Load Profile Generation for Robust Optimization: A Stochastic Approach Based on Conditional Probability Approximation

***Abstract*—With the growing integration of renewable energy sources into distributed grids, accurate household-level load forecasting becomes essential for robust energy management and optimization. This paper proposes a lightweight stochastic profile generation method grounded in conditional probability approximation. First, empirical conditional distributions are mined from historical load data via hourly histogram binning and correlation analysis. Second, a Monte Carlo-inspired "flock" of plausible future load trajectories is generated iteratively, each endowed with an occurrence probability. Validation on the Ausgrid dataset (127 prosumer profiles over one year) shows that the probabilistic mining step requires only 0.5–0.6 s for history depths of 30–180 days, while generating 200 scenarios takes merely 8.1 ms, with a total memory footprint of approximately 200 KB. These computational and storage efficiencies render the approach suitable for online deployment on edge devices, enabling robust optimization under uncertainty in renewable energy communities.**

***Keywords*— Load Profile Generation; Load Forecasting; Optimization Under Uncertainty; Energy Management**

I. Introduction

The world in which we live is being transformed every day. One of such transformations is climate change, which is affecting things taken for granted, even just a few years ago [1]. These changes are threatening our habits and our future. To fight what is considered the major cause of this shift, namely the uncontrolled increase in CO_2 emissions over the last century, it is becoming more and more important to pursue the Green Transition at a steady pace [2].

An increased penetration of Renewable Energy Sources (RES) brings additional tangible benefits, such as reduced air pollution and, even if gradually, a significant impact on energy prices [3]. This trend has also caused a market drop in the cost of plant installation, especially photovoltaic ones, allowing for further and distributed adoption in forms of household generation systems [4]. This domestic application has an important impact on the interaction between domestic users and the grid, creating new figures that absorb or inject energy into the network, called prosumers [5].

Even though these changes are overwhelmingly positive, there are some important issues to address [6][7]. First, the most common and economic RES, i.e., solar and wind energies, are characterized by a high degree of uncontrollability. In a few words there is no way to use them to produce energy on demand. Second, this distributed approach has already led to widespread presence of productions plants, therefore, to reduce transmission losses, it makes sense to coordinate the consumption of the nearby users with such generations [8].

In this context, topics such as demand response [9], optimal power flow [10][11] and Vehicle To Grid (V2G) [12]-[14] have become of primary relevance. It is important to integrate renewable energy sources in the planning of energy usage, generally handled by control systems known as Energy Management Systems (EMS) [15]-[19]. To perform such scheduling, these systems should rely on forecasting of both the production of those uncontrollable but green sources and of the load demand [20][21].

The Load Forecasting, especially at a granular level such as for domestic household, is a tricky problem. There are many techniques to address it, but it is difficult to reach high accuracy, especially considering constraints such as hardware limitations or data scarcity. Since handling this uncertainty is mandatory for robust planning, multiple techniques have been developed to increase the scheduling robustness [22].

To implement an approach like this, forecasting a single profile is not enough: at every iteration, a whole "flock" of possible futures is needed. To be usable, these multiple scenarios must remain consistent with the behavior of the user under management but cover as many possibilities as possible. This leads to handle the Profile Generation problem.

A recent examination of load profile generation methods reveals significant advancements in model design and benchmarking. While sophisticated generative models such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Denoising Diffusion Probabilistic Models (DDPMs) are increasingly utilized for creating synthetic load profiles, their practical application remains limited. This limitation is mainly due to high computational requirements, substantial data needs, and increased energy consumption [23][24][25]. These challenges become particularly pressing when applying these models on edge devices or in resource-constrained environments. To address these issues, researchers are exploring alternative and hybrid strategies that include flow-based models with specific loss functions, reinforcement learning-enhanced InfoGANs, and the integration of VAEs with Non-Intrusive Load Monitoring (NILM) techniques.

For example, Xia et al. [26] introduce a novel full-convolutional normalizing flow architecture. They evaluate its performance using Pinball Loss and Continuous Ranked Probability Score, showing that it surpasses a t-Copula baseline

Dataset	Contents		
	Type of profiles	*Number of profiles*	*Profile length*
Ausgrid	Production and Consumption Profiles	127	8760 hours

Table 1. Ausgrid Dataset content description

in probabilistic forecasting tasks. However, its high computational demands still restrict its application, and they also utilize metadata such as weather conditions to enhance performance.

Lan et al. [27] present a reinforcement learning-augmented InfoGAN model, which is tested using Maximum Mean Discrepancy to ensure it maintains distributional fidelity. Despite this, the model's complexity limits its portability and scalability, and some of the features used may not always be accessible.

In another study, Förderer and Schmeck [28] focus on state-based load modeling for Distributed Energy Resources. Their work emphasizes action mapping and forecasting profiles for a single temporal step, specifically one hour.

In summary, these studies highlight improvements in predictive accuracy, generative diversity, and interpretability. However, they also reveal trade-offs regarding scalability, model transparency, and operational feasibility. The literature stresses the need for next-generation generative models that are not only statistically valid but also efficient enough for practical implementation in real-world, resource-constrained energy systems. Therefore, future research should aim to develop innovative methods that enhance the effectiveness and applicability of synthetic load profile generation.

This work presents a stochastic approach to profile generation, developed with a strong focus on explainability, computational cost, and the quality of the generated flock.

II. METHODOLOGY

This section details the proposed methodology. The recommended approach involves creating a set of probable future profiles by analyzing recent historical data for effective optimization. Specifically, the goal is to identify and leverage the profile distribution to improve forecasting and consequently enhance the system's performance.

It encompasses two distinct phases: first, estimating the conditional probability distributions that characterize the time series in question, and second, producing profiles from the previously gathered data. The next paragraph expands on these procedures, while Fig.5 shows generation diagram.

The method was validated using the Ausgrid datasets to confirm its effectiveness. It includes 127 profiles of production and consumption from prosumers, each covering a year. Table 1 describes the dataset's contents.

A. Step 1: Conditional probabilities approximation

The first step is to approximate the conditional probabilities to feed the profile generator. The underlying idea is that stochastic patterns govern a load consumption time series. For instance, household load profiles show clear daily seasonality, making it reasonable to hypothesize the presence of a correlation between the hours and the existence of conditional probabilities linking past and future timesteps. For simplicity, from this point onward, the chosen timestep is one hour.

The "mining" of the probabilistic properties of a profile starts from its historical data. The history consists of N available days, each counting 24 hours. Thus, it is possible to define Y, the history length, as follows:

$$Y = N * 24 \ [hours] \qquad (1)$$

Fig. 1. Sequences definition in the Dataset and split in H groups.

Then, we define knowledge K as the number of past hours used for generating the future profiles and generation horizon G as the length of hours used to generate those profiles. This allows us to calculate how many sequences we need and their length for segmenting the historical data.

$$l_{seq} = K + G \ [hours] \qquad (2)$$

$$N_{seq} = Y - l_{seq} + 1 \qquad (3)$$

The N_{seq} sequences can be grouped based on similarity, leveraging the property of periodicity, leading to 24 distinct groups. Each group will count N_{seq}^{H} sequences and correspond to a specific hour $H \in [1{,}24\,]$. This procedure is shown in Fig. 1.

Histograms can be created to approximate the distribution of values for each group H at every hour. Each histogram consists of a defined number of bins, N_{bins}, with the first and last centers corresponding to the minimum and maximum values observed during that hour, as shown in Fig. 2. The bin edges are set to ensure equal widths for all bins. For the final G hours, the expected values for each bin are determined by the means of the two edges.

The next step is to investigate the relationship between each of K's past time steps and the target hour. Hence, the correlation and the influence within the past and the future bins are analyzed. Also, to make understanding easier, let us consider $G = 1$ from this point onward.

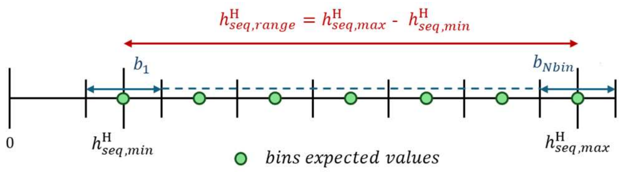

Fig. 2. Histogram bins definition.

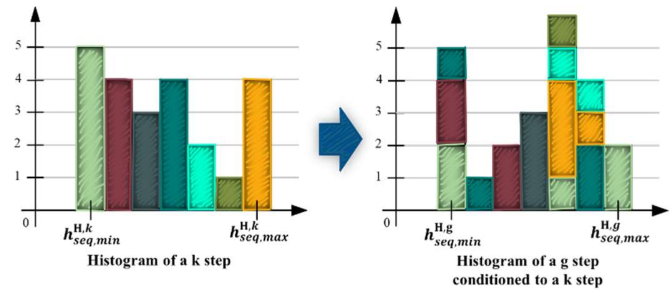

Fig. 3. Correspondence example between histograms at a past step k and a g step

The correlations, $Corr^H_{g|k}$, with $k \in [1, K]$ and $g \in [1, G]$ are computed and stored in an array. The correspondence between the bins of each of the k past steps and the bins of the landing g is analyzed. An example of this step is shown in Fig. 3.

At this point, we have the empirical absolute distribution. To obtain an approximation of the conditional probability $P^H_{g|k}$, the probability of the value assumed at the step g, knowing the value assumed at step k, we must normalize these results by the counts. An example is shown in Fig. 4.

B. Step 2: Flock profile generation

After determining the last K known past values of a load consumption time series, labeled as X_{past}, we can integrate these into the generation of a "flock" of F possible and plausible future trajectories. Each of these profiles extends into the future for a horizon L steps long.

The elements of each possible future profile are generated step by step. For each $l \in [1, L\,]$, starting from the first, the corresponding group H is identified. Then, the 10% of past steps more correlated to this position are selected and defined $K_{10\%}$. For each of the $Nk_{10\%}$ steps, a candidate $X^{l,k}_{land}$ is randomly generated using the corresponding $P^H_{g|k}$ by sampling a bin and assigning its associated expected value.

$$X^{l,k}_{land} \sim Discrete\left(P^H_{g|k}\left(\cdot\,\middle|X_{past}(k)\right)\right) \quad \forall\, k \in\ K_{10\%} \quad (4)$$

Finally, the value X^l_{land} is obtained as a weighted average of $X^{l,k}_{land}$, using correlation values $Corr^H_{g|k}$ as weights.

$$X^l_{land} = \frac{1}{Nk_{10\%}} * \sum_{k \in K_{10\%}} X^{l,k}_{land} * Corr^H_{g|k} \qquad (5)$$

To evaluate the probability of occurrence of X^l_{land}, the conditional probability is reverse using $P^H_{g|k}$.

Step g Landing Bins Counts

Step k Departing Bins	1	2	3	4	5	6	7	Tot
1	2				1		2	5
2	2		2					4
3				3				3
4	1	1				2		4
5					1	1		2
6					1			1
7					3	1		4

Step g Landing Bins $P^H_{G|k}$

Step k Departing Bins	1	2	3	4	5	6	7	Tot
1	40%				20%		40%	100%
2	50%		50%					100%
3				100%				100%
4	25%	25%				50%		100%
5					50%	50%		100%
6					100%			100%
7					75%	25%		100%

Fig. 4. Passage from an absolute relationship to a conditional landing probability.

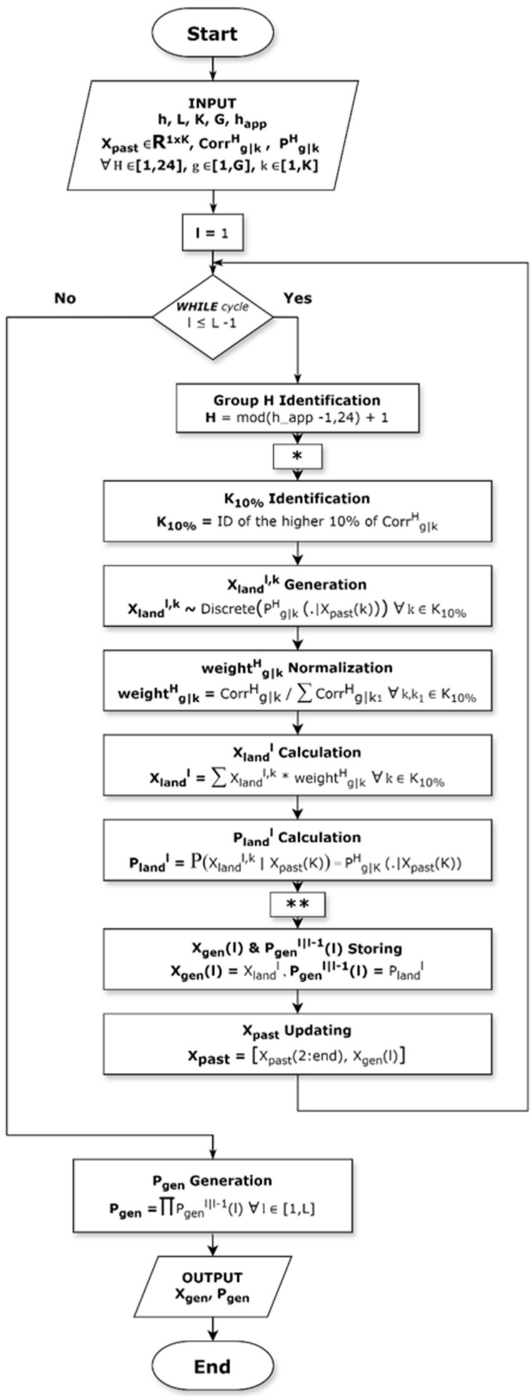

Fig. 5. Step 2 detailed flowchart explanation

The probability P^l_{Xland} is assigned based on the bin to which X^l_{land} belongs within $P^H_{g|k}$. The generated bin is considered "impossible" if the associated probability is zero. In that case, X^l_{land} is replaced with the value corresponding to the bin with the highest conditioned probability concerning the most recent step k and is replaced with this value.

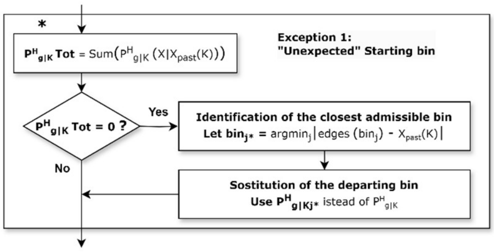

Fig. 6. Exception 1 flowchart explanation

The procedure is iteratively repeated by removing the oldest sample and appending the newly generated one as the most recent observation. At the end of the process, what is left is a newly generated profile X_{land}^{f} of L steps, produced based on the original known history.

Once the profile has been generated, an overall probability of occurrence can be associated by concatenating all the conditional probabilities of each generated step.

$$P_{land}^{f} = P_{l=1|K}^{H} * \prod_{l\in[1,L-1]} P_{l+1|l}^{H} \quad (6)$$

The procedure is repeated for each of the $f \in [1, F]$ desired profiles, resulting in a flock of F distinct and plausible future scenarios, each coupled with its own occurrence probability.

B.1 Limitations of Step 2

Our methodology introduces two exceptions to the procedure. The first exception addresses the arrival of a new input value that cannot be assigned to any admissible bin, thereby making it impossible to define the conditional probability ($P_{g|K}^{H}$) for the subsequent step.

As a bin can be seen as a cluster, it is reasonable to consider the value part of the closest bin_{j*} in terms of edge proximity and utilizing the associated probability of that bin.

$$Let\ bin_{j*} = \arg\min_{j} \left| edges(bin_j) - X_{past}(K) \right| \quad (7)$$

$$X_{land}^{l,K} \sim Discrete\left(P\left(\cdot \,\middle|\, X_{past}(K)\right)\right) = P_{g|Kj*}^{H} \quad (8)$$

The second issue arises when a generated value X_{land}^{l} falls into a bin unreachable from the bin of the previous step $X_{past}(K)$. In such instances, we resolve the problem by selecting the bin with the highest occurrence probability relative to the preceding bin.

$$P_{g|K}^{H}\left(X_{land}^{l} \,\middle|\, X_{past}(K)\right) = 0 \quad (9)$$

$$X_{land}^{l} = E\left[bin_{j*}\right]\ with\ j^{*} = arg\max_{j} P_{g|K}^{H}\left(X_{land}^{l} \,\middle|\, X_{past}(K)\right) \quad (10)$$

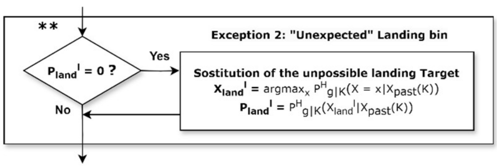

Fig. 7. Exception 2 flowchart explanation.

III. RESULTS

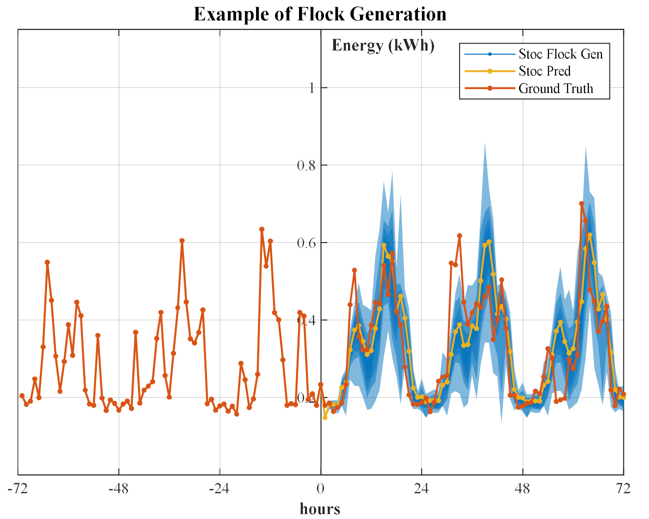

Fig. 8. Example of generation of the flock of profiles, whit the intensity of the blue that represents the density of the generated profiles.

The procedure was condensed in a block that, based on a known past, allows for generating a flock of possible futures. This tool can be used for the implementation of advanced optimization techniques to handle uncertainty in the forecasts. The following results were obtained by testing the procedure on MATLAB R2024a, run on a machine with the following characteristics:

- Processor, Intel Core i9-139000K
- RAM, 32 GB.

One of the advantages of this approach is the simplicity of extracting information from the time series. The approximation of the conditional probability is a fast procedure, and its computational cost is negligible compared to training a neural network. This aspect becomes critical in online time-series applications, where brand new data keep flowing and must be continuously incorporated by updating the information available. In the case of household load-consumption especially, it is essential to consider a high variability in user behavior as the time passes. That means such instruments must be updated frequently to address those changes.

The time required for the "mining" of information depends on the size of dataset representing the user's history so far, from which the stochastic information will be extracted. In all tests so far, this time remained in the 0.5-0.6 s window: 0.5 s for a history depth of 30 days and about 0.6 s for a history depth of 180days.

The generation time cost shows an almost linear dependency on the size of the requested flock. In the test performed, generating 200 profiles took 8.1 ms.

Another important aspect is the memory cost.

$$Memory_{cost} \cong 2 * (N_{bins})^{2} * Nk_{10\%} * H * N_{Byte} \quad (11)$$

$$with\ Nk_{10\%} \approx K/_{10}$$

The memory cost to store this information manifests a quadratic dependency from N_{bins} and a linear one to K, H and N_{Byte}. The latter represents the size of the chosen variable type. For this work it was considered a K = 72 hours, N_{bins} = 10 and the chosen variable type (or single in Matlab), with a weight N_{Byte} = 4 bytes. The resulting memory occupancy will be ~200 KB, potentially allowing implementation of this mechanism on a microcontroller.

For validate our results, we compare the prediction with a Denoising Diffusion Probabilistic Model, and with the VAE and the GAN used in [27]. Regarding the metrics, we choose: Mean Absolute Error (MAE), Dynamic Time Warping (DTW), Rolling Mean Squared Error (MSE), and Continuous Ranked Probability Score (CRPS). The results are presented in Table 2.

MAE computes the average absolute difference between predicted and actual values, reflecting the overall point-wise accuracy of the model by penalizing all errors equally. Rolling MSE, a variant computed over a moving window, captures the model's ability to maintain local consistency and smoothness in sequential data, which is crucial in time-series generation tasks.

DTW measures the minimum cumulative cost required to align the predicted sequence with the ground truth, allowing for non-linear temporal warping; thus, lower DTW values indicate a better match in the temporal structure of the sequences.

CRPS evaluates the accuracy of probabilistic forecasts by measuring the distance between the predicted cumulative distribution function and the actual observation, providing a continuous generalization of metrics like the Brier score and offering insights into both calibration and sharpness of the predicted distributions.

Our Method demonstrates a distinct advantage in probabilistic forecasting, achieving the lowest CRPS among all evaluated models. This finding indicates that it provides the most well-calibrated uncertainty estimates, which are particularly valuable in various application contexts. Furthermore, its performance in Mean Absolute Error is competitive, closely mirroring that of the Variational Autoencoder model, thereby suggesting strong point-wise prediction capabilities.

However, it is important to note that the high DTW score signifies a weaker temporal alignment. This implies that while individual values may exhibit accuracy, the overall sequence shape may not align perfectly with the true trajectory. Nevertheless, the relatively low variance in both MAE and CRPS observed across runs underscores consistent performance, affirming that our method is particularly well-suited for scenarios where probabilistic accuracy and forecast reliability take precedence over precise temporal structure.

Conversely, the VAE displays superior overall performance, characterized by the lowest errors across all metrics. Its low MAE and Rolling Mean Squared Error indicate high point-wise accuracy and smooth predictions. Additionally, the minimal DTW and CRPS associated with the VAE reflect strong temporal alignment and reliable probabilistic forecasts.

Model	**MAE (90% CI)**	**DTW (90% CI)**	**Rolling MSE (90% CI)**	**CRPS (90% CI)**
DDPM	0.500 ± 0.33	4.500 ± 5.59	0.600 ± 0.33	0.400 ± 0.66
GAN	0.370 ± 0.82	5.170 ± 3.78	0.170 ± 0.33	0.370 ± 0.77
VAE	0.170 ± 0.36	3.000 ± 2.84	0.070 ± 0.14	0.170 ± 0.36
Our Method	0.191 ± 0.19	8.991 ± 3.95	0.316 ± 0.11	0.129 ± 0.27

Table 2. Metrics comparison. The mean and the confidence interval (level 90%) of the 50 trials are presented.

These results suggest that the VAE is exceptionally well-suited for applications that require both precision and trustworthy uncertainty quantification.

Moreover, our methodology achieves the minimal confidence interval, indicating robust and stable estimations, along with consistent behavior across runs. This characteristic is advantageous in contexts where reproducibility is essential. Notably, our methodology is designed for ease of implementation and does not necessitate specialized hardware, such as a GPU. The stochastic approach to profile generation proves to be a valuable alternative, particularly when computational resources are limited, enabling significant computational cost savings while delivering performance comparable to more complex techniques.

IV. CONCLUSIONS

The stochastic approach to profile generation proves to be a valuable alternative, especially when computational resources are limited.

By avoiding any explicit training phase, the method achieves significant computational cost savings while delivering performance comparable to more complex techniques.

As outlined, this method was designed for integration within a robust optimization framework and will be extended in future work to enable real-time, robust planning for domestic prosumers.

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https://joint-research-centre.ec.europa.eu/photovoltaic-geographicalinformation-system-pvgis_en (accessed on 1 October 2024).

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