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Forecasting of Electrical Vehicle impact on infrastructure: Markov Chains model of charging stations occupation

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Abstract

Charging infrastructures are under the attention of researchers and companies as they are actually the crucial point for the development of the spread of electric vehicles. For this reason It is essential to have forecasting tools that analyze the behavior of users to try to extrapolate data and useful information. In this work we start from a group of data collected during the Teinvein project and then reworked to obtain a forecasting model based on Markov chains. The method proposed in the paper makes use of information related to the distribution of vehicles in the charging stations, their average plug time, the amount of energy withdrawn, to reconstruct a distribution of occupancy model of a single station and, consequently, the consumption profile.

Keywords: Electric Vehicle (EV), Markov Chains, Charging Infrastructures, EV impact, Data Driven

1. Introduction

Today, charging infrastructures are a crucial point for the diffusion of electric vehicles, which is not only linked to vehicle technology and performance, but also to the availability of an efficient power distribution to charging stations, which integrates with the growing need for electricity in other sectors as well. In

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this context, the problems related to the infrastructure are of different nature: the planning of the distribution of the charging stations, the resistance and reliability of the electrical grid, and consumption patterns aimed at determining pricing or incentive policies. While on the one hand the penetration of electric vehicles is hindered by existing cost and performance barriers, on the other hand it is now unsustainable due to issues related to the presence of charging stations, their optimal location in the urban areas and, specifically, the amount of energy taken from an electricity grid not designed for such a variable and inconstant power flow. [1, 2]. It becomes important to determine occupation patterns and, consequently, the charging profile that can be used for the solution of these problems [3, 4]. The Electric Vehilcle (EV) recharge, in fact, represents a new type of electrical load, very difficult to forecast, especially at a time when penetration is still medium-low and it is not yet easy to have a significant data-set. In these conditions, in fact, it is not possible to have sufficient data to make long-term forecasts; in addition, the data must be correlated with the habits of the drivers and with the presence of other types of load. The systems must therefore be sized to reach a compromise [5, 6, 7, 8] to make the most of the available power, the occupation of the charging stations and the needs of vehicle owners. There are several aspects that make this problem intriguing from the point of view of modeling. The first aspect is that the models of reconstruction of the charging profiles are often linked to the modelling of the state of charge of electric vehicles and their distribution in space. This should include a classification of the main types of vehicles and the potential habits of users to reconstruct the necessary information [9]. Another approach is based on the observation from the charging station side without any knowledge about the vehicles and habits of the users. This point of view works well if we assume that the user behaviours are fairly regular and there are no “statistical” disturbances, such as vehicles that are not normally present in the area considered [10].

Our approach combines the advantages of the two methods starting from the observation of the recharging events made in the charging stations present in a widespread urban area, combined with the monitoring of a fleet of vehicles that

has the predominant use of these suppliers [11, 12, 13, 14, 15]. Our research is based on the presence of a substantial fleet of electric vehicles (about one thousand), all with the same characteristics, used for sharing services. The vehicles are recharged exclusively at public charging stations, although they belong to different operators [16, 17]. Electric vehicles are plugged to the charging stations with a different daily, weekly and yearly probability distribution. All these can be considered periodic. In this paper, as a proof of concept, we will consider only daily and weekly periodicity.
The idea of this work can be summarized as follows:

- Formalize a cyclical model based on a Markov chain to describe the status of charging stations in different parts of the city at different times of the day and the weekday
- Validate the behaviour simulated with the data collected.

In the following, the origin and structure of the available data will first be presented in section 2, a brief presentation of the key concepts of Cyclic Markov chain theory will then be described in section 3, estimation of the parameters of the model obtained using the available data is described in section 4, finally, simulation results will be presented in section 5.

2. The Available Data

The data collected are related to a fleet of car sharing vehicles in the course of the Teinvein project[18]. All the EVs are constantly monitored by the car sharing company and cannot be used outside the urban area. These EVs are small two passenger cars characterized by 150 Ah LiFePO4 batteries, each battery is composed by 24 cells and the rated voltage of the battery is 80 V, the characteristics of each cell is reported in figure 1 and the charging profile is the one shown in figure 2.

The batteries of these EVs are, with few exceptions, charged using a subset of about 40 of the more than 200 public charging station available in the area

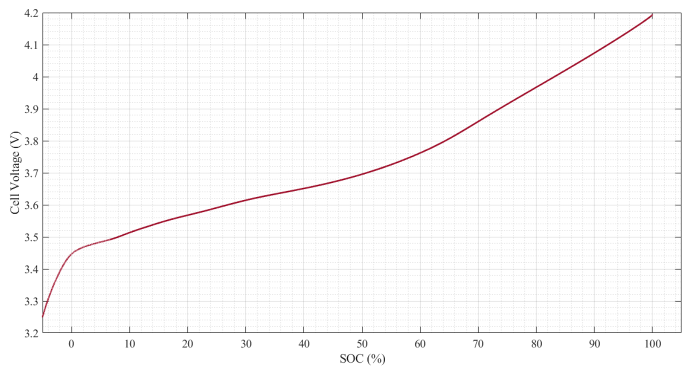


Figure 1: Characteristic curve of the cells composing the battery mounted on the vehicles

considered. In fact, as one can see on the bar-plot, shown in figure 3, many stations are totally inactive for what concerns our specific set of EVs and will not be considered in the following study.
The time resolution for the available data is 15', so that 96 observations for each day are present, and, except for a couple of dozens of missing days due to technical problems, spans about one full year of observations.

Some cumulative statistics on charge event data, that considers all available daily observations and all stations, is presented in Fig.4. In particular, the average duration of charge events is 4.7 hours, see Fig.4a, and the start and end time of day distribution of the charge events are reported in Fig.4b. These EVs are intensively used, and are thus recharged quite frequently, in most cases when the SOC value is relatively small, the distribution of initial SOC values at each charge event is shown in Fig. 4c. The distribution of total energy required by each charge event, expressed in kWh, is shown in Fig. 4d. These corresponds to a median value of charge intervals for all cars of about once every 2.6 days; the distribution of charge intervals is shown in Fig.4e.

Considering only the active stations, the evolution of the number of cars plugged in each station is a stochastic process characterized by a large value of variance. An example is shown in the graph on figure 5a, where the behaviour of three randomly chosen stations in one random day is depicted. There seems to

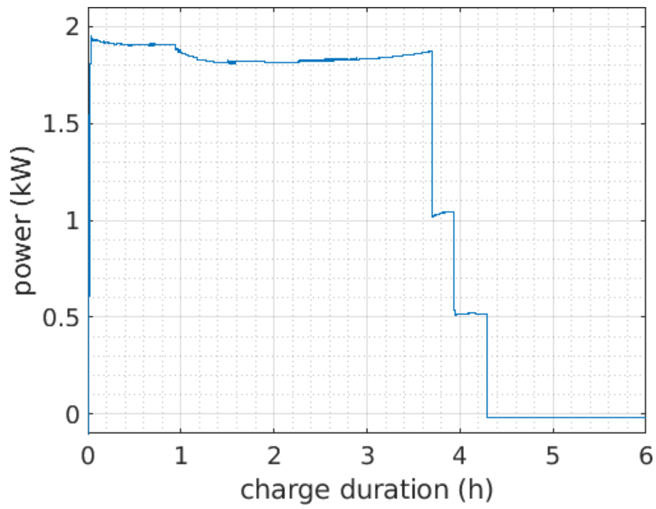


Figure 2: Charging profile of the considered cars

be a significant time evolution during the day, but the variance is too important to try to predict the individual evolution from this mean. This is even more evident from figure 5b, where the mean activity of all stations over one of the most active days is shown along with its standard deviation. It seems then to be unlikely that a simple regression, or any deterministic process may give an interesting model for this kind of data : the huge and stochastic daily variations have to be taken into account, and it seems to be interesting to model it as a kind of random walk determined with a time-evolving Markov transition matrix.

Lastly, the histogram on figure 6 shows that the distribution of the number of EVs plugged in any station at each time is far from Gaussian : in this case the time shown is t=96 (i.e. 0h:00' AM, one of the moments the stations are most occupied in the day). The main observation that can be made here is that even at that time, many stations have 0 or very few cars plugged in.

2.1. Statistic observations for one station

Instead of looking at the profiles for each station during one single day, let's have a look at the behaviour of single stations, and their profile distribution in different days.

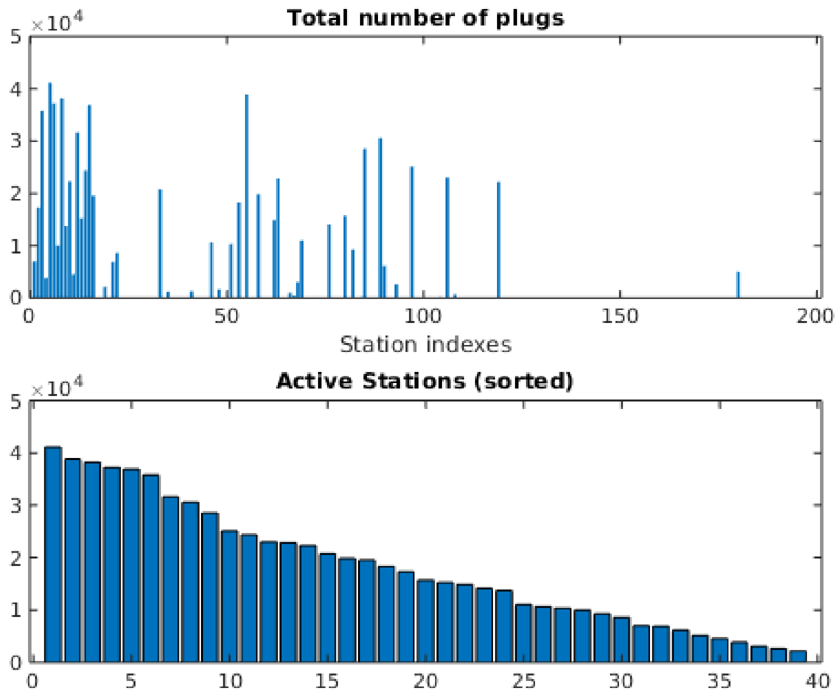
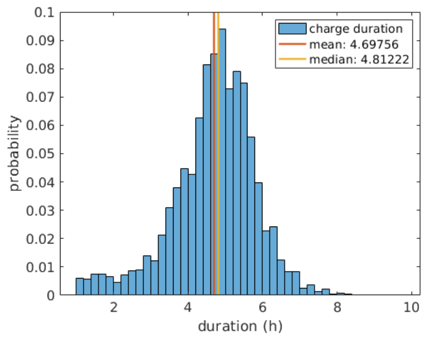
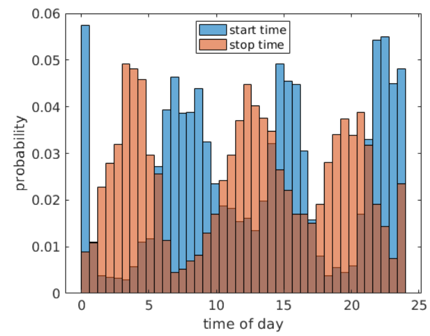


Figure 3: Total number of plug events on the EV-charging stations in the whole observation period.

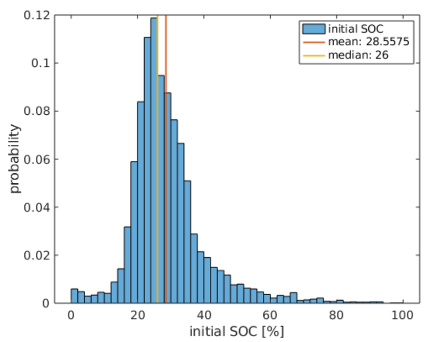
The graphs in Fig.7 show an example of the large variability that exists for the profile of one unique station depending on the day. In figure 7a the behaviour of one of the most active stations over three random days is shown, while in figure 7b the graph shows the mean activity of one single station over all available daily data along with its standard deviation. A few comparisons with other stations revealed the behaviour can often be very different from this one : some stations are mostly active during working days and less during weekends, while other stations have the opposite behaviour. The best explanation for this trend seems to be the location of the stations : their behaviour can be expected to be very different whether or not they are located near city-centers or industrial centers (or any working places). Fortunately, contrary to the distribution according to the stations, it seems that the distribution according to the day is more Gaussian. The histogram on figure 8 shows this behaviour with two active



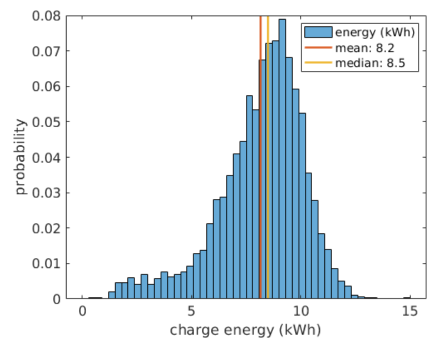
(a) Charge duration.



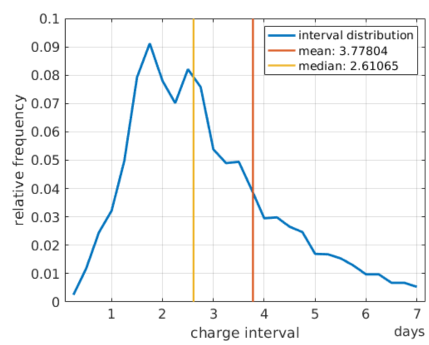
(b) Charge start/stop time of day.



(c) Initial SOC at each charge event.



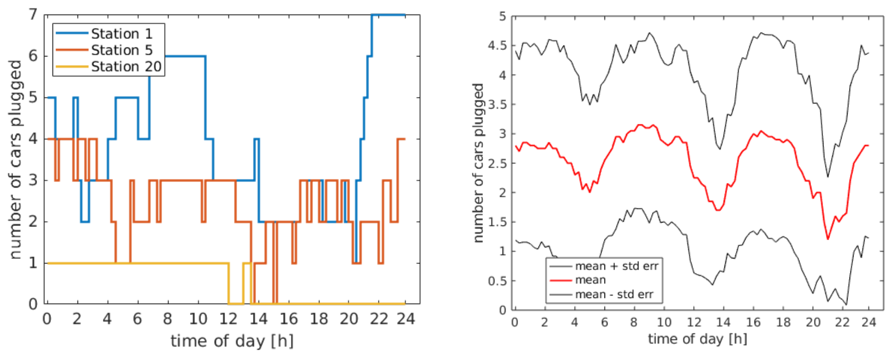
(d) Charge event energy distribution



(e) Time interval between charge events.

Figure 4: Charge event data statistics over the whole observation period.

stations as an example.



(a) Three different stations in the same day.

(b) Mean activity in one of the most active days.

Figure 5: Plug data related to one single day.

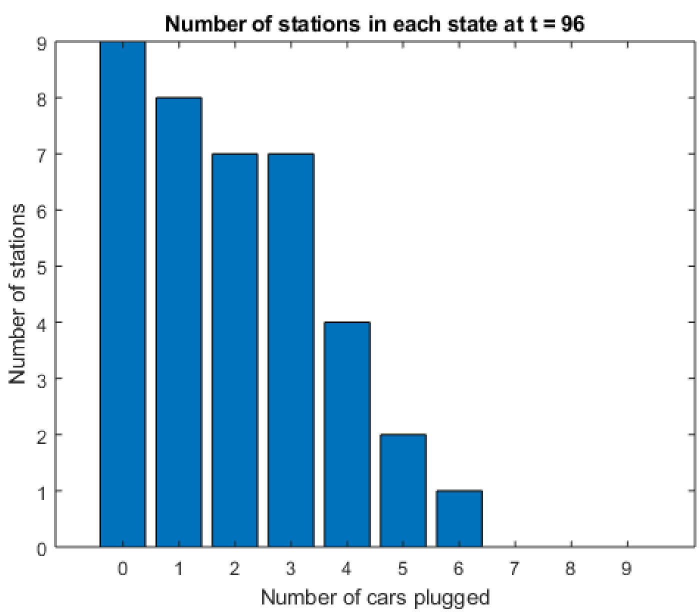
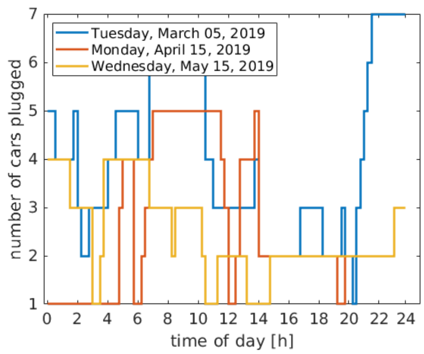
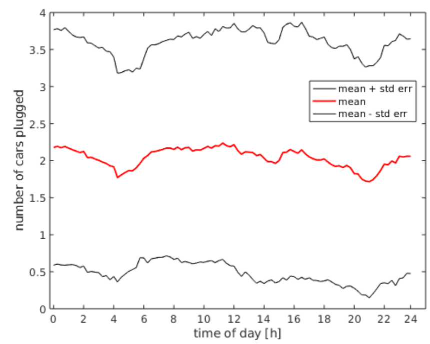


Figure 6: Number of stations in each state



(a) One station in three different days.



(b) Mean activity of one station in different days.

Figure 7: Plug data related to one single station.

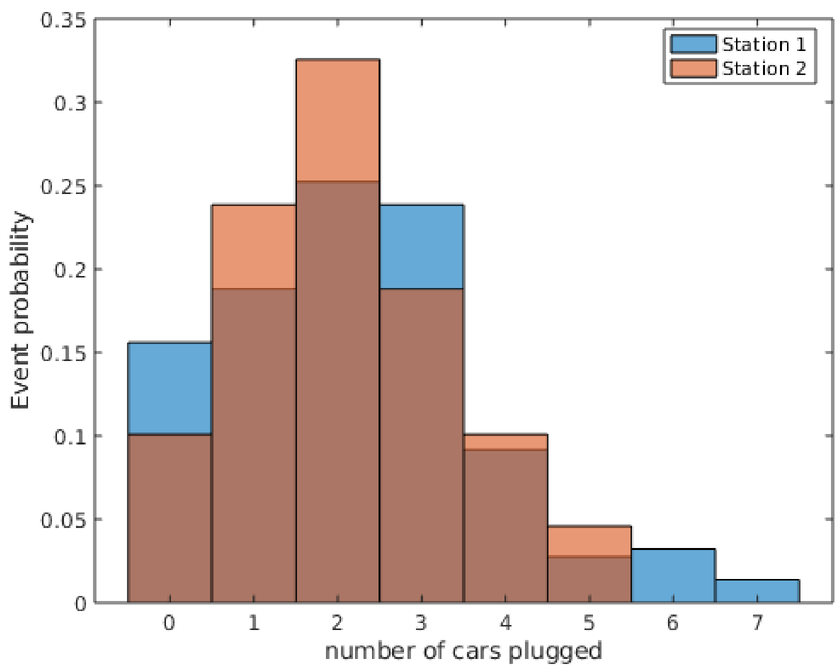


Figure 8: Distribution of plugged cars for two active stations at 11 am.

3. Cyclic Markov Chains

The data described in the previous section is used to estimate the parameters of a *Cyclic Markov Chain Model*. A brief introduction to this class of models follows.

Markov models are very useful to describe the behaviour of systems where the future state depends only on the current state, regardless to the past states and are used to model processes in different fields; some interesting examples more related to the object of this work are concerned with Wind Power availability [19], household electric load profiles [20] and EV charge station use [21].

In some cases, these models also include a time dependence, so that they are called Non-Homogeneous Markov Models (as opposed to the Homogeneous Markov Models, in which there is no time dependence).

Cyclic Markov chains are used to model processes that have some kind of periodicity, of natural or artificial origin (see, e.g. [22, 23, 24]). In our case the periodicity is given by the charging behaviour managed by a single fleet manager, and related to the distribution of state of charge of a vehicle set that shows evident time patterns, as shown in the previous section 2. Let $(X_t)_{t\in\mathbb{N}}$ be a non-homogeneous Markov chain, with a finite state space $E = \{1, ..., R\}$ where $R \in \mathbb{N}$. In the example studied in this paper, one Markov chain process models one single station, or the collective behaviour of a number of stations, and each $r \in E$ represents a number of cars plugged in the station, or, depending on how the data is pre-processed, a proportion of occupancy of the station. In any case, the finite number of states represents the occupancy state of the station. For $(i, j) \in E^2$, and $(t, s) \in \mathbb{N}^2$ (since we are using discrete time), let $p_{ij}(t, t+s) = \mathbb{P}(X_{t+s} = j|X_t = i)$ represent the transition probabilities for the chain (see Fig.9), let $\mathcal{P}(t, t+s) = (p_{ij}(t, t+s))_{(i,j)\in E^2}$ be the transition probability matrix for transitions during the period t to $t+s$, and let $P_i(t) = \mathbb{P}(X_t = i)$ be the distribution of the system at time t. The objective is finding a good estimator $\hat{p}_{ij}(t, t+s)$ for the transition probabilities. Let's assume that the data used as a base for the estimation is composed of N independent, identically dis-

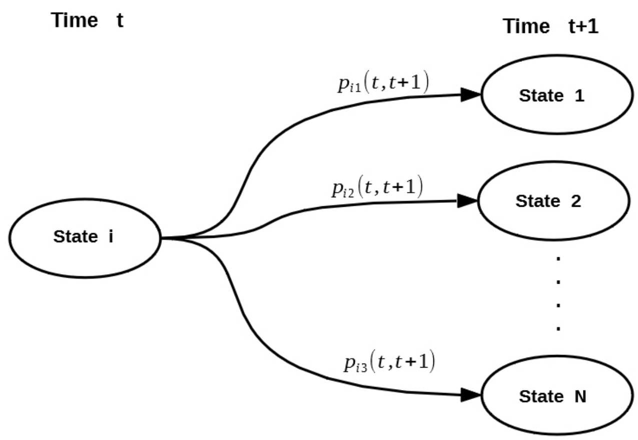


Figure 9: Markov transitions graph

tributed chains (i.i.d) $\{\{X_t^k\}_{t=0}^{\infty}, 1 \leq k \leq N\}$, each one following this Markov model with the above transition probabilities.

3.1. Parameter Estimation

For $i \neq j$ let $M_{ij}(t, t+1)$ be the number of i to j transitions from time t to $t+1$ for the N observed chains, and let $N_i(t)$ be the number of observed chains in state i at time t.

In this case the maximum likelihood estimator of $p_{ij}(t, t+1)$ is given by [25]:

$$\hat{p}_{ij}(t,t+1) = \begin{cases} \dfrac{M_{ij}(t,t+1)}{N_i(t)} \text{ if } i \neq j \text{ and } N_i(t) > 0 \\ 0 \text{ if } i \neq j \text{ and } N_i(t) = 0 \\ 1 - \displaystyle\sum_{k \neq i} \dfrac{M_{ik}(t,t+1)}{N_i(t)} \text{ if } i = j \end{cases} \tag{1}$$

Indeed, for a given time $t \in \mathbb{N}$, let suppose that one observes the event $\{X_t^1 = x_t^1, X_{t+1}^1 = x_{t+1}^1, X_t^2 = x_t^2, X_{t+1}^2 = x_{t+1}^2, ..., X_t^N = x_t^N, X_{t+1}^N = x_{t+1}^N\}$.

Then the likelihood for this event is

$$\prod_{k=1}^{N} \mathbb{P}(X_t^k = x_t^k) p_{x_t^k, x_{t+1}^k}(t,t+1) = (\prod_{k=1}^{N} \mathbb{P}(X_t^k = x_t^k))(\prod_{k=1}^{N} p_{x_t^k, x_{t+1}^k}(t,t+1)) \tag{2}$$

It is clear that the choice of $p_{i,j}(t,t+1)$ that maximises the likelihood will not depend on the value of $\prod_{k=1}^{N}\mathbb{P}(X_t^k = x_t^k)$.

Then, to maximise the likelihood, and using the matrix M that counts the number of transitions from states at each time, the rest of the product can be written as follows :

$$\prod_{k=1}^{N} p_{x_t^k, x_{t+1}^k}(t,t+1) = \prod_{i\neq j} p_{ij}(t,t+1)^{M_{ij}(t,t+1)} \prod_{i\in E} p_{ii}(t,t+1)^{N_i(t)-\sum_{j\neq i} M_{ij}(t,t+1)} \tag{3}$$

by taking the logarithm of this last equality, we have:

$$\log(\prod_{k=1}^{N} p_{x_t^k, x_{t+1}^k}(t,t+1)) = \sum_{i=1}^{R}\sum_{j=1}^{R} a_{ij}\log(p_{ij}(t,t+1)) \tag{4}$$

where $a_{ij} = M_{ij}(t,t+1)$ if $i \neq j$ and $a_{ij} = N_i(t) - \sum_{j\neq i} M_{ij}(t,t+1)$. To maximise the likelihood, maximising $\sum_{i=1}^{R} a_{ij}\log(p_{ij}(t,t+1))$ for each $j \in E$ is enough. For this, there are 2 cases. If $N_i(t) = 0$ then for all $j \in E$, $a_{ij} = 0$ and the sum is null and independent of $p_{ij}(t,t+1)$. One can then take $\hat{p}_{ij}(t,t+1) = \delta_{ij}$ (i.e. 0 if $i \neq j$, else 1).

In the case $N_i(t) > 0$, it is clear that $a_{ij} \geq 0$ and that $\sum_{j=1}^{R} a_{ij} = N_i(t)$.

Define $b_{ij} \equiv \frac{a_{ij}}{N_i(t)}$ (that is actually a probability measure on j for each i). The equation can now be computed as follows, thanks to Jensen inequality :

$$\begin{aligned}\sum_{j=1}^{R} a_{ij}\log(p_{ij}(t,t+1)) - \sum_{j=1}^{R} a_{ij}\log(b_{ij}) &= N_i(t)\sum_{j=1}^{R} b_{ij}\log(\frac{p_{ij}(t,t+1)}{b_{ij}} \\ &\leq N_i(t)\log(\sum_{j=1}^{R} b_{ij}\frac{p_{ij}(t,t+1)}{b_{ij}} \\ &= N_i(t)\log(1) = 0\end{aligned} \tag{5}$$

This inequality proves that, when $N_i(t) > 0$, the value $\hat{p}_{ij}(t,t+1) = b_{ij}$ maximises the sum, and so maximises the likelihood.

3.2. Asymptotic behaviour

Given the estimation methodology described in the previous section, it is possible to represent the transition matrices related to all time instants using a more compact representation. Specifically, we define for the generic time step t

$$P_t \equiv [\hat{p}_{ij}(t, t+1)] \tag{6}$$

where the elements $\hat{p}_{ij}$ of the matrix are those found by the maximum likelihood estimator.

The probability of finding a non-homogeneous Markov chain with transition matrices P_j, in a given state, given an initial state probability vector x_0, after N time steps is given by

$$X(N) = x_0 \left(\prod_{j=1}^{N} P_{j \pmod T} \right) \tag{7}$$

since our Markov chain is cyclic with period T only index from 1 to T are meaningful. This can be written in a more useful way by noting that $P_{kT+m} = P_m \ \forall k, m \in \mathbb{N}$, so that its behaviour at time step $N = kT + m$ given the initial state probability row vector x_0 is described by

$$X(N) = x_0 \bar{P}_N = x_0 \left(\prod_{j=1}^{T} P_j \right)^k \left(\prod_{j=1}^{m} P_j \right) \tag{8}$$

where $m < T$.

If we consider the behaviour over one full period T and its integer multiples, the cyclic non homogeneous Markov chain can be seen as a "simple" (i.e. homogeneous) Markov chain defined by

$$\bar{P}_T = \prod_{j=1}^{T} P_j \tag{9}$$

and the asymptotic behaviour of the Markov chain over full one day periods by

$$\bar{P} = \lim_{k \to \infty} \left(\bar{P}_T \right)^k \tag{10}$$

Note that matrix $\bar{P}_T$, being the product of stochastic matrices, is itself stochastic, i.e. the sum of the elements in each row is equal to one. This means that $1 \in \sigma(\bar{P}_T)$, where $\sigma(A)$ is defined as the spectrum of matrix A, i.e. the set of all its eigenvalues. While the corresponding *right* eigenvector λ_1 is a column vector of identical values, the *left* eigenvector ν_1, i.e. the right eigenvector of the transpose matrix $\bar{P}_T^T$ corresponding to its unit eigenvalue, represents the asymptotic values of state probabilities after a (large) integer multiple of full cycles. Moreover, matrix $\bar{P}$ is an *ergodic* matrix, i.e. a matrix with identical rows, meaning that, asymptotically, the probability of ending in a specific state does not depend on the initial state. If, for example, we consider a generic period $T = \bar{T}$, to account for the hours in one day, the asymptotic probability vector in any one of the 24 hours of a typical day is thus given by

$$X(t) = x_0 \bar{P} \left(\prod_{j=1}^{t} P_j \right) \tag{11}$$

with $0 \leq t \leq \bar{T}$ and, since $\bar{P}$ is ergodic, x_0 can be any vector such that $\sum x_0(j) = 1$.

4. Estimation of the Cyclic Markov Chain Transition Matrices

The maximum likelihood estimator in eq. (1) is implemented, based on the available data, as described in Algorithm 1. The input data is a set of integer matrices C_j, one for each day observed, that, in our case, is organized in 96 rows, one for each 15' sampling time instant, and 40 columns, one for each active charge station. The weekday corresponding to the C_j matrix is stored in variable w_j. The maximum possible occupancy, taking into account also the empty state, M_o is also known, in our case $M_o = 9$ corresponding to a maximum occupancy of 8, i.e. possible states are the integers from 0 to 8. Given this data the Markov model can be built.

The output of the Algorithm is a representation of the Markov model through its set of probability transition matrices. To simplify notation multidimensional arrays are used in the pseudocode, and, in particular, a 5D data structure collecting all transition matrices for all stations modelled is obtained. In our case 40 sets, one for each modeled station, of $96 \times 7 = 672$ matrices, each of size 9×9 are found. These are the P_t matrices defined in eq. (6).

Algorithm 1: Estimation of the Cyclic Markov chain matrices

Input:

N_s: number of charge stations considered;

T_d: number of daily samples (e.g. $4 \times 24 = 96$ for 15' sampling)

$C_j \in \mathbb{N}^{T_d \times N_s}$: daily station occupation matrices;

M_o: max occupancy of largest station incremented by 1;

w_j: weekday of the j-th occupation matrix;

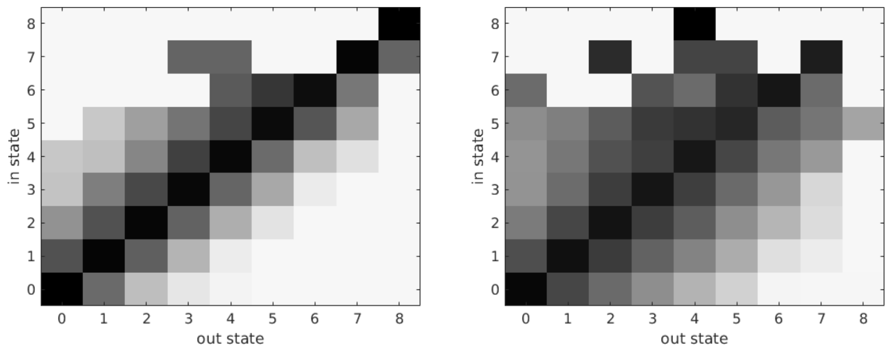
N_C: number of C_j matrices;

Start:

```
initialize M_wd to null 5D matrix of size M_o × M_o × T_d × N_s × 7
initialize M_tmp to null 4D matrix of size M_o × M_o × T_d × N_s
for s = 1..N_s do
    for k = 1..N_C do
        for t = 1..T_d do
            increment M_tmp(C_k(t, s), C_k(t + 1, s), t, s)
        end
        M_wd(·, ·, ·, s, w_k) = M_wd(·, ·, ·, s, w_k) + M_tmp(·, ·, ·, s)
    end
    for w = 1..7 do
        for t = 1..T_d do
            normalize each row of M_wd(·, ·, t, s, w)
        end
    end
end
```

Result: A 5D matrix of size $M_o \times M_o \times T_d \times N_s \times 7$ equivalent to N_s sets (one for each station) of $7T_d$ matrices of size $M_o \times M_o$

Two transition matrix instances are shown in Fig.10 using grey levels to represent transition probability. The matrices shown have been arbitrarily chosen in two different weekdays for the model corresponding to one of the most active stations. In this representation, values above the main diagonal represent



(a) Wednesday, 10:00 PM

(b) Saturday, 12:00 PM

Figure 10: Grey level representation of P_k, one of the Markov chain transition matrices, corresponding to activity at 12:00 pm, in weekends and working days.

probabilities of EVs departures, while those below the diagonal the probability of new arrivals.
Using the transition matrices found it is also possible to evaluate the asymptotic probability of each occupancy state in each 15' time slot as described in eq. (11). The result is shown in Fig. 11. The most probable states are those with low occupancy levels, but the probability of having a full station is not null.

5. Model simulation and results

The transition matrices P_t are first estimated as described in section 4 using the available data; in our case we chose to represent station models at the highest possible resolution, i.e. at 15' intervals over each week, resulting in a total of $24 * 4 * 7 = 672$ matrices for each weekly station model. Different behaviours along weekdays are thus modeled, but seasonal behaviours are ignored in this model.

Once the transition matrices have been found, it is possible to generate instances of charge station use over daily or weekly periods. Each realization of the Markov chain is a sequence of occupancy states for a typical charge station. Given these states and the vehicle charge load profile, a model of the charge station power requirements is easily derived. Cyclic Markov chain simulation is

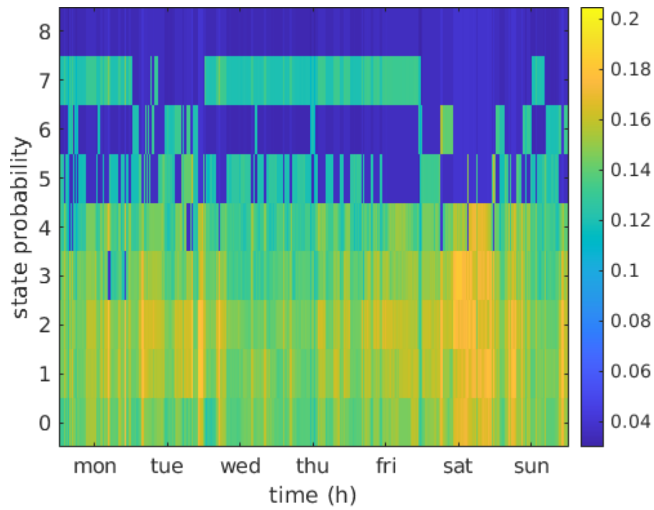


Figure 11: Color map representation of the asymptotic occupancy state probability for a typical charge station over a week.

straightforward and requires, for each simulation, the choice of a random initial state at time 0 and random transitions to the next state by using the appropriate transition matrix, i.e. that corresponding to the current time slot. This will require the computation of the discrete cumulative distribution function both of $p_0(x)$, i.e. the state distribution density at time 0, and, at each iteration, of one row of the transition matrix in use, this is done using the cumulative sum function cumsum$(\cdot)$, from this non decreasing vector of discrete values the *quantile* function, a generalization of the distribution inversion operator, is derived.

$$Q_f(u) \equiv \inf\{x : f(x) \geq u\} \quad \text{with} \quad 0 \leq u \leq 1 \tag{12}$$

We also assume to have a uniform distribution random number generator function rand$(\cdot)$ and, since states are discrete, a rounding function round$(\cdot)$. A simple description of the simulation procedure is summarized as pseudo-code in Algorithm 2.

The initial step of the algorithm, line 1, finds the Cumulative Density Function (cdf) of the initial state of the station being simulated. Using the cdf, the uniform random number generator and the Quantile function defined in eq.

(12), the initial state for the current simulation is obtained in line 2. In line 3 the current transition matrix is selected. Finally, using once more the Quantile function on the appropriate row of the transition matrix, the destination state is found in line 4. This is iterated for the desired length in terms of time samples T and in terms of number of realizations N.

Algorithm 2: Simulation of a Cyclic Markov chain

Input:

T_S: number of time samples;

$P_t, \quad t \in \{1, 2, \ldots, T_S\}$: transition matrices;

$p_0(x)$: distribution of states at time 0;

T: total time of each simulation;

N: number of simulations;

Start:

1 $c_0(x) = \text{cumsum}(p_0(x))$;

for $j = 1..N$ **do**

  $\rho_0 = \text{rand}(0, 1)$;

  $x_0 = \text{round}(Q_{c_0}(\rho_0))$;

2   $x = x_0$;

  for $t = 1..T$ **do**

    $R(j, t) = x$;

3     $k = t \mod T_S$;

    $\tau = P_k\{x + 1, :\}$;

    $\gamma = \text{cumsum}(\tau)$;

    $\rho = \text{rand}(0, 1)$;

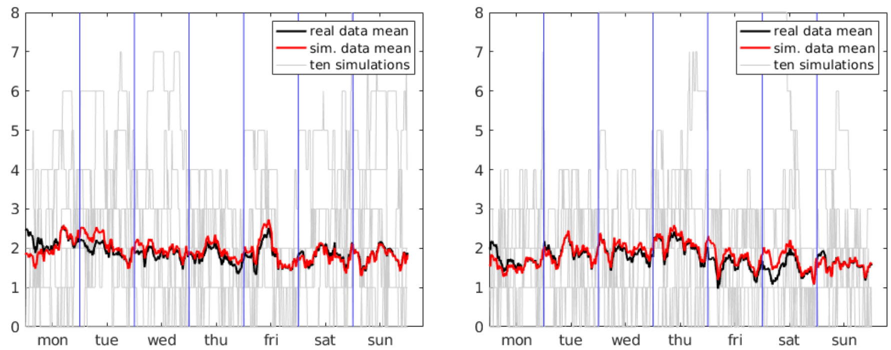
4     $x = \text{round}(Q_\gamma(\rho))$;

  end

end

Result: A $N \times T$ matrix of states R, each row a realization of the Markov chain process.

Using Algorithm 2 described above it is now possible to simulate the Cyclic



(a) Station A

(b) Station B

Figure 12: Average occupancy in two of the most active stations (black) along with the average occupancy obtained from 1000 simulation of the corresponding Markov models (red). Ten model realizations randomly chosen among the 1000 used for the computation of the average are also shown (grey).

Markov process and obtain an arbitrary number of process realizations.
In order to check the model, two of the most active stations have been selected along with the corresponding Markov models. The average distribution of EVs in these charge stations in each time slot obtained by the Markov model is compared to the average value obtained from the available data. In Fig. 12 the mean charge station occupancy measured from real data and that derived from 1000 Markov chain simulations over one week is shown. Along with these two curves, ten realizations randomly chosen among the 1000 simulated have also been shown.

A comparison of the overall distribution in time of charge events, to be compared to the one related to the real data and depicted in Fig. 4b, has also been obtained from a large simulation set composed of 10000 realizations, results are shown in Fig. 13. Each realization considers one full week, but results are summarized over a 24h period obtained by merging results in all weekday. As it can be seen the distribution is very similar to the one obtained from real data, somewhat smoother due to the fact that only the most active stations have been considered.

Using the model it is possible to evaluate the total energy absorbed by a

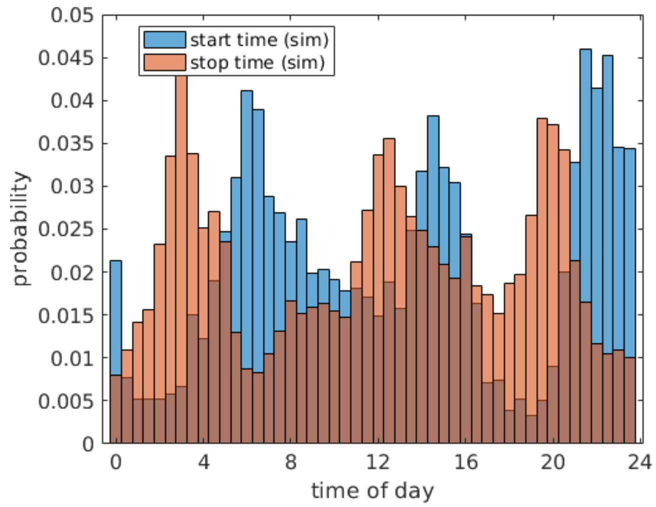


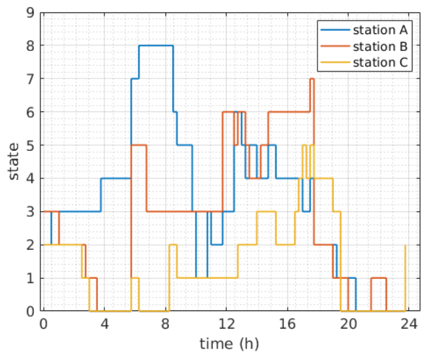
Figure 13: Distribution of charge start and charge stop events during one day and grouping the most active stations obtained by 10000 realizations of the Markov process over one week.

recharge station by using the standard charge profile of the vehicles considered shown in Fig. 2. To this end we will consider three independent realizations obtained from the models of three different stations over a 24h period, this is shown in Fig. 14a. Note that only one of these realizations reaches full occupancy of the charge station.

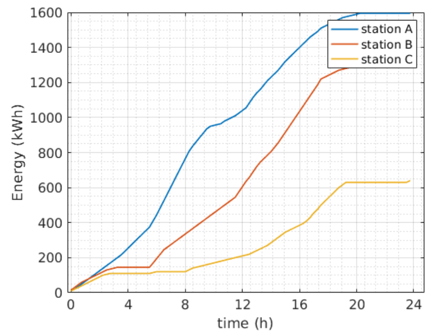
The corresponding Energy requirements are depicted in Fig. 14b

6. Conclusions

This article describes a simple cyclic Markov chain model to reconstruct and predict the behavior of charging stations and derive profiles suitable for simulations of the power grid. Currently the model is based on a set of data whose collection is still underway, new data is collected on daily basis and will allow, in the future, to train the model to achieve a much finer resolution, where seasonal charging behaviour differences and over a finer geographic grid are taken into account. The model we have proposed is used in different types of analysis, among these in the Demand Side forecast of electricity. Even considering the limitation



(a) Three realizations of the Markov process over a 24h time span.



(b) Total Energy in kWh absorbed by three recharge stations during a 24h period.

Figure 14: Three randomly chosen Markov model realizations corresponding to the models of three different active stations and the corresponding total energy requirements over a 24h period. Each one of the three curves represents in the two pictures the same station model.

in available data, the model has been shown to have a good correspondence with available real data.

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