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Enabling charging point operators for participation in congestion markets

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ABSTRACT

This paper explores the viability of electric vehicle charging point operators to act as flexibility service providers in local flexibility markets. The work focuses on the requirements for operating in local intra-day markets and specifically in solving grid congestion at the distribution level. The explored approach assumes an alternative to bilateral agreements constrained to the capacity of the charging point operator to forecast the electric vehicle demand and flexibility effectively.

The current paper analyses the flexibility capacity and proposes a methodology to address the re-dispatch process within the GOPACS (The Netherlands) context.The flexibility estimation methodology comprises two forecasting steps: forecasting the aggregated flexibility capacity and forecasting electric vehicles flexibility. A detailed case study presents data from the real electric vehicle sessions in Amsterdam City. The experimental results validate the effectiveness of the proposed methodology, establishing a robust basis for further research.

1. Introduction

The energy transition is characterized by the electrification of energy-intensive activities, traditionally fed by contaminant fuels, in particular in transport or space heating in the residential and tertiary sectors, and the consequent need to increase renewable generation distributed at different voltage levels in the grid (e.g., individual and self-consumption photovoltaic (PV) installations). This changes how the grid is operated and presents major challenges to the distribution grid due to the presence of reverse flow (when the generation is larger than the demand) and variability of demand due to the increase of peak demand and the volatility of renewable generation. Countries such as Norway, the UK, and the Netherlands are already experiencing grid congestion due to the rapid adoption of electric vehicles (EVs) due to the large power demanded during charging [1].

Moreover, there is a misalignment between the investment plans of distribution system operators (DSO) (linked to retribution schema) and how the grid users (prosumers) are investing in the electrification of their energy needs (often pushed by incentives), including both generation (PVs) and demand (space heating and electro-mobility). From a regulatory perspective, European energy policies (e.g. Directives (EU)2019/944 on the Internal Electricity Market, (EU)2018/2001 on Renewable Energy Sources) or the recent (EU)2023/1791 on energy efficiency claim for direct participation of citizens in the electricity value chain, not only as consumers but also as generators and flexibility (i.e., the capability to increase or reduce either generation or consumption) providers enabled, if necessary, by aggregators and through their participation in demand response programs.

In this context, effectively managing EV charging infrastructures constitutes a challenging scenario. Some countries (e.g., the Netherlands and Norway) are already experiencing distribution grid congestion (i.e., secondary substations reaching the capacity limit at specific periods) due to the concentration of EVs in urban areas. At the same time, these offer an opportunity to increase renewable hosting capacity if charging time can be aligned with periods of major renewable generation. Currently, in these countries, DSOs are under considerable pressure to accept more requests than the grid can handle with normal operation and, consequently, are forced to implement limiting strategies to avoid subsequent congestion [2] and look for a more flexible operation of the grid through demand response programs. There are different approaches that DSOs can implement for procuring flexibility services [3], such as directly managing the generation assets and flexible loads of their customers through bi-lateral agreements or procuring flexibility through a marketplace with specific pricing rules and remuneration rules. The definition of these local flexibility markets can vary from country to country, and there is not yet a clear European regulatory framework with common rules.

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Nomenclature

ACM	Authority for Consumers and Markets (Dutch Regulator)
AI	Artificial Intelligence
ARIMA	AutoRegressive Integrated Moving Average
CPO	Charging Point Operator
CSP	Congestion Service Provider
DBN	Deep Belief Network
DSO	Distribution System Operator
DT	Decision Tree
EV	Electric Vehicle
FSP	Flexibility Service Provider
FC	Fully Connected (neural network layer)
GMM	Gaussian Mixture Model
GOPACS	Grid Operators Platform for Allocating Capacity and Stability
GRU	Gated Recurrent Unit
KNN	K-Nearest Neighbors
KNMI	Royal Netherlands Meteorological Institute
LightGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory (neural network architecture)
MAE	Mean Absolute Error
MC	Markov Chain
MLR	Multiple Linear Regression
MLP	Markov Layer Perceptron
NODES	Nordic Distributed Energy Resources Market
PV	Photovoltaic
RES	Renewable Energy Sources
RF	Random Forest (algorithm)
R^2	Coefficient of determination
SVR	Support Vector Regression
TSO	Transmission System Operator

However, the grid operators (TSOs and DSOs) of countries with congestion issues (e.g., Germany, Netherlands, United Kingdom, or Norway) have already been progressing in adopting flexibility market platforms to trade flexibility at the local level to support grid operation and planning in the mid-term (and some start exploring the operative also for short term). Some examples are NODES in Norway and Germany, LEO in Oxfordshire (UK), Piclo Flex in the UK and Portugal, and GOPACS in the Netherlands. Flexibility service providers (FSP) are the grid users that, either directly or through an aggregation party, use these platforms to offer flexibility for a specific time, location, and price.

Most of these platforms follow a market-based approach (i.e., tenders) for procuring flexibility services in different temporal horizons, typically seasonal, day-ahead, or intraday. However, the pricing rule can vary, such as common approaches such as the pay-as-bid, regulated price, pay-as-clear, or a combination of these mechanisms. For example, pay-as-bid with indications of maximum prices at each substation is applied in the Piclo Flex UK flexibility markets [4]. The remuneration schema can be completely different depending on the regulations of each country. The same happens with the type of flexibility products allowed in every market. The network operators from the UK standardized the naming of flexibility services as ‘sustain’ (scheduled constraint), ‘secure’ (pre-fault constraint), ‘dynamic’ (post-fault constraint), and ‘restore’ (restoration support) [5], the Dutch GOPACS market is specifically designed for day-ahead and intraday demand reduction offers with a diversity of regulated products, and the NODES market has two types of products, the ShortFlex (close to real-time) and LongFlex.

A common challenge in quantifying flexibility demand and settlement in many of these products resides in the definition of a baseline from which flexibility is computed. Flexibility is commonly defined as an increase (upward flexibility) or decrease (downward flexibility) of generation concerning a baseline, or equivalently, upward/downward flexibility can be achieved by decreasing/increasing consumption. Procuring flexibility in local day-ahead or intraday markets is a kind of explicit demand response strategy oriented to better manage the grid and support the critical event (e.g., congestions and over-voltages) management that enables investment deferral. Thus, when a DSO forecasts the possible occurrence of congestion in the grid (based on demand and generation forecasts) and launches a flexibility demand to get the support FSPs to solve the issue through flexibility procurement (i.e., increase generation or decrease demand at a specific time and point of the grid) the effectiveness of this measure is highly affected by the quality of forecasts. The forecast is required to predict the occurrence of such a critical event, estimate the amount of flexibility needed, establish the baseline for each participant from which flexibility is settled, and estimate the amount they can offer. Flexibility is traded at specific times (i.e., market clearance times or specified time before deals) before its activation, so it is necessary to reduce the uncertainty in estimating the baseline from which flexibility demand is computed. Improving the flexibility forecasts will result in a reduction of uncertainty in the flexibility demand, making the demand response programs much more efficient.

Based on the publications proposing the use of forecasting methodologies leveraging the flexibility provided by EVs, Table 1 presents a comprehensive overview of the state of the art in EV flexibility estimation. The table compares the following key aspects:

- Forecasting Methodology: The specific forecasting techniques employed.
- Model Attributes: The attributes or features used in the models.
- Targets/Labels: The targets or labels that the models aim to predict.
- Objective: The primary objectives of the studies.
- Potential enhancements: An analysis of the main possible improvements of each work. The potential enhancements correspond to items 1 to 6 in the numbered list of primary contributions provided below.

This structured comparison highlights existing approaches’ methodologies, model components, objectives, and limitations, providing a clear context for the advancements introduced by the current proposal.

Based on the previous analysis and recognizing the gaps in the current state of the art, the paper proposes a methodology to estimate the flexibility charging point operators (CPOs) can offer at an aggregated level and under different conditions of access to contextual information. A novel approach is proposed to improve the methodology of the flexibility estimation, thereby improving the prediction of flexibility demand and the activation of traded flexibility when needed.

Analyzing the potential enhancements (Pot. enh.) row in Table 1 and comparing previous publications to the current proposal, the primary contributions of this work are as follows:

1. Employs minimal data inputs, optimizing practicality and computational efficiency for real-world applications.
2. Excludes inaccessible or sensitive personal data, such as user identification, ensuring data privacy and compliance.
3. Leverages an established protocol, guaranteeing methodological robustness and alignment with industry standards.
4. Utilizes real-world datasets, enhancing the accuracy, validity, and reliability of the proposed approach.

Table 1
State-of-the-art Flexibility in EV.

Ref.	Year	Work title	Forecasting methodology	Attributes used	Target/s of the model	Objective of the work	Pot. enh.
[6]	2015	Quantifying load flexibility of electric vehicles for renewable energy integration.	Mixed-integer optimization model	Driving profiles of employees and retirees, availability and power of the EV charging points, renewable energy generation data, conventional generation constraints, and driving profiles of employees and retirees.	The model predicts the optimal charging schedule for EVs to maximize the utilization of renewable energy sources and minimize the use of conventional generation.	The main objective is to quantify the potential of EVs to utilize renewable energy sources through optimized charging strategies and to analyze how different factors, such as renewable portfolios and charging infrastructure, impact this potential.	1, 3, 4, 5, 6
[7]	2020	Probabilistic forecasts of time and energy flexibility in battery electric vehicle charging	Quantile regression and MLP	Travel logs data, including time of arrival, time of departure, parking duration, and trip distance. Additional features include location data and historical parking events.	The model predicts parking duration and energy requirements.	The main objective is to develop and validate a method for generating probabilistic forecasts of parking duration and energy requirements to optimize smart charging strategies for battery electric vehicles.	1, 2, 3, 4, 5, 6
[8]	2020	Flexibility - enabling technologies using electric vehicles.	MLR	Historical power production data from various intervals: two days, one day, two hours, one hour, twenty minutes, and ten minutes prior to the prediction time.	The model predicts the optimal scheduling of electric vehicle charging sessions.	The model is used to improve the efficiency and reliability of the power distribution network by leveraging the flexibility of electric vehicle charging sessions. This process helps to balance the network, reduce peak loads, and increase the self-consumption of locally produced renewable energy.	1, 3, 5, 6
[9]	2020	Short-term load forecasting algorithm based on LSTM-DBN considering the flexibility of electric vehicle	Combination of LSTM and DBN.	Start time of charging, battery charging power, and average charging power.	The model predicts the short-term load power of electric vehicles, particularly the total charging load (P).	The main objective is to propose a load forecasting algorithm that considers the flexibility of electric vehicles, aiming to improve the reliability and accuracy of short-term load forecasts for the power grid.	3, 4, 5, 6
[10]	2020	Quantifying the Flexibility of Electric Vehicles in Germany and California—A Case Study.	Computational methods to calculate vehicle availability and energy demands based.	Vehicle identifier, arrival time at home, departure time from home, distance traveled since the last departure from home, and available time at home.	The model predicts the availability of electric vehicles at home and their energy demand.	The main objective is to quantify the flexibility potential of electric vehicles and analyze the impact of different charging strategies on electricity costs and grid stability.	1, 2, 3, 4, 5
[11]	2021	Flexibility management of electric vehicles based on user profiles: The Arnhem case study	GMM	The model uses the start time and the duration of the connection of charging sessions.	The model predicts the flexibility potential of electric vehicle charging sessions.	This method aims to improve the efficiency and robustness of smart charging by optimizing the scheduling of charging sessions according to the flexibility potential of different user profiles.	3, 5
[12]	2021	Flexibility Prediction of Aggregated Electric Vehicles and Domestic Hot Water Systems in Smart Grids	Temporal Convolutional Network combined transformer model.	Historical power consumption data of EVs, and generation data of the distributed resources.	The model predicts the size and maintenance time of the aggregated flexibility of Evs.	The model is used to provide accurate, real-time flexibility predictions for demand response resources to support grid operations, such as load shifting, voltage improvement, and reserve services.	3, 4, 5, 6
[13]	2021	Ultra-Short-Term Prediction of EV Aggregator's Demand Response Flexibility Using ARIMA, Gaussian-ARIMA, LSTM, and Gaussian-LSTM	ARIMA, Gaussian-ARIMA, LSTM, and Gaussian-LSTM	Power load data from EV charging stations, and historical load data with 15-minute intervals.	The model predicts the electric vehicle aggregator's base power load and demand response flexibility.	The model is used to ensure accurate ultra-short-term predictions of EVA's power consumption and flexibility to benefit from energy arbitrage and provide reliable services in the energy and regulation markets.	3, 5, 6
[14]	2021	Application of flexible ramping products with allocation rates in microgrid utilizing electric vehicles	MC	EV location, charging status, renewable energy output, net load, and transition probabilities reflecting driving patterns.	The model predicts the available capacity of EVs for dispatch in microgrid operations.	The main objective is to develop an optimal microgrid scheduling model that integrates EVs as flexible resources, ensuring stability and reduced operating costs while addressing variability and uncertainty in renewable energy generation.	1, 2, 3, 4, 5
[15]	2022	Leveraging the flexibility of electric vehicle parking lots in distribution networks with high renewable penetration	Stackelberg game model.	Renewable energy generation, EV parking lot loads, conventional demand, and network operational constraints.	The model predicts the distribution network net-load ramp rates and operational costs.	The main purpose is to reduce DN operational costs by incentivize EV parking lot operators through tariff discounts, enhancing flexibility and stability in renewable-heavy power grids.	1, 3, 4, 5
[16]	2024	Power system flexibility analysis using net-load forecasting based on deep learning considering distributed energy sources and electric vehicles	LSTM, GRU, and FC models.	Load, wind generation, solar generation, electric vehicle demand, temperature, wind speed, solar radiation, and pressure.	The model predicts the net load and its ramps.	The study aims to investigate the impact of controlled EV charging on power system flexibility and to propose an optimal combination of RESs to enhance future system flexibility	1, 3, 4, 5, 6
[17]	2024	Forecasting flexibility of charging of electric vehicles: Tree and cluster-based methods	LightGBM	User ID, hour, month and weekday.	The model predicts energy delivery and parking duration for charging sessions.	The main objective is to accurately predict the flexibility of aggregated electric vehicles systems to enhance the efficiency of smart grid operations.	2, 3, 5
[18]	2024	Analyzing flexibility options for micro-grid management from economical, operational, and environmental perspectives	DT, MLR, and LSTM.	Renewable generation, storage capacities, dispatchable sources, dynamic line rating, and electric vehicle demand-response.	Day-ahead predictions of photovoltaic and wind turbine outputs.	The main purpose is to optimize the operation of grid-connected micro-grids by integrating various flexibility options and minimizing operating costs, emissions, and power mismatch.	1, 3, 4, 5
X	2024	Enabling charging point operators for participation in congestion markets	KNN, SVR, ML, and RF.	Calendar, session, sociodemographic, and weather data.	The model predicts the aggregated flexibility capacity (power) and the individual EV sessions (hours).	The primary objective is to forecast aggregated flexibility within a geographical area and evaluate individual charging sessions to identify those that can to be interrupted. This algorithm is then integrated into a smart charging framework, facilitating participation in existing market platforms.	

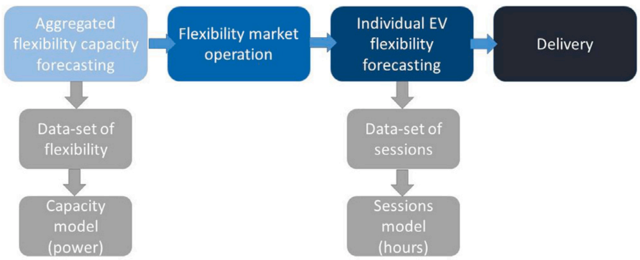

Fig. 1. Block diagram for the proposed flex market participation.

5. Accurately predicts how long sessions can be paused, enabling proactive and effective management while providing an estimation of the available flexibility.
6. Ensures that users remain unaffected, as their charging process experiences minimal intrusion and inconvenience, allowing the necessary charging for each user.

Emphasizing this, the objective is to develop a flexibility forecasting methodology that can integrate into a smart charging framework, enabling participation in existing market platforms. This methodology should be easily adaptable for various countries and use cases. The solution proposed has considered the GOPACS market in the Netherlands as the reference framework, but it could be easily adapted to be implemented to support the dynamic product of the UK flexibility markets or the ShortFlex product of the NODES market (Norway and Germany).

Participation of CPOs in congestion markets, as described in the GOPACS platform, consists of four main steps (capacity forecasting, market operation, EV session forecasting, and delivery). Two of them require forecasting, as can be seen in Fig. 1.

The first step aims to know the flexibility in a geographical or technical area. This area needs to be related to the flexibility offers that the market is providing. The extension depends on the affected area and can vary from a neighborhood to a district or city, as well as technical areas such as substations. Step two consists of performing the operation on the flexibility market and obtaining the market decision from the bidding process. The third step consists of forecasting the flexibility of the sessions to know if they can be interrupted. The last step in the delivery process is applying flexibility, which does not disrupt or affect the charging sessions. Several scenarios are considered and tested for all steps, considering data availability and required hardware and user interaction.

The second and third steps, the forecasting processes, are described in the following sections, together with the data representation and curation.

The data used in the analysis come from public chargers in the city of Amsterdam. Thus, although the previously introduced steps are common to any flexibility market, the analyses have been expressly framed within the context of GOPACS.

In summary, the work focuses on the role of CPOs as FSPs contextualized in the Dutch scenario. With this aim, the paper analyses the operative of the platform GOPACS and, specifically a flexibility product to support congestion management (*Redispatch*) to reaffirm the importance of forecasting both capacity and individual flexibility associated with EV charging at several stages of the *Redispatch* trading process.

2. *Redispatch*: Flexibility trading in the GOPACS congestion market

After closing the wholesale energy market, it could happen that traded energy cannot be delivered because it violates the grid capacity constraints. When this happens in the transmission system, the TSO acts and changes the generators' schedules so that the load can be served (redispatch). Redispatch payments at the transmission system level are usually negotiated in advance, and providers are paid as they bid in a "command and control" fashion without creating a real market. However, when congestion happens at the distribution level, and this is becoming more frequent, redispatch of generators is not a feasible solution, and collaboration of consumers through demand response programs is needed, either through bilateral contracts or through the activation of local markets.

Currently, the platform GOPACS offers support for congestion management to Dutch grid operators (both TSO and DSOs) through two main flexibility products (proposed in 2022 by the Dutch regulator ACM, [19]): *Redispatch* and *Capacity limiting*.

The last, *Capacity Limitation* is a long-term contract between the network operator and users that refers to waiving the use of (contracted) transmission capacity during an agreed period at the request of grid operators, announced before the close of the day-ahead market. Participants can be either a pre-qualified service provider, specifically labeled as a Congestion Service Provider (CSP), or other grid-connected parties. Currently, it is only envisioned as an option for consumers with connection capacities above 1MW, but according to [20] it may be extended to smaller connections in the residential section as well. The contract specifies the agreement on maximum capacity, conditions of delivery, price, contract period, and additional information such as the number of times per year it can be requested and similar conditions.

On the other hand, *Redispatch* is implemented via intraday market platforms (e.g. Etpa platform, which also manages Intraday and Ex-Post markets in The Netherlands), and only the CSPs (pre-qualification is needed) can participate. GOPACS enables the interaction of market parties with the Dutch DSOs and TSO (TenneT) to deliver bids for solving congestion in their grids. The grid operators declare congestion areas in the GOPACS platform, and CSPs place flexibility bids related to adjustable power to solve the congestion on an energy trading platform connected to GOPACS, where the settlement takes place. Buy and sell orders have the particularity (not required in other energy markets) of being linked to transfer point identifiers (i.e. EAN codes identifying the location where energy transfer between CSP and the grid is administratively assigned to a market party). *Redispatch* can be extended to include direct agreements between the grid operator and the CSPs with the *Bid obligation contracts* that assure the participation of CSPs in the *Redispatch* auction (i.e., to make bids) at the request of the grid operator.

Redispatch implies a modification of the generation (or consumption) concerning forecast at the connection point as a result of the activation of one or more flexibility orders to solve congestion in a zone of the grid. *Redispatch* has been designed not to affect the balance at the national level; thus, congestion avoidance offers (e.g., buy orders) in *Redispatch* are combined with other complementary orders (i.e., sell orders) outside the congestion area, resulting in a null or quasi null, unbalance. The price difference between the Buy Order(s) and the Sell Order(s) is called the 'Spread' and represents the resulting cost to the Grid Operators.

The product follows the Dutch Key Code of electricity (Article 9.1 and Annex 11), and it is available for both single or aggregated connections (the grid operator should specify it in the demand) but with a minimum accepted bid of 100 kW. Bids are defined to include the price, location (EAN codes), the assets in MW per imbalance settlement period, the direction, the delivery period, and availability to be called. Bids are submitted to the intraday market, a continuous trading platform operating at quarter-hourly, hourly, or longer intervals, where prices are determined by the pay-as-bid principle (i.e., transactions are finalized upon acceptance of a sell bid by a buyer), ensuring all transactions are concluded at least 5 min before delivery.

3. Enabling CPO as congestion service provider: Flexibility model and forecast

CPOs are linked to geographic areas and are responsible for the management of a substantial amount of energy in one or several transfer points. Consequently, they are foreseen as one of the most important Congestion Service Provider (CSP) since they can manage the flexibility that EVs offer at an aggregated scale in a geographical area. However, the electricity demand associated with the EV charging process depends mainly on the behavioral habits of EV owners and consequently, the management of charging points is affected by a certain degree of uncertainty.

Consequently, major efforts to control the impact of EV charging on the Dutch grid are currently facing curtailment strategies through bilateral agreements between the DSO and the CPO (*Capacity limiting*). Avoidance of possible congestion is faced by limiting the charging power of all active charging sessions in the affected area during the expected critical event without any interaction with the EV user (e.g., FlexPower [21] in Amsterdam and the INVADE project [22] in Arnhem). The FlexPower project is one of Europe's largest smart charging pilots that has demonstrated the potential of EVs to increase the grid hosting capacity [23]. However, these pilots do not exploit the flexibility EVs can offer through the existing Dutch Congestion market. Participating in *Redispatch* is difficult because of the uncertainty of loads (EVs) they manage. Declaration and availability of energy assets are needed for a positive validation of the pre-qualification process. Thus, any effort to reduce the uncertainty of either demand or flexibility, either individually or at a specific grid transfer point or zone, constitutes a step forward to their successful participation in congestion markets.

3.1. Flexibility definition for EV charging

A simple demand profile of an EV connected to a charging point, k, during the interval $[t_i, t_e]$, charging at constant power, P_k, is given by the following expression (1).

$$p_k(t) = \begin{cases} P_k & t_i < t < t_r \\ 0 & t_r < t < t_e \end{cases} \tag{1}$$

Commonly, the charge starts at arrival time (t_i) and ends, either because the car leaves, at the connection time t_e; or before, at time t_r, because the charge has been completed (battery full). In this second scenario, flexibility is given by this extra time ($t_e - t_r$) when the EV is connected and not using the charging point. So, it is a better strategy to manage charge during the whole interval $[t_i, t_e]$ instead of curtailing charging power (reducing P_k) during $[t_i, t_r]$ since the first does not affect the quality of the charging service. Thus, an EV is said to be flexible if the energy required, E_R, is less than the total energy that the charging point can provide during connection time. Thus, without any intervention, vehicles that require E_R at t_i will be charging during E_R/P_k starting at t_i and ending at t_r, and the charging point could provide flexibility by postponing charging up to $\Delta t_f = t_e - t_r$ or interrupting the charging session one or many times up to Δt_f. So, t_r can be calculated using the expression (2) and Δt_f using the expression (3).

$$t_r = t_i + E_R/P_k \tag{2}$$

$$\Delta t_f = t_e - t_r \tag{3}$$

Thus, the flexibility of a CP can be modeled as the power it can curtail (upwards flexibility), P_k, at a given time instant without affecting the quality of service; that is, completing the charge of the EV at t_e. The following expression (4) represents this flexibility model for a single CP, where $E_r(t)$ is the remaining energy charge at time instant t. Observe that in case of not being used flexibility before t, $E_r(t)$ can be easily estimated by $E_r(t) = E_r - P_k \cdot (t - t_i)$.

$$f_k(t) = \begin{cases} P_k & t_i < t < t_e - E_r(t)/P_k \\ 0 & otherwise \end{cases} \tag{4}$$

And for a set of CPs in a given zone (i.e. CPs connected to a node of the grid, a district, or a city), Z, the total flexibility can be estimated at time t as the aggregation of the flexibility of all the charging points in Z as expressed in (5).

$$f_Z(t) = \sum_Z f_k(t) \tag{5}$$

Accuracy in the estimation of the flexibility an EV can provide, from t_i onwards, depends on the user parameters E_R and t_e. The first, E_R, could be known just after t_i when the charging point exchanges information with the EV, and the second could be obtained either by asking the user or as an estimation for frequent or similar users. So, individual flexibility estimation requires user identification and interaction. Trying to estimate Δt_f before t_i is much more complex since the potential user and arriving time are unknown.

Moreover, the flexibility a single car can provide is not enough to participate in most flexibility markets (e.g. *Redispatch* in GOPACS requires at least 100 kW to participate), where an aggregated participation is required. However, the estimation of aggregated flexibility a set of charging points can provide in a bounded geographical area, Z, (for example, to participate in local flexibility markets to support DSO operation) can be carried out from a stochastic perspective, resulting in substantial reduction of the estimation error.

Moreover, the accuracy of those stochastic models can benefit from exogenous variables such as the calendar (day of the week, holidays, etc.) to distinguish between date and time during the day and socioeconomic attributes describing specific urban areas as districts or cities. Using such an approach, the necessity of individual user information, $\{E_r, t_e\}$, can be somehow skipped, and stochastic models describing user profiles of charging behaviors can be used instead.

In the following section, the authors propose a methodology to build these stochastic models from historical data and the feasibility of using them to improve the accuracy of flexibility estimation and enable the participation of CPOs in congestion markets.

4. Flexibility forecast strategies enabling congestion market participation

In the current section, the proposed methodology is described. First, the data representation and generation process is explained. Then, the forecasting of the aggregated flexibility capacity and the forecasting of the individual EV flexibility are depicted.

4.1. Data representation and generation

The first consideration is the availability of reliable data for the forecast. In this paper, the data considered is easily available to any CPO. The required data set consists of historical sessions. These sessions must contain the start, end time, and, ideally, the charging time and power. Also, the sessions need to contain a reference to the area that is under study (i.e. EAN codes, location of transfer point, or substation that feeds the CP).

The first obvious step is to acquire and store the session's data. This data usually presents or easily can be transformed and stored using a session-oriented format as represented in (6):

$$session\_instance = \{cs\_id, CP\_id, t_i, t_e, \Delta t_f, P_k, E_R\} \tag{6}$$

Where cs_id represents the identifier of a session, CP_id is the charger point where the EV is connected, t_i and t_e are the connection and disconnection times respectively, Δt_f is the available time to postpone charging (computed according to Eq. (3)) and P_k is the charging power (assumed to be constant) and E_R the total energy delivered during the session.

The next step is to achieve a dataset of flexibility capacity in an area, starting from this session-related flexibility dataset. All the sessions must be linked to the area where the flexibility must be computed.

To achieve this area dataset, the next step is to select all the sessions that are related to the area where there is a need to forecast. These sessions in the area where the flexibility has to be known must be separated into a subset for further transformations. Once the subset of sessions in an area is generated, to get the aggregated flex_Z (Eq. (5)), the Algorithm 1 can be applied. The ΔT must be the same as the resolution of the prediction we need (e.g., 15 min for *Redispatch* in GOPACS).

```
ΔT ← 15;
flex_Z ← 0;
for cs ∈ sessions_data_set do
    E_r ← cs.E_R ;
    P ← cs.P_i ;
    t_r ← cs.t_e − E_r/P ;
    T ← cs.t_i ;
    while t_r > ΔT and E_r > P/ΔT do
        flex_Z[T] ← flex_Z[T] + P;
        t_r ← t_r − ΔT;
        E_r ← E_r − P/ΔT;
        T ← T + ΔT;
    end
end
```

Algorithm 1: Algorithm for calculation of the flexibility in a zone

Note that in Algorithm 1, the flexibility is rounded to the lowercase, underestimating our real capacity.

The $flex\_Z$ is the flexible (power) profile of the desired area. Observe that if empty timestamps are present, they can be filled with 0, which means that no flexibility is available in this timestamp. This flexibility on $flex\_Z$ will be the target variable for the capacity forecast. All the exogenous variables available for the area under study can be added to achieve better models. The results section studies the use of weather and socioeconomic data on Amsterdam's use case.

4.2. Forecasting of aggregated flexibility capacity

This step aims to know the flexibility in an area shortly. The authors analyze the case of a system for participating in the GOPACS flexibility market in the case study. In this step, it is important to know the time frame of the market as the forecast needs to work in the same time frame. In the case study presented in further sections, the market works on a 15-minute basis at 24 h of anticipation.

During this step, an important consideration is the volume of sessions to achieve accurate results and relevant enough flexibility to be able to participate in flexibility markets. The more aggregated and more sessions the area has, the better the results will be.

This paper analyses two aggregation levels:

1. City-level aggregation, that is the prediction of the flexibility of all the CPOs in the city.
2. District-level aggregation, that is the prediction of the flexibility of all the CPOs in each district.

Extra variables such as calendar and weather can be used in both aggregation levels. Using this model, it is possible to know, in advance, the flexibility in a city or similar aggregations with a good enough accuracy. As a result, a more detailed explanation of the best variables and results on the forecast and interesting findings can be found.

Additionally, at the city aggregation level, socioeconomic data can be added when working at the district level. Adding socioeconomic enables the possibility of performing a unique model that makes predictions based on the socioeconomic data of the district. This kind of model is interesting for exporting the models to similar areas where there is still insufficient data to build models.

4.3. Forecasting of individual EV flexibility

The objective is to know the sessions that can be paused and how long they can be paused. This step is executed once a flexibility offer needs to be applied. Since for every charging point P_k is known, the objective of session forecast is to estimate Δt_f, and at the forecasting instant, some of the previous attributes could not be available.

In Section 5, a study on distinct modeling options and possible exogenous variables is performed.

This step aims to forecast the sessions' flexibility. This flexibility will be used in further steps to pause or not the sessions for applying the flexibility without affecting the charger users.

In this step, the authors analyze an important drawback; the most important variables for this forecasting are the user-related ones but usually, due to confidential reasons, this data is difficult to achieve. Here, the authors studied ways to bypass this lack of relevant data with up to three distinct formulations.

The following solutions for facing the lack of user-related data have been faced:

1. User model: Using personal information on the users. Not tested due to the confidentiality laws.
2. Non-interaction model: Working without any interaction with the user. This option is difficult and only for specific scopes where all the users have the same behaviors.
3. User profiles model: Using a user profiling methodology. This option does not require interaction with the users. So, it does not need extra hardware for this interaction, but it needs an additional study of the data and makes some assumptions about user profiles, as explained in the next paragraph.
4. User interaction model: Interacting with the user at the beginning of the session to request how long he will stay there. This option is interesting in areas where a time payment method is implemented or there is the option to implement the needed hardware for interacting with the users.

For solution number 3, the User profiles model, a variable $profile$ is added to the original data set of charging sessions, assigning to every session a specific user profile. The 'user profile' term refers to a connection pattern in the daily usage of the vehicle (e.g., worktime, commuter, dinner, visitor, etc.). This user-profiling process is the result of the previous work from the authors [11] and also the conference presentation [24] , based on the model-based clustering method called Gaussian Mixture Models (GMM). This methodology has been validated with a data set of charging sessions from the Dutch city of Arnhem in [11], the Norwegian harbor of Borg in [25], and the city of Amsterdam [26]. The charging sessions data set used in this paper already contains the extra column $profile$ obtained after applying the profiling methodology in the Amsterdam case study [26] (see Table 3), to improve the forecasting accuracy using this extra knowledge of every charging session in one of the modeling options.

5. Experiments and results: Amsterdam case study

In this section, experiments and results from the Amsterdam case study can be found. This study is done using a real data set of EV sessions from the public charging infrastructure in Amsterdam, The Netherlands, during the whole year 2021. Most of the public charging infrastructure in Amsterdam uses regular AC charging stations, widely distributed throughout the city, supporting Type 2 connections that offer power output of up to 22 kW. Since this data set is from Amsterdam

Table 2
Table with the features of the proposed methodology, similar to the GOPACS proposal.

Granularity	15 min
Horizon	D-1 (24h)
Length	Day-ahead and intraday
Power	No minimum
Zone	From city to country
Type	Reduction

and GOPACS is based in the market operation in The Netherlands, this study uses this market as a reference.

Also, the authors explore possibilities in modeling that are not directly related to GOPACS to enable the methodology to be applied to other markets. The features of the present case study according to granularity, horizon, length, power, zone, and type of offer are defined in Table 2.

In the next subsections, the data used in this study is described. Then, the forecasting methodologies, which are the aggregated flexibility capacity and the individual EV flexibility, are explained.

5.1. Data description

A sample of this data set can be found in Table 3, showing six sessions obtained from distinct chargers, defining every session's connection times, the charging power in kW, the energy required in kWh, and the number of hours of connection and charging.

The charging sessions are from the whole Amsterdam metropolitan area, and sessions can be grouped by district using session identification. Since GOPACS works at the city level, but other markets work at smaller zone aggregations, districts will be used to study the limits of the methodology in the zone size.

Moreover, for this study, the authors used socioeconomic data on the distinct districts and weather from the aerator meteorological station.

The socioeconomic open data used in this work is obtained from the Dutch Central Bureau of Statistics [27]. Concretely, the 2020 data used is available in [9]. From the total data set, 35 variables have been preselected for 96 districts in Amsterdam, corresponding to the number of residents (also dis-aggregated by age ranges: 0–14, 15–24, 25–44, 45–64, 65–Inf), number of low/mid/high educated people, the density of population, urbanization degree, number of houses, number of 1-person houses, number house stock, average house size, average house value, percentage of full/empty houses, percentage of old/new houses, number of business places (also dis-aggregated by type of business: services, communications, commerce, finances, culture, agriculture and industrial), the density of business, number of cars, density of cars and surface.

On the other side, weather data used in this study is gathered from the Royal Netherlands Meteorological Institute (KNMI) [28], and hourly data from Schiphol is used in this study. In Table 4, a description provided by KNMI on the variables used in this study can be found.

5.2. Forecasting of aggregated flexibility capacity

This forecast aims to know the flexibility in a geographical area in advance. This area needs to be tied to the offers of flexibility the market is providing. Knowing the areas where flexibility can be offered, the methodology's user can participate in the market.

GOPACS is a market where offers can be displayed at distinct aggregation levels, starting at the city level and moving to the upper levels. In the next subsections, a study on the aggregation level is carried out to try with lower aggregation levels, as can be found in markets such as Piclo Flex. Unfortunately, higher aggregations than the city level cannot be tested as this study does not have access to data from other cities.

The next subsections will study the forecasting at the city (Amsterdam) and district level.

5.2.1. City-level aggregation: Amsterdam

At the city level, several forecasting methods were tested, providing good predictions. The method that performed better was Random Forest. In Fig. 2 the results of the prediction over three days can be seen; the model was built using weather and calendar data. The statistics of the shown results are 0.986 R^2 and a mean absolute error (MAE) of 148 kW.

As can be seen, when working at the city level, forecasts of the available flexibility present a very high precision.

5.2.2. District-level aggregation

In this subsection, the authors try to study where the limits on the lower aggregation size are. Here, distinct forecasting options working at a district level are studied.

First, the study uses a model for each district. Second, the approach tries to use district socioeconomic data to build only one single model for all the districts. The first version achieves better results. However, the second option, which includes socioeconomic information, can produce a model that can be used on other cities/districts with similar characteristics.

5.2.2.1. District-level multiple model. Here, the goodness of building a model for each district is studied. In Amsterdam, there are 97 districts with charging sessions in the provided data set. Taking a generic configuration on random forest, some of the models present quite good results (0.82 R^2), and others present inferior performance (−0.3 R^2). All these models can indeed be improved by accurately parameterizing the algorithm for each of the 97 models or even finding a better-performing algorithm, but achieving the best results is not the author's aim at this point.

The relevant point here is that some districts can be predicted easily and others not. Here, the authors found that the number of sessions is crucial to achieving good results. Some of the districts, the ones with more sessions, have more accurate models and can easily achieve results, as well as the ones at the city level. On the other hand, districts with a low number of sessions are not predictable. This is a well-known characteristic when working on load prediction, as the more aggregation on the load to be predicted, generally the better the results.

In Fig. 3, a comparison of the R^2 score against the average sessions per week is depicted. As can be seen, the models with 200 sessions or more per week rarely achieve good results. Some of the models that used between 200 and 300 sessions achieved good models. With more than 300 sessions, nearly all the models are over 0.6 R^2 and up to 0.82 R^2.

Here, it is important to mention that not all the sessions are equally interesting regarding flexibility, that is the forecasting objective. Very short sessions or sessions without or with low charge have no flexibility. This may be the reason why, with the same session number, some of the districts are more predictable than others. Also, the variety of user patterns can play a significant role.

With the present information, the authors assess that the present methodology can be applied to areas where there are more than 300 sessions per week. And the more sessions there are in the area, the better the results.

5.2.2.2. District-level single model. In this subsection, instead of building a model for each of the distinct districts, a single general model capable of predicting the flexibility in each of the districts is created. This general model uses socioeconomic data, weather, and calendar data. Again, the limitations on the sessions in each district are present, so districts with very accurate results and with poor results can be found. The average statistics are 0.774 R^2 and 11.15 MAE (kW) for a random forest model.

The goodness of this model is that it can be used to predict areas where there is still no session data, as this model uses socioeconomic data to learn the sessions a district will have. An example of the flexibility prediction on district 36347 can be found in Fig. 4. As can

Table 3
Example of EV sessions data.

Profile	Session	Connection Start Date Time	Power	Energy Required	Connection Hours	Charging Hours
Work time	S1	2021-02-01 05:30:00	3.7	12.950	9.00	3.50
Morning	S2	2021-02-01 06:15:00	3.7	10.175	2.75	2.75
Work time	S3	2021-02-01 06:15:00	3.7	11.100	7.50	3.00
Work time	S4	2021-02-01 06:30:00	3.7	9.250	8.25	2.50
Work time	S5	2021-02-01 06:45:00	3.7	3.700	8.25	1.00
Morning	S6	2021-02-01 09:30:00	3.7	9.250	7.25	2.50

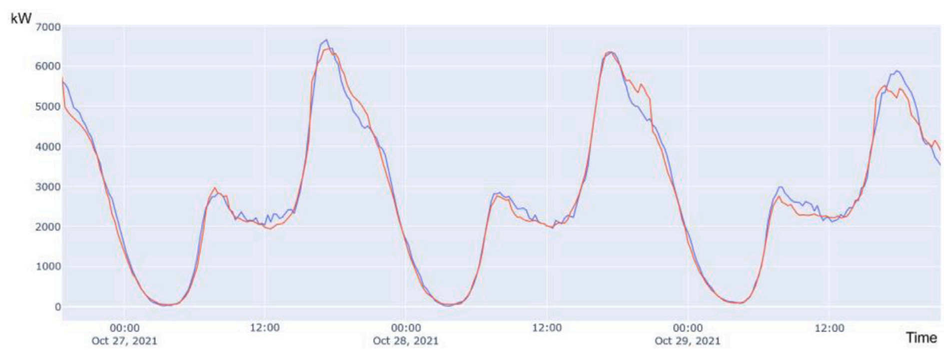

Fig. 2. Forecast of the flexibility in Amsterdam. The Y axis is power in kW, and the X axis is time in 15-minute frequency. The blue line is the real value, and the red line is the forecasted value at d-1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Table with the meteorological variables used for the study.

Wind	Hourly mean wind speed (m/s)
Temperature	Temperature at 1.50 m (Celsius)
Radiation	Global radiation (J/cm2)
Precipitation	Hourly precipitation amount (mm)
Visibility	Horizontal visibility level from 0 to 89. (0= 0 to 100 m;... 89=70km or more)
Clouds	Cloud cover (octants); (9=sky invisible)
Humidity	Relative atmospheric humidity at 1.50 m (in percents)

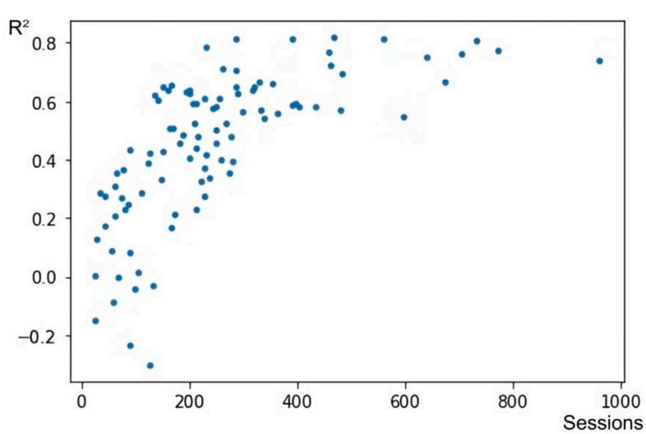

Fig. 3. Comparison on R^2 achieved given an average number of sessions per week. The X axis is the average sessions per week. The Y axis is R^2.

be seen, results can be quite accurate in areas where the sessions are above 300 sessions per week.

Another interesting conclusion that can be extracted from this study is that not all the socioeconomic data is relevant to forecast flexibility; the most relevant are summarized in Fig. 5.

As can be seen, the most correlated variables to the flexibility are day hour from calendar data, humidity, from weather, n_business_services, n_business_culture, n_people_high_educated, n_people_western; these variables are related to areas where more presence of EVs can be found and the usage made of the vehicles.

Finally, the results of this modeling option seem to be slightly lower than those achieved by modeling the districts individually. On the other hand, this modeling is interesting to take into consideration when studies of the implementation of the methodology in other areas are carried out. As it can provide forecasts to areas never seen by the model that are similar to those previously seen.

5.3. Forecasting of individual EV flexibility

In this subsection, forecasting is performed to understand the flexibility of each session. This forecasting is constructed to know in advance when a session starts or when it is ongoing, as well as the total session flexibility in hours. This step aims to help assess the operator of the methodology. The operator needs to pause the sessions to apply the flexibility, so this forecasting is focused on knowing which sessions can be paused without interfering with the final user. Here, the authors analyze the distinct ways of operating and the advantages and disadvantages of each one.

In this forecasting, one of the most relevant points is the data availability, user interaction possibilities, and hardware/computational costs of each option. In the next subsections, the authors will analyze four distinct modeling options, comparing them in terms of data requirements, wellness of the prediction, and computational/hardware costs.

Regarding the attribute relevance, as can be seen in Fig. 6, only the hour of the session has a considerable correlation.

5.3.1. User model

The authors believe that this is the modeling that can achieve the most accurate models in terms of wellness of the session flexibility prediction, but unfortunately, due to privacy laws, this data was not provided and could not be tested in this study. On the other hand, this technique does not easily fulfill requirements.

Regarding the requirements, the first one is data privacy. Knowing each user for how long his car is stationed and where information needs to be protected. The second requirement drawback is a technical one; sessions and users must be related and stored, and it requires hardware

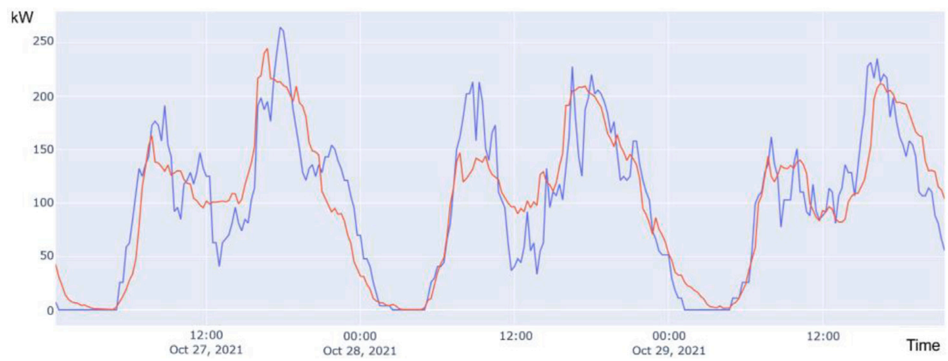

Fig. 4. Forecast of the flexibility in district 36347. The Y axis is power in kW, and the X axis is time in 15-min frequency. The blue line is the real value, and the red line is the forecasted value at d-1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

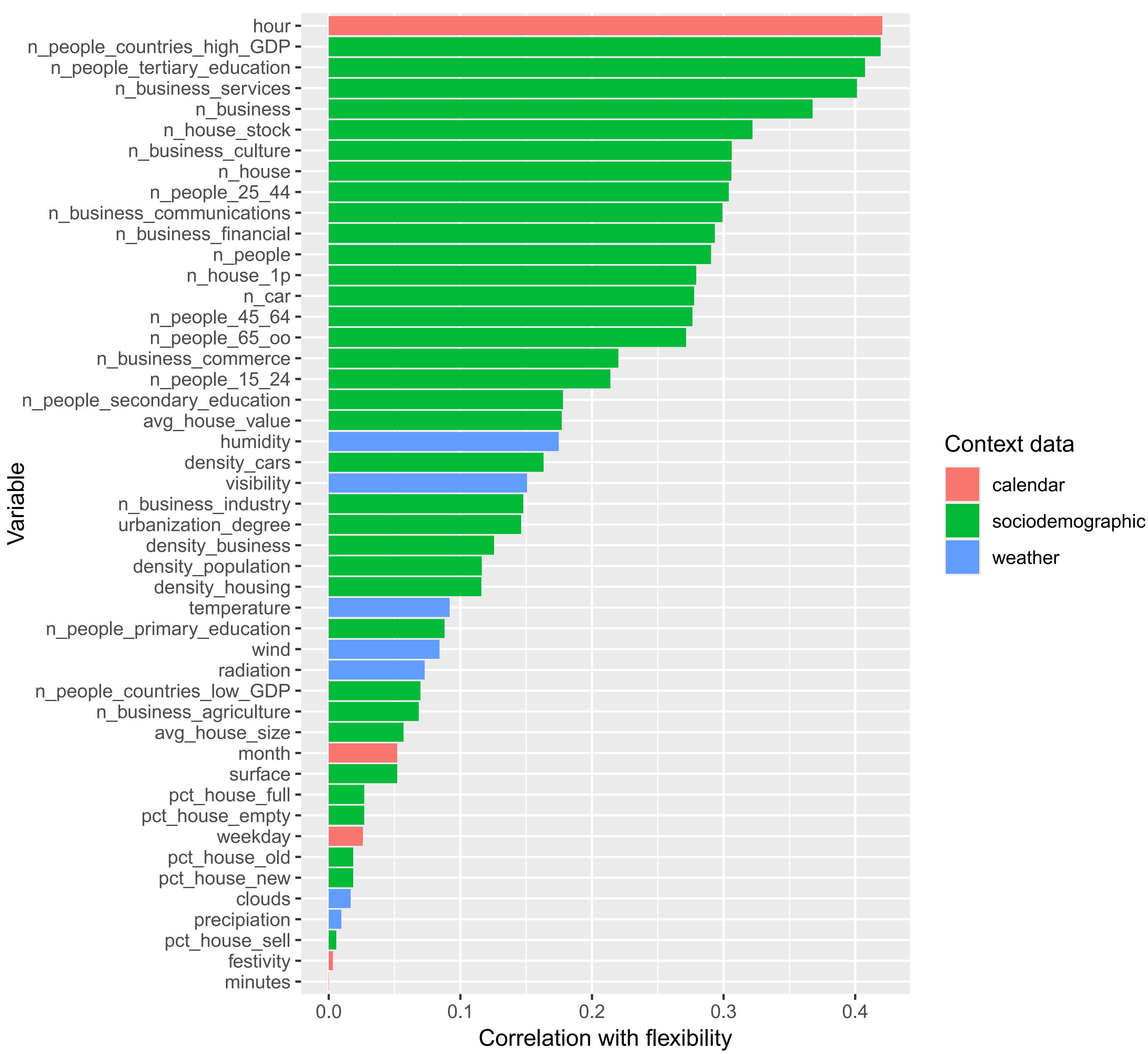

Fig. 5. Correlation of the variables with the district's flexibility. Calendar variables are represented with a red bar, sociodemographic variables with green bar and weather variables with a blue bar. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

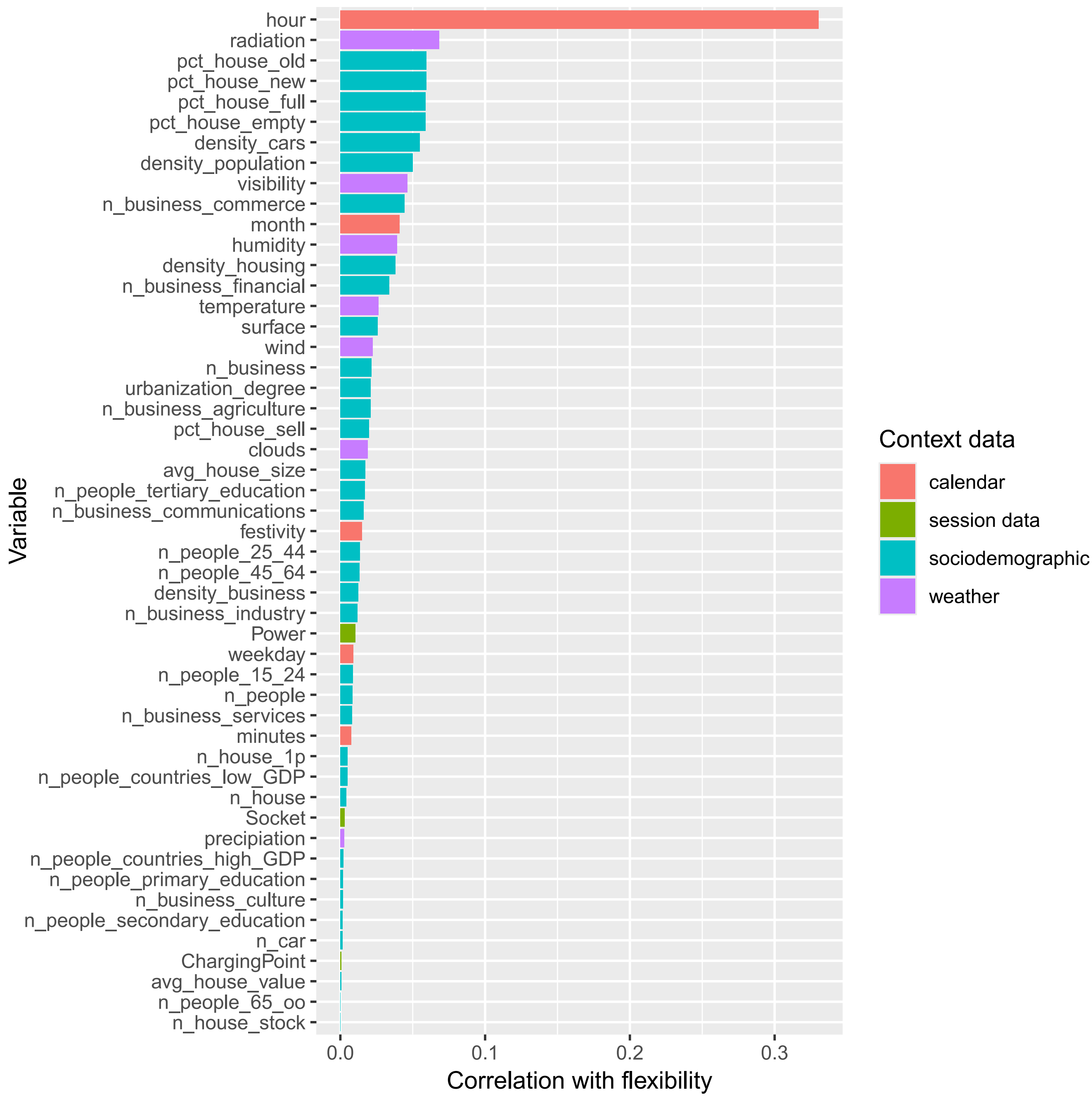

Fig. 6. Correlation of the distinct variables with the session's flexibility. Calendar variables are represented with a red bar, sociodemographic variables with a blue bar, weather variables with a purple bar, and session-related variables in green. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

capable of doing so. The third requirement is also a technical one; building a model for each user requires a huge number of models that may be difficult to maintain and require a lot of resources.

In real scenarios, user models performed with cutting-edge state-of-the-art techniques can easily become too costly for a small improvement. If implemented in real-world user models that can do the work without a huge amount of resources, are very simple models or statistics (i.e., mean flexibility for each user, mean for each user/hour, average charging vs actual charged...)

5.3.2. Non-interaction model

In this subsection, the less restrictive option is studied. This is the least restrictive but also the least performing in terms of the wellness of the predictions. In this forecast, no user identification is needed, and no additional user interaction is needed. Only a charging infrastructure and the necessary hardware to know in real-time the active sessions.

In this subsection, several forecasting methodologies were tested using one year of real session data. The target was predicting the session flexibility in hours, that is the duration of the flexibility. In Table 5 can be seen that all the models produce low-performing forecasts. More parametrization works could indeed be done, but the main problem here is that the variables, that can be achieved without user interaction, present a very low correlation with the session's flexibility.

Table 5
Table with the statistics obtained for non-interaction models. Columns are the distinct algorithms tested, rows are the statistics obtained by each algorithm.

	KNN	SVR	MLP	RF
R^2	0.003	0.032	0.167	0.02
MAE (Hours)	5.05	4.86	4.75	5.03

Table 6
Table with the statistics obtained for user profiles models. Columns are the distinct algorithms tested, rows are the statistics obtained by each algorithm.

	KNN	SVR	MLP	RF
R^2	0.635	0.342	0.886	0.877
MAE (Hours)	2.82	3.81	1.61	1.64

Table 7
Table with the statistics obtained for user interaction models.Columns are the distinct algorithms tested, rows are the statistics obtained by each algorithm.

	KNN	SVR	MLP	RF
R^2	0.91	0.954	0.96	0.96
MAE (Hours)	1.43	0.99	0.87	0.89

5.3.3. *User profiles model*

This solution requires a first study, presented in [26], to achieve the user profile information for every session. This solution has no extra requirements than the previous solution. However, it considers the following assumptions:

- Every EV user belongs to a single User profile.
- The user profile assignment does not contain errors.
- There are no new profiles.

Using the profile associated with each session, the models tested in the previous modeling options achieve the results summarized in Table 6.

Using the user profiles considerably reduces the forecasting error. The main drawback is that this process needs an extra step to calculate these profiles but has no extra costs on hardware and only the extra computational time of the process.

5.3.4. *User interaction model*

In this subsection, data on session duration will be used. To acquire this data is necessary to interact with the user and ask for this information directly or indirectly. A similar study, with nearly the same results, can be done by asking the energy the user wants to charge. In comparison with the other modeling options explored, extra hardware or chargers with user interaction are needed here. This interaction can be easily implemented in charging payment areas by reusing the payment infrastructure but can be difficult in areas where there is no necessary hardware to interact with the user to ask for the session ending time, session duration, or energy to be provided.

Using the session duration associated with each session, the same models tested in previous modeling options can achieve the results summarized in Table 7. In Table 7 it can be seen that results are much better than previous modeling options without accurate parametrization works. Here, the assumption that the user does not lie was made.

6. Conclusions

Charging point operators can manage the enormous amount of flexibility the electric vehicles can provide and consequently could adopt a prominent role as flexibility service provider. In particular, at the distribution level, charging point operators can be determinant to solve congestion issues through their participation in local markets. The principal inconvenience in providing this service is due to the stochastic behavior of the load they manage and the difficulty in forecasting both electric vehicle demand and flexibility. The paper evaluates how forecasting can be improved by considering different levels of aggregation and using various categories of input attributes (i.e., energy data, weather data, socioeconomic data). The work focuses on the re-dispatch process within the GOPACS framework to identify the forecasting requirements and constraints.

Based on the analysis, the authors propose a methodology for quantifying the aggregated capacity of flexibility, aiming to enable market participation and, second, activating the traded capacity by strategically pausing charging sessions that will not be impacted. Thus, flexibility forecasting is analyzed according to these two necessities, resulting in the forecasting of aggregated flexibility and individual electric vehicle flexibility.

Regarding the aggregated flexibility forecasting (capacity), the authors conducted tests across various aggregation levels to identify those levels that can significantly reduce the forecasting error at the same time, can aggregate enough flexibility as flexibility service provider in a specific area. The aggregated flexibility forecasting methodologies yielded the following results: at the city level, R^2=0.986; at the district level using multiple models, R^2=0.82; and at a district level using a single model, R^2=0.774. The study, performed with Amsterdam CPO data, found that areas with 300 or more charging sessions per week are suitable for this methodology, as the forecasting algorithms provide accurate results. Another key finding is that, after analyzing the models, only certain socioeconomic variables, such as being from countries with a high GDP per capita or having tertiary education, provide useful information to improve predictions, while others, like the percentage of new or sold houses, do not contribute significantly.

According to the electric vehicle session forecasting, the authors explored various modeling approaches following the experience gathered in previous works. The electric vehicle session forecasting provided the following results: with the non-interaction model, R^2=0.167; with the profiles model, R^2=0.886; and with the user interaction model, R^2=0.96. The primary challenge lies in obtaining user-related information linked to each session since the most influential variables are those related to users. However, dealing with personal information was not feasible in the study. Moreover, the investigations aim to find generic methods that minimize user interaction and avoid privacy issues. For that purpose, the authors explored the use of clustering methods to learn user profiles and, based on them, infer the number of sessions that could contribute to providing flexibility.

The work demonstrated how charging point operators can participate in flexibility markets as providers without impacting electric vehicle charging customers with promising results.

Finally, the authors wish to emphasize that modifying the amount of energy charged to users has the potential to significantly enhance the overall flexibility of the system. However, altering the total energy charged raises important ethical considerations. Any such adjustments must be conducted transparently, ensuring that users are properly informed and adequately compensated for any impact on their energy usage.

CRediT authorship contribution statement

Joaquim Massana: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Llorenç Burgas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marc Cañigueral:** Writing – original draft, Methodology, Conceptualization. **Andreas Sumper:** Writing – original draft, Methodology, Conceptualization. **Joaquim Melendez:** Writing – original draft, Methodology, Conceptualization. **Joan Colomer:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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