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Unlocking Grid Flexibility: Leveraging Mobility Patterns for Electric Vehicle Integration in Ancillary Services

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Abstract: The electrification of mobility has introduced considerable challenges to distribution networks due to varying demand patterns in both time and location. This underscores the need for adaptable tools to support strategic investments, grid reinforcement, and infrastructure deployment. In this context, the present study employs real-world datasets to propose a comprehensive spatial–temporal energy model that integrates a traffic model and geo-referenced data to realistically evaluate the flexibility potential embedded in the light-duty transportation sector for a given study region. The methodology involves assessing traffic patterns, evaluating the grid impact of EV charging processes, and extending the analysis to flexibility services, particularly in providing primary and tertiary reserves. The analysis is geographically confined to the Lombardy region in Italy, relying on a national survey of 8.2 million trips on a typical day. Given a target EV penetration equal to 2.5%, corresponding to approximately 200,000 EVs in the region, flexibility bands for both services are calculated and economically evaluated. Within the modeled framework, power-intensive services demonstrated significant economic value, constituting over 80% of the entire potential revenues. Considering European markets, the average marginal benefit for each EV owner is in the order of 10 € per year, but revenues could be higher for sub-classes of users better fitting the network needs.

Keywords: electric vehicles; flexibility; smart charging; geospatial planning; open-source data

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1. Introduction

Driven by ambitious emission reduction targets, the energy sector is moving towards the challenge of decarbonization [1]. The decreasing utilization of thermal plants in favor of non-programmable renewable energy sources is increasing the need for alternative providers of flexibility for the grid [2]. Simultaneously, the automobile industry is undergoing a dramatic transformation toward electrification. Based on current energy, climate, and industrial policy settings, every other car sold globally in 2035 is set to be electric. By 2030, almost one in three cars on the roads in China is projected to be electric, and almost one in five in both the United States and the European Union [3]. The proliferation of Electric Vehicles (EVs), without a proper strategy for managing the charging process, could increase the stress on the grid rather than presenting an opportunity for the development of decentralized energy storage [4]. Mobility habits and the associated incremental electricity demand from charging processes tend to overlap with existing demand peaks. However, if managed wisely, EV technology may represent a valuable asset for the network. Despite their impacts on power systems, EVs also offer great flexibility potential on the demand side, defined as a controlled power adjustment sustained for a required duration [5].

Flexibility from Demand Side Management (DSM) is crucial, with EVs fitting well into the spinning reserve and demand response categories due to their rapid response capabilities [6]. User mobility needs impose strict constraints that limit the potential of EVs to provide flexibility services for periods longer than a number of hours. To implement DSM techniques through EVs, it is necessary to alter the charging process. Authors in [7] describe the different charging schemes currently studied: while passive charging is performed at the maximum available power until the battery is fully charged, not allowing for any flexibility, smart charging involves power modulation within the range allowed by the charging point based on instructions from a controller. Demand shifting allows for smoothing demand peaks while maintaining a more uniform number of EVs performing charging processes throughout the day. The time flexibility of EV demand is numerically evaluated in [8] for a real-life study case: defined as the difference between the charging duration and the connection duration during a transaction, demand flexibility is evaluated for charging stations in the Lombok district of Utrecht, the Netherlands. The findings reveal that 59% of current demand is deferrable for over 8 h and 16% for more than 24 h, indicating a potential for aligning charging with next-day PV generation peaks. The effectiveness of a smart charging algorithm was tested in [9]: involving the largest household-based pilot project, smart charging use cases directly contribute to reducing charging costs and increasing the utilization of renewable energy. However, the impact of potential changes in the charging schedule on both infrastructure and market levels is not evaluated.

To determine the potential for grid services, it is essential to model mobility patterns, and consequently, EV users' needs. The top-down approach proposed in [10] offers a comprehensive analysis of the impacts and benefits of electric vehicle diffusion. While this method is extremely effective for drawing conclusions at a national level in terms of policy framework, its ability to isolate impacts at a sub-regional level from the general conclusions is limited. For this reason, the work in [11] exploits an open-source framework, MATSim [12], to model all trips that take place on a typical day. Synthetic drivers are generated starting from a population sample. From socio-demographic attributes, daily driving profiles are assigned to each individual to simulate traffic for the entire study area. Such an approach has great potential, since it leads to a synthetic database with detailed information on energy expenditures, state of charge, and time scheduling of each vehicle. Authors in [13] employ the same tool for a national-scale analysis of EV impact. Specifically, the emission reduction from electrifying the transportation sector in Croatia is assessed, mapping the mobility needs of the region and evaluating the impact of deeper RES penetration. However, relevant limitations include the large amount of specific data and calibration effort required to adapt the model to a specific case study. An alternative approach is proposed in [14], relying on mapping combustion engine vehicles onto electric vehicle equivalents and national traffic studies in Germany. Additionally, the embedded uncertainty was quantified using the Monte Carlo method. The same method is employed in [15] to deal with the uncertainty embedded in the EV charging load on each busbar of a test system. Specifically, a spatial–temporal model was developed to evaluate the impact of large-scale deployment of plug-in electric vehicles on urban distribution networks. The approach uses Origin–Destination analysis to reduce the uncertainties caused by EV mobility. The EV technical and market information provided by a European project were analyzed to obtain generalized EV characteristics, e.g., the correlation between battery capacity and the maximum travel range. Moreover, a peak shaving charging logic is implemented, constrained by the satisfaction of the energy demand of each user at the end of the modeled day. A similar survey-based approach is used in [7]. To represent the availability of vehicles most realistically, the authors directly integrate the results of a travel survey performed in Denmark into the model developed. This approach, on the one hand, guarantees an optimal representation of the current mobility context in an area, but on the other hand, it does not allow for any scenario evaluation. The study limits its evaluation to domestic charging, neglecting the impacts and potentials of daily charging in workplaces or other publicly available charging stations. Finally, the approach in [16] models a district distribution network to study the potential provision of stability from the growing presence of EVs while PV generation rises as well. The model adopts an optimization methodology to minimize the net load variance of the grid, obtaining a meaningful stabilizing effect as the EV share grows. A similar objective is pursued by authors in [17], who focused on the entire country of Sweden. They assessed the impact of EVs on the LV network, highlighting the urgency of reinforcement in larger urban centers to prevent voltage violations. Although the adopted methodologies can accurately simulate the interaction of EVs with a district network, they lack the accurate upstream modeling of mobility habits and the downstream quantification of the available flexibility band potentially offered by EVs throughout the day. These two elements are crucial to broadening the analysis to larger areas and estimating the economic value of such services in the ancillary services market.

As a result of these considerations, the present work introduces two key innovations. First, from a systemic perspective, a transferable methodology that leverages a physical, bottom-up traffic model, extensively detailed in [18], was developed. This methodology is novel in its ability to quantify the incremental impact of EV charging processes while simultaneously evaluating real-life, independent information. By integrating a self-calibrated, survey-based mobility model into the case study, an incremental demand profile that accounts for both temporal and spatial dynamics was generated, offering a comprehensive assessment of the impacts and needs. Second, flexibility-wise, an advanced logic that optimally designs EV participation in the ancillary services market by considering both user behavior and infrastructural constraints was introduced. This innovation results in the precise calculation of flexibility bands that can be offered in the market, considering users and infrastructural constraints. Additionally, these services were embedded within the current European market framework to evaluate their economic viability, ensuring compliance with existing regulations. The potential revenues from the Frequency Containment Reserve (FCR) and manual Frequency Restoration Reserve (mFRR) services are rigorously evaluated and compared, highlighting the financial benefits of our approach.

2. Materials and Method

The objective of this analysis is to evaluate the flexibility potential of a given region in offering grid services. The methodology is broken down into four hierarchical steps: first, the mobility needs of a given study area, imposed by the socio-economic framework, public transportation capillarity, and morphology are gathered and filtered (Section 2.1). Secondly, a spatial–temporal traffic model is built to evaluate the patterns and habits of the inhabitants (Section 2.2). Subsequently, the incremental demand and flexibility potential of EVs can be assessed (Section 2.3) and ancillary services economically evaluated, including the present market framework (Section 2.4).

2.1. Data Gathering and Preprocessing

The present methodology aims to build a transferable and extendable framework relying on open-source data. A pivotal input is the Origin–Destination (OD) matrix, a shared methodology used to quantify and illustrate the mobility needs of a given region. It consists of mobility records that typically include information on the origin, destination, and reason for each recorded trip. To fully exploit the relevance of the information contained in the OD matrix, the methodology incorporates a series of independent geo-informed datasets. Local administrative cells provide a suitable discretization of the study area, including data on the population and workers recorded in each cell. Additionally, relevant amenities such as parking spaces, schools, and universities are collected and aggregated based on administrative cells. In parallel, given the bottom-up approach, the road transportation network is imported. This involves utilizing a large-scale, real-world transportation network modeled as a graph using open-source data. The data includes geometric information representing road segments with coordinates. The roads are filtered and categorized into seven main groups, each defined by its nominal flow speed and capacity. Moreover, primary substations' conventional areas are included to assess the impact on the electric network.

2.2. Traffic Model

The bottom-up GIS-based approach, extensively presented in [18] and in this work, referred to as Traffic Model (TM), is employed in the present work to trace mobility patterns of a given region and estimate the impact of electrification of the light-duty transportation sector. First, a weighted graph, using the region's traffic network layout and traffic flow patterns, is simulated by considering factors such as traffic congestion and road network design. Dijkstra's algorithm is employed to find the fastest paths, given the current traffic condition, for these trips within the road graph.

To enhance the spatial resolution of the trips' origin and destination, a further sectionalization of the region is conducted, incorporating a gravity model using GIS-empowered probability density functions. Specifically, each section is characterized by detailed attributes such as population, number of workers, university presence, and amenities, which are used to build probability functions that estimate the start and end points of trips within the zones. It employs various influential factors for different trip types, such as work, study, leisure, and return home trips. For instance, sections with higher worker populations are more likely to be selected as destinations for work trips. The model calculates the probability of each section being the origin or destination by using discrete probability density functions, with parameters weighted according to their relevance to the trip purpose.

The OD matrix does not provide details about the fuel type of passenger cars used for traveling. Therefore, a method to differentiate between EV and thermal engine vehicles is required. To resolve this issue, a static penetration rate is defined, indicating that a certain percentage of trips are made with EVs. As a result, a corresponding proportion of trips from the travel survey is chosen to create an electric trip, a subset of the trips simulated in the traffic model set that reflects the defined penetration rate. Moreover, three main outputs from previous stages—arrival time, destination, and distance—are used to estimate the vehicle's energy demand. Each EV trip energy requirement is based on an average consumption rate, ACR (Equation (1)). The requested energy is aggregated into the power profile of the corresponding substation.

$$\Delta E^{consumed} = d \cdot ACR \tag{1}$$

Once the energy spent on each single trip is calculated, it is relevant to state that not every EV owner is willing to charge at the end of each travel. A probabilistic approach is employed here, assuming that the higher the energy consumption for the trip, the higher the probability of needing a charge. This means EVs completing longer trips are more likely to require charging compared to those that have only traveled short distances. Moreover, in longer trips, the energy required for charging is likely to match the energy used, while if a vehicle is selected to charge after a shorter trip, it is reasonable that the charging process will last longer than the energy expenditure for the last travel. This is summarized in Equation (2) through a scaling factor sf representing the relation between the consumed energy in the last travel, $\Delta E^{consumed}$, and the energy to be recharged ΔE^{EV}. Specifically, in the first case, the sf is set to 1, while it reaches the value of 10 for very short urban trips.

$$\Delta E^{EV} = sf \cdot \Delta E^{consumed} \tag{2}$$

As a result of all these steps, the output of the TM is a subset of electric trips in the study area and the corresponding energy demand, resulting in a spatial–temporal incremental demand profile.

2.3. Flexibility Evaluation Model

At this stage, each trip is routed on the road graph and associated with an origin, a destination, an arrival time, and the attribute of being electric, including any need to recharge a specified amount of energy. The incremental EV-related electric demand is now an attribute of each subsection of the study area and exhibits a temporal trend.

2.3.1. Temporal Margin for Flexibility

A pivotal consideration in developing the following section is that charging power modulation, shifting away from passive charging, should not impact the needs of the EV owner. In line with this consideration, each trip, associated with a purpose r, is connected to a characteristic stay time st^{EV} derived from a Gaussian distribution in Equation (3). The typical duration is modeled as a function of the travel typology (e.g., for working purposes μ_r is set to 8 h, while for trips returning home it is set to 11 h) while variability is set constant (0.5 h) for all the different travels.

$$st^{EV} \sim \mathcal{N}(\mu_r, \sigma^2) \tag{3}$$

For each travel, it is now possible to define three notable temporal quantities: the arrival time at^{EV}, derived by the traffic model, the end of charge eoc^{EV}, resulting from Equation (5) with a passive charging paradigm, and a departure time dt^{EV} obtained using Equation (6). A graphical description of the described quantities is reported in Figure 1.

$$ct^{EV} = \frac{\Delta E^{EV}}{p^{nom}} \tag{4}$$

$$eoc_{tvl} = at^{EV} + ct^{EV} \tag{5}$$

$$dt^{EV} = at^{EV} + st^{EV} \tag{6}$$

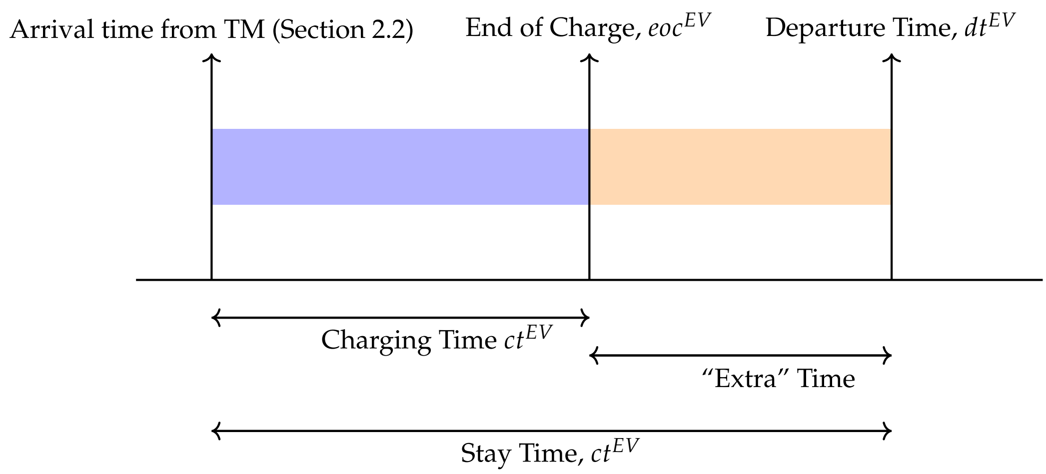

Figure 1. Graphical representation and temporal characterization of the charging process.

2.3.2. Charging Infrastructure Modelling

The model, capable of tracking traffic trends in a region, needs to be integrated with the charging infrastructure network. Despite defining a temporal flexibility margin for each vehicle based on user needs, the availability of a free charging point to connect the EV represents a necessary condition in the evaluation of ancillary service provision. Charging points availability may represent the bottleneck for a given penetration of EVs in terms of offerable bands, the range of power or energy that can be adjusted or controlled within a system to maintain grid stability, balance supply and demand, or optimize energy usage.

From a systemic perspective, the charging infrastructure is adapted to the local reality of the study area, considering the local charging needs. These points are then distributed at a greater granularity using local EV penetration, based on the concept that infrastructure maturity is driven by the charging demand of the population. Nominal characterization is completed with the nominal capacity of each charging point, specifying the nominal power $P_{nom,cs}$. Fast charging has been overlooked due to its still-limited adoption, and public infrastructure capabilities are split between 7.4 kW and 22 kW according to diffusion rate ($p_{7.4kW}$ and p_{22kW}). From an operational point of view, each charging point has attributes related to a time-varying state and power level. Specifically, two possible states have been defined (free and busy) for the attribute of availability S_t, while a numeric value, upper bounded by the nominal power of the charging point, is given for the attribute of charging power $P_{ch,t}$ at each time step.

The infrastructural layer of the charging points can be merged with the physical layer of traffic. EVs requesting charge are labeled and provided with their extensive energy needs. Given the finite number of charging points, a new attribute for each EV requiring charging is defined. Considering the entire stay time, a vehicle's state can range between waiting to be connected, connected, charging, and charged. At the end of each trip, an EV can be directly connected to the charging station, or must wait if all the area's spots are occupied. Once connected, the charging process can start immediately or, as extensively described in Section 2.3.3, be shifted within its stay time. For homeward trips, the states are limited to the last three, as it is assumed that vehicles requiring charging when returning home will always have infrastructure availability. The presented framework is entirely reported in Figure 2.

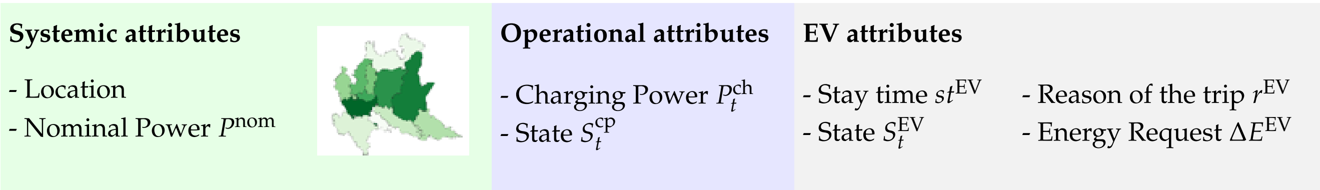

Figure 2. Charging infrastructure and EVs operational framework.

2.3.3. Uncontrolled Charging Power Demand

Given the operational framework described in the previous paragraph, the incremental eMobility-related demand profile can be constructed, resulting from the interaction of the TM and infrastructural layers. To mitigate inaccuracies introduced by the absence of an updated, geoinformed database of public charging points, the capability limit of the infrastructure is evaluated at a province level. In other words, the arrivals of cars, monitored at a high granularity deriving from the TM, are collected and continuously compared with the occupancy level of the charging points in a broader area. Charging will start as soon as the travel ends, employing Algorithm 1 to simulate the process.

Algorithm 1 Pseudo-code for charging process modelization

```
Assign the charging power of the given charging point;
Compute the charging time needed to fulfill the energy request;
Compute the charging end time frame;
Apply a mask to identify time frames where the trip is charging;
Populate the time-varying vector P_t^{ch}.
```

According to the purpose of the travel, as discussed in Section 2.3.2, the charging power is either stochastically determined with a given probability or is a fixed value considering domestic charging infrastructure. The charging power is held constant throughout the process, overlooking the dependence between the power set point and the SoC managed by the battery management system.

To address the issue of a trip ending in a region where charging capacity is already saturated, a logical solution that aligns with real-world practices was implemented. The proposed solution relies on the idea that if a charging point is occupied upon the vehicle's arrival, the charging process does not commence immediately. Most Mobility Service Providers (MSPs) offer applications allowing users to book charging points. These apps provide information on when a charging spot will be available, enabling users to plan their charging accordingly. The chosen approach delays the start of the charging process until a charging spot in the same area becomes free. This ensures that the vehicle can begin charging once a spot is available without unnecessary waiting. It is crucial to ensure that the delay in starting the charging process does not exceed the departure time dt^{EV}, calculated as in Equation (6).

Subsequently, once the charging infrastructure has been characterized, the end of charge eoc^{EV} can be easily computed and compared with dt^{EV}. Since these are independent processes, the charging process may be not completed due to a short stay time and long driving distance. These marginal instances will be labeled as originally incomplete and, with an a posteriori procedure, the two time limits are forced to coincide. Employing the described procedure, the operational attribute, charging power, of each charging point is characterized at each time step. The time-varying passive load profile of a given region, resulting from the subset of charging station C for a given instant t, can be calculated as in Equation (7).

$$P_t^{uncontrolled} = \sum_{c=0}^{C} P_t^{ch} \tag{7}$$

2.3.4. Enhanced Band Development Procedure

EVs can contribute to provisioning grid services, typically high-power, characterized by relevant power interaction for a limited amount of time [19]. To significantly impact grid stability, it is essential to offer a uniform, non-negligible flexibility service throughout the day. To achieve this objective, a novel procedure was implemented to enhance the band available to the aggregator for market bidding. The procedure focuses on the number of available vehicles for providing flexibility services during the most critical hours of the day. The core idea is to delay charging sessions that are scheduled to start during periods when the load profile exceeds its average, thereby filling the valleys and aiming for a more uniform load profile. A more uniform demand profile directly impacts the flexibility provision, reducing the offerable band volatility.

Each time a modification to the charging start time is implemented, two pivotal constraints must be considered based on the type of travel being processed. First, to keep the load-shifting procedure neutral on the user side, energy requirements deriving from the TM must be respected. In other words, the charging, despite being delayed, must terminate within the departure time dt^{EV}. Secondly, flexibility services must not impact the profitability of charging spots limiting the charged energy. In other words, postponing a charging process is acceptable as long as no other vehicles are waiting to charge in the area. Practically, for "Return Home" travels, there are no restrictions related to the availability of the charging spot. While, for the other types of travel, it is necessary to check for any reservations at the charging point in the time windows immediately following the end of the charging process. The entire procedure is summarized in Algorithm 2.

Algorithm 2 FCR–Band Enhancement Procedure

```
for iteration in Iterations do
    Find and select all time windows when the load profile is above its average
    for time window in Time Windows do
        for travel in Travels do
            if travel reason r is Return Home then
                Check if the travel can fulfill its energy need even starting its charging process one-time window later (charging end does not coincide with charging limit). If yes, update the power list P_t^ch postponing the charging.
            else
                Check the same energy constraint and that there is at least one free time frame after charging ends in the availability list of the associated charging point. If yes, update the power list P_t^ch postponing the charging.
            end if
        end for
    end for
end for
```

Concerning Figure 1, the temporal configuration of the charging session has become more complex. The arrival time, denoted as at^{EV}, no longer directly corresponds to the charging start time, cs^{EV}, as presented in Section 2.3.3. Even when a vehicle is connected to the charging infrastructure, the start of the charging process can be delayed to smooth the incremental power demand. Extreme conditions of these charging delays are illustrated in Figure 3. Essentially, a charging process can be postponed between two static user-related temporal boundaries, at^{EV} and dt^{EV}, as long as the charging can still be completed within this window. Additionally, the intermittency of an ongoing charging profile and partial load charging has not been considered in the current charging logic.

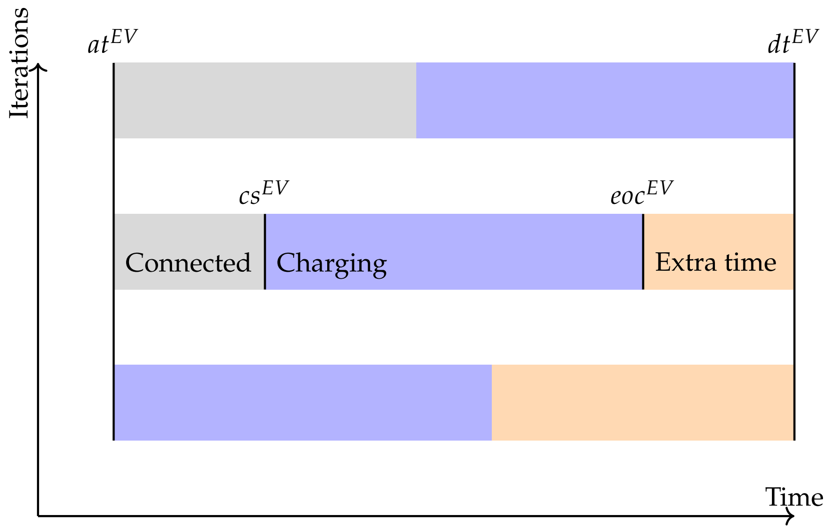

Figure 3. Explanatory application of load shifting algorithm.

2.4. Ancillary Services Modelling

To effectively harness EVs for grid integration, a comprehensive grasp of the regulatory landscape governing their participation in the ancillary services market (ASM) is essential. ASM is the venue where Terna S.p.A., the Italian TSO, procures the resources that it requires for managing and monitoring the system relief of intra-zonal congestions, creating energy reserve and real-time balancing [20]. EVs' aggregations are designated as "Unità Virtuali Abilitate Miste" (UVAMs). Terna defines UVAMs as entities comprising various components such as production units, storage systems, and consumption units. Once qualified, UVAMs must navigate specific procedures for ASM participation. Responsibilities include executing dispatch orders and submitting a daily baseline, with allowances for modification as per guidelines stipulated in the Grid Code [21]. Furthermore, the UVAM manager must communicate power distribution among UVAM points on a quarterly basis and provide structured offers for reserve allocation. These offers encompass quantity–price pairs tailored for the ASM programming phase and the balancing market, ensuring each offer meets or exceeds a threshold of 1 MW in absolute value.

2.4.1. Frequency Containment Reserve

FCR services help to slow and stabilize frequency changes through rapid, automatic adjustments in generator output. These services can be provided by various types of generators, potentially including an aggregate of EVs. Primary reserve is always allocated proactively (well in advance of real-time) through specific auctions in which operators bid for their availability to provide primary regulation reserve during a certain period in exchange for payment [20]. Resources are assumed to provide frequency response based on a droop curve with a deadband, as described in Equation (8) and referenced in [22].

$$K_p = \frac{\frac{\Delta f}{f_{nom}}}{\frac{\Delta P_e}{P_{eff}}} \tag{8}$$

where ΔP_e is the power set point of the frequency regulation, $\frac{\Delta f}{f_{nom}}$ the frequency deviation in p.u., and P_{eff} is the BESS nominal power.

According to their resource capabilities and technical characteristics, ancillary services can offer flexibility in one or both directions. Specifically, within the framework of FCR, a resource can increase its power output if the measured grid frequency exceeds the upper bound or reduce it if the frequency falls below a threshold. Services that operate in only one direction are referred to as one-direction services, while those that operate in both directions are called both-direction services. Given that charging is modeled as occurring at the nominal power of the charging point, a one-direction service that decreases charging power is most suitable for EV charging. However, for this study, a both-direction service is designed. To ensure the capability limits of charging points are not exceeded, the undisturbed charging power was fixed to 90% of P^{nom}. The presented framework regarding charging point capability dependence on the case study is reported in Figure 4.

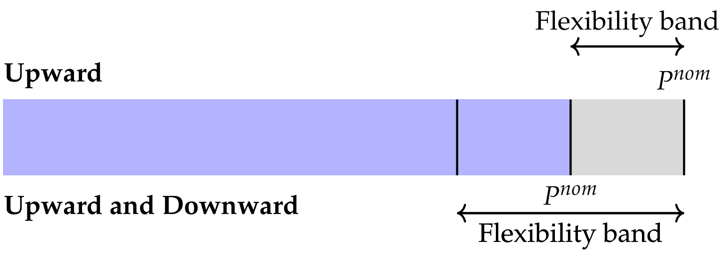

Figure 4. Flexibility margins of charging points.

2.4.2. Restoration Reserve

FCR services act to slow and arrest changes in frequency and are not limited to primary frequency reserve. Specifically, to restore the margin used, TSO can call single producers. This, non-automatic restoration service falls under the name of mFRR. In Italy, Terna allows each qualified unit to participate in the market, offering couples energy–price restorations for each hour of those between each session of ASM. The energy bid on the market corresponds to a reduction or increase in the power output of the plant. In the case of the study, EVs' aggregate may be selected for mFRR in certain hours, the energy uptake must be reduced or increased to a certain value and the new set point reached must be kept for the whole hour duration. The longer time scale of the required variations for this service makes it more challenging to keep the constraints regarding the full charge of single vehicles satisfied. mFRR modelization can be broken down into three subsequent, hierarchically ordered steps, illustrated in Figure 5.

Firstly, as in FCR, mobility needs represent the bottleneck concerning the amount of energy the aggregator can offer on the market. In line with Section 2.4.1, the principles of neutrality on the user side in terms of charging duration and infrastructure availability also guide the modelization of this service. The flexibility margin calculation is case-sensitive, depending on the direction, upward or downward, of the service. In the first case, given an expected charging schedule for each charging vehicle, the quantity Δ, the maximum admitted charging power necessary to supply the required energy within the temporal boundaries, is calculated. As anticipated, a necessary condition for each vehicle to contribute to the offerable band is the infrastructure availability, i.e., the absence of vehicles waiting for the charging point to be free. If this condition is satisfied, the vehicle that has a sufficiently long stay time to complete the charging at a lower charging power, will offer a band bnd^{EV} resulting from Equation (9). On the other hand, when increasing the charging power for stability purposes, the bottleneck is represented by the battery capacity: Δ is in this case the maximum increment that can be imposed on the charging power given the energy demand of the vehicle. The offerable band is again calculated, employing Equation (9). The two calculation mechanisms and the original charging profile are reported in Figure 6. Aggregating charging stations, the available bands are calculated as in Equation (10).

$$bnd_t^{EV} = \min(\Delta, 0.1 \cdot P^{nom}) \tag{9}$$

$$bnd_t^{tertiary} = \sum_{c=0}^{C} bnd_t^{EV} \tag{10}$$

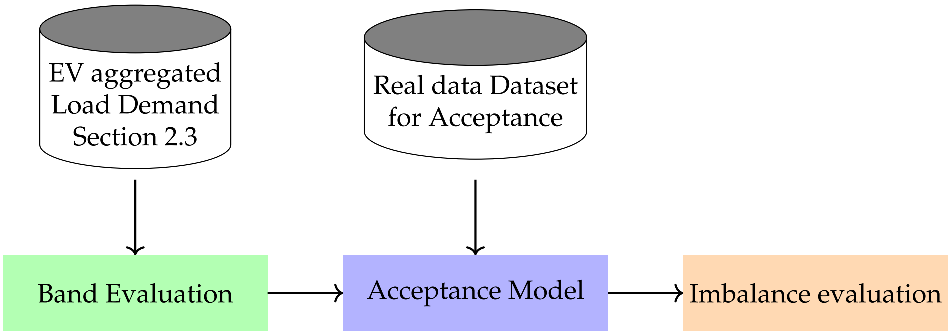

Figure 5. mFRR evaluation procedure.

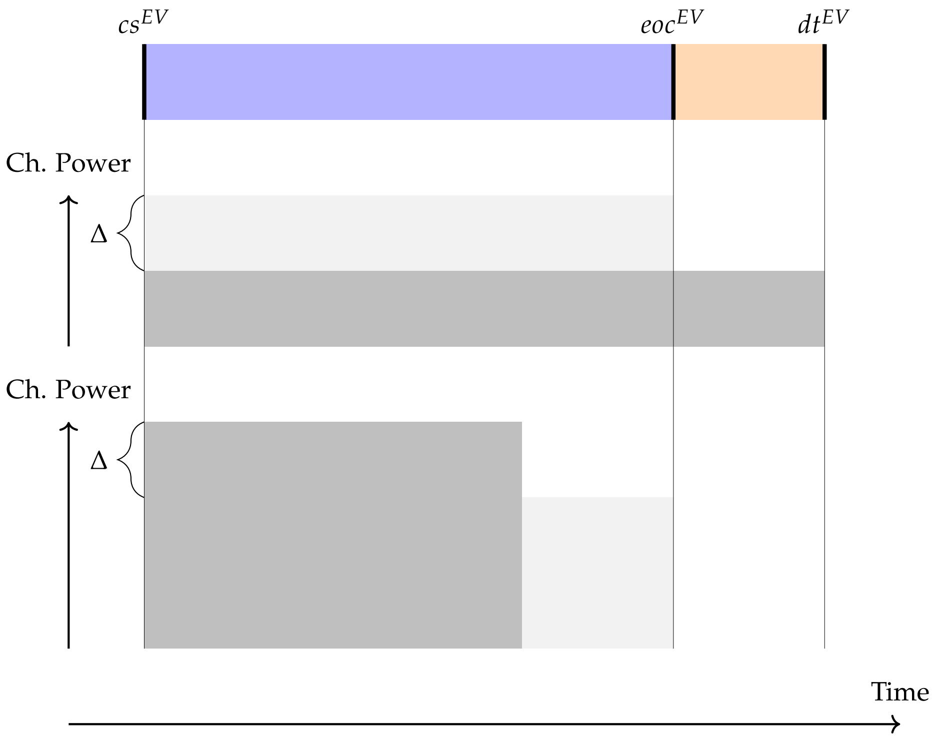

Figure 6. Alternative charging processes for tertiary reserve. The original charging schedule is indicated in light gray, with dark gray for the resulting charging strategy.

As anticipated, while in FCR, set-point variations are automatically triggered by frequency deviation; for mFRR, services are required from the TSO. Understanding recurrences and the criteria for acceptance employed is pivotal to model this service. For this reason, a data-based acceptance model was developed to evaluate the effectiveness of participating in the market as an EV aggregator. This acceptance model relies on an acceptance probability matrix $AP^d_{p,b,h}$ with $d \in D$, where D is the set containing the two possible directions of the energy flows (i.e., injecting or absorbing energy). Moreover, as evident in the matrix definition, the acceptance probability is modeled as a function of the offered power (i.e., the energy offered over a time window of one hour can be translated in power terms) and the price [23,24]. The index h represents the temporal coordinate: a different matrix is available for each time step of the simulation. Note that, concerning the temporal granularity set by the traffic model, the same matrix is repeatedly employed over the same hour. Applying a random selection process, according to the case study definition, given the hour of the day and the flexibility band for tertiary reserve deriving from Equation (10), it is possible to derive the acceptance probability, ap, from the TSO to provide the service.

The last step of the procedure involves the load profile and the imbalance evaluation. To satisfy the request from the TSO, the aggregate needs to generate a deviation from the set point equal in power, keeping this new condition for the whole hour in which it is called to provide the service. On the other hand, to complete the charging process, energy deviation must be counterbalanced in the following time steps. At this point, additional complexity is added to the methodology: as with any other participant in the market, aggregators must submit their net consumption in advance, and, although not always detrimental, the impact of imbalances must be included in the economic assessment. The impact is strongly dependent on the "zonal imbalance" which corresponds to the total deviation computed as the sum of all the imbalances of the single production and consumption units belonging to a specific zone. If the imbalance of the single unit has the same sign of the zonal one, it means the plant is exacerbating the existing deviation. Conversely, if the sign of the imbalance of the unit is opposed to the zonal one, the unit is relieving the local imbalance. The TSO can adopt two different approaches when dealing with imbalances: the single pricing (SP) or the dual pricing (DP) algorithm, presented in Table 1.

Table 1. SP and DP remuneration logics.

		Unit Imbalance [+]	**Unit Imbalance [−]**
Zonal Imbalance [+]	SP	Receives: min (avg ASM upward; DAM)	Pays: min (avg ASM upward; DAM)
	DP	Receives: min (min ASM upward; DAM)	Pays: DAM
Zonal Imbalance [−]	SP	Receives: max (avg ASM downward; DAM)	Pays: max(avg ASM downward; DAM)
	DP	Receives: DAM	Pays: max(max ASM downward; DAM)

2.5. Economic Feasibility Analysis

To conduct a feasibility assessment of the economic value of the flexibility service potential for an area, an economic analysis is performed to estimate the potential revenues generated by the proposed services. Economical values should be assigned to each evaluated service to provide an overall estimation of the possible revenues for the study area. In the current Italian regulatory framework, no remuneration is provided to plants that contribute to primary frequency control, as it is conceived as a mandatory service for relevant plants. Despite this condition, the capacity market in Central Europe offers the possibility to perform a preliminary economic assessment. The market model in place remunerates band availability with a temporal frequency of four hours. Moreover, the existing regulatory framework mandates the service to be offered in both directions. Thus, numerically, the offerable band must be computed as the minimum band that operators can safely offer on the market:

$$bnd_{mw} = \min(\min(\text{Upward Band}), \min(\text{Downward Band})) \tag{11}$$

where mw is one of the six four-hour market windows.

In the remuneration of mFRR, the price deviation from DAM plays a crucial role, since it not only influences the margin for the aggregator but also has an impact on the acceptance probability.

3. Case Study and Input Data

Numerical assumptions, input profiles, and scenario characterization are presented in this section. Firstly, the OD matrix, which maps the mobility needs of a specific area, is pivotal. Data for this case study are provided by Regione Lombardia in [25]. The heatmap in Figure 7 captures the large-scale pattern on a regional scale. The number of trips is represented on a logarithmic scale to highlight non-diagonal elements. Similarly, Figure 8 illustrates the temporal distribution of recorded events, highlighting the varying patterns associated with different travel purposes. Work-related travels are predominantly concentrated in the early morning hours, reflecting typical commuting times. Similarly, study-related travels follow a similar early morning peak, aligning with school and university schedules. In contrast, leisure and return home travels exhibit a different pattern, with a pronounced peak in the afternoon and more temporal dispersion. This suggests that these types of travel are more flexible and spread out across the day, unlike the more regimented schedules of work and study travel. Numerical assumptions for μ_r in Equation (3), which pertains to the average, reason-dependent stay time for each travel instance, are detailed in Table 2.

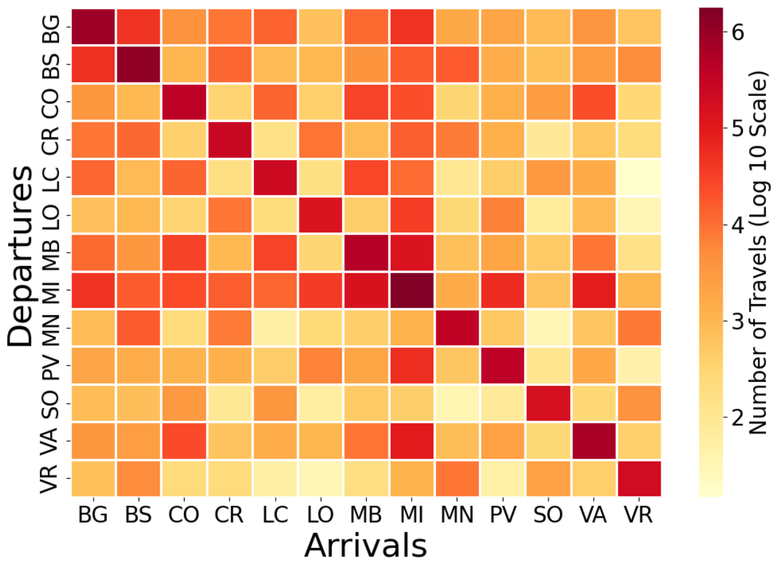

Figure 7. Mobility flows representation on a province level.

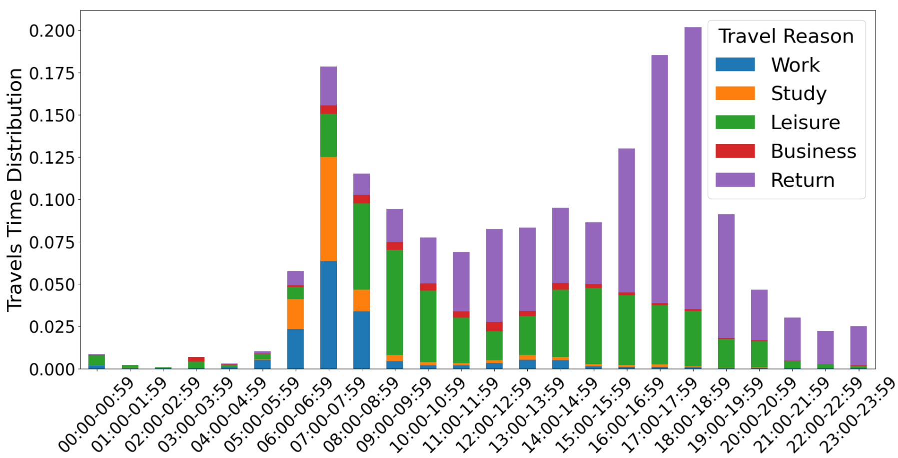

Figure 8. Temporal distribution of the OD travels during a typical working day.

Table 2. Average stay time as a function of travel's purpose.

Staytimes μ_r			
Work	Study	Return Home	Leisure
8 h	6 h	11 h	4 h

Secondly, information on the current electrification level of the light-duty transportation sector is taken from [26]. Although the current level of EV penetration in Lombardy is below 1%, a 2.5% penetration scenario is assumed to be a reliable depiction of a likely near-future condition. Additionally, EVs are geographically distributed, as shown in Table 3, which reports the current distribution in the study region. This distribution is assumed to be the result of the combined effects of morphology, economic factors, and local mobility habits, and is therefore considered invariant over time. Infrastructure-wise, the number of public charging points was set to 15,000; possible nominal power outputs are 7.4 kW and 22 kW, distributed, respectively, with a share of 80/20% [27]. Private charging was assumed to be performed uniquely at 7.4 kW nominal power. A travel-independent ACR equal to 0.2 kWh/km was selected.

In parallel, two relevant profiles are needed to evaluate the ancillary service potential of the study area numerically: first of all, a real-life frequency record is imported into the framework. To fit within the temporal granularity of the mobility model, the worst measurement (i.e., widest deviation) measured over a time window of five minutes, the temporal discretization time step of the TM, was considered. TSO's intervention was assumed to be triggered whenever the frequency value deviates more than 20 mHz from the nominal frequency of 50 Hz. A graphical representation of the considered profile is offered in Figure 9. Economically-wise, as anticipated in Section 2.5, the capacity market in central Europe, the TSOs of those areas of 50 Hertz for Germany, and Tennet for the Netherlands, is taken as a reference [28]. Prices are reported in € /MW and are constant for a given time window.

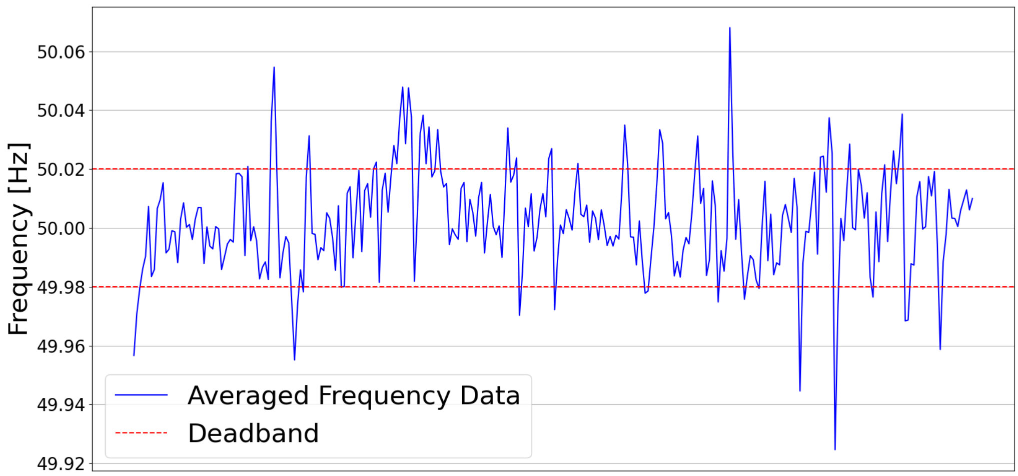

Figure 9. Daily averaged frequency profile.

On the other hand, concerning mFRR, the database of calls by Terna is included in the analysis. Probabilities, derived from historical records and employed in this work, are represented in Figure 10. Finally, the imbalances' economic evaluation relies also on the record for DAM and ASM prices from [29].

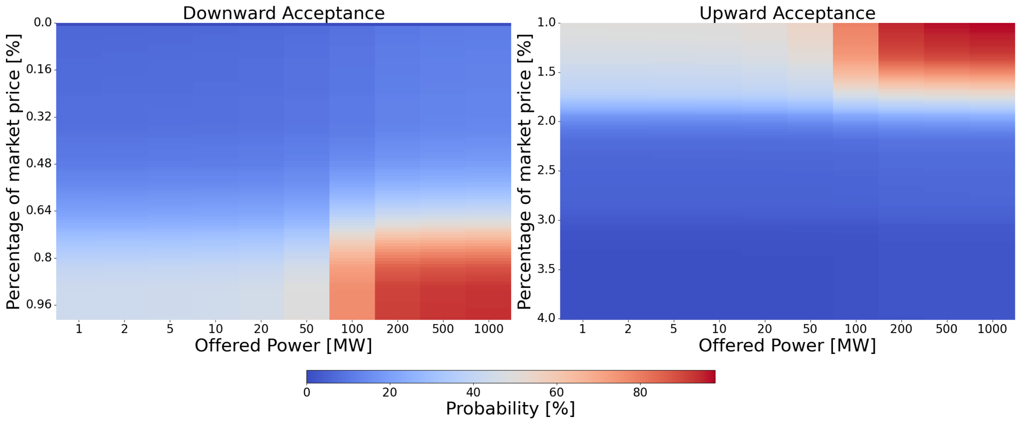

Figure 10. Acceptance probability for mFRR.

Table 3. Probability of assigning an electric travel to each province in Lombardy.

BG	BS	CO	CR	LC	LO	MN	MI	MB	PV	SO	VA
11.4%	14.4%	7.4%	3.1%	3.8%	1.6%	3.2%	38%	8.9%	3%	1.7%	3.4%

4. Results and Discussion

The objective of this procedure is to numerically evaluate the ancillary service potential for a given EV penetration scenario in a specified study area. The chosen case study is the Lombardy region, the most populated and economically significant area in northern Italy. In this section, two different use cases are discussed and compared. Specifically, the additional demand in Simulation 1 is constructed using uncontrolled charging, while Simulation 2 employs the band enhancement algorithm.

4.1. Traffic Model Output and Uncontrolled Charging Profiles

The most relevant output of the TM is the spatial–temporal mapping of each recorded travel of the OD matrix. The two coordinates are depicted in Figure 11, illustrating the additional demand imposed by EV charging on equivalent primary substation areas. The incremental load is not uniform over time due to drivers' habits. Uncontrolled charging reflects this new class of load, representing the mobility needs of EV users. Specifically, peak demand occurs in the late afternoon, induced by return home travels and coinciding with high stress already in place on the electric network. The impact is not equally distributed among the areas. Highly urbanized locations experience the greatest impact due to the combination of population density and economic factors. However, a single conclusion cannot be drawn for semi-urban or rural areas. For certain areas, local mobility, characterized by higher average travel ranges due to nearby commercial or industrial areas, is more impacted compared to localized communities with lower mobility indices.

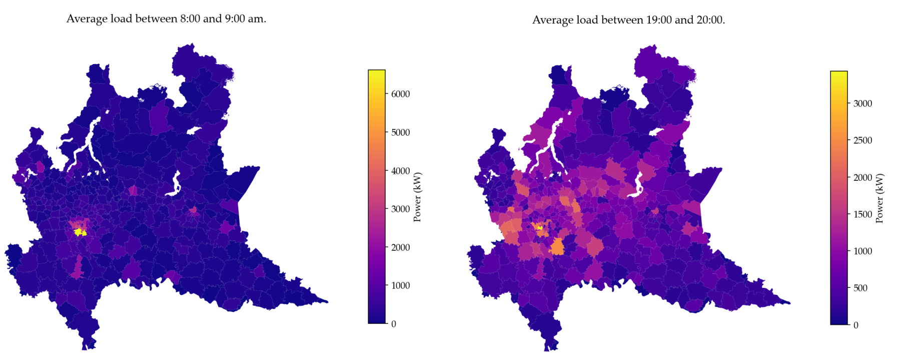

Figure 11. Incremental EV-related demand aggregated on a primary substation equivalent area.

A similar conclusion can be partially derived from Figure 12, which represents the power delivered by public chargers in each province. Although this figure primarily captures work-related demand, as home charging typically occurs on private wallboxes, it is evident that local characteristics significantly influence power demand. Furthermore, given the independent modeling of charging infrastructure capacity based on EV penetration and the mobility needs of each area, the infrastructure's capacity becomes saturated, as illustrated by the province of Brescia (BS) in orange.

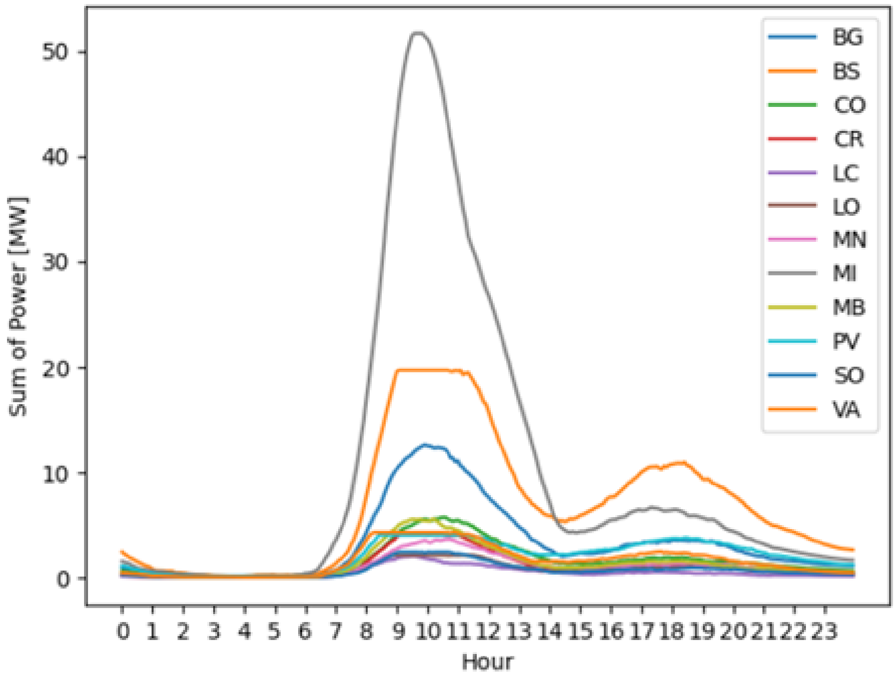

Figure 12. Incremental EV-related load due to public charging processes on a province scale.

An aggregated result for the total demand is reported in Figure 13. Aggregating on a spatial level, the incremental demand of the entire study area is reported in red, split into public charging and home charging. Guided by population habits, the profile shows two peaks: one in the morning between 9 a.m. and 12 a.m. that is mostly attributable to morning travels for work reasons that start charging once arrived at the workplace, and a second, which is located around 8 p.m. and is instead related mostly to return home trips that exploit domestic charging to fulfill their energy needs.

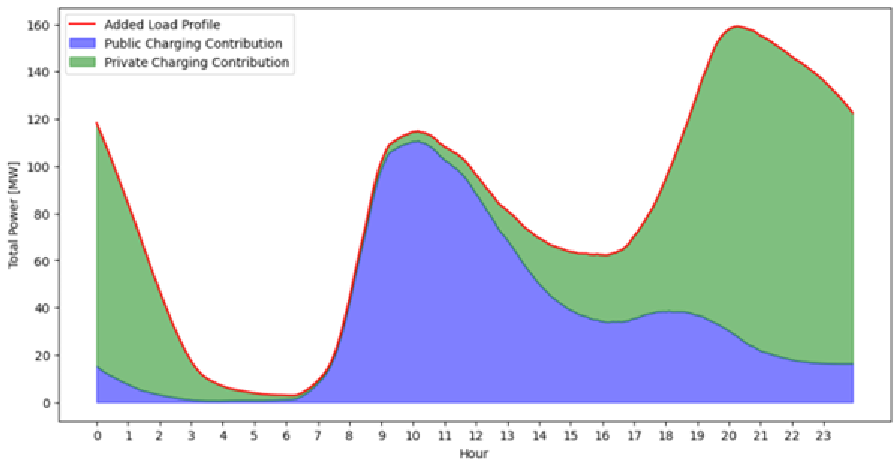

Figure 13. Incremental EV-related load profile with contributions from public and domestic charging.

The additional demand, combined with the stay time of each vehicle, allows for the computation of ancillary service bands using the routines described in Section 2.4. From a flexibility perspective, the available band is a time-varying attribute, dependent on the number of connected EVs and the drivers' needs. For each time interval, the power deviation that the aggregator can handle while satisfying all constraints is reported in Figure 14. Considering the factors mentioned above, it can be concluded that the difference between the blue and red curves is due to the significance of the second constraint over the first. In other words, it can be observed that the available band in the "Increase Charge Direction" directly follows the corresponding load profile trend, as the number of connected EVs is the primary bottleneck, and higher charging powers simply reduce the charging duration. Conversely, delaying full recharges beyond a certain threshold can be unacceptable from both user and infrastructural perspectives. Consequently, the band difference is most pronounced in the middle of the day, when public charging is predominant. The additional limitation, imposed in energy terms, present for tertiary reserve service is evident when comparing the blue lines of Figures 14 and 15: being more energy intensive, the offerable upward band is greatly restricted due to the lower stay time and finite infrastructural capacity.

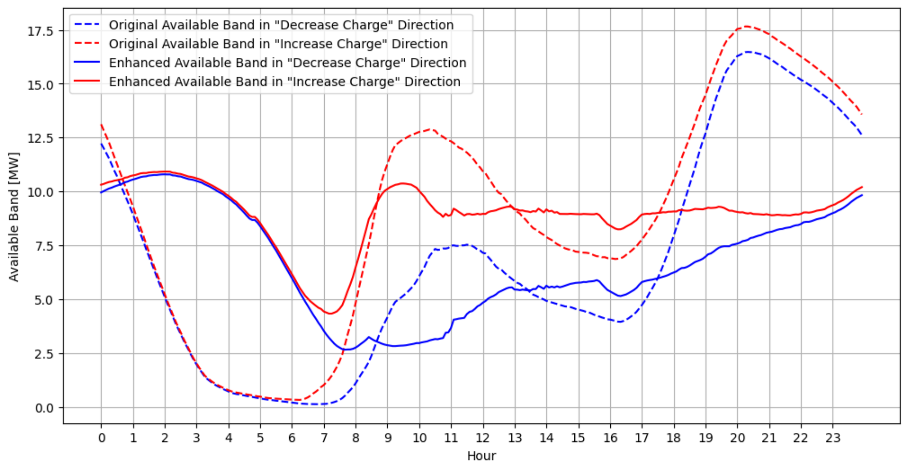

Figure 14. Available bands for FCR.

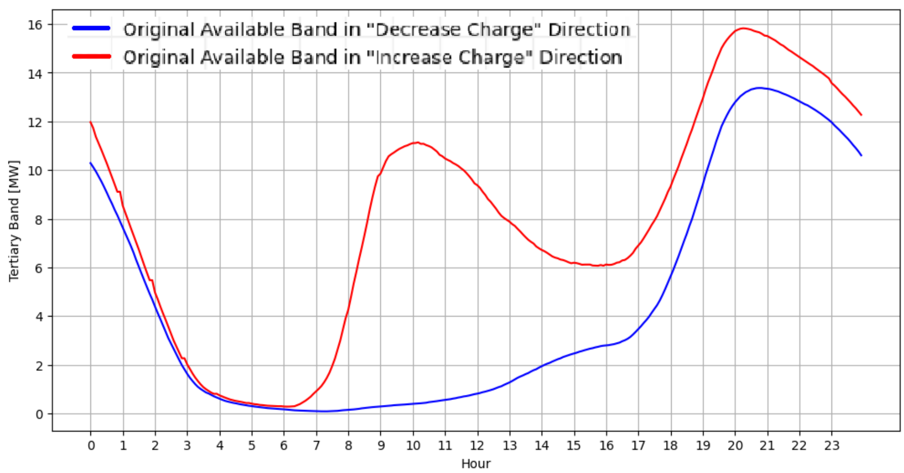

Figure 15. Available bands for mFRR.

4.2. Band Enhancement Impact

Dealing with a single class of consumers in a power network can significantly hinder flexibility and operational efficiency. This is primarily because a homogeneous consumer tends to exhibit similar consumption patterns, leading to periods of synchronized high demand.

The application of Algorithm 2 on the power demand derived from uncontrolled charging logic in Figure 13 results in a more regular profile with reduced valley-to-peak difference. In Figure 16, the evening peak is easily shifted over the night, exploiting the wider stay time of return home travels. Numerically, the global peak is reduced by 37.9%. On the other hand, the work-related peak demand is only partially mitigated due to the intrinsic limitation of public charging infrastructure. The benefits are not limited to mitigation of grid congestion, as decoupling the power provision from the user habits allows us to enlarge the effectiveness of ancillary services. Specifically, bands for primary frequency control are more regular, showing less variability and better fitting in the four-hour window market framework. Employing Equation (11), the offerable band on the market is highly affected by the demand shifting, as is visible in Table 4. Tertiary bands are also enlarged, though to a limited extent due to stricter constraints. The impact of this approach is also evident from a spatial perspective: visually, the absence (Figure 17) and the very localized band availability (Figure 18) are not only spread over time but also diffuse across space, enabling a more homogeneous service.

Table 4. Flexibility bands in MW considering the two strategies.

Time Slot [h]	0–4	4–8	8–12	12–16	16–20	20–24
Uncontrolled charging	0.77	0.13	1.08	4.07	3.95	12.67
Band Enhancement	9.78	2.66	2.75	4.84	5.15	7.58

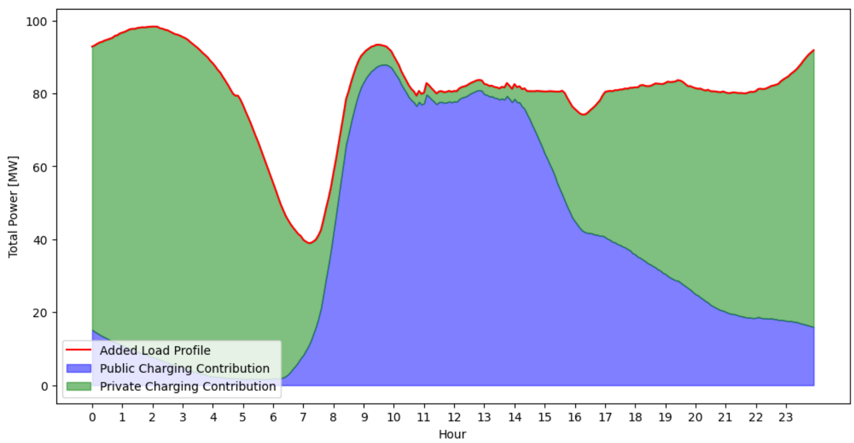

Figure 16. Aggregated demand after the application of band enhancement algorithm.

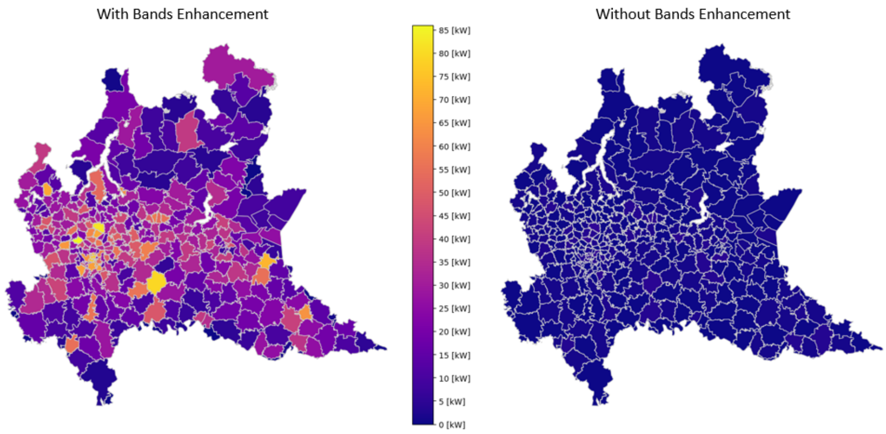

Figure 17. Spatial distribution comparison at 5 AM of FCR band.

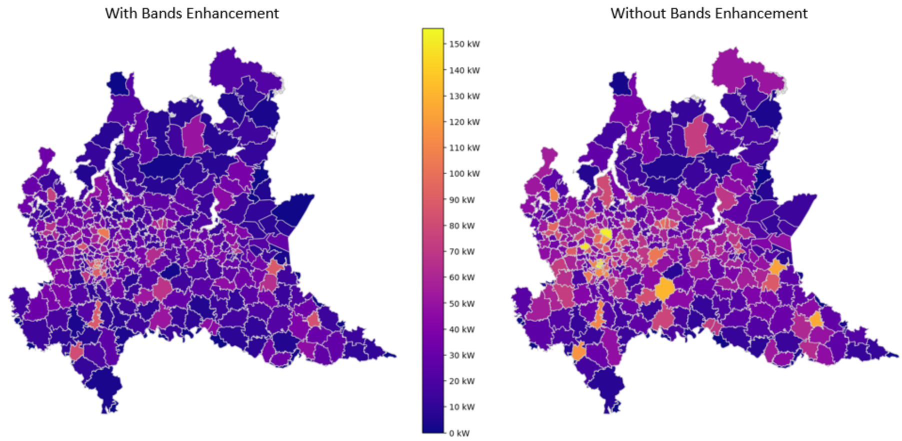

Figure 18. Spatial distribution comparison at 8 PM of FCR band.

4.3. Economic Evaluation

To assess the potential revenues generated by the modeled services, an economic analysis is performed. Economical values are associated with each of the proposed services to gain an estimation of possible revenues, determining technology maturity and competitiveness.

Combining the input dataset presented in Section 3, the economic comparison of the possible alternatives is reported in Figure 19.

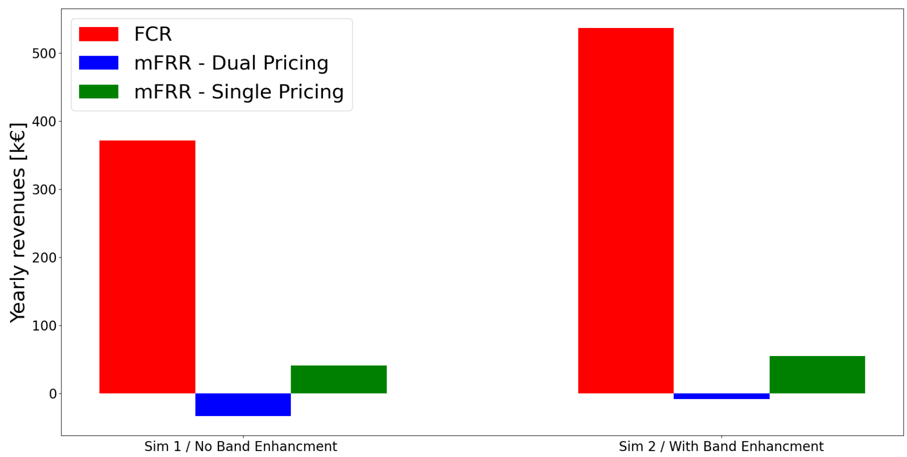

Figure 19. Aggregated demand after the application of band enhancement algorithm.

Multiple considerations are possible: firstly, primary frequency regulation, a power-intensive service, represents the most relevant source of value imposing fewer constraints on the charging processes. In contrast, given the simulated level of penetration and the modeling of the charging infrastructure, energy-related services such as tertiary reserves are less suitable. Secondly, the effectiveness of the band enhancement algorithm is testified by a better economic result: the offerable band in the six market window is greater, and the same improvements are testified by better results in tertiary revenues. Finally, the dual pricing paradigm resulted in far more of a penalization for the evaluation of imbalances, entirely counterbalancing the revenues deriving from the mFRR. Regardless of the simulation number, and considering the total number of vehicles contributing to the economics in Figure 19, the direct marginal economic benefit for each EV owner is limited to below EUR 10/year, which, alone, is insufficient to justify massive participation. However, it is worth noticing that this represents an average value, shared among all the different resources (i.e., EV owners) regardless of the flexibility offered. In other words, the yearly revenues may increase for a subclass of users (i.e., domestic users charging during the evening) better fitting their charging profile and the network infrastructure necessities.

4.4. Policy Implications

Policy-wise, ensuring consistent bandwidth availability throughout the year for flexibility, whether on a 24-h basis or for specific 4-h periods, is essential for effective remuneration. Additionally, while providing greater bandwidth during peak periods (e.g., 17–20) may yield higher ASM prices, it is important to prevent strategic behaviors that could disrupt system stability. Therefore, it is recommended to promote or mandate Time-of-Use (ToU) tariffs for Charging Point Operators (CPOs). Such measures would incentivize better load management and naturally smooth out peak demands, particularly during critical system hours, ensuring a more stable and efficient energy distribution. As an example, the energy cost in two possible electricity bill schemes, namely fixed vs. ToU, and ASM prices for mFRR, as per German 2023 data, is reported in Table 5 [28].

Table 5. Capacity prices for mFRR in Germany in 2023, the data source comes from Ref [28].

Time Slot [h]	0–4	4–8	8–12	12–16	16–20	20–24
Average capacity prices [€/MW/h]	0.46	1.14	3.48	1.52	5.00	3.41

The proposed opportunity value in EUR/MWh is the net value of withdrawing energy and then selling upward flexibility on ASM, considering a fixed award rate for ASM bids (i.e., 20%) and the actual mileage for the mFRR (the activated MWh per awarded MW) in each time slot. Only variable costs are considered, since other costs (e.g., grid costs) are invariant in the proposed analysis. Assuming fixed the total consumption throughout a day, a positive opportunity value in an hour indicates that it is worth increasing the consumption in that hour, to increase available upward flexibility. As can be seen in Figure 20, in the case of a fixed consumer's bill cost, the opportunity value is positive during the evening peak (i.e., 17–21), highlighting a push towards consuming in this period. In contrast, with a well-designed ToU tariff, there is significant convenience in consuming during daylight (i.e., 13–16) and during the night (i.e., 0–4), shaving the peak during the evening.

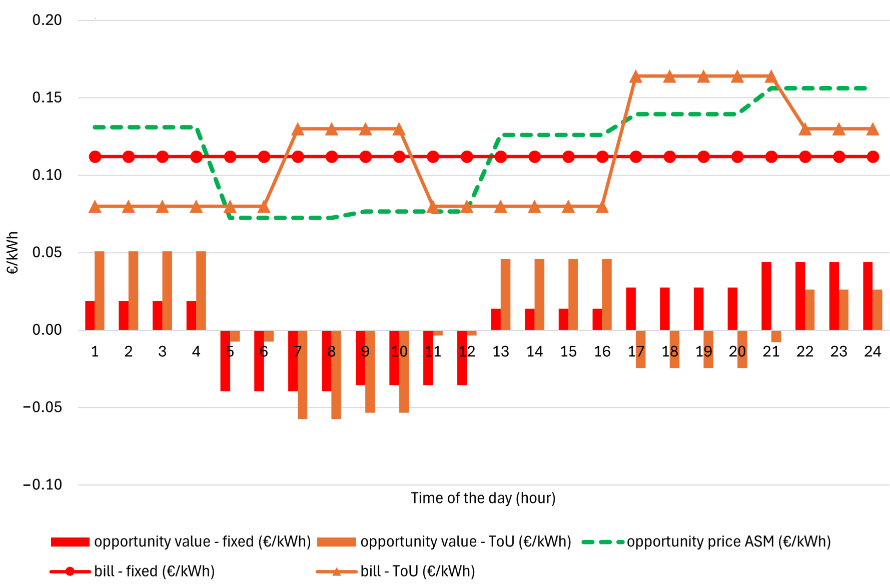

Figure 20. Opportunity value of consuming in different hours, considering bill costs and provision of upward service on ASM.

Secondly, on the market side, single price will definitively be the method used in the future, and is already in use at present in the EU. This approach, elected as the most cost-reflective, also proves itself effective for flexibility provision, as evidenced by the fact that valuable tertiary resources yield a positive net value only under the SP model. In contrast, under the DP model, it is not economically viable to make these resources available. Therefore, adopting and maintaining a SP model is crucial to ensure the efficient utilization and availability of tertiary resources, leading to a more stable and profitable energy market.

Moreover, the band enhancement strategy offers significant benefits to the system by reducing peak demand and peak withdrawal. This can be seen when comparing Figures 13 and 16, roughly halving withdrawal during the evening peak. Nonetheless, if the downward service is provided during peak hours, the withdrawal could increase despite the efforts of the resource. Therefore, it could be beneficial to apply network costs exclusively to charging withdrawals, exempting any dispatching services provided. This is already applied or under discussion in many regulatory frameworks. Additionally, implementing non-firm connections—where withdrawal power is not guaranteed in all time slots—can be a cost-effective solution. These connections should be priced lower, with a specific valuation for any reduction in power during critical hours, to further incentivize peak demand management and enhance overall system efficiency.

As a result of these considerations, indirect economic benefits may contribute to the limited direct profitability deriving from the service provision, increasing the marginal benefit for the EV owner.

5. Conclusions

In an era where the integration of renewable energy sources is accelerating, the increased demand for ancillary services highlights the strategic importance of efficiently managing EV charging processes. The proposed methodology seamlessly combines the accuracy and realism of bottom-up models with the estimated ancillary services potential for wider areas. Additionally, a GIS-based bottom-up methodology has proven effective in assessing the combined impact of mobility and the electric network using sparse information, resulting in outputs that are easy to interpret and apply. Uncontrolled charging limitations from a network perspective are identified through a direct comparison with a novel enhanced charging algorithm. This algorithm mitigates network stresses, by 37% in terms of global peak, while respecting user mobility needs and charging station availability.

In this framework, FCR and mFRR are configured in simulations considering the updated regulatory framework. Starting from the expected power demand, offerable bands are numerically calculated for each time step of the simulations and economically evaluated. FCR was more competitive with respect to mFRR due to the less stringent constraints, higher offerable bands, and a more suitable market framework. This study highlights that the current selection logic for mFRR disproportionately penalizes the resources with limited power capabilities, such as aggregates of EVs. It suggests establishing a framework that facilitates distributed storage resources when technically feasible, as they can offer economically competitive prices with no marginal cost for providing this service. From an MSP's perspective, the ancillary service potential of a specific subarea can serve as a strategic indicator for planning mobility operators' investments. This geo-informed approach can identify areas with high mobility flows but limited charging capacity, helping to prioritize investments based on spatial needs.

Market-wise, results on remuneration appear to be too modest to solely motivate an EV owner's participation in ancillary services, especially given the range anxiety of users and battery degradation. However, for a certain subclass of users, capable of offering flexibility in specific hours, the economic result may be different. In general, to harness the EVs potential as a distributed storage resource, a dedicated regulatory framework should be implemented to norm EVs' participation in ancillary service provision.

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Abbreviations

The following abbreviations are used in this manuscript:

ASM	Ancillary Service Market
DAM	Day-Ahead Market
DP	Dual Pricing
DSM	Demand Side Management
EV	Electric Vehicle
FCR	Frequency Containment Reserve
mFRR	manual Frequency Restoration Reserve
MSP	Mobility Service Provider
OD	Origin–Destination
PV	Photovoltaic
SOC	State Of Charge
SP	Single Pricing
TM	Traffic Model
TOU	Time Of Use
TSO	Transmission System Operator
UVAM	Unità Virtuali Abilitate Miste
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home

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