2018**, *172*, 1748–1764. [CrossRef]
17. Pourghaderi, N.; Fotuhi-Firuzabad, M.; Moeini-Aghtaie, M.; Kabirifar, M. Commercial Demand Response Programs in Bidding of a Technical Virtual Power Plant. *IEEE Trans. Ind. Inform.* **2018**, *14*, 5100–5111. [CrossRef]
18. Abbasi, M.H.; Taki, M.; Rajabi, A.; Li, L.; Zhang, J. Coordinated Operation of Electric Vehicle Charging and Wind Power Generation as a Virtual Power Plant: A Multi-Stage Risk Constrained Approach. *Appl. Energy* **2019**, *239*, 1294–1307. [CrossRef]
19. Tarazona, C.; Muscholl, M.; Lopez, R.; Passelergue, J.C. Integration of Distributed Energy Resources in the Operation of Energy Management Systems. In Proceedings of the 1st IEEE-PES/IAS Conference on Sustainable Alternative Energy, SAE 2009—Proceedings 2009, Valencia, Spain, 28–30 September 2009; pp. 1–5. [CrossRef]
20. Samadi Gazijahani, F.; Salehi, J. IGDT Based Complementarity Approach for Dealing with Strategic Decision Making of Price Maker VPP Considering Demand Flexibility. *IEEE Trans. Ind. Inform.* **2019**, *16*, 2212–2220. [CrossRef]
21. Huang, C.; Yue, D.; Xie, J.; Li, Y.; Wang, K. Economic Dispatch of Power Systems with Virtual Power Plant Based Interval Optimization Method. *CSEE J. Power Energy Syst.* **2016**, *2*, 74–80. [CrossRef]
22. Majidi, M.; Zare, K. Integration of Smart Energy Hubs in Distribution Networks under Uncertainties and Demand Response Concept. *IEEE Trans. Power Syst.* **2019**, *34*, 566–574. [CrossRef]
23. Julier, S.J.; Uhlmann, J.K. Unscented Filtering and Nonlinear Estimation. *Proc. IEEE* **2004**, *92*, 401–422. [CrossRef]
24. De Menezes, L.R.A.X.; Thomas, D.W.P.; Christopoulos, C.; Ajayi, A.; Sewell, P. The Use of Unscented Transforms for Statistical Analysis in EMC. In Proceedings of the IEEE International Symposium on Electromagnetic Compatibility, Hamburg, Germany, 8–12 September 2008. [CrossRef]
25. De Menezes, L.R.A.X.; Ajayi, A.; Christopoulos, C.; Sewell, P.; Borges, G.A. Efficient Extraction of Statistical Moments in Electromagnetic Problems Solved with the Method of Moments. In Proceedings of the SBMO/IEEE MTT-S International Microwave and Optoelectronics Conference, Salvador, Brazil, 29 October–1 November 2007; pp. 757–760. [CrossRef]
26. De Menezes, L.; Ajayi, A.; Christopoulos, C.; Sewell, P.; Borges, G.A. Extracting Statistical Moments of Output Quantities from a Small Number of Time-Domain Simulations. *Int. J. Numer. Model. Electron. Netw. Devices Fields* **2009**, *22*, 143–157. [CrossRef]