Sustainable Energy, Grids and Networks 42 (2025) 101657

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Machine learning approaches for the prediction of public EV charge point flexibility

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ARTICLE INFO

Keywords:
Electric vehicles
Public charge points
Demand-side flexibility
Machine learning
Causality

ABSTRACT

The increasing number of electric vehicles on the road can play a key role as a source of flexibility for a reliable power system operation. Charge point operators, in particular, can adjust individual electric vehicle charging loads to provide system operators with aggregated energy flexibility, e.g. for congestion management, ancillary services or greenhouse gas emission reduction. However, managing individual charging sessions requires information about the expected session duration and energy demand, which are not available at the beginning of a session. In this work, a novel predictive workflow based on two causality-informed machine learning approaches with different levels of generalization is proposed to predict individual session duration and energy demand. Our key contributions include the development of a cluster-based predictive model for charge points and a user-based predictive model to capture individual charging behaviours, and the comparison of these models using a large-scale, real-world dataset. The proposed approaches were tested on real charging data provided by TotalEnergies, showing that considering user-specific charging behaviours enhances the accuracy performance by 16.1% and 37.9% for predictions of session duration and energy demand, respectively. By leveraging clustering and feature selection techniques, accounting for charge point- and user-specific charging patterns, and utilizing a large-scale real-world charging dataset, the proposed predictive workflow enables a comprehensive comparison of machine learning techniques in terms of accuracy performance when predicting public electric vehicle charge point flexibility.

1. Introduction

In recent years, electric vehicles (EVs) are becoming more popular due to the switch from fossil fuel to zero emission transport, with the global EV fleet projected to reach 145 million units by 2030 [1]. On the one hand, the added energy demand from the growing EV supply equipment (EVSE) required for the charging poses new threats to the reliability of the power system [2]. On the other hand, the increasing number of EVs on the road can play a key role as a source of flexibility for a reliable system operation if their charging schedules are properly optimized. The additional storage capacity offered by EVs can support the system to deal with the operational uncertainty resulting from the integration of renewable and distributed energy resources. This would allow an improved utilization of the existing grid assets and a consequent reduction of the investment costs to reinforce the network equipment [3].

EVs in combination with the EVSE can be seen as a distributed energy resource (DER) able to provide flexibility to the power grid. More precisely, this DER can provide flexibility if it can shift its production (in case of Vehicle-to-Grid technology) or consumption of energy in time within the boundaries of end-user comfort requirements, thus without changing its total energy consumption or production [4]. In [5], the time flexibility of an individual EV charging session is defined as the difference between the connection time and charging duration, and similarly as the fraction of the connection time that is not spent on charging in [6].

There are several common objectives when optimizing the EV charging or discharging [7]. The main objective is the revenue maximization for EV owners, fleet or charge point operators (CPOs), participating in energy and balancing service markets. From a system operator's perspective, EV modelling is similar to modelling energy storage systems used for the operational objective to fulfil the grid physical constraints, and balance supply and demand. CPOs, in particular, can adjust individual EV charging loads in order to provide system operators with aggregated energy flexibility for congestion management, ancillary services, such as frequency response, or greenhouse gas emission reduction. This optimization is commonly known as 'smart charging'.

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https://doi.org/10.1016/j.segan.2025.101657
Received 22 August 2024; Received in revised form 19 December 2024; Accepted 12 February 2025
Available online 24 February 2025

Nomenclature

AMB	Approximate Markov Blanket
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
CP	Charge Point
CPO	Charge Point Operator
DER	Distributed Energy Resources
DNN	Deep Neural Network
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FS	Feature Selection
GP	Gaussian Process
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MB	Markov Blanket
ML	Machine Learning
OCPI	Open Charge Point Interface
RF	Random Forest
SHAP	SHapley Additive exPlanations
SMAPE	Symmetric Mean Absolute Percentage Error
SVM	Support Vector Machine
TAN	Tree-Augmented Naïve
XGBoost	eXtreme Gradient Boosting

However, actively managing individual charging sessions requires information about session duration and energy demand, which are not available to CPOs at the beginning of a session, as there is no direct communication between the EV user and the CPO. Predicting such parameters is crucial to manage the charging and exploit the flexibility of each individual charging session, while staying within the boundaries of EV user comfort. According to the definition provided in [4], the flexibility of an individual EV charging session can be quantified by multiplying the desired charging energy (or energy demand) by the connection time period in which the EV is not charging (also defined as time flexibility).

An extensive body of research has focused on non-controllable charging, aiming to forecast the EV load using models trained on historical data. An autoregressive integrated moving average (ARIMA) model was used in [8] to predict the EV charging demand, which was then provided as input to a chance-constrained scheduling problem to cope with the uncertainty in the charging behaviour. To capture the patterns in user behaviour, a combination of clustered multi-node learning (CMNL) and Gaussian processes (GP) was proposed in [9]. The CMNL component considered clusters of different charging stations, while the GP component was specific to each station. The method was validated on a real-world dataset in Utah, showing superior performance when compared against benchmark models such as linear regression, ARIMA, or neural networks (NNs). When estimating the individual load at each charging stations, the authors make the assumption that EVs are charged uniformly. Similarly, a clustering methodology based on a bivariate Gaussian mixture model was presented in [10], which proposed the user profile concept as a tool to group sessions into similar flexibility levels. Subsequently, two smart charging scenarios were used to schedule the charging session of each user profile according to its most convenient optimization objective. The methodology was validated on a real-world dataset of EV charging sessions from the middle-sized city of Arnhem, in the Netherlands. When optimally scheduling the EV charging process (smart charging), historical data is no longer indicative of future charging demand, while charging session parameters become essential for scheduling and subsequent flexibility quantification. Specifically, decoupling the modelling of each parameter and utilizing data-driven forecasting approaches result in improved predictive performance and scalability advantages, as demonstrated in [11]. Authors in [12] emphasized the importance of predicting charging session parameters, even when these parameters are declared by the EV user in advance, such as through a mobile application, as users lack the incentive to provide accurate estimations for their charging session duration and energy demand [13]. Nevertheless, incorporating this new information can still enhance the accuracy of flexibility prediction.

Machine learning (ML) techniques have been widely investigated for the prediction of EV charging session parameters [11]. In [14,15], aggregated models for sets of two CPs, located in California and Morocco respectively, were trained using random forest (RF), support vector machine (SVM), extreme gradient boosting (XGBoost) and several NN models, e.g. recurrent NNs and long short-term memory (LSTM). Similarly, RF, SVM and XGBoost were compared in [16] for the prediction of the EV charging duration at three public charging sites, with XGBoost providing the overall best results. On the other hand, authors in [17], used tree-based classification algorithms to train individual models for each CP and for each anonymized user, resulting in improved accuracy performance when focusing on the CP. The superior accuracy performance of tree-based models for predicting charging session parameters was demonstrated in [18]. Here, the authors evaluated the forecast error and computational performance of tree-based and cluster-based approaches using the ACN-Data dataset of EV charging sessions in California. They concluded that the choice of forecast model is significantly influenced by the availability of training data. Specifically, tree-based methods showed superior performance, particularly when dealing with large datasets. The work in [19] focused on the prediction of the charging pattern in combination with the flexibility quantification, using XGBoost, NNs and k-nearest neighbours as models and several input features related to weather and EV user behaviour, e.g. average session duration derived from the user's previous sessions. XGBoost resulted in the highest performance, however no information related to the CP were considered in the training. The high performance of the XGBoost model was also demonstrated in [20], where it was compared to random forest and gradient boosting algorithms to predict the time flexibility of a set of 1747 public CPs in the Netherlands using historical charging data provided by the Dutch knowledge center ElaadNL. The most relevant features for prediction were the time of day when the charging session started and energy consumption. Similarly, XGBoost model outperformed the other models for the prediction of the time flexibility in [21], with energy consumption, charging duration and time of the day being the most relevant features.

While previous studies have addressed the task of predicting charging session parameters, there is a lack of research investigating the heterogeneity of user behaviours, which affect prediction performance. The authors in [22] attempted to predict individual residential charging requirements. However, their study utilized short observation periods and data from a limited number of vehicles, thereby neglecting the differences in prediction performance across a diverse range of vehicles. This research gap was addressed in [23], where several ML algorithms were employed to predict individual EV charging requirements using a large dataset of real-world residential charging sessions from 300 EVs. The dataset included a wide variety of vehicles in terms of model and brand, with diverse battery sizes. Nevertheless, differences in user behaviours were not considered, as the study focused primarily on residential charging patterns. In contrast, the work in [24] employed a novel jointly trainable artificial deep neural network (DNN) framework to predict stochastic EV user behaviour using a large-scale dataset of individual EV users' charging transactions collected at a multi-site campus at the University of California, Los Angeles. Proper inference techniques were applied to determine the essential attributes of each charging session from the time-series data, which were then fed as inputs to the DNN framework. However, this approach does not capture the temporal dependencies, thus failing to model the recurring behaviour of users over time. Finally, a systematic review and meta-analysis of ML, deep learning, and ensemble learning approaches in predicting EV charging behaviour was conducted in [25] to assess the performance of various models, but the study did not consider the aspect of flexibility. To the best of the authors' knowledge, an extensive comparison of ML techniques for predicting EV charging sessions parameters and, consequently, the corresponding EV charge point flexibility, across a comprehensive variety of charge points and EV users remains a key research gap in the state-of-the-art.

1.1. Proposed approach

In this paper, two machine learning approaches with different levels of generalization are proposed and compared to predict session duration and energy demand, hence quantify flexibility of individual public EV charging sessions:

1. A charge point (CP) cluster-based approach with a predictive model for each cluster of CPs;
2. A user-based approach with a predictive model for each user or class of users with similar charging behaviours.

The definition of flexibility for EV CP is taken from [26] and discussed in Section 2. This work goes beyond the definition of public EV CP flexibility and explores ML techniques for its prediction. The key novelty of this study lies in the adoption and comparison of ML techniques across a comprehensive variety of CP classes and EV user archetypes using a large-scale real-world charging dataset. By leveraging clustering and feature selection techniques, the proposed workflow addresses the identified research gaps by capturing different levels of generalization and enabling an extensive comparison in terms of accuracy performance when predicting the public EV CP flexibility. The full predictive workflow is depicted in Fig. 1. The methodology consists of the following steps:

1. Data pre-processing: Historical charging sessions, EV user information and external features, such as time of day, weather data or public holidays, were selected as input features, then cleaned and transformed;
2. Clustering: For the cluster-based approach, a rule-based clustering technique was used to classify public CPs into four classes: hybrid, home, short-stay and work chargers [27]. Conversely, for the EV-user based approach, EV user archetypes were defined based on frequent EV users' arrival times at different CP classes;
3. Model learning: The causal relationship between the input features was informed to train the predictive models using a Markov Blanket (MB)-based feature selection (FS) approach [28]. Thus, only the highly relevant and causal features were used for training, resulting in better trade-off between predictive performance and training computational times. The Shapley additive explanations (SHAP) method was used to demonstrate the high relevance of the features selected using the MB-based FS approach. XGBoost models were trained for each CP class in the cluster-based approach, while in the user-based approach LSTM models were used to predict time-series charging sessions for individual EV user. The main benefit of LSTM models is their ability to capture temporal dependencies, thus user-specific behaviours recurring in a consistent manner over time;
4. Prediction: The predictive performance of both approaches was evaluated.

The described methodology enables a detailed comparison of ML models and provide valuable insights into the prediction of public EV CP flexibility. The proposed ML approaches were tested on real charging data from one entire year, which was provided by TotalEnergies, and compared against state-of-the-art models. This dataset included over 2 millions charging sessions and 5317 public CPs across the Netherlands. In comparison to private CPs generally owned by individuals or business for personal or restricted usage, the public CPs included in the dataset are accessible to any EV users and are both owned and operated by TotalEnergies, granting full access to the charging data and complete operability for flexibility provision. The rest of the paper is structured as follows. Section 2 introduces the mathematical formulation of flexibility for individual charging sessions, while Section 3 describes step-by-step the proposed data-driven approaches for flexibility prediction. Subsequently, Section 4 presents the case study with the comparison between the different predictive models, the main results and a few limitations of the work. Section 5 finally draws the conclusions.

2. Individual EV charging session flexibility

An individual EV charging session can be described as the time period during which an EV is connected to the EVSE. The parameters of an uncontrolled charging session are shown in Fig. 2. In case of uncontrolled charging, the aim is to charge the EV as soon as it is connected to the CP without considering any external factors, such as the electricity price or grid congestion. Therefore, at the arrival time t_{arr}, the EV starts charging at the maximum charging power P_{max} (constant and set by the CPO) until the state-of-charge (SoC) of 100% is reached at t_{ch} [29]. Subsequently, the session stops at departure time t_{dep}. ΔE is the total energy consumed by the EV during the charging time Δt_{ch}. The time period Δt_s in which the EV is connected to the EVSE is called session duration and can be calculated as follows:

$$\Delta t_s = t_{dep} - t_{arr} \tag{1}$$

while the charging duration is

$$\Delta t_{ch} = t_{ch} - t_{arr} = \frac{\Delta E}{P_{max}} \tag{2}$$

When assuming direct control for the EVSE, which allows no communication with the EV user, the total energy consumed ΔE also represents the desired charging energy. Finally, the time flexibility of the session can be derived as follows:

$$\Delta t_{flex} = \Delta t_s - \Delta t_{ch} = t_{dep} - t_{ch} \tag{3}$$

Since EV users tend to plug-in their vehicles to a public EVSE and simultaneously use it as a parking spot, the session duration often exceeds the charging duration, thus allowing for flexibility provision. According to [4], the flexibility Δf can be quantified as

$$\Delta f = \Delta E \cdot \Delta t_{flex} \tag{4}$$

As the quantification of charging session flexibility is the product of time and energy, the unit of flexibility is kWh^2. This is not a standard unit but serves an interpretive measure to quantify flexibility [26]. Predictions of the session duration and the energy consumption allow to derive the charging duration and the time flexibility according to Eqs. (2)–(3) respectively, thus predicting the flexibility Δf as shown in Eq. (4).

3. Prediction of charging session parameters

This section describes step-by-step the training of ML models with different levels of generalization for the prediction of EV charging session duration and energy demand.

3.1. Level of generalization

The level of generalization can be described as the extent to which a sample is analysed. For example, an EV user can have different charging behaviours at specific CPs by default. In Fig. 3, three approaches with different levels of generalization are illustrated: aggregated, CP-based and user-based models. All historical charging data for combined CP and EV user IDs are used to train the aggregated model. The main benefit of such an approach is the large amount of data available and

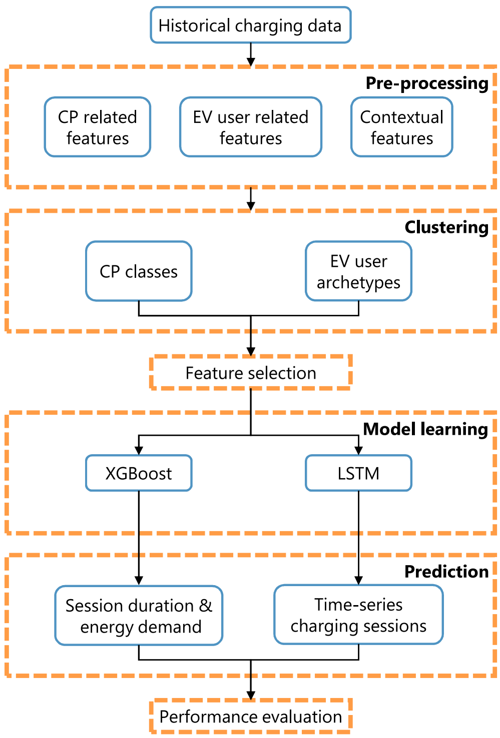

Fig. 1. The proposed predictive workflow.

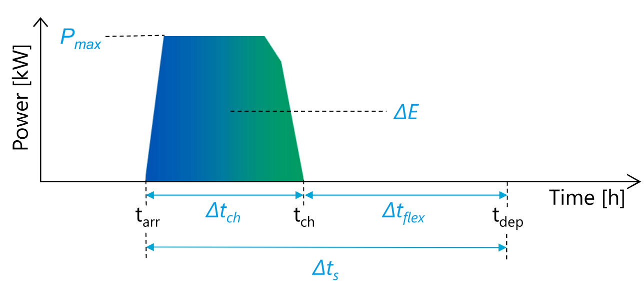

Fig. 2. The parameters of an individual EV charging session.

the low computational effort. However, the resulting predictive performance is low as charging patterns of individual CPs and users are not captured. In the CP-based model approach, a different model is trained for each CP or for cluster of CPs with similar charging demand, allowing to identify specific charging patterns according to the charger type. This may result in low generalization ability and in scarcity of training data. Finally, in the user-based model approach, the level of generalization is the user ID's perspective, i.e. a different model is trained for each user or class of users with similar charging behaviour. The predictive accuracy of such models may be significantly higher than previous approaches as individual users often show periodic charging patterns. However, the historical data for new users would be insufficient to train a ML model, resulting in the well-known "cold start" problem. This problem is expected to be rare in the near-future with the growing uptake of EVs. In this work, the three levels of generalization are compared in terms of the model's predictive performance.

3.2. Data pre-processing

The first step is to clean the historical charging data collected from public EVSEs to detect and handle missing or zero values, and outliers. Historical charging data may include, for each session, arrival and departure times, anonymized CP and user IDs, CP location, and finally session duration and energy demand, which are the target features. Contextual data can be added to enrich the training dataset and improve the predictive performance, such as weather data, or additional information related to the day when the charging session takes place, e.g. day of the week or of the month, week or month of the year, weekend or weekday, or national holiday. The data cleaning aims to remove all extreme values that are either faulty or not informative for the ML model training. For example, negative values of charging energy demand are not physically feasible.

The second step is the data transformation. Cyclical features, e.g. arrival hour, are transformed into Sin and Cos components, resulting into two new features as follows:

$$X_{\sin} = \sin \frac{2 \cdot \pi \cdot t_{arr}}{\max(t_{arr})}$$
$$X_{\cos} = \cos \frac{2 \cdot \pi \cdot t_{arr}}{\max(t_{arr})} \tag{5}$$

Subsequently, the categorical features, such as the day of the week, are transformed into numerical values by one-hot encoding. More precisely, each category is represented as a binary vector, with only one element of the vector being set to 1, while all other elements are set to 0. Finally, feature engineering is used to create new features able to capture user- or CP-specific charging patterns, such as moving average of session duration and energy demand for each CP and EV user. The moving average ensures that the average is calculated only on the previous available charging sessions at the time of the connection.

3.2.1. CP clustering

The CPs are classified based on their charging demand in order to overcome the challenge of data scarcity for training and improve the robustness of the predictive model. Although several ML approaches have been proposed for CP clustering, such as K-Means in [30], where CPs are clustered according to popularity, utilization and temporal usage pattern, a rule-based clustering approach is used in this work [27]. Compared to more advanced clustering techniques, this approach results in highly explainable patterns. Each charging session at different CPs is classified according to the matrix shown in Fig. 4. More precisely, a charging session is classified as short if the duration is less than 6 h, otherwise as long session. The four time intervals of the arrival time represent morning, noon, evening and night charging sessions. Since there are 8 different sub-matrices, a maximum number of 2^8 clusters can be identified, and predictive models are trained for each of the largest 10 clusters.

3.2.2. EV user archetypes

Historical charging data collected from public EVSEs may also contain relevant information about user-specific charging behaviour [31]. For example, authors in [27] used Gaussian mixture models to identify different types of users, e.g. office hours, overnight and non-typical users, based on arrival times and duration of their charging sessions, time and location distance between sessions. However, since a user can charge at CPs operated by different CPOs, and there is no continuous data sharing between users and a single CPO, the time-series charging data of individual users cannot be retrieved from a single CPO. Therefore, the key potential of time-series charging data cannot be fully exploited. By using charging data of frequent users on the same CPO network, EV user archetypes can be derived based on their arrival times at different CP classes, i.e. home, work chargers and short-stay chargers [27], and time-series charging data can be generated per archetype. We focus on the archetype of EV users who charges at home in the morning and in the evening for a duration between 6 and 12 h, and at a work/ short-stay charger during the day for less than 4 h. The trimodal distribution $f(x)$ can be fitted to the historical arrival times t_{arr} of all users with such a charging behaviour:

$$f(t_{arr}) = \sum_{i=1}^{3} \frac{1}{\sigma_i \sqrt{2\pi}} \, e^{-\frac{1}{2}\left(\frac{t_{arr}-\mu_i}{\sigma_i}\right)^2} \tag{6}$$

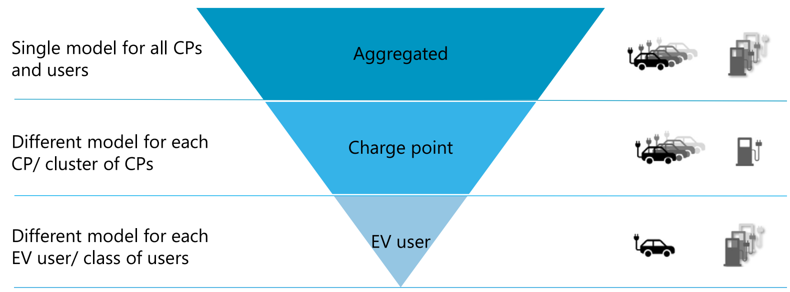

Fig. 3. Levels of generalization of the predictive models. The aggregated level serves as the state-of-the-art model against which the proposed approaches, corresponding to CP and EV user levels, are compared.

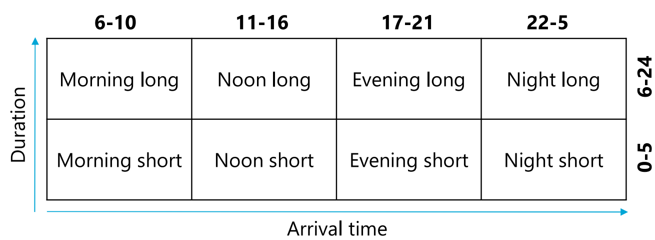

Fig. 4. The rule-base clustering matrix for charging sessions.

with μ_i, σ_i being the mean and standard deviation of the ith distribution. To generate time-series historical data of a synthetic user, three arrival times per day, one in morning, one in the afternoon and one in the evening, are sampled from the trimodal distribution in Eq. (6). For each sampled arrival time $\bar{t}_{arr}$, the energy demand and session duration are calculated as conditional expectation as follows:

$$\begin{aligned} \overline{\Delta t_s} &= \mathbb{E}(\Delta t_s | t_{arr} = \bar{t}_{arr}) \\ \overline{\Delta E} &= \mathbb{E}(\Delta E | t_{arr} = \bar{t}_{arr}) \end{aligned} \tag{7}$$

Three arrival times for each day are sampled such that there is no time overlap between successive sessions, and the same between overnight and subsequent morning sessions. Assuming that the EV charges as soon as it is connected to the CP, time-series charging data $x_{ch}(t)$ for a specific EV user over several days can be constructed as follows:

$$x_{ch}(t) = \begin{cases} 1 & \text{if } \bar{t}_{arr} < t \leq \bar{t}_{arr} + \overline{\Delta t_s} \\ \overline{\Delta E} & \text{if } t = \bar{t}_{arr} \\ 0 & \text{otherwise} \end{cases} \qquad \forall \bar{t}_{arr} \tag{8}$$

3.2.3. Feature selection

A causality-based FS approach is used to identify the most relevant features for the prediction of session duration and energy demand, which are the target features [28]. This approach has been widely exploited for dynamic security assessment of power systems, but has not been applied to the prediction of the EV charging session parameters. It uses the training data to derive a directed acyclic graph, also known as Tree-Augmented Naïve Bayes (TAN) model, representing the causal structure between the target and input features. In this model, each feature has as parents the target and at most one other feature. The constructed TAN model is used to identify the MB of the target feature. The MB of a feature provides a complete picture of the local causal structure around it and in TAN model is unique and consists of parents, children and spouses of the feature itself [32]. Since all of the features are target's children in the TAN model, the MB of the target includes all features. In order to select the most relevant features for classification by taking advantage of the causal dependence structure of the TAN model, an approximation of the MB (AMB) is derived. Generally, the AMB-based FS algorithms discard features which are included in the MB of another feature as redundant to it, hence irrelevant to classification. Since the causal dependencies between features are already known in the derived TAN model, the MB of the target can be directly approximated by performing correlation-based pairwise comparisons between each parent and children nodes. The mutual information is used as correlation measure. The proposed approach is beyond using the concept of causality for feature selection and brings a key advantage over other FS approaches that are exclusively data-driven, such as standard filter and wrapper approaches, resulting in improved accuracy performance of the trained models and reduced computational efforts.

The SHAP method is used to evaluate the performance of the MB-based FS approach. This method is based on the concept of Shapley values from cooperative game theory, which provide a way to fairly distribute a value among a group of individuals based on their contributions [33]. The contribution of each feature is determined by calculating the difference between the predicted values with and without the inclusion of each feature across all possible combinations, and then averaging the results. Thus, the Shapley value represents the average marginal contribution of each feature across all permutations. This value helps to understand which input features are most relevant to the target feature, thereby allowing evaluation of the featured selected using the MB-based FS approach.

3.3. Machine learning models

XGBoost and LSTM models are used for the CP cluster-based and user-based approach, respectively.

XGBoost is a gradient boosting algorithm that uses multiple decision trees to create a higher-performance model. The decision trees are constructed in a sequential manner, thus the errors of previous trees are taken into consideration by subsequent trees, which frequently leads to superior performance. Given a training dataset $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$ with n data points , the mathematical formulation for XGBoost models is shown in Eq. (9), where $\hat{y}_i$ represents the predicted value for the ith data point, K is the number of decision trees, f_k is the kth decision tree [34].

$$\hat{y}_i = \sum_{k=1}^{K} f_k(\mathbf{x}_i) \tag{9}$$

LSTM is a recurrent neural system designed to overcome the exploding gradient problems that typically arise when learning long-term dependencies, e.g. time-series training data. The architecture consists of a set of recurrently connected sub-networks, known as memory block. The idea behind the memory block is to maintain its state over time and regulate the information flow thought non-linear gating units, i.e. input, forget and output gates [35]. The equations for the three gates $i^{(t)}, f^{(t)}, o^{(t)}$, the cell $c^{(t)}$, the block input $z^{(t)}$ and the block output $y^{(t)}$ are shown below:

$$\begin{aligned} i^{(t)} &= \sigma(W_i x^{(t)} + R_i y^{(t-1)} + p_i \odot c^{(t-1)} + b_i) \\ f^{(t)} &= \sigma(W_f x^{(t)} + R_f y^{(t-1)} + p_f \odot c^{(t-1)} + b_f) \\ o^{(t)} &= \sigma(W_o^{(t)} + R_o y^{(t-1)} + p_o \odot c^{(t)} + b_o) \\ c^{(t)} &= z^{(t)} \odot i^{(t)} + c^{(t-1)} \odot f^{(t)} \\ z^{(t)} &= g(W_z^{(t)} + R_z y^{(t-1)} + p_o \odot c^{(t)} + b_z) \\ y^{(t)} &= g(c^{(t)} \odot o^{(t)}) \end{aligned} \tag{10}$$

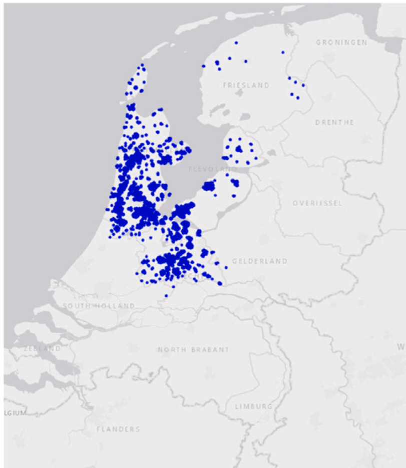

Fig. 5. Geographical location of all public CPs included in the input dataset.

with W, R, p being the weights associated with input x, output y and cell value c, b the bias weight, σ and g the activation functions, and $\odot$ the point-wise product.

3.4. Performance metrics

The performance of XGBoost and LSTM models are assessed using the mean absolute error (MAE) and the symmetric mean absolute percentage error (SMAPE). The MAE measures the average of the absolute difference between the predicted values and the actual values. It is an interpretable metric that quantifies the error magnitude:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{11}$$

where n is the number of observations, y_i and $\hat{y}_i$ are the actual and predicted values, respectively.

The SMAPE is a percentage-based metric that measures the symmetric mean of the absolute percentage differences between the predicted and actual values as it follows:

$$\mathrm{SMAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| - |y_i|)/2} * 100\% \tag{12}$$

with same notation as in Eq. (11).

4. Case study

This section provides an overview on the predictive performance of the two proposed causality-informed ML approaches using real charging data provided by TotalEnergies in the Netherlands, showing the need to consider user-specific behaviours for more accurate flexibility predictions.

4.1. Training data exploration

The input dataset collected by TotalEnergies was accessed through application programming interface (API) calls using file formats standardized by the open charge point interface (OCPI) protocol. The data was cleaned and anonymized to ensure user privacy. Specifically, the user ID was replaced by alphanumeric codes to prevent linking the charging session information to any specific user or EV. The dataset included 5317 public CPs, which are mainly located in the north-west region of the Netherlands, as shown in Fig. 5, with 2,481,403 charging sessions and 178,221 unique users between November 2021 and November 2022, with no smart charging implemented during this time period. Table 1 describes the available parameters collected from the CPs and contextual parameters. To train the ML models, cyclical and categorical parameters were transformed into numerical features, and new features were created to capture charging patterns of specific user and CP IDs. The target features were the session duration and energy demand, while the input features included the contextual parameters from Table 1 and the new features summarized in Table 2, with the statistical metrics being calculated for both the target features. The target feature distributions were analysed to identify correlations with input features that may impact the CP clustering. For instance, the median and quartiles of session durations, and the density functions of arrival times for each day of the week are shown in Figs. 6 and 7, respectively, highlighting that in comparison to other real charging datasets, the difference between weekdays and weekends was not significant. It can only be noted that during the weekend, the median duration value was slightly smaller and the arrival time was slightly delayed.

Table 1
List of all the available parameters.

Historical	Contextual
Session ID	Wind speed
Arrival time	Temperature
Departure time	Sunshine
Energy demand	Radiation
Session duration	Hourly precipitation
Charging time	Fog
User ID	Rainfall
Charge point ID	Snow
Location ID	Thunder
Address	Ice formation
City	Public holiday
Postal Code	Day of week
Latitude	Day of month
Longitude	Day of year
	Week of year
	Week of month
	Week/weekend day

Table 2
Description of all transformed and new features.

Name	Description
Cos arrival time	Cyclical encoded arrival time (cos)
Sin arrival time	Cyclical encoded arrival time (sin)
User moving average	Historical average based on user ID
User moving std	Historical std based on user ID
User moving min	Historical min based on user ID
User moving max	Historical max based on user ID
User moving frequency	Historical session count based on user ID
CP average	Historical average based on CP ID
User_CP moving average	Historical average based on user ID and CP class
User_CP moving std	Historical std based on user ID and CP class
User_CP moving min	Historical min based on user ID and CP class
User_CP moving max	Historical max based on user ID and CP class
User_CP moving frequency	Historical session count based on user ID and CP class

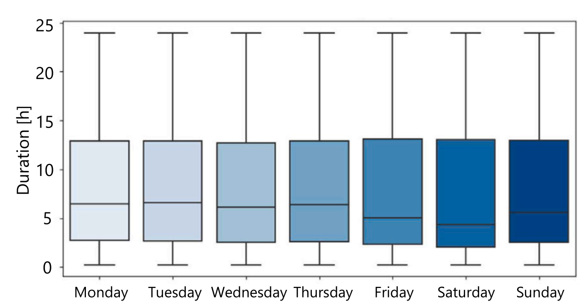

Fig. 6. The boxplot of session durations for each day of the week.

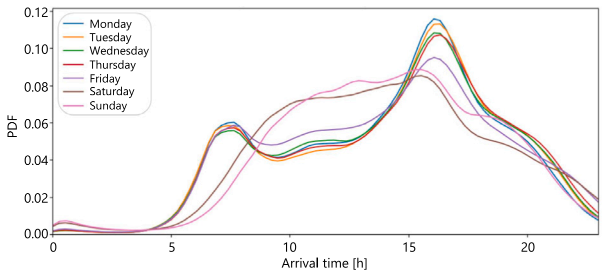

Fig. 7. The density functions of arrival times for each day of the week.

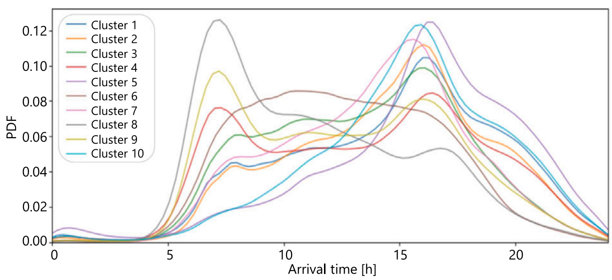

Fig. 8. The density functions of arrival times for each of the 10 CP clusters.

Table 3
Accuracy performance of the aggregated and cluster-based approaches for the 10 CP clusters.

Cluster	Class	MAE			
		Aggregated model		CP cluster-based model	
		Duration [h]	Energy [kWh]	Duration [h]	Energy [kWh]
1	Hybrid	3.4	7.3	3.3	7.1
2	Hybrid	3.8	7.3	3.8	7.1
3	Hybrid	2.9	6.9	2.8	6.5
4	Hybrid	3.1	7.2	3.1	7.1
5	Home	3.6	7.4	3.6	7.3
6	Short-stay	2.1	6.5	1.6	4.5
7	Hybrid	3.8	6.9	3.8	6.7
8	Work	2.3	6.4	2.1	5.5
9	Work	3.0	6.9	2.9	6.4
10	Home	4.1	7.8	4.1	7.8
Overall		3.2	7.1	3.1	6.6

Table 4
Accuracy and computational times of the aggregated model with and without the MB-based FS approach.

Metric	Without MB	With MB
MAE [h]	3.3	3.2
Training time [s]	1714	553
Evaluation time [s]	0.3	0.1

4.2. Performance of CP cluster-based approach

The CPs were clustered according to the rule-based approach described in Section 3.2. 92 unique cluster patterns were identified, and only the 10 largest clusters, corresponding to 86% of all available CPs, were selected for the following analysis. The heatmaps of arrival times and session durations for the charging sessions of each of the 10 clusters are shown in Fig. 9. The density functions of arrival times for each of the 10 clusters is also provided in Fig. 8. Based on these two charging session parameters, four main classes were identified among these clusters, also shown in Fig. 9:

- Work: CPs with most charging sessions starting in the morning and aligned with the conventional 9 am–5 pm working pattern;
- Home: CPs with most charging sessions starting in the evening and lasting all night;
- Short-stay: CPs with charging sessions mainly of short duration within the day and located in service areas, e.g. shopping centres;
- Hybrid: CPs utilized for diverse charging requirements, e.g. home. work and short-stay sessions.

It is worth noting the low density of charging sessions during typical working hours due to the potential access to private chargers at workplaces. The violin plots of the actual values of the two target features, i.e. session duration and energy demand, for each of the 10 clusters are shown in Fig. 10. Wider sections represent a higher probability of the targets taking that specific value. Due to the high availability and accessibility of home charging infrastructure, the clusters classified as home chargers, specifically clusters 5 and 10, exhibited longer session durations. This highlighted the higher flexibility potential of home chargers, enabling CPOs to participate more effectively in energy markets.

The training, testing and validation split was 80%/10%/10%, using all the available charging sessions in the entire year for all models. The chosen split is recommended for large datasets, such as in this work, to ensure sufficient training data and prevent overfitting [36]. The following approaches were compared in terms of predictive performance: (a) two aggregated XGBoost models to predict the session duration and energy demand, respectively, were first trained for all the CPs included in the 10 clusters, and were used as baseline, (b) different XGBoost models were trained for each cluster for both the two aforementioned target features. The MB-based FS approach was applied for all models, mainly selecting user moving average, user_CP moving average and arrival time as the most relevant features. For a few clusters, also the user moving max, user_CP moving max and the week/weekend day features were selected. Here, all the statistical metrics refer to both the target features. Consistently, the features selected using the MB-based FS approach showed the highest mean absolute Shapley values, demonstrating their high relevance and contribution to the prediction. For instance, when predicting the session duration and energy demand using the aggregated models, all the features selected using the MB-based FS approach were among the 10 features with the highest mean absolute Shapley values shown in Fig. 11. All the models were finally validated on each of the 10 clusters and the resulting MAE values are shown in Table 3.

Both approaches resulted in higher predictive performance for short-stay and home chargers, with improvements of 23.8% and 30.8% for session duration and energy demand, respectively, for the short-stay CPs (cluster 6) when using approach (b). However, the overall improvement when using approach (b) rather than approach (a) is not significant due to the large number of hybrid chargers in the used dataset, which do not show a unique charging pattern as the other classes. Therefore, an accurate prediction of individual session flexibility can be achieved only when considering specific CP classes, e.g. short-stay chargers. The MB-based FS approach, in particular, significantly reduced the training computational time by 68%, but only slightly improved the accuracy, as shown in Table 4 as an example for the aggregated model to predict the session duration. The SMAPE was used to compare the accuracy performance of the predictive models for session duration and energy demand. When using the aggregated models, the SMAPE values for session duration and energy demand were 48% and 33%, respectively, indicating that the wider and more dispersed distributions of session duration in Fig. 10 led to slightly lower predictive performance.

Although not interesting from a CPO perspective, Fig. 12 shows superior accuracy performance when predicting the aggregated flexibility by summing up the individual predictions of all chargers. The reason behind this enhancement lies in the normal distribution of the

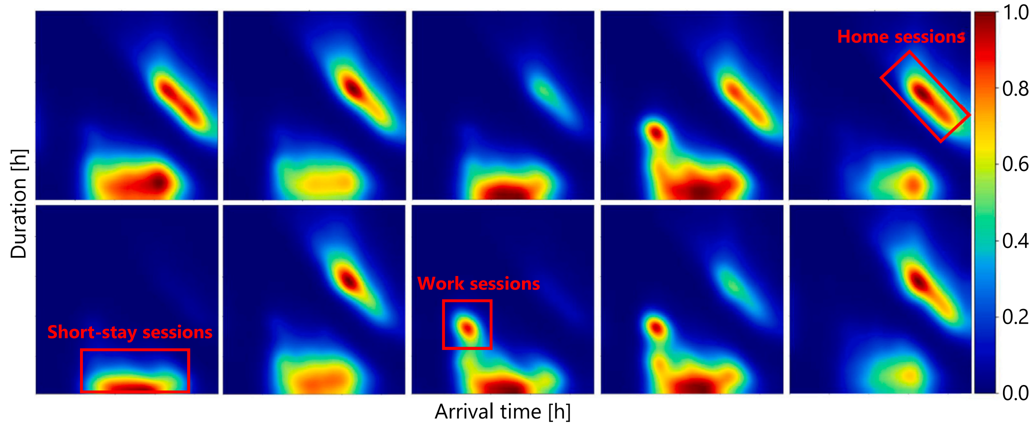

Fig. 9. Heatmaps of arrival times and session durations for the charging sessions of each of the 10 CP clusters. The scale is normalized to the range [0, 1]. The highest frequency per cluster are [14964, 7658, 2688, 2458, 1558, 2881, 1153, 1282, 1114, 624]. The red boxes highlight charging sessions at home, work and short-stay chargers. Charging sessions at hybrid chargers fall within one of these boxes, depending on the charging requirement. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

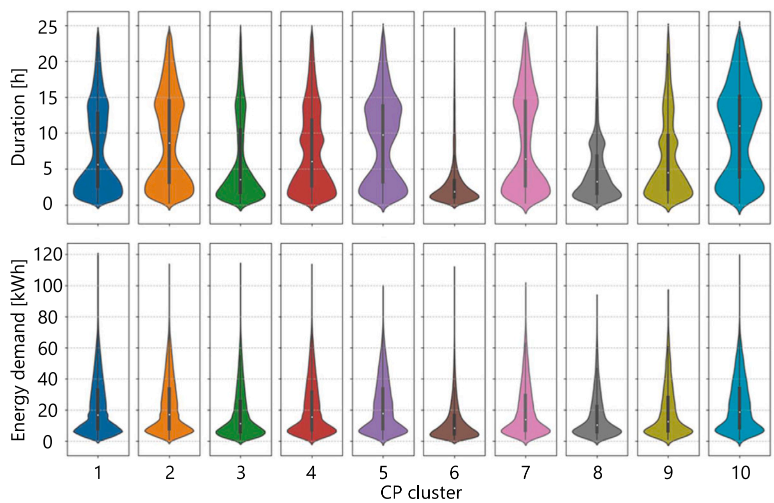

Fig. 10. Violin plots of actual session duration and energy demand for each the 10 CP clusters.

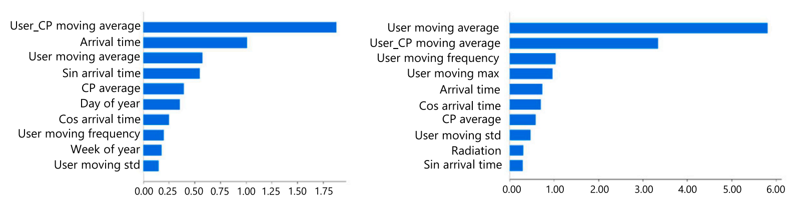

Fig. 11. The 10 features with the highest mean absolute Shapley values using the aggregated models for the prediction of session duration on the left and energy demand on the right.

prediction errors, which balance each other out, smoothing out the individual discrepancies and resulting in a more accurate aggregated prediction. This may be a relevant information to grid operators, which are interested in the quantification of nodal flexibility, but it is not informative when it comes to managing individual charging sessions, as in the case of CPOs.

4.3. Performance of user-based approach

In order to test the proposed user-based approach, EV user archetypes were generated from the collected public CP data. More specifically, CP archetypes were first created according to the following steps: (1) using the Dutch land registry, each CP address was associated to residential, work or service areas (e.g. shopping or sport centres), (2) the charging sessions were then classified as home or work sessions if they are located in residential and work areas, respectively, and their duration is between 6 and 12 h, otherwise as short sessions if located in a service area and the duration is less than 4 h. The probability density functions of arrival times for home, work and short-stay sessions are shown in Fig. 13, representing the archetypes for home, work and short-stay CPs, respectively. In comparison to the identified and classified 10 CP clusters in Section 4.2, there was no archetype corresponding to the hybrid class as each CP was assigned to an unique type of area (i.e., residential, work and service) based on its address in this case. By comparing the density functions of arrival times of the CP archetypes

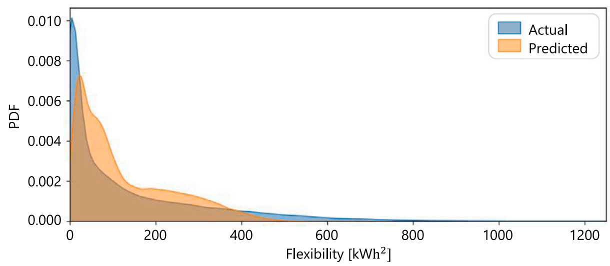

Fig. 12. Actual and predicted probability density functions of aggregated flexibility.

with those of the 10 clusters in Fig. 8, it can be noted that the density functions of the clusters classified as home, work and short-stay classes corresponded to the CP archetypes in Fig. 13.

The derived archetypes were also compared to existing Swiss archetypes provided in [37], to further validate our approach irrespective of the country where the initial dataset was collected. The archetypes from both countries show very similar charging patterns. The only differences relates to the second highest peaks for home and work CPs that are not present in the Swiss archetypes. Such differences can be explained considering that the Swiss archetypes were derived from household travel surveys and not from real e-mobility data. For example, the morning peak in the home CP archeptype in Fig. 13 are related to car pre-heating during winter or battery recharging as a result of energy loss during low temperature nights. On the other hand, the evening peak in the work CP archetypes may be related to the presence of commercial EV fleets in the available dataset, which usually perform daily services and charge at nights.

Based on the CP archetypes, the EV user archetype shown in Fig. 14 was derived according to the methodology described in Section 3.2.2 using the real charging data of frequent users from the input dataset. Such users charge three times per day, one morning session at home, one work/ short-session during the day and the last overnight home session. Arrival times for a fleet of 10 EVs, all falling within the same user archetype definition, were sampled from the trimodal distribution in Fig. 14 and the corresponding session duration and energy demand were calculated according to Eq. (7). This sampling approach spans the different CP classes as the defined EV user archetype charges at different CP classes over the day, enabling a fair comparison between the user- and cluster-based predictive models. The hourly time-series charging data for the 10 EVs between January 1st and August 31st, 2022 were derived using Eq. (8) and used as input features to train the LSTM, in addition to the contextual features in Table 2 and Cos and Sin components of the hour of the day, which are also time-series. More specifically, the first 7 months were used for training/testing and the month of August for validation. The temporal discrepancies between testing and validation data were mitigated by considering categorical features, such as public holidays or week, month of the year. The MB-based FS was applied and a different LSTM model was trained for each EV in the fleet. The main selected features were the charging pattern, hour of day and hourly temperature. The input and output rolling windows of the LSTM models were one week and 15 h, respectively, as no longer sessions were present in the sampled dataset. At each EV arrival time, the next 15 h charging pattern was predicted and the session duration was calculated by counting the hours the EV was connected consecutively, i.e. $x_{ch}(t) > 0$. The overall MAE values for the session duration and energy demand for all 10 EVs were 2.6 h and 4.1 kWh, resulting in improvements of 16.1% and 37.9% when compared against the overall performance in Table 3 of the CP cluster-based approach.

4.4. Discussion

The CP cluster-based approach resulted in improved predictions for short-stay and home CP classes. However, the improvement in the overall accuracy across all classes was not significant when compared against state-of-the-art models, such as the aggregated predictive models for all CPs, primarily due to the large number of hybrid and home chargers in the dataset. CP and EV user archetypes were also derived from the collected charging data to test the user-based approach, resulting in improvements of 16.1% and 37.9% compared to the cluster-based approach. By extensively comparing ML techniques across a wide variety of CP classes and EV user archetypes in terms of their predictive performance, and utilizing a large-scale real-world charging dataset, this work emphasizes the need to account for user-specific behaviours to achieve more accurate predictions of both individual and aggregated flexibility for public CPs.

The performed analysis of predictive performance still has a few limitations that need to be considered. The input dataset included public CPs owned and operated by TotalEnergies but classified as home and work CPs, which are generally privately owned. However, due to the extensive reach of the public charging network and the limited availability of private chargers in the Netherlands, TotalEnergies' CPs are widely utilized for home and work charging. The under and overestimation of the charging session parameters have different implications for CPO operations. Overestimating the charging duration may result in more severe consequences, as there is a risk that the EV may not be fully charged before the driver's departure time, leading to dissatisfaction among EV users. In all the studies within this work, the ML-based predictive models consistently produced a balanced distribution of underestimated and overestimated parameter values. The normal distributions of forecast errors when using the aggregated models among all the CPs to predict the session duration and energy demand are shown in Fig. 15, in blue and green, respectively, but similar conclusions can be drawn for the other models. The mean and standard deviation of these two forecast error distributions are also provided. A constant maximum charging power set by the CPO was assumed per session. However, in practice, the charging power is higher at the start and decreases as the battery approaches the maximum SoC. This variation is influenced by factors such as battery temperature or the number of EVs simultaneously connected to the same CP. The main challenge arising from this assumption is the risk to excessively delay the charging without fulfilling the user's energy request. Our proposed ML models predict the maximum allowable delay within a session before requiring maximum charging power. To address the risk of excessively delayed charging on a practical level, two strategies can be adopted: (i) prioritize EVs with limited predicted flexibility to maintain the maximum charging power within their sessions; (ii) employ alternative smart charging strategies, such as reducing the charging rate from 11 kW to 6 kW rather than completely stopping the charging, ensuring sufficient energy is charged even in cases of prediction inaccuracies. As future work, it is therefore recommended to investigate specific smart charging strategies tailored to different CP classes. For instance, maintaining a higher charging rate for short-stay chargers could be a viable strategy. Moreover, not all CPs were included in the 10 largest clusters when using the rule-based clustering approach. In future research, different clustering approaches, such as K-means, can be investigated in order consider all the CPs within a charging pool, or the smallest clusters could be merged with the distance-closest ones. Similarly, we showed the performance of the user-based approach using a single user archetype. However, additional archetypes of frequent users can be identified within the available dataset. Since the user archetypes were derived from the pre-identified CP classes, where the CP cluster-based approach outperformed state-of-the-art methods, the performance of the user-based approach for different user archetypes was also expected to be similar. To validate this, we tested the approach on other archetypes, such as users with two charging sessions per

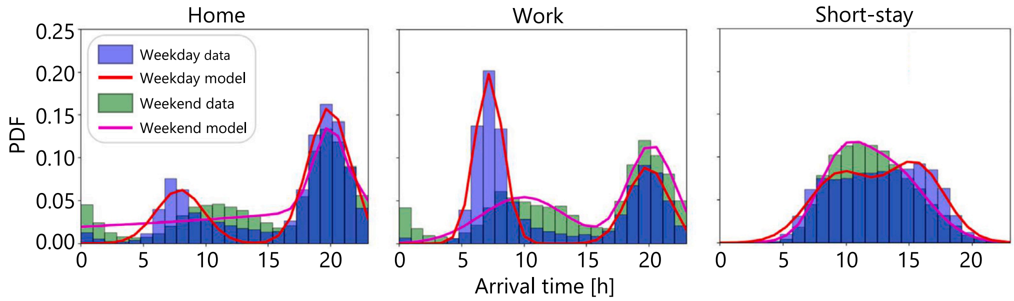

Fig. 13. Density functions of arrival times for different CP archetypes. The darkest-coloured areas indicate overlapping data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

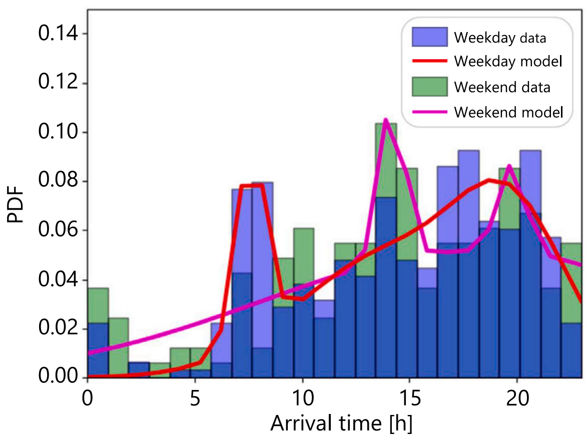

Fig. 14. Trimodal density functions of arrival times for EV user with 3 charging sessions per day.

day, and observed comparable results. Additionally, the time-series charging data of the selected user archetype was synthetically sampled from the input dataset collected by TotalEnergies. Further testing of the proposed ML-based predictive models on real time-series charging data of individual users collected across multiple CPOs would provide additional validation. An interesting finding was the superior accuracy performance when predicting the aggregated flexibility of all chargers. As future work, it would be worth investigating whether this superior performance persists when reducing the level of aggregation, for instance, at the district level for EV participation in congestion markets. However, this was not the focus of this work as it is not relevant to CPOs who are primarily interested in predicting individual session flexibility. In terms of model training, a single data split was used in this work, but performing more random splits might better prevent biased models. Similarly, training the models using charging data from several years may enhance the performance as allows to capture seasonal or yearly patterns, such as holidays during summer or winter breaks. Although the obtained forecast errors for session duration and energy demand might indeed seem not significant, it is essential to contextualize these errors within the framework of the input dataset, which stands out for its size and diversity in terms of available CP classes compared to existing studies in the literature. In real-time applications, the predictive models would need to be periodically updated as new charging data is continuously collected. The MB FS approach significantly reduced the training computational times by 68% using a standard machine with 12 CPU cores and 64GB RAM. This reduction could be further enhanced with a larger number of CPU cores to quickly identify the relevant features. Other FS approaches could be compared against the MB-based FS approach in terms of the trade-off between predictive performance and computational efforts. Finally, although XGBoost and LSTM models have demonstrated high performance in predictive applications in the literature, it would be worth investigating additional ML models and comparing them against the proposed approaches as part of future work.

5. Conclusion

The electrification of urban mobility can support the grid decarbonization through provision of demand-side flexibility. However, operational tools to manage the uncertainty surrounding the EV charging behaviours are needed. This paper proposes to leverage data-driven and statistical techniques to predict the flexibility of public individual EV charge points. A novel predictive workflow based on two causality-informed ML approaches with different levels of generalization to account for CP- and user-specific charging patters is proposed. By leveraging feature selection and clustering techniques and utilizing a large-scale real-word charging dataset, the proposed predictive workflow enables an extensive comparison of ML techniques in terms of accuracy performance when predicting EV charging session parameters, thereby quantifying the flexibility of public EV CPs. The results demonstrate that considering user-specific charging behaviours can significantly enhance the predictive performance, highlighting the need to reshape the regulatory framework to incentivize EV users to actively participate into flexibility provision schemes. Future work will use the proposed predictive tools to develop site- and network-level charging algorithms for multi-market flexibility provision.

CRediT authorship contribution statement

Federica Bellizio: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bart Dijkstra:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Data curation. **Angelika Fertig:** Writing – review & editing, Supervision, Resources, Data curation. **Jules Van Dijk:** Writing – review & editing, Supervision, Resources, Data curation. **Philipp Heer:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bart Dijkstra, Angelika Fertig, Jules Van Dijk report a relationship with TotalEnergies SE that includes: employment.

Acknowledgments

The work of Federica Bellizio was supported by the SWEET PATHFNDR project, funded by the Swiss Federal Office of Energy (grant Nr. SI/502259-01).

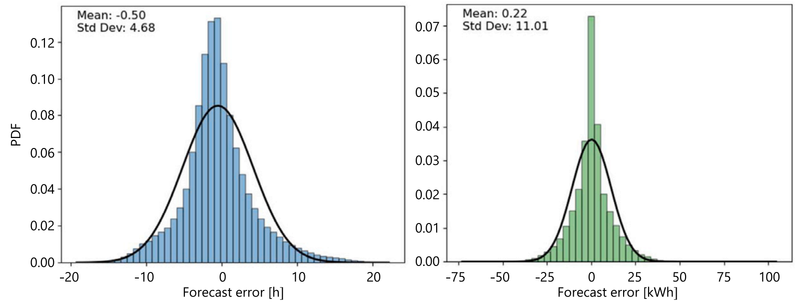

Fig. 15. Density functions of forecast errors when predicting the session duration and the energy demand, in blue and green respectively, using the aggregated models. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Data availability

The data that has been used is confidential.

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