Extended Cooperative Soft Gating Ensemble

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Abstract—This article is about an extension of a recent ensemble method called Cooperative Soft Gating Ensemble (CSGE) and its application on power forecasting as well as motion primitive forecasting of cyclists. The CSGE has been used successfully in the field of wind power forecasting, outperforming common algorithms in this domain. The principal idea of the CSGE is to weight the models regarding their observed performance during training on different aspects. Several extensions are proposed to the original CSGE within this article, making the ensemble even more flexible and powerful. The extended CSGE (XCSGE as we term it), is used to predict the power generation on both wind- and solar farms. Moreover, the XCSGE is applied to forecast the movement state of cyclists in the context of driver assistance systems. Both domains have different requirements, are non-trivial problems, and are used to evaluate various facets of the novel XCSGE. The two problems differ fundamentally in the size of the data sets and the number of features. Power forecasting is based on weather forecasts that are subject to fluctuations in their features. In the movement primitive forecasting of cyclists, time delays contribute to the difficulty of the prediction. The XCSGE reaches an improvement of the prediction performance of up to 11% for wind power forecasting and 30% for solar power forecasting compared to the worst performing model. For the classification of movement primitives of cyclists, the XCSGE reaches an improvement of up to 28%. The evaluation includes a comparison with other state-of-the-art ensemble methods. We can verify that the XCSGE results are significantly better using the Nemenyi post-hoc test.

I. INTRODUCTION

The main goal of machine learning (ML) is to create models from a set of training data that have a high capability of generalization. Often the ML problems are so complex that one single model cannot handle the whole scope. A common approach is to have multiple prediction models instead of using only one single model. The approach of combining multiple estimators is called ensemble method or short ensemble. In [1] and [2], it is shown that ensembles often lead to better results than using one single estimator. Despite their good generalization performance, well-known ensemble methods such as boosting [3], bagging [4] or stacking [5] have the disadvantage that the aggregation function is not human-readable. They can be considered as black box models. This article deals with a novel ensemble method called CSGE. The proposed ensemble method attempts to circumvent this decisive disadvantage by weighting the models according to different, potentially influencing aspects that are easy for humans to comprehend. The different factors can be seen in Figure 1. In the following, the example of wind power forecasting is considered. Several ML models provide predictions that are evaluated by four different factors. In particular, local factors depending on the current situation, are included in the calculation. This includes, for example, the current weather. Furthermore, global factors are taken into account, e.g. the error scores of the models on validation data or the position of the wind farm. In addition, it makes sense to understand various processes as a time series (time-dependent and time-lagged). The mentioned aspects can be found in many task positions of the ML. The presented ensemble unites all these mentioned aspects in a very understandable way for humans. It evaluates the models according to the mentioned criteria providing a weight aggregation for multivariate predictions.

A. Contribution

The presented ensemble algorithm is mentioned in [6], [7], and [8] initially. However, the CSGE is strongly designed and evaluated to the needs of wind power forecasting. In this article, we present a general approach of the CSGE, which allows the use for regression as well as classification tasks. In addition, we have extended the XCSGE to forecast multivariate predictions and use arbitrary error scores. Furthermore,
we have generalized the concept of local weighting and gained the possibility to use an arbitrary machine learning method for this purpose.

We investigate the performance of the extended CSGE (XCSGE) on two use-cases, which include both regression and classification tasks. Both use cases have very different requirements and can be solved efficiently with ensemble approaches. Besides the different sizes of the two data sets, the number of features differs strongly (30 or 65 features for wind- and solar power forecasting, respectively 738 features for classification of movement primitives). On the one hand, we use the implemented XCSGE to predict the power generation of both wind- and solar farms. In addition, the weather models, which we use as the basis for our predictions, are subject to fluctuations that are taken into account by the XCSGE. On the other hand, we use the XCSGE to predict the state of motion of a cyclist using smart devices. The main difficulty lies in a large number of physical features originating from the smart devices sensors (i.e. accelerometer and gyroscope). On both applications, we reach state-of-the-art performance, which we prove with statistical tests. Finally, we also include an evaluation of the models that estimate the expected error for the local weighting.

B. Structure

In the following, we give a short overview of the article by summarizing each chapter. Chapter II (Related Work) gives a short overview of common ensemble methods. Besides, we consider ensemble methods that are especially used in the fields of power generation and motion prediction. In Chapter III (Methods), a brief overview of the necessary fundamentals of ensemble methods and a detailed description of the XCSGE is given. In addition, the developed extensions, which are included in this article, are explained. In Chapter IV (Renewable Energy forecast), we apply the XCSGE to predict the power generation of wind- as well as solar farms. A detailed evaluation of the trained XCSGE and a comparison with state-of-the-art ensemble methods is given. We further investigate the performance of the local weighting models. In Chapter V (Cyclists Basic Movement Detection), we apply the XCSGE to predict the motion primitives of cyclists using smart devices. A detailed evaluation of the trained models is given. The article closes with Chapter VII (Conclusion and Outlook).

II. RELATED WORK

This chapter gives a short overview of common ensemble methods. Afterwards we discuss ensemble methods, which are specifically used in the field of power forecasting as well as motion prediction.

The reason why ensembles often achieve better results than individual models is due to their diversity. According to [9], diversity is a measure of how differently the individual ensemble members spread their errors over the feature space. The greater the diversity between the individual ensemble members, the greater the ensemble’s ability to generalize.

According to [10], there are several principles to achieve diversity. The most important are data diversity, parameter diversity as well as structure diversity.

- With the data diversity principle, further training sets are generated from the original training set, on which an ensemble member is trained. Well-known examples are Boosting [3] and Bagging [4].
- The parameter diversity principle varies the parameters of the learning algorithm to create different models. A common example is multiple kernel learning (MKL) [11].
- Using the structure diversity principle, different learning algorithms are used to train diverse ensemble members. An overview of those can be found in [12].

In the following, we will point out popular ensemble approaches which are used in the fields of power forecasting. The authors of [13] give an overview of different ensemble methods that are used in the area of power forecasting. Often the meteorological properties of weather forecasts are used as features to build models on them. Therefore, the approaches are differentiated mainly according to the use of weather forecasts. The three most important approaches are single-model ensemble, multi-model ensemble and time-lagged ensemble.

- With the single-model ensemble [14] different weather models are generated by varying hyperparameters (parameter diversity), on which then arbitrary power forecasting models are trained.
- The multi-model ensemble [15] uses weather models from different providers to train power forecasting models. The structure diversity principle (different providers use different learning algorithms) and the data diversity principle (different providers measure different physical characteristics) are used here.
- time-lagged ensembles [16] usually use a single weather model and a single energy prediction model. Diversity comes from a variation of the point in time from which a prediction is made (data diversity).

In the following, a survey of works is given, which deals with the motion detection of cyclists, respectively, humans. An overview of state-of-the-art techniques in the field of human activity recognition based on wearable sensors is given in [17]. In [18] an ensemble approach to predict physical activities such as sitting, running, etc. is presented. First various models (structure diversity) like an MLP [19] and a decision tree [20] are trained. These models are then combined using a voting classifier [21]. The results strongly suggest researchers applying an ensemble of classifiers approach for activity recognition problems.

In [22] different ensemble approaches such as boosting, bagging and ensembles of nested dichotomies (END) [23] are used to predict six everyday activities using smartphone sensor data. The activity classes are: walking, walking upstairs, walking downstairs, sitting, standing, and lying. Accuracy rates of up to 99.22% are achieved. In [24], multiple Kalman filters are used to determine the position of cyclists using GPS data. For this purpose, the MMAE (multiple models adaptive estimation) algorithm is used, which allows several Kalman filters to run in parallel using different stochastic models (parameter
In [25], the authors use a Stacking ensemble to classify the state of motion of cyclists. This ensemble implements the structure diversity principle. On the one hand, a convolutional neural network (CNN) [26] is trained on the basis of camera images. On the other hand, a classifier is being trained on smart device based sensor data. These two classifiers serve as a basis to train a stacking ensemble, which uses an extreme gradient boosting classifier [27] as a meta-learner.

In [28], the state of motion of cyclists is predicted with the help of smart devices. For this purpose, an XGBoost (extreme gradient regression trees) [29] classifier is trained for each smart device (data diversity). These three classifiers are then used to train another XGBoost classifier as a meta-learner. On the one hand, the meta-learner is being trained on the outputs of the three smart device classifiers. On the other hand, the meta-learner is being trained on the outputs of the three smart devices and the fused feature space.

III. Method

In this chapter, we first give a brief overview of basic concepts in ensemble methods, followed by an introduction to the XCSGE. After that, a short overview of the three weighting aspects that the XCSGE takes into consideration is given. Based on this description, we introduce the Soft Gating Principle, the key concept of the XCSGE, which computes a weighting from the estimated error. Afterward, the three mentioned weighting aspects are explained in detail. The chapter closes with an overview of the training process of the XCSGE.

A. Ensemble Methods

The approach of combining multiple estimators is called ensemble. Each estimator of an ensemble is called ensemble member, base estimator or base learner. Most ensemble methods use one single type of machine learning algorithm for their ensemble members. These ensembles are often called homogenous ensembles. Some ensembles use different machine learning approaches as ensemble members which leads to heterogeneous ensembles.

According to [2], ensembles can be categorized in one of three types: combining classifiers, mixture of experts and ensembles of weak learners. In this paper, we mainly consider combining classifiers or regression models. When creating an ensemble of combining classifiers, multiple strong learners are combined to improve the performance. Strong learners are estimators that could also work on their own and have an acceptable performance. In contrast, weak learners are estimators that have a poor performance on their own and could only be used in a swarm.

To solve many problems with machine learning algorithms efficiently, it is often necessary to include the changes in the input values over time in the prediction. Furthermore, the domain often requires predictions of targets in the future. This process is also called time series forecasting. The forecasting timestep \( t \) is often called leadtime. Both applications, described in Chapter IV and V, can be modelled as time series forecasting.

B. Coopetitive Soft Gating Ensemble

In this section, the Extended Coopetitive Soft Gating Ensemble (XCSGE) is introduced. It is a recent ensemble technique which is proposed in [6]. In the field of ensemble methods, there are two paradigms to combine individual ensemble members. Weighting combines all ensemble members in a linear combination, while gating selects only one ensemble member. The idea of the XCSGE is to gain the possibility to have a mixture of both weighting as well as gating and let the ensemble itself choose which concept to use for the combination of different predictions. With the weighting concept, all ensemble members contribute to the overall prediction - they cooperate. Instead, the selection paradigm uses the winner take’s it all concept - the ensemble members are in a competition. Since the XCSGE can work in selection- or weighting mode, the name coopetitive is a suitcase word which combines the words cooperation with competition. Thus, the XCSGE is considered to be a combining classifiers ensemble, since it uses strong learners. There are no specific requirements on the type of the ensemble members learning algorithm, therefore the XCSGE is neither a pure homogenous, nor a pure heterogenous ensemble.

In the following we take advantage of the Hadamard operations [30], which allows us to compute elementwise operations on two vectors. Fig. 2 shows the principle of the XCSGE as described in the following. The ensemble includes \( J \)-ensemble members, with \( j \in \{1, ..., J\} \). Each ensemble member provides multivariate estimations \( \mathbf{p}^{(j,t)} \in \mathbb{R}^M \) for the input \( x \in \mathbb{R}^{N_{features}} \). Let \( t \) denote the leadtime, with \( t \in \{0, ..., K\} \), where \( K \) is the maximum leadtime. Furthermore let \( M \) be the number of target variables and \( N_{features} \) the number of features.

For each prediction the XCSGE calculates a weighting, regarding three aspects: global-, local- and time dependent weighting and joins them. These three aspects are the core components of the ensemble and are explained in detail later. After estimating the weighting aspects, all \( j \) weights get normalized and each prediction \( \mathbf{w}^{(j,t)} \) gets weighted using the corresponding weight \( \mathbf{w}^{(j,t)} \in \mathbb{R}^M \). In the last step, the ensemble’s prediction is obtained by aggregation of the weighted predictions. Formally, we can express the weighted aggregation of the ensembles prediction using the following equation:

\[
\mathbf{\tilde{p}}^{(t)} = \sum_{j=1}^{J} \mathbf{w}^{(j,t)} \odot \mathbf{p}^{(j,t)}
\]

Let \( \odot \) denote the Hadamard product. To ensure that the prediction is not distorted we have the following constraint:

\[
\sum_{j=1}^{J} \mathbf{w}^{(j,t)} = 1 \quad \forall t \in \{0, ..., K\}, \forall m \in \{1, ..., M\}
\]

The main goal of the XCSGE is to adjust the weights \( \mathbf{w}^{(j,t)} \) optimal regarding the individual performance of the ensemble members. To compute the strongness, respectively, the weakness of a model, we use error scores, like the root-mean-squared error (RMSE). The performance of an ensemble
member is computed by three aspects described in the following.

The **global weights** are calculated for each ensemble member regarding the overall observed performance of a model during ensemble training. This is a fixed weighting term. Thereby, overall strong models have more influence than weaker models. **Local weighting** considers the fact that different ensemble members have diverse prediction quality over the feature space. As an example, when considering the problem of renewable energy prediction [6], an ensemble member could perform well on rainy weather inputs but has worse quality when using sunny weather inputs. Therefore, the local weighting rewards ensemble members with a higher weighting, that performed well on similar input data. These weights are adjusted for each prediction during runtime.

The **time dependent weighting** aspect is used when performing predictions on timeseries. Sometimes ensemble members perform differently for different leadtimes. When considering the problem of renewable energy prediction again, we can see that the persistence method often achieves superior results in short time horizons, while quickly losing quality for long time predictions. Other methods may perform worse on short time predictions, but have greater stability over time.

To calculate the overall weighting for the j-th ensemble member \( w^{(j,t)} \), we use the following formular:

\[
    \hat{w}^{(j,t)} = \hat{w}^{(j,t)} \odot \sum_{j=1}^{J} w^{(j,t)}
\]

where \( \hat{w}^{(j,t)} \in \mathbb{R}^{M} \) denotes the global weighting, \( w^{(j,t)} \in \mathbb{R}^{M} \) the local weighting and \( w^{(j,t)} \in \mathbb{R}^{M} \) the time dependent weighting.

### C. Soft Gating Principle

The main goal of the **Coopetitive Soft Gating Ensemble** is to increase the quality of the prediction by weighting solid predictors greater than predictors with fewer quality results for each weighting aspect. Therefore, a function is implemented which maps the dependency between error of the predictor and its weighting. To do so, the function \( \varsigma_\eta(\rho, \Omega) \) is used. It is defined as follows:

\[
    \varsigma_\eta(\Omega, \rho) = \sum_{j=1}^{J} \rho \odot \eta + (\hat{\epsilon}_1, \ldots, \hat{\epsilon}_M), \eta \in \mathbb{R}^+
\]

Let \( \Omega \) be a set which contains the reference errors of all \( J \) ensemble members, and \( \rho \in \mathbb{R}^M \) be the error of the ensemble member that is to be weighted.

Let \( \odot \) denote the **Hadamard exponentiation**, \( \hat{\epsilon} \) is a small constant to prevent a division by zero. The parameter \( \eta \) is chosen by the user. It controls the linearity of the weighting. For greater \( \eta \) the XCSGE tends to work as a selecting ensemble, whereas smaller \( \eta \) result in a weighting ensemble.

By taking a closer look on \( \varsigma_\eta \), we can discover the following characteristics:

- The function \( \varsigma_\eta \) is falling monotonously (see Fig. 2).
- For greater \( \rho \) or the error of an ensemble member, \( \varsigma_\eta \) returns smaller weightings.
- For \( \eta = 0 \) every ensemble member is weighted with \( \frac{1}{J} \), disrespecting the error of it’s prediction.

To ensure that \( \sum_{j=1}^{J} w^{(j,t)} \equiv 1 \forall m \in \{1, \ldots, M\} \), \( \varsigma_\eta(\Omega, \rho) \) is normalized in the following way:

\[
    c_\eta(\Omega, \rho) = \varsigma_\eta(\Omega, \rho) \odot \sum_{j=1}^{J} c_\eta(\Omega, \Omega_j)
\]

Besides the fact of having only one parameter (\( \eta \)), the soft gating function offers the advantage of operating directly on errors of the ensemble members and, therefore, directly links to the actual data.

### D. Global Weighting

The **global weighting** is calculated during ensemble training and then remains constant. Ensemble members that performed well on the training data get greater weights compared to those that performed worse. Therefore, the difference between estimation and ground truth is calculated with
The error (RMSE) of a predictor is drawn on the x-axis, while the y-axis contains the corresponding weights computed by $\varsigma_r$. For greater $\eta$ a higher error gets more regulated with less weighting than for smaller $\eta$.

$$e_n^{(j)} = \frac{1}{N_{\text{samples}}} \sum_{n=1}^{N_{\text{samples}}} S(p_n^{(j,t)}, y_n) \quad \text{with} \quad 1 \leq n < N_{\text{samples}} \quad (7)$$

Let $p_n^{(j,t)} \in \mathbb{R}^M$ be the prediction of the $j$-th ensemble member on leadtime $t$ and $y_n \in \mathbb{R}^M$ be the corresponding ground-truth.

Let $S$ be an arbitrary error metric, which for example could be the root-mean-squared-error (RMSE) for regression or the Log Loss for classification. The only condition that has to hold is that it has to be falling monotonously with increasing errors to work properly with the soft gating principle, see Eq. (4). Since the global weighting is independent of leadtime, we sum over all leadtimes. The error score $R^{(j)} \in \mathbb{R}^M$ of the $j$-th ensemble member is calculated by:

$$R^{(j)} = \frac{1}{N_{\text{samples}}} \sum_{n=1}^{N_{\text{samples}}} e_n^{(j)} \quad (8)$$

$$R = \{R^{(1)}, ..., R^{(j)}, ..., R^{(J)}\} \quad (9)$$

The set $R \in \mathbb{R}^M$ contains all error scores of the $J$ ensemble members. By that, the global weight of the $j$-th ensemble member is calculated by:

$$w_g^{(j)} = \varsigma_{\text{global}}(R, R^{(j)}) \quad (10)$$

We use the parameter $\eta_{\text{global}}$ for the soft gating principle. $\eta_{\text{global}}$ is chosen during ensemble training, as described in Section III-G.

### E. Local Weighting

The local weighting considers the quality difference between the predictors for distinct situations over the whole feature space. Therefore, the local weighting rewards ensemble members with a higher weighting, that performed well on similar input data. In contrast to the global weighting, the local weighting is calculated for each ensemble member and each prediction at runtime. First, we use the training set $X_M$ and make predictions for all ensemble members. Afterward, we calculate the error per sample using the scoring function $P$. Then, we train an arbitrary regression model $M_{\text{local}}^{(j)}$ per ensemble member, which has the feature space as input and the previously calculated error as output. The regressions model $M_{\text{local}}^{(j)}$ estimates the expected error for the respective ensemble member based on the input. As a intuitive approach, we use a $k$-nearest neighbor regressor [31], unless otherwise stated.

To calculate, the local error score $q^{(j)} \in \mathbb{R}^M$ for an ensemble member $j$ is given by

$$q^{(j)} = M_{\text{local}}^{(j)}(x) \quad (11)$$

In the following, we calculate the weighting analogous to the global weighting by using the soft gating formula $\varsigma_r$

$$Q = \{q^{(1)}, ..., q^{(j)}, ..., q^{(J)}\} \quad (12)$$

$Q \in \mathbb{R}^M$ contains all local error scores of the $J$ ensemble members. Then, the local weight $w_l^{(j)}$ is calculated by using the soft gating principle:

$$w_l^{(j)} = \varsigma_{\text{local}}(Q, q^{(j)}) \quad (13)$$

### F. Time Dependent Weighting

The time dependent weighting considers the fact that the quality of an ensemble member may vary for different leadtimes. $P_n^{(j,K)} \in \mathbb{R}^M$ contains all predictions of training sample $n$ of ensemble member $j$ for a specific leadtime $t \in \{0, ..., K\}$.

$$P_n^{(j,K)} = \{p_n^{(j,0)}, p_n^{(j,1)}, ..., p_n^{(j,K)}\} \quad (14)$$

The error for a specific leadtime $t$ is calculated by averaging the error over all training samples:

$$r^{(j,t)} = \frac{1}{N_{\text{samples}}} \sum_{n=1}^{N_{\text{samples}}} S(p_n^{(j,t)}, y_n) \quad (15)$$

With $p_n^{(j,t)} \in P^{(j,K)}$ and $y_n$ being the corresponding ground truth. It holds $R^{(j,t)} \in \mathbb{R}^M$. To calculate the error score for leadtime $t$ of ensemble member $j$, we use the following equation:

$$r^{(j,t)} = \frac{R^{(j,t)}}{\sum_{t=0}^{T} R^{(j,t)}} \quad (16)$$

$r^{(j,t)} \in \mathbb{R}^M$ is a score that compares the error of the prediction with the leadtime $t$ to the average error in the leadtime interval $\{0, ..., t, ..., K\}$. The weight $w_k^{(j,t)} \in \mathbb{R}^M$ is calculated analogous to global- and local weighting using the soft gating principle

$$P^{(t)} = \{r^{(1,t)}, ..., r^{(j,t)}, ..., r^{(J,t)}\} \quad (17)$$
The prediction of the time delay of a sensor is known to compensate for this delay. Since the weighting is recalculated and normalized for each time instance, we use the following equation:

$$w_k^{(t)} = \zeta_{\text{time}}(P^{(t)}, p^{(j,t)})$$

(18)

We use the parameter $\eta_{\text{time}}$ for the soft gating principle. $\eta_{\text{time}}$ is chosen during ensemble training as described in Section III-C.

G. Model Fusion and Ensemble Training

To calculate the output of the $J$ ensemble members, we use the following equation:

$$\hat{p}^{(t)} = \sum_{j=1}^{J} w^{(j,t)} \cdot p^{(j,t)}$$

(19)

As mentioned in Section III-C, the parameter $\eta$ is chosen by the user and controls the non-linearity of the system. Since there are three aspects, global-, local- and time dependent weighting, it follows that there are also three $\eta = (\eta_{\text{global}}, \eta_{\text{local}}, \eta_{\text{time}})$ to be chosen. Let $f_{\text{XCSGE}}(x_n, \eta)$ be the prediction of the XCSGE for the input sample $x_n$ with the set of $\eta$. Then the following minimization problem solves the task to adjust the set of $\eta$:

$$\sum_{n=1}^{N_{\text{samples}}} [y_n - f_{\text{XCSGE}}(x_n, \eta)]^2 + c \cdot \sum_{s=1}^{3} \eta_s$$

(20)

Where $\sum_{n=1}^{N_{\text{samples}}} [y_n - f_{\text{XCSGE}}(x_n, \eta)]^2$ are the summed errors over the training data, while $c \cdot \sum_{s=1}^{3} \eta_s$ is a regularization term to control overfitting.

H. Time Lagged Ensemble

In the following, we will discuss a technology that is particularly interesting for time-critical applications, especially when several sensors measure data. In practice there is often a delay in the arrival of the data in the prediction models. A possible approach is to train the models on time-delayed data. In this approach, the ground-truth is shifted forward by one time unit at a time. All in all, this results in $t \cdot j$ ensemble members, where $j$ is the number of different ML models, and $t$ is the number of time units by which a shift should take place.

Since the weighting is recalculated and normalized for each prediction, it is also possible to exclude specific time-shifted models from the ensemble prediction. This is of interest if a time delay of a sensor is known to compensate for this delay.

IV. RENEWABLE ENERGY FORECAST

In the following, we investigate the XCSGE on its application on renewable power forecast. Power forecasts on wind farms using the CSGE has already been investigated in [7], [8] and [6]. Power forecasts are an essential tool to schedule the power supply. Wind farms, as well as solar farms power generation demands on volatile weather situations, which makes them hard to predict. Since the proportion of renewable energy is growing strongly, better prediction models are necessary to ensure power grid stability. In this section, the XCSGE is used to predict the power generation of wind farms (see Section IV-C) as well as solar farms (see Section IV-D). We use the meteorological properties of weather forecasts as features to build models on them. The problem can be modeled as a regression task. On the one hand, the difficulty of the problem lies in the non-linear relationship between weather and power generation. On the other hand, the quality of the weather forecasts, and thus the quality of the input features decreases over leadtime. Since the XCSGE considers the quality fluctuation of the ensemble members over leadtime, it is suitable for this task.

Next to an evaluation on the datasets, a comparison with other state-of-the-art ensemble methods, such as the stacking ensemble method, is given. For both forecasting problems, the same type of ensemble members are trained, as detailed in Section IV-A. Next to the ensemble members, the training process of the XCSGE itself is identical for both wind farms and solar farms. It can be found in Section IV-B. The description of the datasets as well as the preprocessing and evaluation is given in the corresponding sections, since they are diverse for each forecasting problem.

A. Ensemble Members

For each wind farm respectively solar farm, four ensemble members are trained using the structure diversity principle. The trained models are: support vector regression (SVR) [32], linear regression (ridge regression) [33], neuronal network (MLP) [19] as well as a gradient boost regressor tree (GBRT) [27]. For the sake of runtime, the ensemble members are trained with fixed parameters.

B. Ensemble Training

The ensemble members as well as the XCSGE and stacking are evaluated by using a ten-fold cross-validation. In each fold, the data is split in a training set (90%) and a test set (10%). The test set is not shuffled to keep the structure of time indices. Furthermore, the training fold is split into a base learner set (70%) and into an ensemble set (30%). The base learner set is used to train the four ensemble members, while the ensemble set is used to train the XCSGE and stacking. For stacking a linear regression as well as an MLP as metalearner is evaluated. A gridsearch optimizes the hyperparameters of the ensemble methods. We use a $k$-nearest neighbor regressor as the machine learning model $M^{(j)}$ to calculate the local weighting. For the XCSGE a gridsearch on the parameter $k$ is executed, which controls the number of nearest neighbors for
the \textit{k-nearest neighbor regressor} $M^{(j)}_{\text{local}}$. The parameter $k$ is chosen in the range \{9, 50, 100\}. The set of $\eta = (\eta_1, \eta_2, \eta_3)$ is optimized as pointed out in the training process of the XCSGE. For the \textit{stacking} with the MLP as metalearner the possible hidden layer sizes are optimized using a gridsearch. The hidden layer sizes are chosen in a range of \{50 – 100\}. For the \textit{linear regression metalearner} there is no need to optimize the model parameters. The \textit{mean squared error} is used as the XCSGE’s errorfunction $S$.

C. Wind farms

In this chapter, the XCSGE is applied to wind farm datasets. First, a short overview of the structure of the data, as well as general information, is given in Section IV-C1. After that, Section IV-C2 gives a summary of the preprocessing. The training process of the machine learning models, which are used as the ensemble members of the XCSGE as well as the \textit{stacking}, is pointed out in Section IV-A. The evaluation method, as well as the ensemble training, can be found in Section IV-B. A presentation of the final results of the experiments is given in Section IV-C4 and IV-C3.

1) Dataset: The XCSGE is evaluated on 70 different wind farms. The wind farms are spread all over Europe, containing both onshore and offshore wind farms. Every wind farm dataset contains measured power generation, which is captured every hour on two consecutive years resulting in a maximum of 17520 measured samples. Nevertheless, some wind farms only have 50% data samples of the two years captured. The measured generated power of the wind farm is averaged hourly by the maximum power of the wind farm. Besides the measured generated power of the wind farm, the datasets contain a corresponding day-ahead weather forecast for the wind farm’s location. The day-ahead weather forecast is updated every day and it covers the weather situation in one hour steps up to 24 hours for the next day. The weather forecast contains seven meteorological features which are:

- Air Pressure
- Humidity
- Temperature
- Wind Direction \{Zonal, Meridional\} 100m
- Wind Speed \{10m, 100m\}

2) Preprocessing: First, every feature is standardized while the ground-truth is normalized by the maximum power. The scaling of the ground-truth (power generation) is necessary to compare the error of the wind farms among themselves in Section IV-C2. Furthermore, the four features wind speed 100m, wind speed 10m, wind directional zonal 100m and wind directional meridional 100m are time shifted up to two time units both in the future as well as in the past (+/-2 hours) to model the time dependency between the features. After the preprocessing, the datasets contain 30 features. Since the weather model gets updated every 24 hours, the \textit{time dependent weightings} property $k$ is $(k_{\min} = 25, k_{\max} = 48, \Delta = 1)$.

3) Analysis of local weighting models: To calculate the \textit{local weighting}, we take advantage of models that estimate the expected error of an ensemble member for a specific sample. For this purpose we use a \textit{k-nearest neighbor regressor} as the local error model $M^{(j)}_{\text{local}}$. We evaluated these models within a six-fold cross-validation. The results can be seen in Figure 5. The local error models are equally good at predicting the error for their respective ensemble member with an R2-score of about 0.3

\begin{table}[h]
\centering
\begin{tabular}{c|cccc}
\hline
\textbf{Model} & \textbf{GBRT} & \textbf{MLP} & \textbf{SVR} & \textbf{Ridge R} & \textbf{XCSGE} & \textbf{MLP Stacking} & \textbf{Linear Stacking} \\
\hline
\textbf{Mean} & 0.1365 & 0.1407 & 0.1439 & 0.1516 & 0.1349 & 0.1356 & 0.1356 \\
\textbf{Variance} & 0.0013 & 0.0011 & 0.0014 & 0.0017 & 0.0012 & 0.0012 & 0.0012 \\
\textbf{Minimum} & 0.0761 & 0.0704 & 0.07107 & 0.0799 & 0.0711 & 0.0711 & 0.0827 \\
\textbf{Maximum} & 0.2664 & 0.2686 & 0.2777 & 0.3015 & 0.2608 & 0.2610 & 0.2587 \\
\textbf{Skill Score} & 9.92% & 7.18% & 5.09% & 0.0% & 11.01% & 10.24% & 10.54% \\
\hline
\end{tabular}
\caption{RMSE of 10-fold cross-validation. The best score for each wind farm is highlighted bold.}
\end{table}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{prediction.png}
\caption{Prediction of Windfarm Error}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{errors.png}
\caption{Box plot of RMSE and R2-score of wind farms.}
\end{figure}
The ranked performance of the algorithms among all of the 70 wind farms is furthermore analyzed using the **Friedman test** [35] in conjunction with the **Nemenyi post-hoc test** [35]. The results are given in Fig. 7. The **Friedman p** value given in the figure indicates that the ranks are significantly different, using a significance level of $\alpha = 0.05$. As it can be seen from the **Nemenyi test**, the stacking ensembles have not a significantly better ranked performance in comparison to the ensemble members. However, the **XCSGE** achieved a significantly better performance than the ensemble members, which is not given for the other ensemble methods.

![Fig. 7: Evaluation of ranked performance of the models using the Nemenyi post-hoc test. As can be seen from the figure, the XCSGE is significantly better than its ensemble members.](image)

### D. Solar farms

In this section, the **XCSGE** is applied to solar farms to predict the power forecast. First, we will give a short overview of the data in Section [IV-D1] followed by a summary of the preprocessing in Section [IV-D2]. The training process of the machine learning models, which are used as the ensemble members of the **XCSGE** as well as the **stacking** is pointed out in Section [IV-A]. The evaluation method, as well as the ensemble training, can be found in Section [IV-B]. Finally, the section concludes with a short evaluation of the trained models in Section [IV-D4] and [IV-D3].

**1) Dataset:** We also evaluated the **XCSGE** on 114 different solar farms, which are spread all over Europe. In comparison to wind farms, every sample is captured in a three hour circle. Every dataset contains measured power generation, which is captured in three hour circles on two consecutive years resulting in 3871 measured samples. The measured generated power of the solar farm is averaged over three hours. Next to the generated power, the dataset also contains a corresponding day-ahead weather forecast for the solar farm’s location. The day-ahead weather forecast is updated on a daily basis, and it covers the weather situation in one hour steps up to 24 hours for the next day.

The weather forecast contains 50 meteorological features, including:

- Sun Position \{Theta Z, Extra Terr, Solar Height\}
- Clear Sky \{Direct, Global\}
- Relative Humidity At 0

- Net Solar Radiation \{Direct, Diffuse\}
- Snow \{depth, fall\}

**2) Preprocessing:** First, every feature is standardized while the ground-truth is normalized by the maximum power. The scaling of the ground-truth (power generation) is necessary to compare the error of the solar farms among themselves in Section [IV-D4].

To model the time dependency between the features, the features are time shifted. The time shift is done both in the past as well as in the future up to one time unit (+/- 3 hours). After the preprocessing, our dataset contains around 65 features. The weather model is updated every 24 hours leading to the **timedependent weightings** property ($k_{min} = 25, k_{max} = 48, \Delta = 3$).

**3) Analysis of local weighting models:** For the calculation of the local weighting, we also use a k-nearest neighbor regressor as the local error model $M_{local}^{(j)}$. We evaluated these models within a six-fold cross-validation. The results can be seen in Figure [8]. The local error models for the **GBRT** and ridge regression respectively achieve significantly better results in predicting the error compared to the two models for **SVR** and **MLP**.

![Fig. 8: R2-score of the local weighting models $M_{local}^{(j)}$.](image)

**4) Evaluation:** Table [III] and [IV] show the **RMSE** and the **R2-score** of all 114 solar farms averaged over all ten folds. The setup of the folds is pointed out in Section [IV-B]. The full tables can be found in the Appendix [VII] [VIII] [IX] and [X]. Next to the mean, we also calculated the skill score using the worst model as reference. We can see, that the **XCSGE** performs the best achieving a skill score of 30.00% on **RMSE** and 15.27% on the **R2-score**. In addition, the results are visualized by a boxplot in Figure [9]. When considering the ensemble members **RMSE** and R2-score we can observe, that **GBRT** as well as the **ridge regression** performs the best over nearly all solar farms. The **MLP** and the **SVR** have the worst scores on all wind farms. When comparing the **R2-score** of the **ridge regression** on the wind farm datasets (0.60955) with the one on the solar farm datasets (0.8751), we can assume that the correlation between weather and energy yield is more linear for solar farms compared to wind farms.

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**TABLE II:** R2-score of 10-fold cross-validation. The best score for each wind farm is highlighted bold.

| Model          | GBRT | MLP | SVR | Ridge R. | XCSGE | MLP Stacking | Linear Stacking |
|----------------|------|-----|-----|----------|-------|--------------|-----------------|
| Mean           | 0.6614 | 0.6430 | 0.6309 | 0.6095 | 0.6719 | 0.6652 | 0.6608          |
| Variance       | 0.0864 | 0.0774 | 0.0763 | 0.0542  | 0.0726 | 0.0856 | 0.1013          |
| Minimum        | -1.2140 | -1.0909 | -1.0162 | -0.2478 | -0.9674 | -1.1180 | -1.4362         |
| Maximum        | 0.8370 | 0.8144 | 0.8198 | 0.7038  | 0.8442  | 0.8447 | 0.8465          |
| Skill Score    | 8.52%  | 5.489% | 3.502% | 0.0%    | 10.237% | 9.13% | 10.08%          |

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**TABLE III:** R2-score of 10-fold cross-validation. The best score for each solar farm is highlighted bold.

| Model          | GBRT | MLP | SVR | Ridge R. | XCSGE | MLP Stacking | Linear Stacking |
|----------------|------|-----|-----|----------|-------|--------------|-----------------|
| Mean           | 0.6614 | 0.6430 | 0.6309 | 0.6095 | 0.6719 | 0.6652 | 0.6608          |
| Variance       | 0.0864 | 0.0774 | 0.0763 | 0.0542  | 0.0726 | 0.0856 | 0.1013          |
| Minimum        | -1.2140 | -1.0909 | -1.0162 | -0.2478 | -0.9674 | -1.1180 | -1.4362         |
| Maximum        | 0.8370 | 0.8144 | 0.8198 | 0.7038  | 0.8442  | 0.8447 | 0.8465          |
| Skill Score    | 8.52%  | 5.489% | 3.502% | 0.0%    | 10.237% | 9.13% | 10.08%          |

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**TABLE IV:** R2-score of 10-fold cross-validation. The best score for each solar farm is highlighted bold.

| Model          | GBRT | MLP | SVR | Ridge R. | XCSGE | MLP Stacking | Linear Stacking |
|----------------|------|-----|-----|----------|-------|--------------|-----------------|
| Mean           | 0.6614 | 0.6430 | 0.6309 | 0.6095 | 0.6719 | 0.6652 | 0.6608          |
| Variance       | 0.0864 | 0.0774 | 0.0763 | 0.0542  | 0.0726 | 0.0856 | 0.1013          |
| Minimum        | -1.2140 | -1.0909 | -1.0162 | -0.2478 | -0.9674 | -1.1180 | -1.4362         |
| Maximum        | 0.8370 | 0.8144 | 0.8198 | 0.7038  | 0.8442  | 0.8447 | 0.8465          |
| Skill Score    | 8.52%  | 5.489% | 3.502% | 0.0%    | 10.237% | 9.13% | 10.08%          |
In urban traffic situations, there are many different road users e.g. cars, buses, cyclists. Especially cyclists are very vulnerable since they are easily overseen by other road users. Therefore, advanced driver assistance systems can help the driver of a vehicle to anticipate possible dangerous situations and execute a stop to avoid a potential collision [36]. To do so, those systems need to detect the current movement state, e.g. waiting and moving, and subsequently need to forecast the cyclist’s future trajectory. To gain information about the cyclist’s movement, we use the sensors of smart devices. Smart devices such as smartphones or smartwatches have seen an enormous increase in performance over the last few years. The increase in performance is not only limited to battery life and computing power but also the precision of the contained sensors is continuously increasing. Therefore, they are an ideal way to gain information as nearly everybody has one with them all the time. It is of particular challenge to develop models from this information that can be used to detect the current cyclist movement state. In the following, we refer to the movement state as movement primitives. Data from multiple smart devices, e.g. smartphone, smartwatch, and a smart sensor-equipped helmet, can be combined to quickly detect the cyclist current movement state and communicate it to nearby intelligent vehicles using G5 [37]. This is especially helpful to resolve occlusion situations, e.g. cyclist is entering the road occluded by another vehicle or object. In this section, we will use the XCSGE to classify the movement primitives of cyclists. The difficulty of the problem results from different aspects. On the one hand the dimensionality of the feature space is extremely high and for the considered amount of data is extremely large (738 features and 210452 samples). There are several sensors used, which capture a great number of different physical properties e.g. acceleration. On the other hand, we have to track a lot of samples over a relatively short time horizon for a precise classification of the cyclist’s movement primitive. The great amount of features and data requires an appropriate pre-processing to develop strong models.

A. Dataset

The considered dataset is captured in several experiments on a public crossing in Aschaffenburg. A picture of the crossing can be seen in Fig. [11]. In total, 50 different cyclists took part in the experiments. Every cyclist was equipped with a Samsung Galaxy S6 smartphone and two Motorola Moto 360 smartwatches, which tracked the data:

- Smartphone carried in the pocket of the trousers (Phone).
- Smartwatch fixed on the wrist of the right arm (Watch).
- Smartwatch integrated into the helmet (Helmet).

A cyclist is identified with an ID, also called VRU (Vulnerable Road User), to make them distinguishable. The captured data is labeled with the four movement primitives: “waiting” (class 0), “starting” (class 1), “moving” (class 2) and “stopping” (class 3).

To label the captured data by the four movement primitives, a wide-angle stereo-camera system is used to triangulate the cyclist’s head. The triangulation area is depicted in Fig. [11]. Both cameras have a sampling rate of 50 Hz. The period of time when the cyclist enters the viewport and leaves the viewport of the camera is called a scene.

B. Preprocessing

Each smart device captured data provided by three sensors, including an accelerometer, a gyroscope as well as a rotation-vector sensor. All supplied data are relative to the coordinate...
system with the device as the origin. Since the devices are fixed on different positions on the cyclist’s body, there are three different coordinate systems in total. To boost the predictor’s quality, all coordinate systems are transferred in a coordinate system relative to the cyclist [38]. For the process of segmentation, a sliding window approach is used as described in [39]. Every feature is calculated for different window lengths. For feature extraction minimum, maximum as well as the energy are chosen as calculation methods, see [40] and [38] for further details. For each device, 246 features are extracted, which results in 738 features in total.

C. Ensemble Members
The ensemble members are trained as pointed out in [28] using the data diversity principle. Since the number of features is very high, a feature selection is necessary to reduce the dimension. A combination of filters and wrappers is used to decrease the number of features for all three smart devices. After the feature selection, a XGBoost (Extreme Gradient Regression Trees) [29] classifier is trained for each smart device. The classifiers are optimized regarding the F1-score.

D. Ensemble Training
The three pre-trained classifiers from Section V-C are used as the ensemble members for the XCSGE. Altogether we have trained four different XCSGE ensembles which will be explained later in detail. For all experiments, the XCSGE is optimized on the log loss score. For the reason that the ensemble members predictions are class propabilities, the log loss score is suitable. We evaluated four different XCSGE variants, described in more detail below:

XCSGE with 4 PCA dimensions per smart device: As already pointed out, there are 246 features for all three smart devices. After the fusion of the feature spaces the dataset contains $3 \cdot 246 = 738$ features in total. The great amount of features increases the computational effort when using a k-nearest neighbor regressor for the local weighting. Therefore, we reduce the dimensionality. We applied a PCA on the dataset. The reduced dataset contains four features per smart device, resulting in $3 \cdot 4 = 12$ features in total. We use the reduced dataset to train a k-nearest neighbor regressor, which we then utilize for the local weighting aspect.

XCSGE with 50 PCA dimensions per smart device:
To investigate the influence of the PCA dimension, a PCA is applied on the dataset, but this time to obtain a reduction to 50 features per smart device. The reduced feature set contains 50 features per smart device, resulting in $3 \cdot 50 = 150$ features in total. We use the reduced feature set to train a k-nearest neighbor regressor, which we then utilize for the local weighting aspect.

**XCSGE time-lagged:**
As a next approach, a XCSGE with time-lagged ensemble members is trained. Therefore, the predictions of all three smart devices are shifted back in time ($t = -14$). This approach results in 14 ensemble members for each smart device. With a sampling rate of 0.02 seconds, a timespan of $14 \cdot 0.02s = 0.28s$ is covered. Because of $14 \cdot 3 = 42$ ensemble members, the runtime of the XCSGE is already relatively long. Therefore a PCA with four dimensions for each smart device is applied to shrink the feature space.

**XCSGE with MLP regressor for local weighting:**
In this approach, we use all 738 features to train an MLP regressor, which we use for the local weighting model $M_{local}^{(j)}$, for details see Section III-E. We choose Rectifier as the activation function and an architecture with 4 hidden layers and 100 neurons each.

1) Analysis of local weighting models: We have investigated the models, which are used for the estimation of the local error, in a six-fold cross-validation. The MLP regressor was able to estimate the expected error best. The results can be seen in Figure 12. For each ensemble member, it achieved a $R^2$-score of 0.9.

![Prediction of Cyclists Error](image)

Fig. 12: $R^2$-score of the local weighting model $M_{local}^{(j)}$ using a MLP regressor.

E. Evaluation
To evaluate the models, a six-fold cross-validation is executed. The results can be seen in Table V and VI. In each fold, the data is split in a training set (75%) and in a test set (25%). The XCSGE variations are trained on the training set. Since the ensemble members are already pretrained [28], there is no need for an extra training set. The data is split by the VRU to keep the structure of the scenes. An evaluation of the four
different XCSGE ensembles is given below. The results can be seen in Tables [V] and [VI].

**XCSGE with 4 PCA dimensions per smart device:**
The XCSGE with 4 PCA dimensions increased its log loss value at around 7% compared to the best smart device model (Phone). When considering the F1-score, the XCSGE is as good as the best smart device model (Watch).

**XCSGE with 50 PCA dimensions per smart device:**
The XCSGE with 50 PCA dimensions increased its log loss value also at around 7%. When considering the F1-score, there is no significant improvement compared to the best base estimator (Watch).

**XCSGE time lagged:**
The time lagged XCSGE increased the log loss value at around 8% compared to Phone. When considering the F1-score, an improvement at around 0.6% compared to the best smart devices models (Watch) can be seen.

**XCSGE with MLP regressor for local weighting:**
The XCSGE increased the log loss value at around 10% compared to Phone. When considering the F1-score, an improvement at around 1.5% compared to the best smart devices model (Watch) can be seen. Furthermore, we evaluated the trained MLP regressor, which is used for the local weighting. At a three-fold cross-validation the MLP regressor achieved a R2-score of 0.95, as well as a mean-squared-error of 0.062 per smart device. A further advantage over to the MLP regressor approach lies in the comparatively much lower time required for training.

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**Fig. 13:** Box plot of log loss and R2-score of cyclists movement detection.

**Table V:** Log loss of six-fold cross-validation. The best values for each criterium are highlighted bold.

|                | Phone | Watch | Helmet | XCSGE (PCA Dim. 4) | XCSGE (PCA Dim. 50) |
|----------------|-------|-------|--------|--------------------|--------------------|
| Mean           | 0.77387 | 0.79147 | 0.72231 | 0.78613             | 0.70325            |
| Variance       | 0.00035 | 0.00013 | 0.00027 | 0.00041             | 0.00016            |
| Minimum        | 0.75498 | 0.77354 | 0.69707 | 0.76211             | 0.77949            |
| Maximum        | 0.80952 | 0.80757 | 0.74246 | 0.81978             | 0.81517            |
| Skill Score    | 6.66%  | 8.37%  | 0.0%   | 8.12%               | 9.94%              |

**Fig. 14:** Confusions matrix of the XCSGE with a MLP regressor as local learning model.

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The ranked performance of the algorithms among all of the cyclists is furthermore analyzed using the Friedman test in conjunction with the Nemenyi post-hoc test. The results are given in Fig. [15]. The Friedman p value given in the figure indicates that the ranks are significantly different, using a significance level of $\alpha = 0.05$. As can be seen from the Nemenyi test, the XCSGE has a significantly better ranked performance in comparison to ensemble members.

When considering the results of Table [V] and [VI], it is conspicuous that all models have relatively good F1- and log loss scores compared to the confusions matrices, while having big
problems to identify “moving” and “stopping” correctly. The distribution of the training data gives more insight into this problem. Most of the captured data is labeled as “waiting” (69.2 %) and “starting” (14.1 %). This fact explains why the $F1$- and log loss score is relatively good compared to the confusions matrices. The results allow some conclusions to be drawn. On the one hand, the results of the classifiers of the smartwatch on the wrist is significantly more reliable than those of the classifiers of the smartwatch integrated in the helmet and the smartphone in the pocket. This is particularly noticeable in the motion primitive “starting”, “moving” and “stopping”. This is probably caused by the movement of the head of the cyclist to orientate himself in road traffic. On the other hand, we could see that the selection of the machine learning algorithm $M^{(j)}_{\text{local}}$ to estimate the expected error for the local weighting has a significant influence on the classification performance.

VI. CONCLUSION AND OUTLOOK

In this article, we have presented an extended version of the CSGE. Besides the possibility of using it for both regression and classification tasks, multivariate predictions are also introduced. Furthermore, it is now possible to choose any machine learning algorithm for estimating the expected model error and therefore estimate the local weighting. Among the methodological aspects, one focus of the article is the evaluation and application of the XCSGE to two challenging domains. In both applications, the XCSGE was able to improve the prediction quality. On the wind farm dataset, the XCSGE outperforms the baseline by 11%. When considering the solar power forecasting, the XCSGE improves by 30% compared to our baseline. In addition, the CSGE outperformed the two Stacking reference ensembles in terms of both $R2$-score and RMSE. In the classification of motion primitive, the CSGE achieved a skill score of 28.14% outperforming all trained single models.

Although the XCSGE has achieved significant improvements, there are some ways to achieve even better results. During the experiments, it was observed that the selection of features for local weighting has a large influence on the prediction quality. This could be improved by a feature selection. In addition, we observe that the selection of the learning algorithm for the local weighting has an equally large influence. The learning algorithm of the local weighting affects not only the prediction quality but also the runtime of the XCSGE, since the local weighting has to be recalculated for each prediction. In future work, we aim to predict probability distributions in the context of regression. Such an approach has already been discussed in [7]. Furthermore, the implemented possibility for multivariate prediction facilitates this approach.

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TABLE IX: RMSE of 10-fold cross-validation for each solar farm. Cell color are from green (good results) over orange (medium results) to red (worst results). Furthermore the best RMSE score for each solar farm is highlighted bold.

| Solar farm | GBRT | MLP | SVR | Ridge Regression | CSGE | ANN | Stacking | Linear Stacking |
|------------|------|-----|-----|------------------|------|-----|----------|-----------------|
| Mean       | 0.000769 | 0.00086 | 0.00081 | 0.00081 | 0.00081 | 0.00081 | 0.00081 | 0.00081 |
| Variance   | 0.0411 | 0.0516 | 0.0509 | 0.0509 | 0.0509 | 0.0509 | 0.0509 | 0.0509 |
| Minimum    | 0.000699 | 0.000699 | 0.000699 | 0.000699 | 0.000699 | 0.000699 | 0.000699 | 0.000699 |
| Maximum    | 0.000800 | 0.000800 | 0.000800 | 0.000800 | 0.000800 | 0.000800 | 0.000800 | 0.000800 |
| Skl Score  | 0.88197 | 0.79083 | 0.77049 | 0.87510 | 0.87510 | 0.87510 | 0.87510 | 0.87510 |

TABLE X: R2-score of 10-fold cross-validation for each solar farm. Cell color are from green (good results) over orange (medium results) to red (worst results). Furthermore the best R2-score for each solar farm is highlighted bold.

| Solar farm | GBRT | MLP | SVR | Ridge Regression | CSGE | ANN | Stacking | Linear Stacking |
|------------|------|-----|-----|------------------|------|-----|----------|-----------------|
| Mean       | 0.528682 | 0.579683 | 0.710480 | 0.566619 | 0.566619 | 0.566619 | 0.566619 | 0.566619 |
| Variance   | 0.53133 | 0.632272 | 0.715290 | 0.529792 | 0.529792 | 0.529792 | 0.529792 | 0.529792 |
| Minimum    | 0.527738 | 0.624825 | 0.660752 | 0.545934 | 0.545934 | 0.545934 | 0.545934 | 0.545934 |
| Maximum    | 0.533887 | 0.651586 | 0.738860 | 0.595963 | 0.595963 | 0.595963 | 0.595963 | 0.595963 |
| Skl Score  | 0.853811 | 0.83565 | 0.827041 | 0.86758 | 0.86758 | 0.86758 | 0.86758 | 0.86758 |

TABLE XI: Log-loss of 6-fold cross-validation. Cell color are from green (good results) over orange (medium results) to red (worst results). Furthermore the best values for each criterion are highlighted bold.

| Solar farm | GBRT | MLP | SVR | Ridge Regression | CSGE | ANN | Stacking | Linear Stacking |
|------------|------|-----|-----|------------------|------|-----|----------|-----------------|
| Mean       | 0.559988 | 0.56555 | 0.72944 | 0.54866 | 0.54866 | 0.54866 | 0.54866 | 0.54866 |
| Variance   | 0.00022 | 0.01525 | 0.00205 | 0.00114 | 0.00114 | 0.00114 | 0.00114 | 0.00114 |
| Minimum    | 0.51391 | 0.57396 | 0.66575 | 0.49036 | 0.49036 | 0.49036 | 0.49036 | 0.49036 |
| Maximum    | 0.63677 | 0.67489 | 0.78307 | 0.58715 | 0.58715 | 0.58715 | 0.58715 | 0.58715 |
| Skl Score  | 0.7272 | 0.8574 | 25.03% | 24.94% | 24.94% | 24.94% | 24.94% | 24.94% |