# Forecast Model for Electromobile Loads at Stuttgart Airport and Fair

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*Abstract*—To achieve national climate protection goals, the decarbonisation of the transport sector is of primordial importance. In this regard, electromobility has become one of the most promising automotive trends.

However, a large-scale adoption of electric vehicles (EVs) would considerably burden the existing energy grid, especially in high-traffic areas. From the power industry's perspective it is essential to anticipate the power capacities required for EV-charging in order to ensure sufficient power transmission. As a consequence, spatial-temporal forecast techniques for electromobile loads become more and more important for power system planing and operation.

Since airports and fairs accommodate the world's largest parking facilities and therefore are particularly affected by EV mass deployment, the present paper<sup>1</sup> seeks to analyse the forthcoming EV energy demand on these locations in more detail. Based on project experience at Stuttgart Airport and Fair, a novel forecast model for electromobile loads is introduced within this work, followed by a discussion of the predicted energy demand and its influence on local power consumption.

# Keywords— forecast model; electric vehicles; demand profiles; airport; trade fair; energy consumption; Matlab<sup>®</sup>

#### I. INTRODUCTION

Over the last few years, German airports made considerable efforts to reduce ground emissions involved in the entire aircraft handling process. Most projects thereby focus on electromobile aircraft taxiing, towing and loading to mitigate negative effects of conventional apron vehicles on people and the environment [1][2][3]. Beside testing these new technological approaches, extensive life cycle analyses were conducted to attest the efficiency and ecological meaningfulness of air-sided EV-deployment [4]. However, only few initiatives focus on electrifying the land-sided traffic even though airports draw thousands of passenger cars per day and therefore are particularly suited to act as EV-aggregators to participate in electricity markets [5]. In the Netherlands, a consortium of researchers and architects developed different design scenarios for sustainable passenger transport at Schipol Aiport by combining wireless EVcharging with renewable energy generation and customized EV services [6]. Concerning the resulting network load, the study predicted local power peaks up to 30MW arising from six thousand EVs by 2030. An alarming trend given the fact that the world's largest trade fair in Hanover provides

more than 29000 parking lots. Still, specific knowledge on travel behaviour modelling and simulation is considered the greatest deficiency of [6] which emphasises the need for more accurate forecast techniques.

Regarding the energetic impact a widespread EV-use would impose on large venues such as fairs, comparatively little literature is available. In contrast to traffic hubs like airports, the occupancy rate of those locations is primarily eventdriven which leads to a more concentrated EV energy demand that further aggravates the grid situation. In such cases, the EV load is often approached by historic parking data [7]. Yet, this method alone allows no reliable conclusions concerning the vehicles' state of charge (SOC) upon arrival and therefore needs to be complemented with mobility behaviour analysis.

The power capacity required for EV-charging is influenced by many factors, such as the number of electric vehicles, their spatial distribution, their individual usage, their technical features such as battery capacity or charging performance and most importantly the owner's driving behaviour. A comprehensive review on modelling the EV mobility behaviour is given in [8], stating that generally rough assumptions were made when addressing mobility issues in energy network calculations. These assumptions often base on aggregated data composed of field test results [9] and national mobility studies that derive universal driving patterns and average trip distances depending on the vehicle use [5][10][11]. In recent years, there has been a rapid development in traffic research due to modern data sensors, analysis software and communication systems (such as ITS, GIS, GPS or roadside video detection) that have considerably facilitated data acquisition in the transport sector. In [12], an origin destination analysis from intelligent transportation research was used to reduce uncertainties related to vehicle motion. Despite their accuracy, those approaches often fail due to budget constrains or missing data.

Another shortcoming of related literature is the negligence of technical progress when predicting the forthcoming EV energy demand [5][8][10][11][12]. The EV battery capacity can be assumed to rise significantly over the next few years which leads to higher charging performances and EV ranges. Both developments will considerably change the present charging behaviour in public places. Besides, existing studies often do not provide sufficient information on load probabilities but display maximum or average EV loads only. The present paper aims to address those shortcomings and

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is structured as follows: Section II presents the case study and introduces all variables and constraints used within the modelling process. Section III focuses on elucidating the forecast model for the use cases airport and fair, whereas Section IV deals with the EV load discussion. A summary assessment is given in Section VI.

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#### II. CASE STUDY DESCRIPTION

#### A. Case study

The present work is an integral part of the Strategiestudie Elektromobilität which has been conducted in 2016/17 by the Fraunhofer IAO on behalf of Stuttgart Airport and Fair as part of their sustainability strategies [15][16]. The project aimed to develop a coherent concept for land-sided charging infrastructure roll-out on both locations. Beside identifying upcoming charging infrastructure needs, the project dealt with the spatial location and technical design of new charging poles. The here mentioned forecast model for electromobile loads has been developed within this project. Its objective is to predict the upcoming EV energy demand at Stuttgart Airport and Fair from 2017 to 2027 arising from passengers, visitors, exhibitors and employees in order to (a) ensure a demand-orientated charging infrastructure roll-out, (b) to identify possible load shift potentials and (c) to evaluate the necessity of grid-strengthening measures. The model outputs are typical EV peak loads throughout the day (in kW) and site-specific energy turnovers (in kWh/d) depending on the EV market penetration and technological progress.

Stuttgart Airport ranks amongst the busiest international airports in Germany, covering 100 destinations worldwide. However, with an annual passenger volume of approximately 10.5 million and ten thousand people working on-site, the airport still belongs to the smaller ones when compared to international aviation hubs. This is further illustrated in Figure 1 (above) whose schematic overview provides a better knowledge on the paper's validity. Since land-sided EV loads on airports are not only dependent on passenger figures but on their belonging model split as well, the following results may still be valid for larger (supposingly innercity) airports which are better connected to public transport systems. Tokyo Airport, for example, has a passenger volume eight times higher than Stuttgart but features only one third of its parking capacity which leads to the conclusion that electromobile grid impacts at Stuttgart Airport will be more significant. As evident in the chart below, similar comments apply for Stuttgart Fair in international comparison. It is the tenth biggest fair in Germany with an exhibition area of approximately  $86.500m^2$  and a total of 1.3 million visitors in 2016.

Although EV deployment on one of the two locations already represents a challenging task, the poignancy of the present work gains further weight when taken into account that both sites are situated next to each other, sharing the same local energy network.

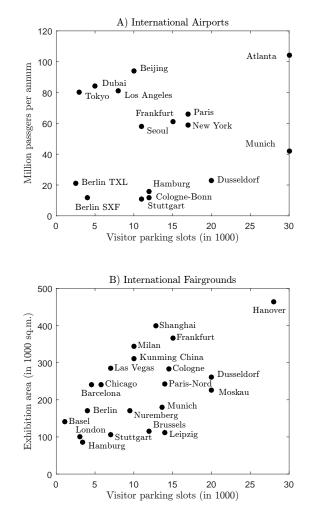


Fig. 1. Overview international airports and fairs according to own research

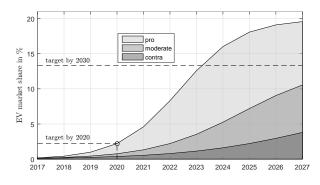


Fig. 2. Assumed EV market penetration over time including the major goals of the German federal government

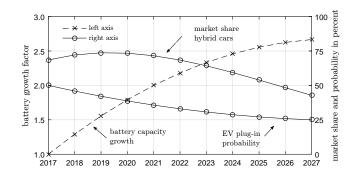


Fig. 3. Assumed plug-in probability, battery capacity development and market share of hybrid cars

## B. Scientific approach and general assumptions

The forecast model has been implemented in  $Matlab^{\mathbb{R}}$ and methodically divides into two parts:

*First*, the mobility behaviour of all passengers, employees, visitors and exhibitors is reconstructed for half an year. For this purpose, site-specific data were integrated into the model to identify essential peak-times during the day and to draw reliable conclusions regarding the SOC of potential EVs. As data basis served current flight schedules, event calendars, passenger surveys, employment figures, typical work shift patterns as well as historic parking data. *Second*, all trips are omitted which statistically do not result in a loading EV. To assess the eventuality of a charging event, different probability factors are determined to account for multiple scenarios and charging technologies. The factors are strongly influenced by four time-dependant variables to account for different forecast horizons. Those variables are:

- 1) the *market share of electric vehicles* until 2027 as assumed in Figure 2 for a pessimistic, moderate and optimistic EV scenario
- 2) the increasing *battery capacity* due to technical progress as anticipated in Figure 3 which heightens the storable energy amount of the underlying EV pool
- the decreasing *plug-in probability of electric vehicles* due to a rising number of (public) charging stations, larger battery capacities and consequently higher EV ranges (see Figure 3)
- the proportion of plug-in hybrid electric vehicles (PHEV) compared to full electric vehicles as illustrated in Figure 3

Since the present work focusses on the forecast method, the underlying assumptions for the time-dependant variables will not be explained any further. The model has been implemented in a way that allows these variables to be replaced quickly if needed. Furthermore the following constrains have been made:

- It is supposed that the EV consumption of averagely 20kWh/100km remains constant during the next 10 years due to the annihilation of efficiency gains through further developments towards autonomous driving.
- The mobility behaviour is assumed to remain stable until 2027.
- In the present work, only land-sided traffic is considered except for taxis, public buses or business fleets.
- Due to simplicity reasons only charging performances of 22kW for normal charging and 50kW for DC-fast-charging are regarded. Both charging processes are assumed to be *rectangular in time* with no SOC or temperature dependencies.
- In order to account for different vehicles types, the battery capacities of 36 full EVs and 33 plug-in-hybrids were considered which are currently available on the German market [14]. The distribution of all battery sizes is displayed in Figure 4. Moreover, a usable battery capacity of 80% is assumed which is multiplied by the battery growth factor defined in Figure 3 according to the forecast horizon.

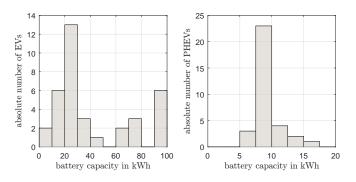


Fig. 4. Battery size distribution of the underlying EV pool as extracted from [14]

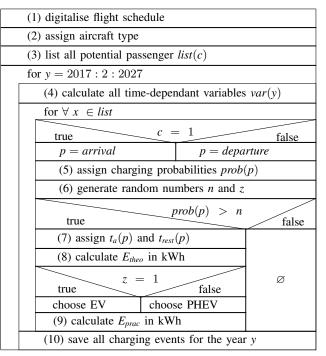


Fig. 5. Simplified modelling procedure for passenger events

#### III. FORECAST MODELLING

This section describes the forecast model for Stuttgart Airport and Fair in more detail by emphasizing its methodical procedure. The aim is to heighten the method's comprehensibility to permit a proper assessment of the simulation results.

#### A. Airport passengers

As schematically illustrated in Figure 5, the following procedure is applied to predict the EV energy demand arising by landing and departing aircrafts:

First of all, the flight schedule of Stuttgart Airport is digitalised from 30<sup>th</sup> October 2016 to 25<sup>th</sup> March 2017 in order to gain knowledge about the aircrafts' flight pattern such as daily arriving and departure times (1). Each arriving and departing plane corresponds to a flight number which can be associated to a specific *ICAO aircraft type designator* [13]. With the help of these alphanumeric codes, the corresponding aircraft type is identified with its maximum number of passenger seats (2). To simulate the greatest possible passenger movement on the airport, all potential

passengers and their belonging timestamps – date and time – are listed by assuming fully occupied airplanes. Each line of the list corresponds to a single passenger (3). According to the forecast horizon, all time-dependant model inputs as illustrated in Figure 2 and 3 are calculated (4). Next, each passenger is matched with several probability factors which indicate whether this passenger (or his attendant) triggers a charging event or not (5).

There are six different probability factors for landing passengers per year depending on the chosen scenario (pessimistic, moderate or optimistic EV market penetration) and the charging performance applied (normal AC-charging or DC-fast-charging). Figure 6 displays the composition of all factors for landing passengers in 2027. The central question is how many EV-charging events result proportionally from an arriving aircraft. In case there are as many charging processes as the aircraft has passenger seats, the probability factor would be 100%. In praxis, this percentage is reduced by the aircraft's average load factor, the share of passengers that leaves the airport by public transport, the vehicles' occupancy rate, the EV market penetration, the share of vehicles that actually park and the users' plug-in probability. Some of those partial factors are subjected to great uncertainties and therefore are strongly dependant on the user's charging behaviour and price-sensitivity. In Figure 7 the chargingprobabilities for departing aircrafts are depicted featuring additional factors for self-driving people who distinguish themselves in higher resting times and parking probabilities. To each probability factor and passenger a random number between zero and one is assigned (6). In case the random number is inferior to its belonging probability factor, the passenger becomes a valid result and triggers a charging event.

By means of statistical variance, the passenger's arrival at the airport is computed with the help of the assumptions made in Table I. The spreadsheet provides further information on the EV resting time which slightly differs according to the chosen charging technology and user group. The passenger origin serves to estimate the vehicle's SOC upon arrival. In this context, Table II shows the destination (in km) of all passengers arriving via plane (see arrival share) and the origin of those who intend to take off (see departure share). Based upon these distances, the theoretical energy demand of each EV is calculated by two terms: The first one represents the amount of energy which is required to get to Stuttgart Airport. The second one signifies a randomly chosen energy demand to account for EVs that did not head to the airport straight away or were not fully charged beforehand (8).

According to the PHEV-share defined in the previous section, the EV type is statistically determined for each valid charging event. The practical possible energy demand is therefore limited by the EV resting time and the vehicles' battery size (9). Next, all valid charging events are stored for latter use with their belonging data such as the date and forecast year, EV arrival and resting time, required energy amount, charging duration and performance as well as the EV scenario (10). Finally, the steps (4) to (10) are repeated in an automated fashion in order to determine the charging events for each forecast horizon.

reduction of the overall probability by:	probability factor	data source
arriving aircraft with a maximum of xx seats	= 100%	flight schedule and airport homepage
average aircraft load factor	x 75%	balance sheet airline company
amount of passengers travelling by car	picked up x 35%	passenger survey 2015
average load factor car (1 person = 100%)	x 50%	own assumption
EV market share (here for 2027)	contra x 3,8% mod. x 10,5% pro x 19,6	
chosen parking area (TA = terminal access, 10% outside)	parks TA   x 30% x 60%	passenger survey 2015
AC and DC share	AC DC AC/DC 100%	derived from parking data
plug-in probability (here for 2027)	x 25% X 25% X 0%* *due to parking ban	see assumption Figure 3
overall probability 2027 (of ten thousand passengers)	con <sub>AC</sub> con <sub>DC</sub> mod <sub>AC</sub> mod <sub>DC</sub> pre   2.6 1.1 7.2 3.1 13	

Fig. 6. Composition of all probability factors for landing passengers

reduction of the overall probability by:		probability factor	¥	data source
departing aircraft with a maximum of xx seats		= 100%		flight schedule and airport homepage
average aircraft load factor		x 75%		balance sheet airline company
amount of passengers travelling by car		brought x 49%	self-driven x 17% *	passenger survey 2015
average car load factor (1 person = 100%)		x 50%		passenger survey 2015 own assumption see assumption Figure 2
EV market share (here for 2027)	contra x 3,8%	moderate x 10,5%	pro x 19,6%	see assumption Figure 2
chosen parking area (TA = terminal access, 10% outside)	parks x 30% X 60	· ()	() par 80	
AC and DC share	AC DC 30%	AC/DC 100%	DC A 0% 50	
plug-in probability (here for 2027)	X X 25%	x 0%	x x 25	
overall probability 2027 (of ten thousand passengers)	con <sub>AC</sub> con <sub>SAC</sub> con 3.6 2.4* 1.6		modsac moddd 6.7* 1.3	рголс ргозас ргодс 18.9 13* 8.1

Fig. 7. Composition of all probability factors for departing passengers

TABLE I Assumptions arrival and resting time

[		arriving aircraft	departing aircraft	
		$t_A$	t <sub>D</sub>	
EV	DC	$t_A + 10 \min$	<i>t</i> <sub>D</sub> - 120min	
arrival	AC	$t_A + 10 \min$	<i>t</i> <sub>D</sub> - 120min	
time	Ŧ	30min normally distr.	45min normally distr.	
EV	DC	10-60min	10-60min	
resting	AC	30-90min	30-90min , AC <sub>self</sub> : >8h	
time	Ŧ	equally distributed	equally distributed	

TABLE II Assumptions catchment area passengers

arrival	departure	passenger	distance	variance
share	share	provenence	in km	in km
11%	11%	Boeblingen	19	±5
11%	14%	Esslingen	16	$\pm 5$
2%	3%	Goeppingen	38	$\pm 10$
-	3%	Heilbronn	74	±15
5%	8%	Ludwigsburg	30	$\pm 10$
-	3%	Ostalbkreis	94	$\pm 20$
37%	14%	Stuttgart	13	±7
4%	6%	Tuebingen	33	$\pm 5$
4%	9%	Rems-Murr-Kreis	52	$\pm 10$
4%	4%	Reutlingen	30	$\pm 5$
22%	25%	Other	50	±45

#### B. Airport employees

The charging events arising from airport employees are approached in a similar manner. Whereas the procedures (4) to (10) of Figure 5 remain methodically the same, the steps (1) to (3) have to be adjusted accordingly.

For this purpose, all employment groups that are permanently stationed at the airport are identified with their belonging headcount and work model. Table III illustrates in a simplified form the employment structure at Stuttgart Airport for approximately 8000 employees. As shown in Table IV, five different work models are considered: core hours, flight operation, the flight crews' work schedule, 24h shift operation and the opening hours of divers shops and restaurants which have been extracted from the airport's information booklet. Due to the long business hours at airports, some work models involve shift system so that corresponding employees need to be divided appropriately. By listing all employees with their belonging work shift and duplicating them from 30<sup>th</sup> October 2016 to 25<sup>th</sup> March 2017, the mobility behaviour of the airport staff is reconstructed. Analogous to the previous section, each employee movement is matched with different probability factors indicating whether a charging event is triggered or not. When contemplating Figure 8, it becomes apparent that DC-charging is no longer considered here. In general, employees remain approximately eight hours at work, therefore their vehicles can be charged slowly throughout the day to lessen grid impacts. However, additional probability factors for weekends are introduced to account for lower staff requirements on Saturday and Sunday.

#### C. Fair visitors, exhibitors and employees

To reconstruct the mobility behaviour at Stuttgart Fair, there has to be distinguished between visitors and exhibitors on one side and employees on the other. The main difference is that data on the first group are already available in car figures, which considerably shortens the corresponding probability path displayed in Figure 9. As underlying data basis served an internal event calendar for 2016 providing detailed information on the start and end of each event, the number of parking vehicles (from exhibitors and visitors) and the hall occupation. The daytime distribution of all arriving cars is determined by means of mobile data analyses from *Google Analytics*.

As for the fair staff, 300 regular employees were considered, thereof 50% working in core hours and 50% with eventdriven working schedules. For each event a minimum of 20 people as event-team is assumed plus additional 2% of the actual car traffic this day in order to account for external contractors occupied with event execution, catering and technical support. Besides, a build-up-team is assumed which is responsible for stand construction and dismantling, technical infrastructure, hall decoration and cleaning. Stuttgart Fair provides nine different exhibition halls including the International Congress Centre (ICS). The day before an event starts, 40 employees are assumed for each occupied hall for preparation purposes. Furthermore, the same number of employees are assumed on the evening of the last event day for the dismantling process. Due to the concentrated vehicle arrival only normal charging is considered within this section.

TABLE III EMPLOYMENT GROUPS AND THEIR ASSUMPTIONS

1	1 (		1.	1	1 . 0	
share	employment group	working model in %				
%	(perm. stationed at airport )	C	F	P	24	0
27%	airline staff, flight crew	-	50	50	-	-
20%	domiciled companies airport	90	10	-	-	-
13%	runway monitoring, passenger handling, ground handling ser- vices and flight operations	-	85	-	15	-
10%	customs, (federal) police, secu- rity service and flight safety	-	95	-	5	-
7%	haulage and cargo handling	40	60	-	-	-
6%	retailers and restaurant business	5	25	-	-	70
5%	energy and water supply, cleansing and waste disposal	5	65	-	30	-
3%	commercial department, inter- nal services, public relation	90	10	-	-	-
3%	facility and IT management	80	-	-	20	-
6%	other (accumulated)	100	-	-	-	-

TABLE IV Assumptions work models & shifts

	name of the working model	from - to hh:mm	no. of shifts	shift begin hh <sup>rst</sup> /hh <sup>nd</sup> /hh <sup>rd</sup>
C	core hour	8:00 - 17:00	none	8
F	flight operation	6:00 - 23:30	3	4/10/16
Р	flight crew	4:00 - 20:00	none	equally distributed
24	24h operation	0:00 - 0:00	3	5/13/21
0	opening hours	variable	1-2	airport booklet

reduction of the overall probability by:		probability factor		data source
number of employees (gross)		= 100%		derived from employment figures
number of employees (net) (on vacation or business trip, sick)		x 85%		own assumption
self-driver (car)		x 56%		study on commuters
average car load factor (1 person = 100%)		x 100%		derived from study on commuters
EV market share (here for 2027)	contra x 3,8%	moderate x 10,5%	pro x 19,6%	see assumption Figure 2
AC and DC share	AC DC 0%		()	derived from parking data
plug-in probability (here for 2027)	x x 25%	, D		see assumption Figure 3
reduced staff on weekends	WE WD x 66% X 100%	]		own assumption
overall probability 2027 (of ten thousand employees)	conwe conwd I   30.1 45.2 I	mod <sub>WE</sub> mod <sub>WD</sub> 83.3 125	prowe 155	рго <sub>wd</sub> 233

Fig. 8. Composition of all probability factors for airport staff

reduction of the overall probability by:	<u>path 1:</u> probability factors ← employees	
number of employees (gross)	= 100%	- persons -
number of employees (net) (on vacation or business trip, sick)	x 85%	Present data record: - cars -
self-driver (car)	x 56%	, ← path 2:
average car load factor (1 person = 100%)	x 100%	probability factors exhibitors & visitors
EV market share (here for 2027)	contra x 3,8%moderate x 10,5%pro x 19,6	
AC and DC share	AC DC () (	<u>)</u>
plug-in probability (here for 2027)	x x 25%	
overall probability 2027 (of ten thousand)	con <sub>P1</sub> con <sub>P2</sub> mod <sub>P1</sub> mod <sub>P2</sub> 45 95 125 263	ргорі ргорі 233 490

Fig. 9. Composition of all probability factors for Stuttgart Fair

### **IV. SIMULATION RESULTS**

This section analyses the predicted EV load on both locations and discusses its influence on local power consumption. The EV demand profiles are derived from the charging events reconstructed in the previous chapter according to a method applied in [17]. Every single charging event in 2017 is represented by a rectangle spanned by the parameters charging power and duration. The resulting area indicates the charged energy in kWh. By assembling all charging rectangles day by day according to their temporal occurrence, daily demand profiles are derived. Next, all daily load profiles are stacked one above the other to determine the maximum, average and median EV load for any time of the day at Stuttgart Airport and Fair by using the *boxplot* function within the Matlab environment. In doing so essential peak-times are identified whose knowledge is important to develop site-specific load management strategies for selected user groups.

This procedure is repeated for each forecast horizon to illustrate the maximum load development from 2017 to 2027 to evaluate the necessity of grid-strengthening measures. Furthermore, the daily energy demand required for EVcharging is analysed for each forecast year and EV scenario to facilitate a cost-effective operation of the charging infrastructure. Last but not least, the predicted EV demand is compared the load profile of Stuttgart Airport and Fair in order to assess the impact of electric vehicles on existing demand profiles.

#### A. Stuttgart Airport

In course of the e-mobility study outlined in section II, three main locations for EV-charging infrastructure were identified. Most charging events from passengers and employees are assigned to a central location which features a grid capacity of 420kW for AC- and DC-charging. Due to the large expansion of the airport area, a second site is chosen with exclusively AC-charging poles for employees. A third location of 332kW is envisaged to host AC- and DC-charging infrastructure for e-taxis and fast-charging passengers. For reasons of space, the following EV loads are concentrated in one single location even though all three sites were analysed individually during the project.

Figure 10 displays the maximum and average EV loads depending on the forecast year and EV scenario. Since most of the charging events occur at the central location mentioned above, the belonging connected load of 420kW is considered the limiting factor. As can be seen from the vertical axis, this limit is exceeded in 2025 for the first time but only for an optimistic EV market penetration. Therefore, gridstrengthening measures are not required in the medium term. However, in order to prevent cost-intensive grid expansion in the long term, the exploitation of existing load shift potentials is recommended. The staff user-group is well suited for this purpose since employees cause half of the EV-charging events and usually remain long on the airport premises. The energy supply of belonging EVs could be reduced dynamically according to the site's overall power consumption.

Analogous to the maximum load, Figure 11 displays the average energy demand per day and forecast year. By 2027 the daily required energy amount corresponds to roughly

50 Smart full-charges (17.6kWh each) for a moderate EV market penetration. Under the given assumptions, the DC-share represents 25% of the total energy. However, the usage of DC-charging infrastructure will predominately be price-driven in future.

In general, it can be said that relatively large energy amounts are turned over each day at relatively moderate power rates. The main reason for this lies in the continuous operation of the airport, which prevents any critical power peaks. Figure 12 confirms this statement by displaying the electromobile load throughout the day for an optimistic EV scenario in 2027.

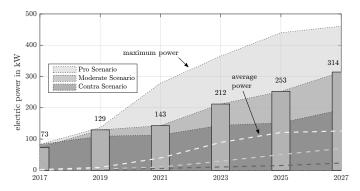
In Figure 13, the latter is compared with the airport's overall energy consumption. It becomes apparent that even in long term electromobile loads arising from passengers and employees will have no significant influence on the overall energy consumption and generation. Even the maximum EV load of nearly 0.5MW by 2027 represents only 12.5% of the airport's base load and 7% of its peak load. Nonetheless, EV grid impact will rise when further taking into account (a) air-sided EV deployment and (b) additional land-sided loads from electromobile taxis, buses, business fleets and delivery vehicles.

#### B. Stuttgart Trade Fair

The maximum EV load at Stuttgart Fair is strongly characterised by few major events which result in high power peaks as depicted in Figure 14 and 16. Compared to Stuttgart Airport, the predicted maximum loads are three to four times higher. In contrast to the high power peaks, the averagely charged energy amount per day is relatively small. In late summer, the fair usually hosts few events which slightly falsifies the average EV loads displayed in Figure 15. The energy quantities charged on major events will be considerably higher, especially on trade fairs with electromobile focus.

The fair's event-driven occupation is not favourable for a cost-effective operation of the charging infrastructure either. From an economic point of view, it is not recommended to scale the charging infrastructure at maximum load, since many stations would remain unused most of the time. Mobile charging possibilities, which can be settled up demandorientated, might be a convenient solution to prevent unnecessary operating costs. Furthermore, the airport's proximity should be used to outsource charging events on major events. In Figure 17, the EV load is compared with the fair's overall energy consumption. It can be seen that the building load is also subjected to strong power fluctuations, strongly correlating with the electromobile power peaks. The maximum EV load in 2027 with approximately 1.8MW represents half of the average fair load, but only 9% of its peak load which has been 16MW once. Since it can be assumed, that building and EV peaks continue to correlate in future, electromobility will always play an inferior role in terms of overall energy consumption. However, the existing power network is already considerably stressed on major events so EV-deployment further aggravates the situation. Therefore load shifting potentials arising from exhibitors and employees should be used mandatorily.

1200 1000



Predicted average and maximum EV loads at Stuttgart Airport Fig. 10.

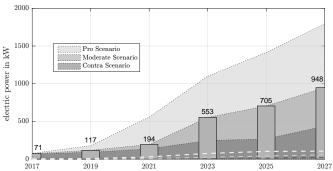


Fig. 14. Predicted average and maximum EV loads at Stuttgart Fair

Range Pro

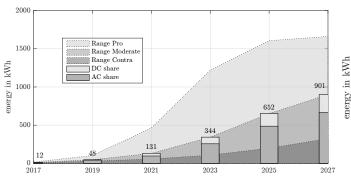


Fig. 11. Predicted energy amounts charged per day at Stuttgart Airport

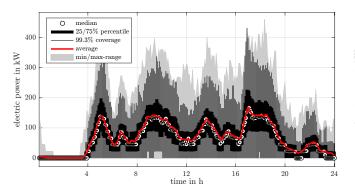


Fig. 12. Airport: predicted EV loads by 2027 for an optimistic EV scenario

7

6

5

electric power in MW

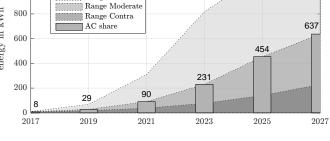


Fig. 15. Predicted energy amounts charged per day at Stuttgart Fair

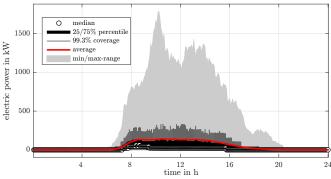


Fig. 16. Fair: predicted EV loads by 2027 for an optimistic EV scenario

B) fair vs. electromobility load

e fair load

12 16 2024

time in h

obile load @2027 mobile load @2027

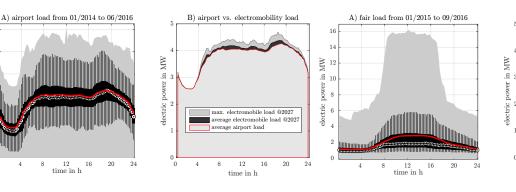


Fig. 13. Airport load compared to the predicted EV load by 2027

Fig. 17. Fair load compared to the predicted EV-load by 2027

power electric

#### V. CONCLUSION

The present work introduced a transferable model for electromobile loads at airports and fairs. Due to the integration of site-specific data and the consideration of technical progress and its influence on the user behaviour, the approach permits an accurate reconstruction of future EV-charging events. The paper proves in the first place that alarming power peaks up to 30MW as predicted in [6] by 2030 are rather improbable for the considered use cases. For an optimistic EV market penetration of 20%, uncontrolled EV loads up to 0.5MW for Stuttgart Airport respectively 2MW for Stuttgart Fair - are judged to be more realistic by then. Generally, it can be said that electromobile loads arising from passengers, visitors and employees will continue to play a minor role when compared to the sites' overall energy consumption. However, EV loads further burden the existing power grid which is partially already stressed by major events such as electricity-intensive trade fairs. At this point, it has to be mentioned that public transport remains the most effective method to mitigate negative impacts on power systems and the environment. The planned expansion of the suburban railway station at Stuttgart Airport and Fair into a regional and longdistance station will prove very valuable in this regard. Apart from that, airports and fairs - as potential energy supply companies - are rather well suited to benefit from electromobility due to the opportunities that arise from local load shift potentials and renewable energy generation.

The model further allows a wide range of applications. Due to the fact that the mobility behaviour of every single passenger, visitor, exhibitor and employee is reconstructed, the maximum number of parallel charging events can easily be simulated for various scenarios, which is particularly useful for infrastructure dimensioning. By additionally providing information on the likelihood of EV loads, a cost optimized charging infrastructure roll-out can be achieved. Moreover, the indication of maximum loads serves to evaluate the necessity of grid-strengthening measures. The latter can be significantly reduced by this model since it identifies essential peak-times and load shift potentials to derive usergroup specific load management strategies. Based on the average energy turnovers per day, first economic and ecological assessments can be done to ease infrastructure financing and to estimate future CO2-savings. Those data also serve as decision basis on weather additional power generation capacities are required to satisfy future EV demands or not. Due to the simulation of the vehicles' resting time, individual billings systems can be developed in order to heighten the site-specific occupancy rate of the charging infrastructure. Nonetheless, further research is needed to improve the model. First of all, a SOC dependant charging curve could be implemented to heighten the model's accuracy with DC-charging processes. Furthermore, the model assumed statical power performances of 22/50kW only. This might be improvable by attributing a maximum power performance to each EV. Due to the long-term simulation, a temperature dependant approach would be imaginable to account for higher EV energy consumption in winter.

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