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A Competitive Scenario Forecaster using XGBoost and Gaussian Copula

Master's Thesis (30 ECTS)

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Abstract:
The main goal of this thesis is to provide a competitive baseline, as it is needed for future researchers, for scenario forecasting on GEFCom2014 dataset. Scenario forecasting is important for settings, where downstream optimization is used, such as Renewable energy production prediction. That's why GEFCom2014 is used, as it is a dataset consisting of 3 diverse tracks, and have seen multiple other works and experiments. To ensure that the acquired forecasting scores are competitive, the results from [DWL+22] paper have been used for performance evaluation, as it is current state of the art. Dumas' et al. assessment methods are also used for fair comparison. XGBoost is an established high-performance model, used in diverse set of tasks as default modeling choice. XGBoost has shown good results in forecasting setting as well, that's why it is chosen as counterpart for state of the art models. XGBoost has outperformed the best models of [DWL+22] paper on two out of three tracks, and significantly outperformed in monetary value on downstream optimization task.

Keywords:

- XGBoost
- Gaussian Copula
- Quantile forecasting
- Scenario forecasting
- Energy forecasting
- Time series

CERCS:
CERCS code and name: `https://www.etis.ee/Portal/Classifiers/Details/d3717f7b-bec8-4cd9-8ea4-c89cd56ca46e`

Tüübituletus neljandat järku loogikavalemitele

Lühikokkuvõte:
One or two sentences providing a basic introduction to the field, comprehensible to a scientist in any discipline.

Two to three sentences of more detailed background, comprehensible to scientists in related disciplines.

One sentence clearly stating the general problem being addressed by this particular study.

One sentence summarising the main result (with the words “here we show´´ or their equivalent).

Two or three sentences explaining what the main result reveals in direct comparison to what was thought to be the case previously, or how the main result adds to previous knowledge.

One or two sentences to put the results into a more general context.

Two or three sentences to provide a broader perspective, readily comprehensible to a scientist in any discipline, may be included in the first paragraph if the editor considers that the accessibility of the paper is significantly enhanced by their inclusion.

Võtmesõnad:

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Contents

Unsolved issues

1 Introduction

Probabilistic forecast is a powerful method, that is useful in many tasks that have to take uncertainty into account. There could be many potential uses of this method, but this work focuses on renewable energy production and demand analysis. Since energy production facilities, such as sun and wind farms, rely on weather, it is inherently unpredictable in terms of the amount of energy produced. Renewable energy systems have to be supplemented with either energy storage facilities or less desirable non-renewable generators. The cost and risk of renewable energy sources has to be analyzed for a more reliable supply of energy and better energy efficiency. Thus, better forecasting and analysis methods are incredibly important for faster and wider adoption of renewable energy sources. This has been the aim of many researchers and competitions, such as GEFCom2014.

This work focuses on scenario forecasting, which is a way to represent uncertainty in forecasts. This thesis complements the work of [DWL+22] by comparing it to a more established algorithm, XGBoost [CG16] in the same setting. The experiments have shown that current State of the Art models do not outperform XGBoost algorithm with copula-based scenario generation technique.

Section 2 is devoted to description of dataset used, methods used in modeling, and previous work this thesis is based on. It is important to establish the background for proper understanding of later chapters. Section 3 describes the differences between this work and [DWL+22], mainly data representation and evaluation metrics used. The section describes implementation details of practical part in-depth. Section 5 analyses the results of experiments and speculates about the differences in performance between tracks and models. Section 6 concludes this work and summarizes the results. It also states the possibility of future research and development of probabilistic methods of XGBoost algorithm.

2 Background

2.1 GEFCom2014

Most of the field of forecasting is focused on marginal or point forecasts, a.i. prediction of a single point. However, there are different applications where probability of an event have to be taken into account. One such application is renewable energy industry, as it is inherently uncertain, and so the probabilistic methods make more sense.

GEFCom2014 was a competition, aimed to gather Computer Science students and researchers to improve forecasting approaches in renewable energy setting [HPF$^+$16] using probabilistic forecasting techniques. The organizers of the competition site the probabilistic forecasting methodologies, their application to energy sector, and different maturity levels between techniques as one of the challenges, aimed to be addressed by the Competition. As such, the competition have included a diverse set of time-series datasets, which were called tracks.

The three datasets employed were:

1. Load track - history of load demand, collected over 5 years, 2006 - Jan 2012 in America. Input consists of 25 parameters of temperature readings, output is a load value for the hour.

2. Wind track - power production of wind farm, collected over 2 years, 2012-Jan 2014 in Australia. Has 10 different zones, depends on wind speed and direction at 10m and 100m altitudes. Output parameter is an amount of power produced.

3. Solar track - power production of solar farm, collected over 2 years, Apr 2012-Jul 2014 in Australia. Has 3 different zones. Depends on multiple weather features.

Competitors have employed a lot of different algorithms, but notably XGBoost and Random forest trees have shown good performance on multiple tracks, implemented by teams such as **dmlab** for wind and solar tracks. Interestingly, none of the top teams used Tree-based models on load track. This could be due to lower performance of such models, as the load track is the only one, where XGBoost did not beat state of the art models.

Forecast quality was evaluated with **Pinball loss**, averaged over 100 quantiles. Detail description of this method can be found in subsection 2.4.1, This is the same setup as in [DWL$^+$22], as well as this work.

2.1.1 Load track

The aim of the GEFCom2014-L was to forecast the quantiles of hourly loads for a US utility on a rolling basis. The forecast horizon was one month. Hourly historical

load and weather data for the utility were provided. In addition to the data provided by the competition organizer, the contestants were also allowed to use US federal holiday information. However, it hasn't been used in this work, as Dumas et. al have not used it to train the models. Thus, for the purposes of a fairer comparison, holidays have not been included. Figure 1 shows the distribution of load across time, and 2 shows the correlation between temperature and load consumed.

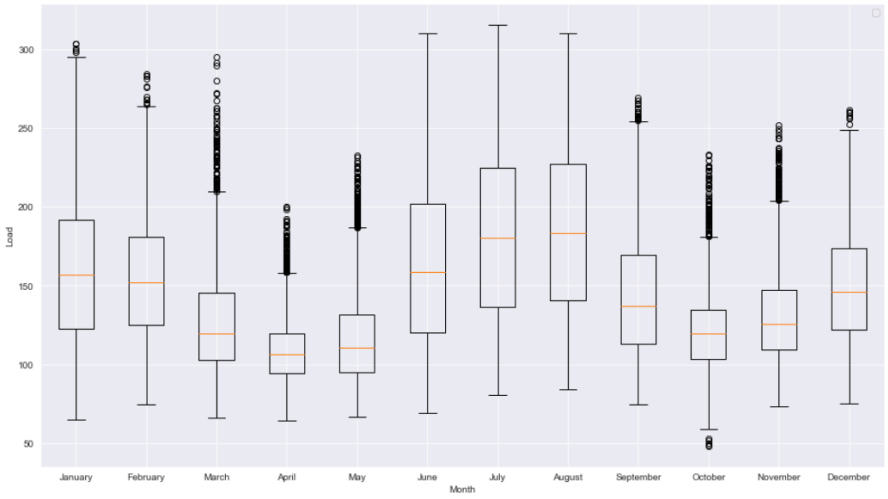


Figure 1. Load distribution

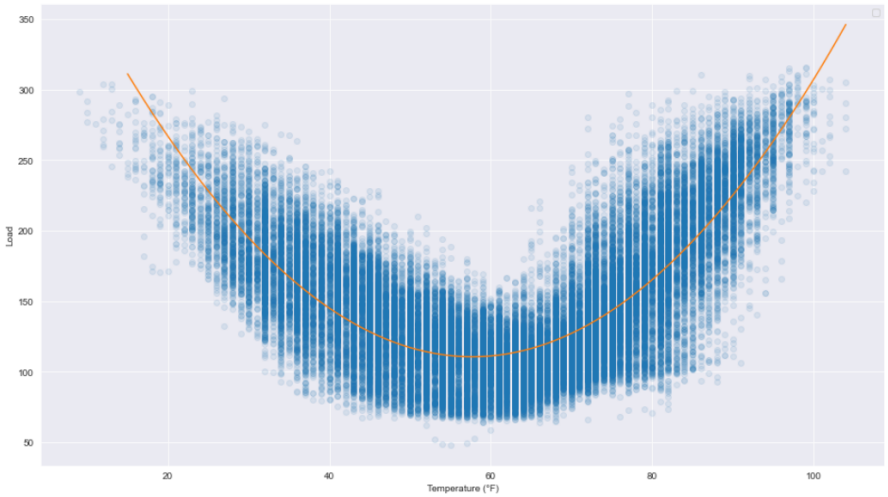


Figure 2. Correlation between load and temperature

From these two figures it can be clearly seen, that Load is highly dependant on temperature in U-shaped manner. Thus, it can be assumed, that in the winter month and the hottest times of summer the load is going to be the highest. Figure 1 shows exactly that, where high peaks occur in winter month (around January) and summer months (around July), with troughs in between. And while seasonal features could make sense, but temperature has already been provided as main input feature, thus making any seasonal features redundant.

Organizers of the competition also cited three other challenges imposed by Load track:

1. Weather station selection. Competition organizers provided 25 weather stations, but no geographical data to identify their locations. It was done so competitors would developed an advanced algorithm to identify and select better weather stations.

2. Multi-horizon load forecasting. The one-month ahead load forecasting was chosen as a competition topic, so that contestants to have room to develop short-term load forecasts to improve few days ahead forecast.

3. Scenario generation. Organizers expected that some competitors would investigate possibility of scenario generation methods. It was claimed that ten years of data provided would be enough to evaluate that method.

2.1.2 Wind track

The objective of the probabilistic wind power forecasting track in GEFCom2014 was to make predictions about the wind power generation of ten wind farms located in Australia. This was done by predicting the wind power generation 24 hours in advance, for ten different zones that corresponded to the ten wind farms, on a continuous basis. The wind power output series from these wind farms are shown in Figure 3. The locations of these 10 wind farms were not disclosed during GEFCom2014. The forecasts were to be expressed in the form of a set of 99 quantiles, with various nominal proportions between 0 and 1.

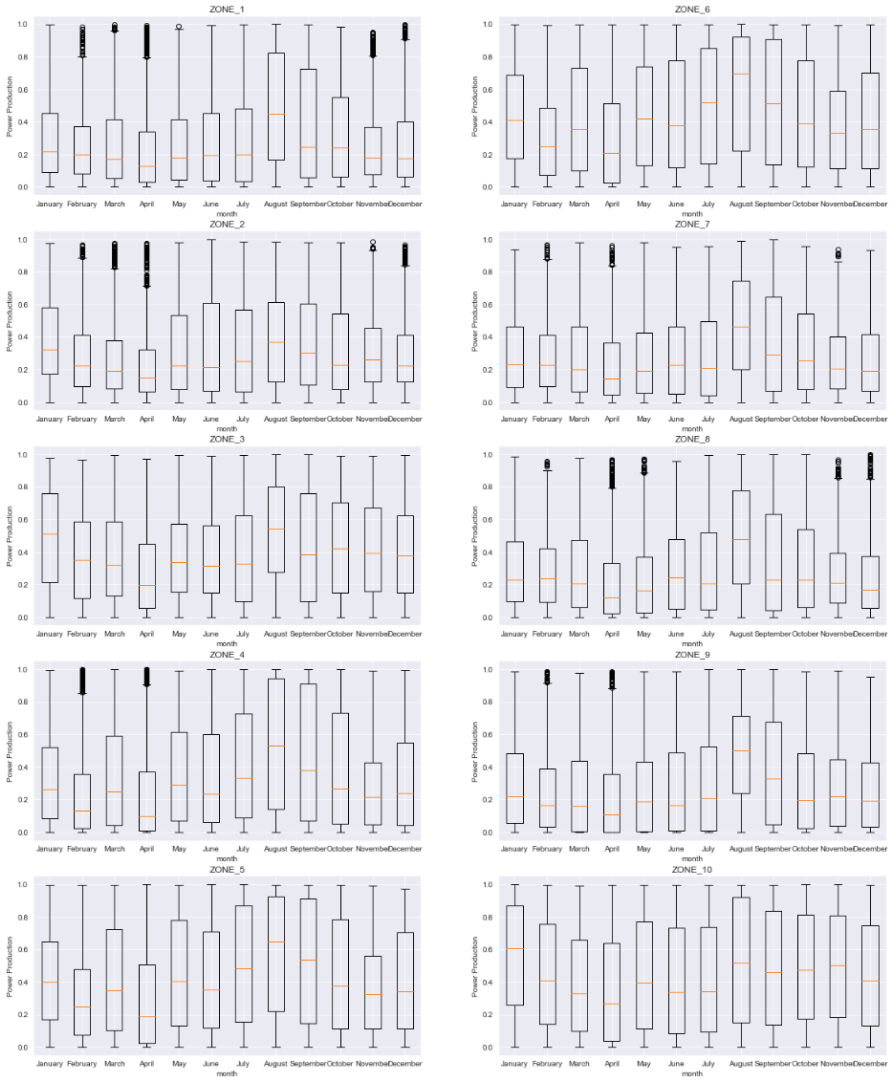


Figure 3. Distribution of wind speed

The input parameters for the forecasting model comprised of wind speed forecasts, which were obtained from the European Centre for Medium-range Weather Forecasts (ECMWF). The forecasts provided wind speed estimates for two different heights, namely, 10 meters and 100 meters above ground level, for both the zonal and meridional wind components. These components were represented by the projections of the wind vector onto the west-east and south-north axes, respectively. Figure 4 shows the scatter plots between wind power generation and wind speeds. Overall, it's hard to point out any concrete correlations in either of the two figures. Though, it can be pointed out that overall all power to speed correlations Follow a U-shape, with more power produced

towards the leftmost and rightmost side of the graph.

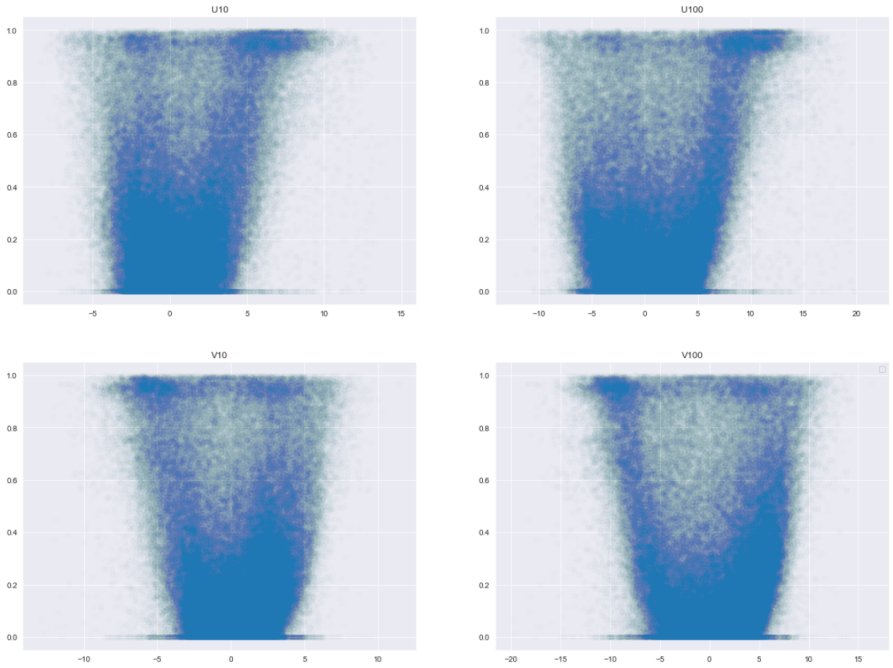


Figure 4. Correlation between wind speed and power production

2.1.3 Solar Track

The design of the probabilistic solar power forecasting problem in GEFCom2014 was similar to that of the wind track. The forecasting task involved predicting the solar power generation on a rolling basis, 24 hours ahead of time, for three different solar power plants located within a specific region of Australia. The solar power generation profiles are shown in Figure 5. The exact locations of these plants were undisclosed during the competition. The forecasts were expressed as 99 quantiles with nominal proportions ranging from 0 to 1. Participants had access to weather forecasts for 12 weather variables, obtained from the European Centre for Medium-range Weather Forecasts (ECMWF). These variables are summarized in Table 1.

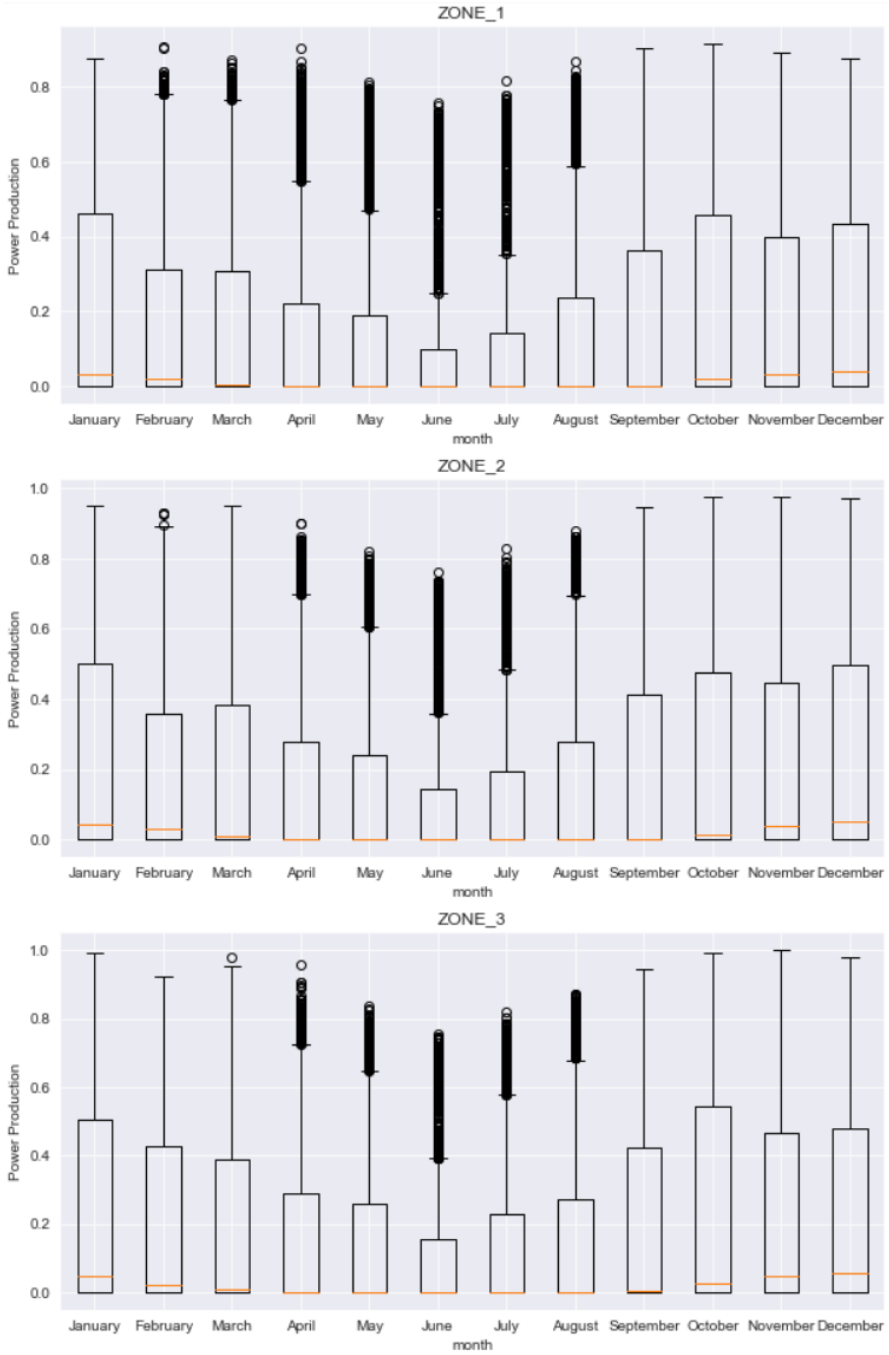


Figure 5. Distribution of Solar power production

Variable name	Units	Comments
Total column liquid water (tclw)	$kg * m^{-2}$	Vertical integral of cloud liquid water content
Total column ice water (tciw)	$kg * m^{-2}$	Vertical integral of cloud ice water content
Surface pressure (SP)	Pa	
Relative humidity at 1000 mbar (r)	%	Relative humidity is defined with respect to saturation of the mixed phase
Total cloud cover (TCC)	0-1	Total cloud cover derived from model levels using the model's overlap assumption
10-metre U wind component (10u)	$m * s^{-1}$	
10-metre V wind component (10v)	$m * s^{-1}$	
2-metre temperature (2T)	K	
Surface solar rad down (SSRD)	$J * m^{-2}$	Accumulated field
Surface thermal rad down (STRD)	$J * m^{-2}$	Accumulated field
Top net solar rad (TSR)	$J * m^{-2}$	Net solar radiation at the top of the atmosphere. Accumulated field
Total precipitation (TP)	m	Convective precipitation + stratiform precipitation (CP + LSP). Accumulated field

Table 1. Solar track variables

2.2 Dumas et al. contribution

The paper [DWL$^+$22] introduced the current state of the art model for probabilistic forecasting. Another major impact of this work is improvement of evaluation process, which allows to combine the prediction quality of 3 tracks and combine them in a practical assessment method.

The three models, considered in the original paper, are: Normalizing flows [KSJ$^+$16]; Variational autoencoders (VAE) [QHD$^+$20]; Generative adversarial networks (GANs) [GPAM$^+$14]. While the inner working of these models are not relevant to this work, performance comparison is the most interesting part between these three. NFs have outperformed the other two models on 2 out of 3 tracks, as well as generating the highest net profit. VAE did outperform the NFs on the Wind track, making it second best out of 3 proposed.

Second important contribution of [DWL$^+$22] was thorough qualitative and quantitative evaluation setup, which used 8 different evaluation metrics. However, if a model

was outperforming others, all evaluation metrics were consistent in their judgement. Therefore, two most important for the task of scenario forecasting have been chosen for this work.

The quantitative part was a setup, representing a downstream task of a machine learning setup. It aimed to optimize pricing for an energy provider, relying on generated scenarios. It is crucial for the final analysis of model performance, as it combines the results of all three tracks and simulates real world cost-benefit analysis. It also gives researches good estimation of potential upside of the new model over existing one.

2.3 XGBoost algorithm

XGBoost stands for eXtreme Gradient Boosting [CG16], is a high-performance machine learning algorithm, which ensembles multiple Decision Trees to approximate certain function. The simplest representation of decision trees can be seen in Figure 6. The basic idea is to combine multiple weak function approximations to come up with more resilient one. The paper [CG16] describes the algorithm in use, optimization of that algorithm, implementation of different scalability features and analyses the resulting performance in comparison to existing solutions.

To decrease overfitting it uses shrinkage [Fri02], which reduces the weight of newly added trees buy a certain factor. Another technique is column subsampling [Bre01], as well as row subsampling which is supported. This is an overwiev paper, aiming to present the most important points described in original paper.

The algorithm is a tree-ensambling model employing second order objective [FHT00]. For a certain data, it creates a number of trees. Each leaf contains continuous score. For given example, each tree calculates the value for corresponding leaves, which is summed up afterwards, giving a score for the example.

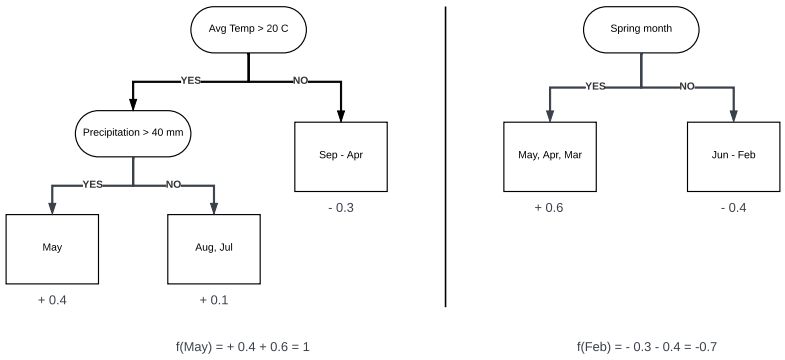


Figure 6. XGBoost algorithm representation

Since such a model contains functions as parameters, it cannot be optimized using traditional gradient descent algorithms. It is optimized in an additive manner, adding the tree that improves predictions the most in a greedy manner.

2.4 Pinball loss and Energy score

2.4.1 Pinball loss

Pinball loss, also called Quantile loss or Quantile score (QS) is a metric, used to assess the performance of a quantile forecast. The loss is similar to Absolute loss function, however it assigns higher weight to points in smaller quantile and lower weight to bigger quantile. At quantile $\tau = 0.5$ the loss formula is exactly equal to Absolute loss.

Let τ be the desired quantile, y be the real value, and z be the predicted value. Than Pinball loss L_τ is written like this [**?**]:

$$L_\tau(y, z) = \begin{cases} (y - z)\tau, & \text{if } y \geq z \\ (z - y)(1 - \tau), & y < z \end{cases}$$

Figure 7. Quantile loss formula

The resulting graph for this formula can be seen in Figure 8.

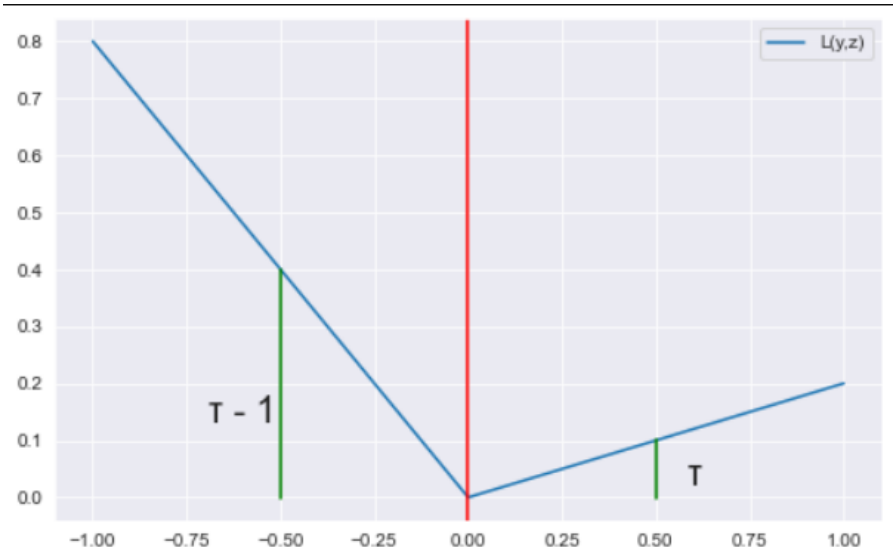


Figure 8. Pinball loss graph

2.4.2 Energy distance

Energy distance, or Energy score (ES) is a metric, representing the distance between two probability distributions. The idea of energy is analogues to the potential energy of bodies in physics, where the potential energy is zero only if the distance between two objects is zero. And the energy between objects, and by proxy - distributions, increases with distance between them.

Definition of energy score is as follows: Let X and Y be independent random vectors in R^d , with cumulative distribution function (CDF) F and G, respectively. In what follows, $|| \cdot ||$ denotes the Euclidean norm (length) of its argument, E denotes expected value, and a primed random variable X0 denotes an independent and identically distributed (iid) copy of X; that is, X and X' are iid. Similarly, Y and Y' are iid. The squared energy distance can be defined in terms of expected distances between the random vectors and the energy distance between distributions F and G is defined as the square root of $D^2(F, G)$ [Ene].

$$D^2(F, G) = 2E||X - Y|| - E||X - X'|| - E||Y - Y'|| \geq 0$$

Figure 9. Energy distance formula

2.5 Copula

Copula functions are used to describe correlation between random variables. Consider a random vector $(X_1, X_2, ...X_{24})$ with continuous marginals, where cumulative distribution functions $F_i(x) = P[X_i \leq x]$ are continuous. A random vector will have uniformly distributed marginals, if probability integral transform is applied to each component.

$$(U_1, U_2, ...U_{24}) = (F_1(X_1), F_2(X_2), ...F_{24}(X_{24}))$$

The copula for $(X_1, X_2, ...X_{24})$ is defined as a joint cumulative distribution function $(U_1, U_2, ...U_{24})$

$$C(u_1, u_2, ...u_{24}) = P[U_1 \leq u_1, U_2 \leq u_2, ...U_{24} \leq u_{24}]$$

In the experiments, they have been used to obtain the dependencies between hours of the day. It is necessary for further scenario generation, as by definition, scenarios have to take into account previous values. An example of Copula function in matrix form can be seen in figure 16.

2.6 Scenario Forecast

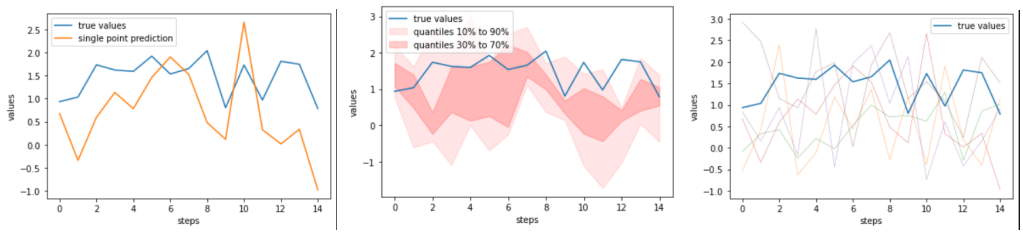
Scenario forecasting is a method used to anticipate and evaluate various possible future outcomes based on different assumptions about the variables that are likely to impact the

situation under analysis. The goal is to develop multiple plausible scenarios, rather than relying on a single prediction of the future, to help decision-makers better prepare for a range of potential outcomes.

A single scenario is a specific prediction of what the future might look like based on a set of assumptions about how different variables will change over time. However, it is often difficult to accurately predict the future with certainty, and relying on a single scenario can be risky. To address this, scenario forecasting involves developing multiple scenarios that reflect a range of possible futures, based on different assumptions about how key variables might evolve.

Examples of single point, quantile and scenario forecast can be seen in Figure 10. In Single point example there is only true values for each step and predictions for the step. In quantile figure there is predicted distribution for each step. And in Scenario example there are 5 different scenarios predicted for all 15 steps.

By generating a range of scenarios, decision-makers can explore the potential implications and consequences of different future outcomes and develop more robust and adaptive strategies that can be better suited to handle a range of different scenarios. The purpose of scenario forecasting is to provide organizations with a more informed and comprehensive understanding of the risks and opportunities associated with different future outcomes, and help them prepare accordingly.



(a) Single Point Forecast (b) Quantile forecast (c) Scenario forecast

Figure 10. Forecast examples

3 Method

[DWL+22] established a solid framework of experiments and assessment of scenario forecast. It does not rely only on conventional methods of evaluation with different quality metrics and measures, but also conducts a downstream evaluation that is based on monetary evaluation of Scenario Forecasts. This is extremely important for any future research, as it provides a comprehensive overview of the each model forecast strengths and weaknesses. Such an assessment is also tremendously useful to demonstrate practical implications of research in the field to potential users.

[DWL+22] have not compared results to a more established Copula - based approaches. This work also bridges this gap by using Copula scenario generation in tandem with well-regarded algorithm XGBoost. However, due to major differences between the approaches, there are several key changes to the setup of original work. These changes are outlined in this section. Another important contribution of [DWL+22] work is an establishment of assessment framework. It takes into account both conventional Machine Learning rule of Quantile Score, slightly less known Energy Score, introduced in [GR07], as well as lays out a process for downstream economic evaluation. This monetary evaluation of forecast quality provides a clear and practical view of the problem of forecasting quality in a much wider picture.

In our work we used Quantile Score and Energy score metrics from [DWL+22]. The reason why only two have been chosen is of a relevancy for specific task of Scenario Forecasting, Quantile score representing a Univariate metric, and Energy score – Multivariate metric. These two metrics adequately represent the differences in performance between models. Following the results of [DWL+22], metrics from the same family provide similar performance evaluation.

Other specific metrics have not been, as they were required for specific experimental setup of [DWL+22]. Statistical analysis have not been performed, as it was used to reinforce the results, obtained with other metrics.

The process flow of this work is shown in Figure 11

Monetary analysis of predictions is performed by solving optimization problem, using forecasted values as input. It uses licensed Gurobi API. It uses predictions of 50 Test days, each day containing 50 scenarios.

3.1 Data preparation

[DWL+22] used data to train multiple models capable of producing multiple outputs. The data preparation had to be done in a different manner of the original paper, while making sure the train-test-validation split is the same to guarantee proper evaluation.

The only additional variable included in **Load** was an hour feature. Average load is highly dependant on the hour of the day, and while the transformation in [DWL+22] accounted for it by producing 24 different outputs, XGBoost in quantile setting can take

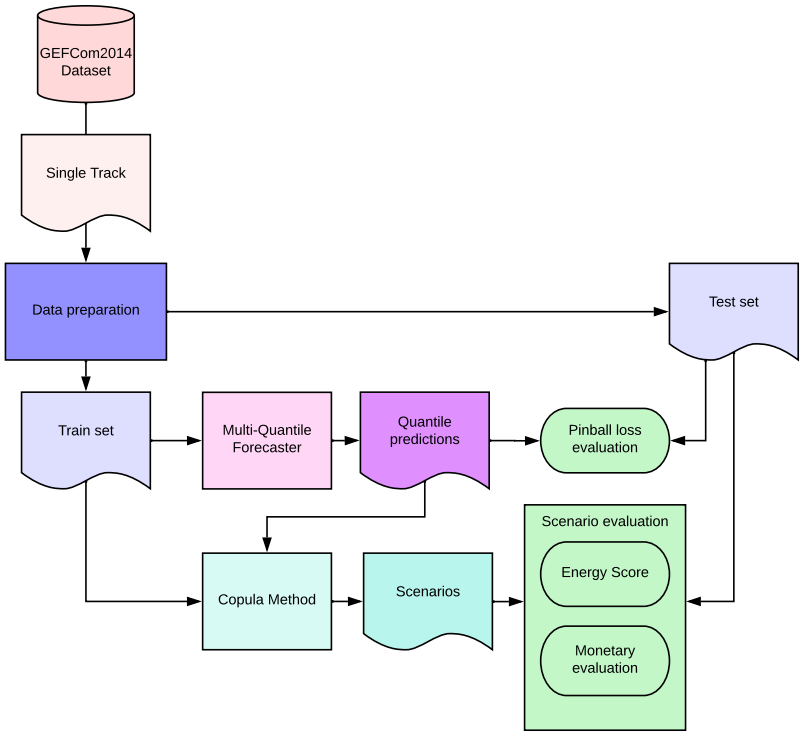


Figure 11. Process flow chart

the hour of the day as feature as an input. Month of the year has also been added as a feature, as well as average load of the predicted hour. However, both features had not produced significant impact, as month would only reflect average temperature trend, which is directly accounted by data inputs, while average load of the hour seems to be captured well by the model during training.

Wind track had no significant change in data preparation, compared to [DWL$^+$22]. Model has been trained in a setting with just the original features of GEFCom2014 dataset, as well as with additional features created in [DWL$^+$22] work. Those features are:

1. WS10 and WS100 - wind speed at an altitude of 10 and 100 meters respectively
2. WE10 and WE100 - wind energy at altitude of 10 and 100 meters
3. WD10 and WD100 - wind direction at 10 and 100 meters

The model was able to outperform Variational Auto Encoders both with and without

these six additional features, but there has been a slight increase in average quantile and energy score results.

Solar track had similar features added to it, as a Load track. Hour feature was as important as in the case of Load track, while month feature had no significant result on performance. The reasoning of monthly feature was similar in both tracks: the data had significant differences across different month, but it has been captured well already by predicting solar irradiation of the surface of the earth for the hour.

Last important part of data preparation was splitting it for Train and Test purpose. Since no hyperparameter tuning has been done in this work, validation part of the split was not used. [DWL+22] have randomly picked 50 days for testing with a certain random state. To reproduce their split on different format of data transformation the dates of those 50 test days have been picked directly from original split, and applied on new data format, reproducing the original test set.

3.2 XGBoost-Gaussian Copula

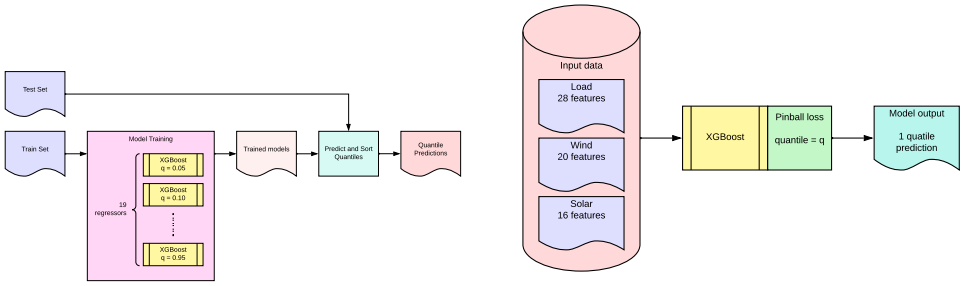
Extreme Gradient Boosting regressor is a powerful algorithm, that is outperforming other models in tabular data setting. This has been shown in the work of [BLS+21], where gradient boosting methods have best and second best results across multiple datasets, with one neural network model showing higher performance on one out of five datasets. This makes gradient boosting a go-to choice for a tabular data setting, with forecasting being part of it.

The dominating performance of XGBoost on tabular data is the reason for the following hypothesis: XGBoost should be one of the main algorithms that a model have to outperform to claim State of the Art status. Therefore, we propose a combination of XGBoost and Gaussian Copula (XGBoost - GC) as an established method for scenario forecasting.

3.2.1 Quantile forecast step

There are some implementations of XGBoost that allow to perform multi label classification and multi regression task. However, for quantile forecasting setting there is no possibility to pre-define a model with multiple target quantiles and train it in a single runtime. Flow chart of quantile predictions can be seen in Figure 12.

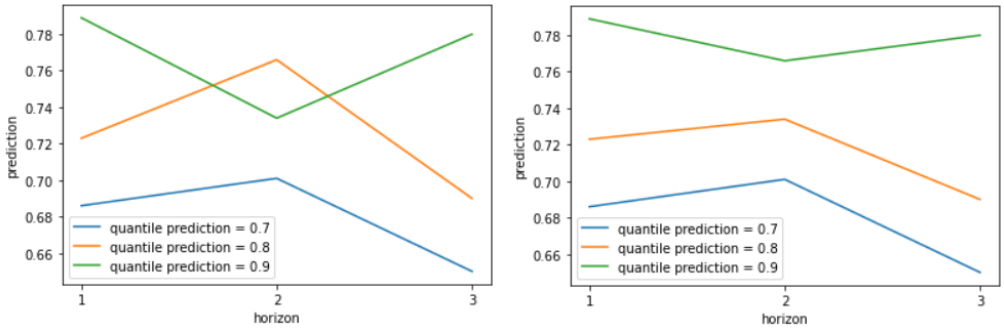
After predicting the data on the test set, because the quantiles are predicted by 99 different models, the predictions have to be sorted. Otherwise, a quantile crossing could occur, see example in Figure 13 at step 2, where 0.8th quantile prediction "crosses" with 0.9th prediction. It is a toy example, models in this work are predicting for 24 steps. This is very undesirable, as it significantly decreases quality of the forecast as well as interferes with downstream tasks. It is important that quantiles are strictly increasing, meaning each subsequent prediction of the quantile have to be larger then the previous



(a) Quantile prediction flow (b) Single model flow

Figure 12. Quantile forecast step flow chart

one. In this case, because numerical precision have not been set, it's unlikely that 2 quantiles would have exactly same values.



(a) Quantile Crossing Example (b) Quantile Crossing Correction

Figure 13. Quantile Correction

3.2.2 Copula based Scenario generation

Quantile forecasts of XGBoost can produce marginal forecasts. It could be thought of as independent scenarios on each leadtime of the horizon. In order to produce meaningful scenarios marginal forecasts must be coupled and their interdependencies modeled. Therefore, Gaussian Copula functions is used to couple the marginal forecasts. Steps required to achieve such coupling are depicted in Figure 14.

To generate the copula function, Training set and quantile predictions are used as inputs.

Copula Estimation is done in several steps:

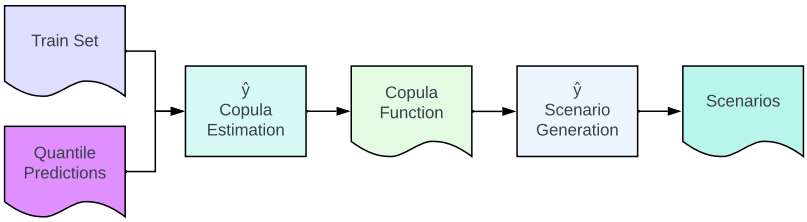


Figure 14. Copula flow chart

1. An identity matrix is created and samples of all training set days are provided
2. The covariance for a single day is calculated and added to the identity matrix with a certain forget factor.
3. The matrix is then standardized to ensure that all values are falling in range between 0 and 1.
4. Steps 2 and 3 are repeated for all the days in training set.

Forget factor defines how much information is retained from the previous iteration and how much is added from a new day. It balances between retaining enough information between iterations, while picking new values from a sample. The end result of this step is a Copula Function.

Copula function is used in Scenario Generation, to simulate multiple scenarios by drawing random samples from the copula distribution and transforming them using the input Quantile Predictions. This will create scenarios that are consistent with the input probabilistic estimates and capture the dependencies between the variables. This step produces scenarios, which are evaluated with Energy score and passed down to monetary evaluation.

4 Experiments

Multiple models have been trained on 99 different quantiles, from 0.01th to 0.99th quantile with a step of 0.01.

Hyperparameters used are displayed in Table 2. These hyperparameters were hand-picked during several trial runs. The two important factors to balance between were forecasting quality and resource usage, aiming for training time of 30 minutes per model and performance better than [DWL$^+$22] on quantile forecasting.

name	value
learning rate	0.05
number of estimators	600
maximum depth	7
minimum leaf samples	9
minimum samples split	9

Table 2. Hyperparameters

The hardware and system used during training are displayed in Table 3. The system used has been a limiting factor during training time, as there are no GPU acceleration implemented for Windows yet. The Model used is GradientBoostingRegressor from ensemble module, from Scikit-Learn library (version 1.0.1).

Operating system	Windows 10
RAM	16 GB
Processor	AMD Ryzen 5 5600 H
Model library	Scikit-learn v. 1.0.1

Table 3. System specifications

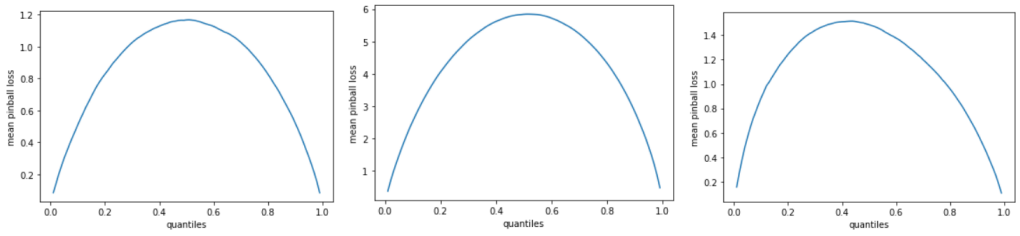
Forget factor of 0.99 has been chosen for generating copula, which means that matrix before the update step has a weight factor of 0.99 and new sample has 0.01 weight in the new matrix. While values less then 0.99 produced unstable results, where covariances did not match between runs. This indicates that last example impacted the final result too much.

To replicate the setup of [DWL$^+$22], 100 scenarios have been sampled for each of 50 tested dates and assessed with Energy Score.

5 Results and discussion

5.1 Quantile score, copulas and energy score

5.1.1 Quantile score distribution



(a) Load, $\overline{QS}$ = 0.83 (b) Wind, $\overline{QS}$ = 4.22 (c) Solar, $\overline{QS}$ = 1.11

Figure 15. QS distribution by quantile

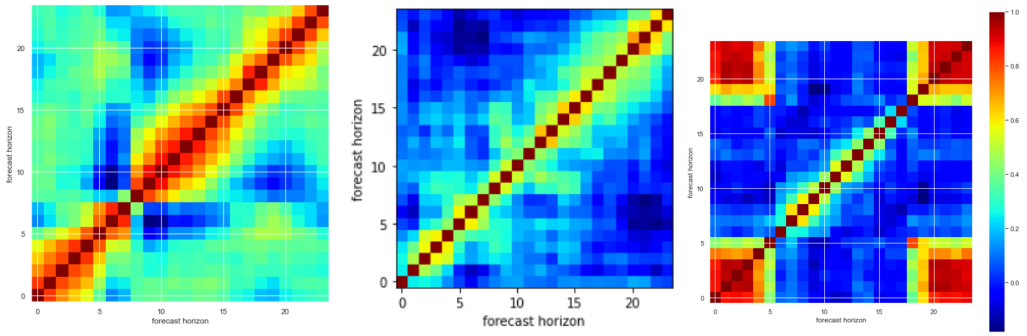
Figure 15 shows the quantile scores per quantile for each track. Importantly, all tracks have have different scales, where (b) Wind has the highest maximum QS on marginal (≈6), while (a) Load has the lowest (≈1.2). This is also indicated by mean $\overline{QS}$, where again they are distributed from highest to lower in order: (b) Wind, (c) Solar, (a) Load.

Notably, (c) Solar track has a different shape from the other two, where maximum QS value is skewed to lower quantiles (≈0.4). It shows that (c) Solar model had a slight bias for lower quantiles. This could be due to difference in distribution of (c) Solar dataset, as it follows a pattern of solar radiation during the day, while two had less inherit periodicity.

5.1.2 Copula analysis

All tracks had very different distributions of covariances in copula functions, as they are created from covariance between hours of the day. Figure 16 contains Estimated Covariance Matrix using Multivariate Gaussian Distribution, the scale near Load is universal for all of them.

Important note: for Wind and Solar tracks separate covariance matrices have been generated for each zone, improving performance from 54 average energy score to 53 on Wind track. Impact for a Solar track was less significant, as Zones are more similar for Solar track. The three figures in 16 represent Copula functions, trained on different tracks. They show the universal copula example, where a single copula have been trained for all zones of the track. Colours closer to brown-red represent higher covariances between hours, while blue represents low covariance. The gradient can be seen on the rightmost of the figure. The common feature between all three tracks is a diagonal of



(a) Load (b) Wind (c) Solar

Figure 16. Universal copula for each track

brown color (covariance = 1), because covariance of an hour with itself is always going to be 1. However, that is the only similarity and otherwise they are different in every other way.

A **Load** track has highest overall covariance between neighbors inside three distinct "regions", a.i. parts of the day:

1 0-8 hours - night and morning, where load typically is the lowest, as most people sleep during this time of the day, or start their day off, which leads to higher consumption around 6-8, and higher covariance during these hours.

2 9-16 hours - are the typical day work hours, where businesses and public establishments are main drivers of power consumption. Since it has high covariance between neighbors in this region, we can conclude that consumption is pretty stable during this time of the day. During summer this is the hottest time of the day, which also necessitates air conditioning and cooling of houses and workplaces.

3 17-23 hours - evening hours, most of the consumption comes from people using more home appliances during this time, and requires lighting both indoors and outdoors. Covariance lower, relative to previous time of the day, meaning consumption is less stable throughout these hours.

B **Wind** track overall has smaller degree of correlation between hours of the day, as it is more chaotic, due to less predictable nature of wind. However, it's a non-zero correlation levels for 3-6 neighboring hours, which means that most of the time weather stays windy for certain periods. The copula also indicates that some particular hours have a slight increase in correlation (2-4, 5-6, 12-15, 20-23), which might be due to local weather patterns.

C **Solar** track is quite distinct from the other two. It has very high degree of correlation for the first 4-5 hours and last 5-6 (depending on the time of the year). This is because no power is produced during the nighttime. However, correlation for sunny part of the day is relatively low, because solar power production has high natural dependency on the angle of sunlight, as well as absence of clouds. Both factors can change relatively quickly, thus leading to overall low correlation during the productive part of the day.

5.1.3 Difference in energy score between zones

Wind track has significant differences in performance between zones, which can be seen in Figure 17. While Solar has relatively lower gap between zones, shown in Figure 18.

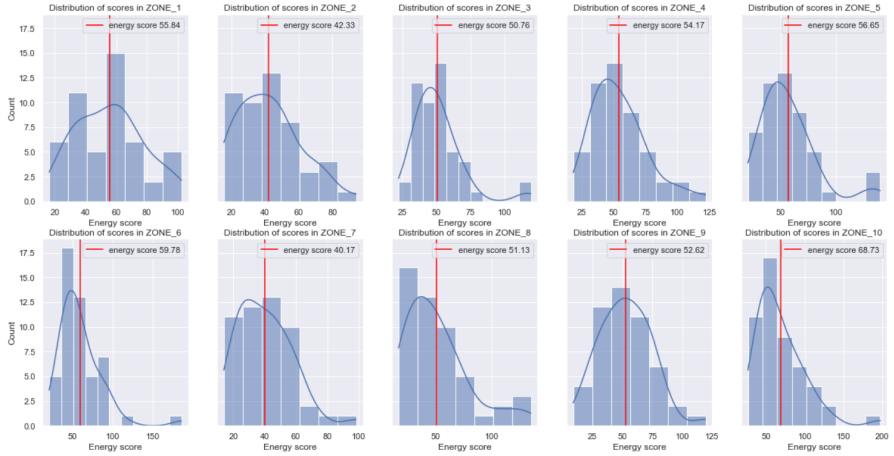


Figure 17. Wind zones energy scores

Figure 18. Solar zones energy scores

It isn't obvious why Wind zones are so wildly different. It's easy to see that better performing zones, like 2 and 7, don't have very bad days, while Zone 10 has both worse days on average AND one of the worst days captured for all zones overall. This could be due to either unfavorable positioning of the wind turbine, compared to others, or due to mechanical failure on the day. However, it also might be an artifact of a relatively small test subset of only 50 samples, and otherwise these zones are more comparable with one another.

5.1.4 Analysis of the best vs worst days and zones

The load track does not have different zones, so only the best and worst days have been analyzed. You can see them in Figure 19. Pretty much the only difference between them is how far the predicted marginal of scenarios is from the actual ground truth. This lowered the overall accuracy of forecast for the worst day, as true distribution was very far from predicted quantiles, leading to bad energy score as well.

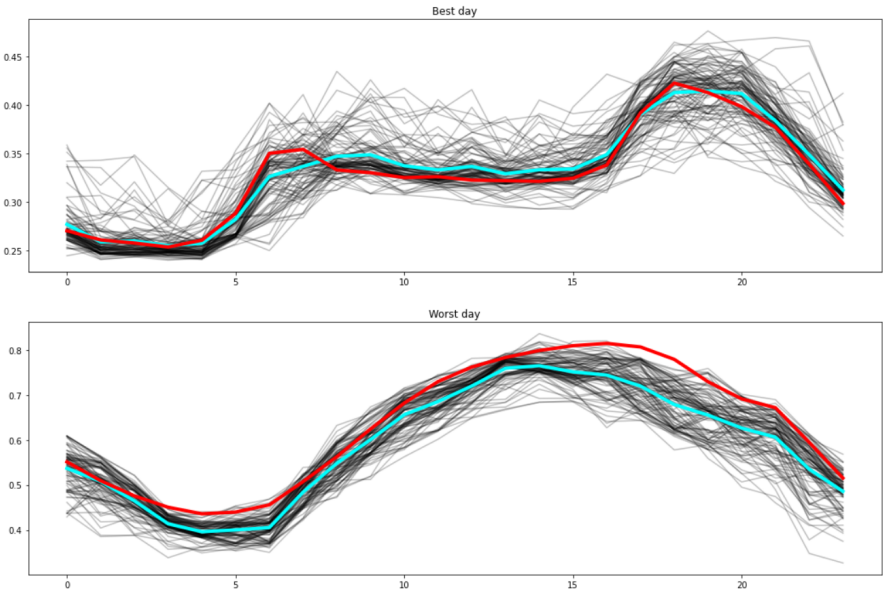


Figure 19. Best and worst days of load track

Wind track has in general less of a stable performance as other tracks, and it can be seen in both zones comparison and differences in days in best as well as worst performing ones in Figure 20. Wind features are plotted in the same graphs for a day forecast, importantly on a different scale, depicted on the right of the graph. On the worst day of the worst zone it could be argued that the weather features did not reflect the power production of the day, as feature have little to no correlation with actual power

produced, while the model was predicting power output relying on the input wind speeds. For the worst day of the best zone the situation is quite different, where the wind features have changed rather dramatically between hours 10 and 16, and predicted scenarios have underestimated power output potential.

For the best performing days of both zones situation is fairly similar, where the low energy score is a result of good approximation of low power production for the day due to forecasted slow winds.

It is interesting to see that for the worst performing zone copula function graph has higher correlation at the end of the day, hours 14-24. Perhaps, that might be due to weather characteristics of the region, which are very different from other 9 Zones. Due to the model being trained on all examples at once, not being split by-zone basis, it has been a primary contributor of high energy scores. This can be seen in Figure 17 as well. Thus, following hypothesis is could be formed: model trained separately on all zones would have yielded better results.

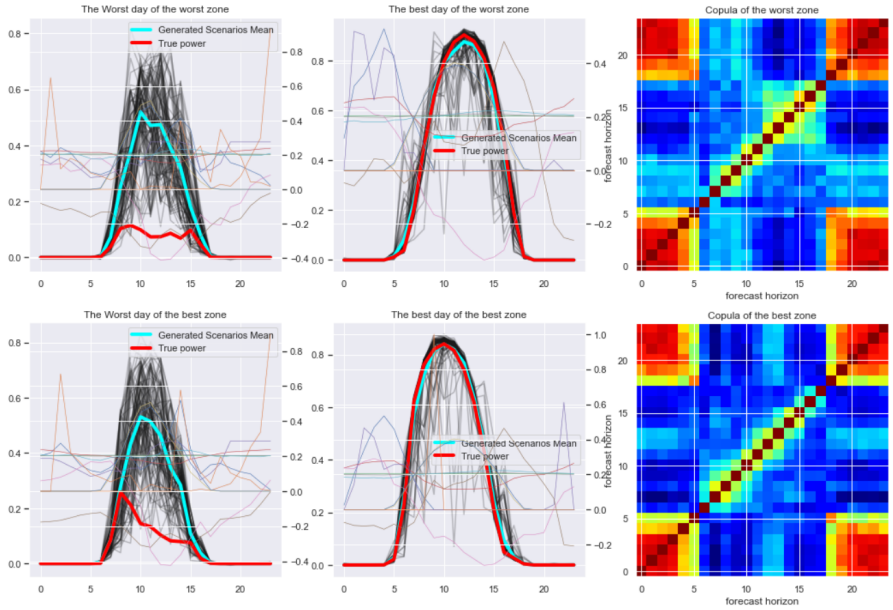


Figure 21. Best and worst days and zones of solar track

5.2 Results comparison

The paper [DWL+22] have used several scoring methods, however the most applicable to scenario forecasting are mean quantile score ($\overline{QS}$) and mean energy score ($\overline{ES}$). Table 4 shows highest performing models from the paper, Normalizing flows (NF) and Variational autoencoders (VAE), results of random prediction (RAND), and the one tried

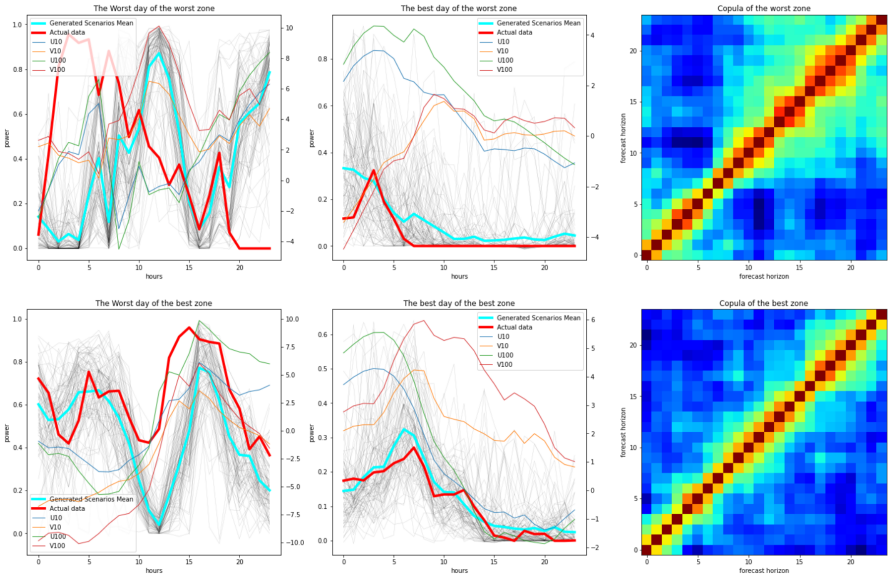


Figure 20. Best and worst days and zones of wind track

Solar track had much less of a difference between the zones in terms of performance, and it had failed in a similar way on the worst forecasted days — by predicting high production on a bad day. Could have been due to general cloudiness, rain, or some other natural cause. For example, dust particles, lifted by wind, could decrease overall effectiveness.

The problem for solar track is we don't have direct features to predict such events. Weather forecast of **wind speed** and **likelihood of clouds or precipitation** would substantially increase forecast quality, especially in cases of rain or dust storms. Considering the model is a probabilistic one and operates with quantiles, it should be able to interpret probabilistic inputs well and generate better predictions, as it can take uncertainty of input features into account.

in this work, Regularizing Gradient Boosting (XGBoost). XGBoost have outperformed all models on Wind and Solar tracks, however it haven't beaten the Normalizing Flows model on Load. Though, it is important to note that it has very close results, much closer then Variational Autoencoders. Since fine-tuning haven't been done for this thesis due to resource limitations, it might be the case that with proper technique XGBoost could outperform NF.

The work of [DWL+22] has also implemented an economic assessment method, which takes into consideration planned production, which are prediction results from Solar and Wind tracks; and price per kilo-Watt $\times$ hour, which is the prediction results for consumption. You can see the results of this optimization in Table 5.

XGBoost has outperformed both best version of Normalizing Flows (NF-UMNN)

Track	Score	XGBoost	NF	VAE	RAND
Wind	$\overline{QS}$	**4.22**	4.58	4.45	8.55
	$\overline{ES}$	**53.26**	56.71	54.82	96.15
Solar	$\overline{QS}$	**1.11**	1.19	1.31	2.48
	$\overline{ES}$	**21.7**	23.08	24.65	41.53
Load	$\overline{QS}$	0.83	**0.76**	1.39	3.40
	$\overline{ES}$	9.76	**9.17**	15.11	38.08

Table 4. Score comparison

XGBoost	NF-UMNN	NF-A	VAE	RAND	O
122	107	101	97	-181	298

Table 5. Profit per model, k€

and Variational Autoencoders models, by 15 thousand Euros. It is a good practical demonstration of how relatively low and seemingly insignificant increases in test scores can result in substantial economic benefit. Random column (RAND) indicates profit for random predictions, which would result in 181 thousand Euros loss. While RAND does not necessarily indicate maximum possible loss, it still gives an idea about potential economic damage of bad model. Oracle (O) column indicates maximum possible profit if model had perfect knowledge of the future. It is not perfect, as it doesn't account for uncertainty within data, but it gives hard upper limit on possible profit.

5.3 Resource usage

The training of 99 XGBoost quantile models took different amount of time for each track. The fastest was Load track, which can be trained in 3.5 hours, with Solar track being close second - around 4 hours. Wind track took much longer to train, with 12 hours per experiment.

The assessment of scenarios for downstream task by Gurobi optimization software took around 2 hours per experiment.

Overall, the slow training process and inability to train in parallel prevented the use of validation set for hyperparameter tuning.

6 Conclusion and future work

6.1 Conclusion

After assessing differences between tracks and performance, it can be easily seen that XGBoost models outperformed models presented in [DWL+22] paper overall. However, the performance on Load track has been slightly lower than best performing model. This could be improved with some model adaptations and tuning. Nevertheless, acquired results can be used as a competitive baseline for future research in scenario forecasting, especially the one focused on Decision Tree models.

Since the copula-based approaches are the most studied and well-established for scenario generation, combined with high performance models, such as boosting algorithms, they produce highly accurate predictions. Therefore, we propose to use Copula-based Boosting pipeline as a baseline for any future scenario generation model proposals, as they produce very competitive results, only beating which the new models could claim **State of the Art** status.

6.2 Future work

Decision tree algorithms could also be further improved for probabilistic forecasting. Energy Score could be used as a loss function to train the distribution directly. Another possible route is to sample voting trees to assess certain quantile.

The field of energy forecasting benefits greatly from improvement in forecasting techniques and models. With ongoing development of XGBoost library version 2.0 [CG16] and optimization of training process for quantile forecasting, it would be possible to use validation set during training and train multiple quantiles in a single runtime. This should increase the overall performance of XGBoost in quantile forecasting setting.

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