

Simulation of Flexibility Management with Coordination Function Based on Synthetic Data

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Abstract—The simulation of applications for Smart Cities often requires the use of artificially generated datasets to model and test various scenarios. This paper examines the generation of such artificial datasets and presents an innovative approach. First, an overview of the current state of the art will be provided, and existing systems for generating artificial datasets will be examined. Special emphasis is placed on their ability to adequately model the dynamics and growth of renewable electric vehicles as new loads. Additionally, the problem of dynamic growth in new loads is discussed in detail, along with how it can be generated for simulations. Conventional static approaches often fail to fully capture the complexity and variability of such dynamic systems. To address this issue, a new method for generating dynamic datasets is presented, integrating the growth of electric vehicles into the simulation. These approaches enable more realistic modeling of energy generation and consumption and contribute to improving the efficiency and sustainability of applications for Smart Cities. By applying these methods, decision-makers and developers of Smart City solutions can conduct more effective tests and make more targeted optimizations.

Index Terms—Smart Grid, Load Management, DSO / TSO-Electricity Grid, Metering Infrastructure, Coordination Function

I. INTRODUCTION

It can be observed that fossil energy sources in mobility and in private households are increasingly being replaced by electrical energy. The significance of fossil energy sources in mobility is continuously decreasing, as evidenced by the growing number of vehicles with electric propulsion being sold instead of gasoline and diesel cars [1]. This trend is also reflected in private households, where gas and oil heating systems are increasingly being replaced by heat pump systems and electric infrared heaters [2]. This leads to an increasing demand for electrical energy and underscores the growing importance of a reliable electrical energy grid.

Ensuring uninterrupted grid operation becomes an growing significant challenge for grid operators due to the heightened load. This has also been recognized by some states, which

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enable the reduction of solar panel production or the throttling of the use of wallboxes and heat pumps to prevent overload situations through new laws. The requirement for consumers to be dimmable was regulated in Germany as of January 1, 2024, through the amendment of §14a of the Energy Industry Act [3]. This regulation primarily applies to new installations of private charging facilities like wallboxes, electric energy storage systems, and heat pumps. According to this provision, these systems must be controllable so that they can be reduced to a reference load of 4.2 kW in overload situations [4].

Furthermore, the law stipulates that economic incentives should be sent to consumers to encourage grid-friendly behaviour. Additionally, users should have the option to provide their flexible loads as contractually agreed flexibility to the grid operator outside of emergency regulations. This takes precedence over the control of individual consumption devices in grid-oriented operation. This means that measures aimed at optimizing grid stability and efficiency should primarily be promoted through incentives and contracts for adjusting grid connection capacity before considering the controllable consumption devices.

Against this background, two central challenges arise: firstly, the cost-effective expansion of the grid, and secondly, the implementation of intelligent systems such as coordination functions (COF) to prevent overload situations in the grid. One of the tasks of such a coordination function is to prevent overload situations by effectively coordinating flexibilities. These flexibilities may, for example, involve the time shifting of the use of heat pumps or electric vehicles (EV) to later time windows to avoid overloads [5]. However, it is still important to ensure the charging of vehicles to accommodate the users' needs while simultaneously stabilizing the grid.

Intelligent systems like a COF are typically developed, trained, and validated using simulations. For this purpose, realistic datasets are required to accurately reflect reality. This paper introduces procedures and methods for generating realistic data and contextualizes them within the framework of a long-term increase in controllable consumers. This enables the evaluation of central control mechanisms for their adaptability.

II. STATE OF THE ART

Now, several methods utilized by other authors for generating data on user behaviour and consumption patterns are presented. The main focus is on data related to electric vehicles.

In [6], it is assumed that each household owns at most one EV and a single charging station for electric vehicles. The battery capacity of an EV is assumed to be 24 kWh. It is also assumed that all EVs leave the system after 6:00 a.m. according to a Poisson distribution and return to the system with fully discharged batteries after 4:00 p.m. Consequently, the number of charging EVs changes over time. Additionally, this publication highlights the risk of overload situations in the grid with an increasing number of EVs and analyzes the critical point at which uncontrolled charging becomes problematic.

In [7], the authors consider a maximum of 500 EV in the distribution system, where the actual number of connected EVs depends on their mobility and state of charge (SoC). The arrival times of the EVs are generated from the data of the Pecan Street dataset. Since this dataset contains only about 80 EVs, the daily arrival times of these EVs are extrapolated, and a Gaussian Mixture Model is fitted to the probability distribution function. The departure times of the EVs are not included in the dataset, so the dwell times of each EV are randomly drawn from a Gaussian distribution with a mean of 8 hours and a standard deviation of 2 hours. The departure time of each EV is then calculated by adding the dwell time to its arrival time. EVs are disconnected from the grid when they are fully charged or manually unplugged, whichever occurs first. The battery size of each EV is randomly selected from four of the most popular models, considering battery capacities of 16 kWh, 30 kWh, 42 kWh, and 75 kWh. The SoC of each EV at the time of arrival is assumed to be uniformly distributed between 0 and 0.1. The data is designed for 10-minute time intervals.

In their study [8] on modeling EV charging load in the distribution network, the authors focused on critical parameters. The arrival and departure times of the EVs were generated from Gaussian distributions with a mean around 5:30 p.m. and a standard deviation of 1:00 hour for the arrival time, and a mean around 7:47 a.m. with a standard deviation of 0:23 hours for the departure time. The load model generated SOC values for each EV at the time of grid connection based on a Gaussian daily driving distance distribution with a mean of 40.0 miles and a standard deviation of 5.0 miles. Each EV is equipped with a 60 kWh battery pack and an onboard charger of 7 kW, resulting in approximately 30 A AC current for a nominal voltage of 240 V. All EVs were modeled with the same configuration.

In [9], actual meter readings from 42 households for a weekday in winter are used to generate the load demand. The data regarding the distances traveled by EVs and their availability are sourced from the results of the Australian "Smart Grid Smart City" EV trial for a typical weekday in winter [10].

The experiment documentation provides detailed monitoring data for 20 electric vehicles, including their commuting and charging data. Based on the findings from [11], the SoC used for EV journeys throughout the simulated day is estimated. The nominal power ratings for charging and discharging are considered for home charging via standard outlets at 1.8–3.6 kW. The efficiencies of the EV batteries are arbitrarily assumed to be between 90% and 95%. The SoC thresholds of all EV batteries are considered as 10% for minimum SoC and 90%–100% for maximum SoC values. The availability of the EVs is assumed when they are connected to the home outlet.

The presented papers have conducted extensive analyses on the emergence and management of overload situations, exploring various approaches such as decentralized multi-agent solutions. However, what has not yet been coordination function in conjunction with decentralized, semi-autonomous agents. These agents should be allowed to behave freely under normal circumstances but must navigate restrictions during overload situations. Additionally, the data set for overload analysis needs to be adapted to central coordination. Furthermore, there is a lack of an approach for generating data that allows. Could include, for example, the increase in electric vehicles in the system over time or adaptation to regional differences in the use of the power grid. It is important to incorporate such dynamic aspects into the evaluation of the solution to ensure its long-term robustness and effectiveness.

III. CHALLENGE AND RESEARCH QUESTION

In this context, only overload situations that can be solved using controllable consumers and are depicted in Fig. 1. are considered. Firstly, the broader context is examined. An overload that can be avoided through grid flexibility is influenced by two analysable factors. Environmental conditions such as fluctuating solar panel input on sunny days contribute to closing gaps in charging power demand. At the interface between environmental conditions and the power demand of controllable consumers, combined factors come into play. These include influences such as battery capacity or increased electrical vehicle consumption during cold months. Additionally, the demand for heating through the use of heat pumps or air conditioners falls within this domain.

The most challenging area in assessing the power demand by controllable consumers is user behaviour. The algorithm of a coordination function should be able to adapt to some extent to user behaviour, as this can vary greatly regionally. User behaviour includes, for example, continuity, meaning that a consumer's behaviour is consistent at certain time intervals. Additionally, synchronicity plays a role, which means that users have similar behaviour, such as all returning from work at the same time. Cost affinity refers to whether users respond to price incentives. Thus, the question arises whether users shift their charging process when prices for charging are cheaper at another time. Finally, growth also plays a role. More and more countries are planning to phase out combustion technology in vehicles, so some growth can be expected. The question then is how well an algorithm can handle this growth.

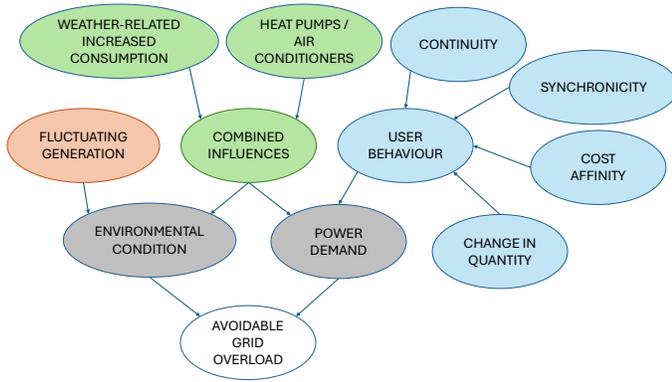


Fig. 1. Dynamic influencing factors of private households in this work. White: Objective Function. Grey: Relevant influencing factors. Blue: Most influence. Green: Limited influence. In red: Without influence.

To appropriately assess the influences in context, it is advisable to create a large network model with a variety of households and a variable share of EVs to also consider the growth rates. By simulating different user behaviours, the defined demands can be implemented by the agents in various ways. This way, the evaluation of the performance of an algorithm cannot only be based on coping with fixed scenarios under various operating conditions. The focus of this paper is on the increase in electric vehicles over a period of several years.

IV. COORDINATION FUNCTION WITH AGENTS

The generated consumption data is intended to simulate and optimize the operation of a central COF. Various communication use cases between the COF and the consumers are available for this purpose. The use cases are defined in VDE AR-E-2829-6-1 [12].

- **Limitation of Active Power Consumption:** The Limit of Power Consumption allows the ad-hoc reduction of the consumed power of a controllable consumer to 4.2 kW during an overload situation.
- **Monitoring of Grid Connection Point:** Here, the electrical measurands at the building's grid connection point are captured and transmitted to the COF at regular intervals.
- **Time of Use Tariff:** The aim of this use case is to send financial incentives to consumers in order to motivate them to shift their energy consumption to cost-efficient time slots.
- **Power Demand Forecast:** The user has a daily time window available during which they provide information to the COF about the planned power consumption.
- **Power Envelope:** There are time windows in which a reduced power consumption is defined in advance. This prevents overload situations.

This results in tasks and degrees of freedom for the COF, which must be processed algorithmically and validated accordingly in the simulation. The tasks of the COF function can be summarized as follows:

- Predictive detection of grid bottlenecks

- Creation of a schedule for a time unit
- Monitoring the current grid status to detect overloads
- Immediate readjustment when critical situations occur
- Continuous selfoptimization

V. CONCEPT FOR LOAD GENERATION

A. Vehicles and Growth

To generate loads for simulation, we are considering three different popular vehicles.

- **Opel Corsa E:** The aim of this use case is to send financial With a battery capacity of 48 kWh and an average consumption of 16 kWh/100 km, the Opel Corsa E is a very small vehicle in the compact segment.
- **VW ID3:** The VW ID3 has a battery capacity of 77 kWh and a combined consumption of 15.8 kWh/100 km. It belongs to the compact class.
- **BMW i7:** As a vehicle in the luxury segment, the BMW i7 has a battery capacity of 101 kWh and a combined consumption of 19 kWh/100 km.

For the growth rate of electric vehicles over time, based on current values in Germany, it is assumed that the share of electric vehicles in 2024 is approximately 5% and will increase to 90% by 2045. This results in a growth rate approximated by a third-order function. Fig. 2. illustrates the estimated growth of vehicles over time, where the X-axis represents the years, and the Y-axis represents the percentage share of EVs. Along this temporal function, it is decided daily when a new car and which model is added. This happens on a daily basis. The vehicle type is determined by a random generator. The probability for an Opel Corsa is 40%, the probability for a VW ID 4 is 40%, and the probability for a BMW i7 is 20%. Over time, this results in the growth rate depicted in Fig. 3.

B. Grid Model

For illustration, a small-scale model is chosen here, referring to 300 households connected to a transformer. The power consumption of the households has been recorded hourly over five years, serving as the dataset. The data is associated with this single substation, meaning that a granular allocation and analysis of overload situations is not possible here. It is apparent that under normal operation, no overload is expected. In the model, 80% of households own a car.

C. Movement Model and Charging Behaviour

The given information pertains to the total distance of the round trip. Of the individuals, 50% travel a distance of 10 km, 30% travel a distance of 35 km, and 20% travel a distance of 75 km. Additionally, it is considered that 3 trips of 10 km are made for errands or personal use of the car during the week. No commute to work is assumed on weekends. Once the system determines that a new vehicle is generated, not only a model is assigned but also a commute to work. It is assumed that the battery is fully charged at the time of purchase. It is assumed that users charge their vehicle daily. Over time, there is an increasing additional demand for energy, which varies

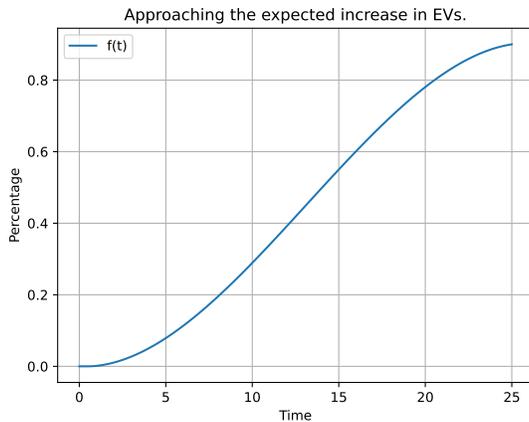


Fig. 2. Percentage of electric vehicles over time

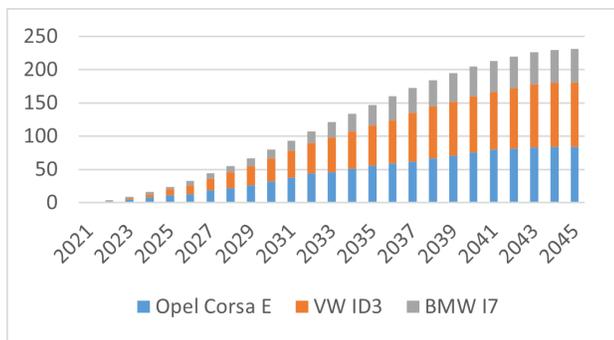


Fig. 3. The random growth of different types of vehicles

depending on the day of the week. This demand is illustrated in Fig. 4 for January of Year 10 and in Fig. 5. for January of Year 15.

D. Reference Analysis of Charging Events Based on the MOP Dataset

The German Mobility Panel (MOP), conducted by the Institute for Transport Studies (IfV) at the Karlsruhe Institute of Technology (KIT), is a continuous, representative survey of travel behaviour among private households in Germany [13]. Data were collected annually from 1994 until January 31, 2024, with the most recent diary covering 2022/2023. The dataset includes detailed household characteristics, vehicle use, travel activity, and charging events related to battery electric vehicles (BEVs). Its panel structure allows longitudinal analysis of individual mobility patterns.

This analysis focuses on recorded BEV charging events. Relevant information includes charging start and end times, charging location, state-of-charge, and vehicle-specific parameters such as model year and rated power. Battery capacity values were assigned according to vehicle type and year of manufacture to enable energy estimation.

The energy withdrawn per charging session is derived assuming a constant charging power of 11 kW, which is

generally considered non-critical for grid stability and not subject to throttling. The charging energy is calculated as

$$E_{\text{charge}} = 11 \text{ kW} \times t_{\text{charging}}$$

where t_{charging} is the charging duration in hours, obtained by converting start and end times to minutes since midnight. Each charging event is recorded with vehicle information, charging times, duration, and estimated energy consumption.

This structured dataset enables disaggregated analysis of charging behaviour across vehicle types, household profiles, and temporal dimensions. By leveraging duration data from MOP's charging logs together with the fixed 11 kW assumption, energy usage per cycle can be accurately computed. The resulting estimates provide a reliable basis for research on infrastructure planning, grid impact assessment, and the development of targeted charging strategies.

E. Comparison of Model Data with MOP Dataset

In the developed and shown model, several assumptions were made, which were subsequently compared with data from the MOP dataset of the KIT to assess the model's alignment with real-world conditions.

In a first step, the average energy consumption was examined. Taking into account the probabilities of vehicle selection and the corresponding consumption values, the model produces an average consumption of 16.7kWh/100km. Analysis of the MOP dataset produces a comparable value of 16.06kWh/100km, indicating that the model provides a reasonable approximation of real-world consumption.

Mobility data were also evaluated. The simulated model data indicate an average annual mileage of 11,080km, whereas the MOP dataset reports 10,192km/year. According to the Federal Motor Transport Authority, the average annual mileage in 2022 was 12,470km [14]. Hence, the chosen model lies between the two reference values and plausibly represents reality.

Regarding charging behaviour, a more nuanced picture emerges. In the MOP dataset, the participant with the highest charging frequency increased the battery state of charge by 77% per cycle, while the participant with the lowest usage achieved only a 13% increase. The average increase per charging cycle was 42.9%.

In the proposed model, the battery state of charge increases between 5% and 33%, as it is assumed that all vehicles are charged daily. Furthermore, it is assumed that each vehicle is connected to the charging station immediately upon return, resulting in a relatively uniform daily charging pattern. Comparison with real-world data suggests that users do not necessarily charge their vehicles daily but often wait until the battery state falls below a certain threshold.

VI. OUTCOME AND EVALUATION

As a reference, Fig. 6 shows the consumption data for a year without artificially generated loads. Day one corresponds to January 1st and day 365 to December 31st. It is evident that

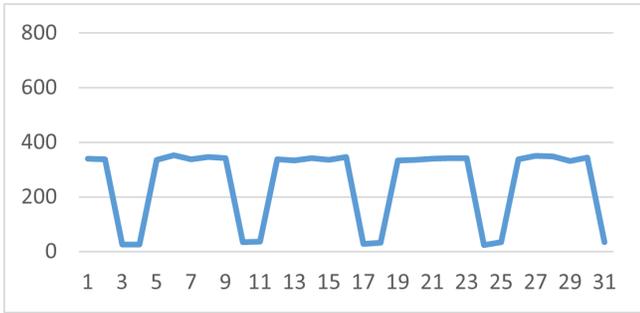


Fig. 4. Daily demand for electric energy due to electric vehicles in Year 7



Fig. 5. Daily demand for electric energy due to electric vehicles in Year 10

electricity consumption is significantly higher in the winter months compared to summer.

Hours are plotted on the secondary axis, and it can also be observed that consumption is higher during the daytime than at night. The power intake in per unit (pu) represents power relative to the transformer's rated capacity. It is noticeable that there is no overload at this substation under normal operation. Fig. 7 illustrates the network utilization situation in year 7. Here, there is a significant increase in power demand during the time when electric vehicle users return home from work. Even though there is a peak demand on some winter days in December, no controlling intervention is necessary. The situation is different in Fig. 8, which represents the demand in year 10. It can be seen that on some days in December of the year, the power demand is so high that controlling intervention may be necessary if previous measures such as price incentives or contractually agreed flexibility usage are not possible.

The depicted demands and the underlying generation concept provide an initial foundation for researching solution algorithms. This enables the optimization and evaluation of allocation algorithms or reduction calculations, as envisaged in §14a EnWG. Since simply changing the parameters of the data generation function can alter utilization or user behaviour, evaluating an algorithm's adaptability is straightforward.

An expansion of the presented load generation algorithm is advisable. In particular, attention should be given to weather-dependent solar energy generation and the consumption of heat pumps. Additionally, the prevalence of Energy Management Systems (EMS) is increasing, which autonomously calculates optimized surplus charging for households with solar panels and electric vehicles.

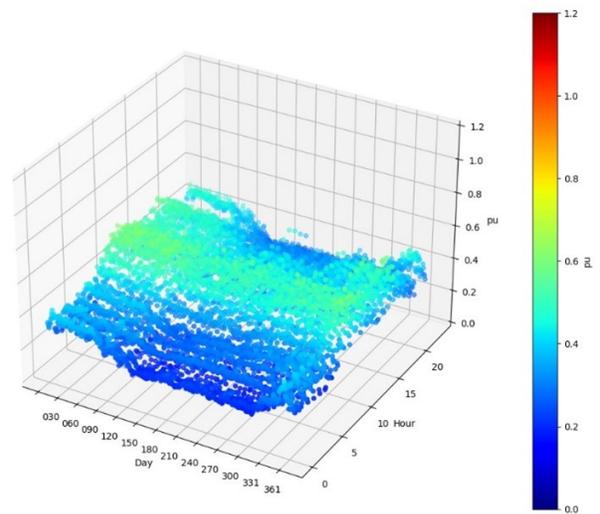


Fig. 6. Consumption data for without generated loads

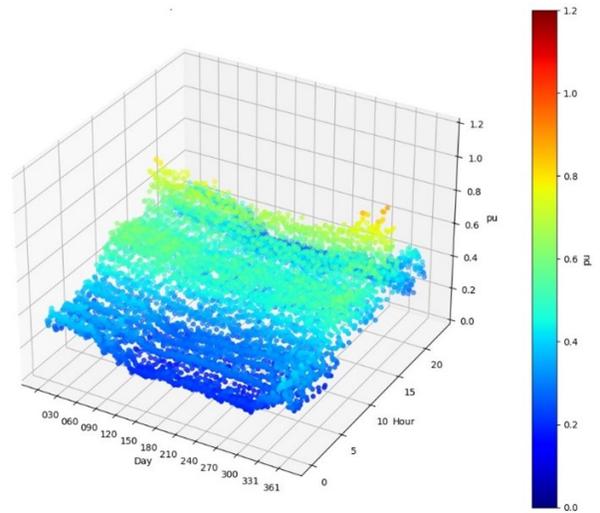


Fig. 7. Total consumption in year 7

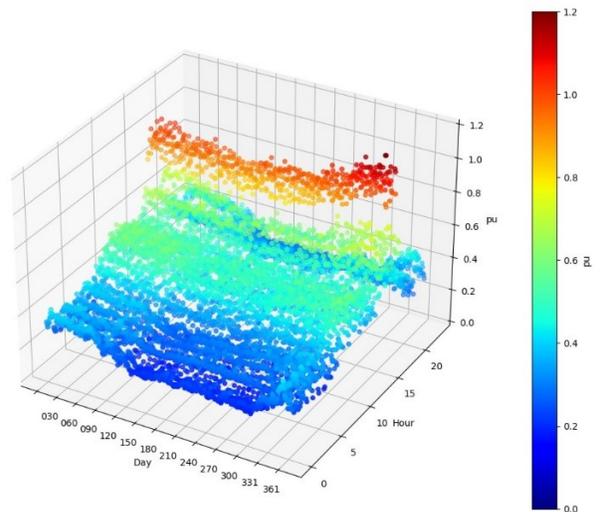


Fig. 8. Daily demand for electric energy due to electric vehicles in Year 10

Integrating these factors is beneficial for a comprehensive evaluation of COF algorithms and further extends the possibilities for evaluation. The differences in charging behaviour between the model and the MOP dataset did not lead to a significant change in the projected grid expansion requirements, as higher charging loads were, on average, mutually compensated. Consequently, the presented model is suitable for estimating future grid expansion needs at the considered scale of participants.

VII. OUTLOOK

Currently, work is underway on an agent-based simulation environment capable of processing generated load data at the household level. Each agent then calculates its own behaviour based on the energy demand. Additionally, individual responses to price signals are considered. Furthermore, each agent autonomously communicates with the central COF in the manner presented. The simulation also offers the opportunity not only to consider energy demands but also to evaluate voltage behaviour or phase shifts. This possibility simultaneously allows the chance to analyze other system services such as optimized reactive power provision. The technical capabilities for this are already available in many generation facilities and are defined in DIN VDE AR - N 4105. In summary, the energy and mobility transition presents a wide range of research tasks that will need to be addressed in the coming years.

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