Investigating Electric Vehicles as a Promising Alternative to Static Storage Solutions

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***Abstract*—The rapid advances in the area of Smart Grid has led to the increased penetration of distributed energy resources such as photovoltaic panels and wind parks, as well as empowered the rise of the Electric Vehicles (EV). Futuristic scenarios are currently being investigated, one of which focuses on the use of EVs as a collective flexible storage, that could be utilized in a smart city neighbourhood to address unpredictability and intermittent behaviour of renewable resources, as well as a mean to increase the self-consumption factor. Our research focuses on the assessment of EVs as a promising alternative to static storage solutions. We use real-world data in simulations with the aim to investigate the relationship between different setups in smart cities and their impact. The results point out towards a promising future for EVs, as they can play a key part as part of a collective flexible storage.**

***Index Terms*—Electric Vehicles, Energy Management, Smart Grid, Microgrid, Renewable Integration, Energy Storage, Variable Storage**

I. Motivation

The Smart Grid vision [1] foresees increased distributed grid generation (DER) and increased interaction among existing and future energy related stakeholders. The aim is a transition towards a more efficient system, with lower energy losses, but also lower CO_2 emissions and increased distribution where the energy demand is synchronized with the supply and is produced in clearer ways where and when needed. To that sense we have seen the rise especially of renewables such as Photovoltaic (PV) and wind farms in smart cities as well as sophisticated efforts for their interaction with the consumers such as demand side management (DSM) and demand–response (DR) [2]. In Europe significant efforts [3] have been devoted in the last years towards the goal of realising the Smart Grid vision.

The increase of DER and especially the renewable integration, leads to a highly dynamic behaviour that is increasingly difficult to be forecasted, and hence the deployment of storage solutions to deal with it play an increasing key role [4]. The traditional way to deal with energy deviations between demand and supply, is with the deployment of static storage solutions in key points of the infrastructure that can absorb in case of energy excess or feed-in energy deficit. However, in the Smart Grid era, this approach is challenged as the grid grows dynamically and static solutions may need to be more flexible and mobile to better address localized needs. Still, their cost is relative high [4] and "free" storage capacity is available due to the increased penetration of Electric Vehicles (EV), which is already proposed to be clustered as a variable storage [5].

Especially when considering microgrids, the coupling of DER and (variable) storage solutions can complement other efforts also targeting demand and supply balance. In the microgrid, maximizing "self-consumption" may enable the creation of self-sustained communities that are more resilient and cost-effective, while they take optimal advantage of their available resources [6]. In this work we perform simulations using real world data in order to investigate the potential of different storage solutions to increase the self-consumption factor within a microgrid. Static and dynamic storage approaches are compared and discussed. We take a closer look to storage needs within the microgrid, that correspond size-wise to the low percentage of the average daily load of a stakeholder, as these pose as a good replacement candidate by a variable storage (constituting the sum of available storage in EVs). In addition we look at the economic side of using EV batteries, as well as what kind of business actions could arise in order to motivate EV users integrate their cars in storage programmes.

II. Experimental setup and considerations

Our scenario assumes a microgrid in a residential area. The electric energy is locally produced from renewable sources i.e. wind and solar power. If energy consumption exceeds the local energy production, the additional energy is bought from the national energy market. Within the microgrid, the target is the maximization of the self-consumption of renewable energy generation, and to achieve this, two electric energy storage solutions are considered, i.e. static and dynamic. The storage systems are charged on-demand by local-only overproduction and discharged when needed, in order to cover local energy deficits. The storage units are simulated individually, thus each unit has its own dynamics (and SOC) in connecting and disconnecting from the grid, making it respectively available and unavailable as storage.

The self-consumption factor, is defined as the difference between the total energy consumption E_{con} and the energy imbalance in the consumption $E_{imb,con}$ divided by the total energy consumption. The variable $E_{imb,con} \in [0, E_{con}]$ describes the gap in the consumption, which could not be supplied with the local energy production. The value $E_{imb,con} = E_{con}$ registers that nothing of the local consumption could be covered by local production, while $E_{imb,con} = 0$ shows that the entire consumption is supplied by the local produced energy.

$$\mathcal{E} = \frac{E_{con} - E_{imb,con}}{E_{con}} \quad (1)$$

The factor $\mathcal{E} \in [0, 1]$ describes the autonomy from the grid and the energy market. In case of $\mathcal{E} = 0$, no local energy could be used to meet the needs of the consumers, and $\mathcal{E} = 1$ indicates that all the consumption is covered with the local produced energy. As an Example: The consumption of a village E_{con} is 5 MWh and 1 MWh can be covered by local production. This lead to $E_{imb,con} = 4MWh$ and a self-consumption factor $\mathcal{E} = 0.2 = 20\%$.

We approach the investigation of the storage role in an experiment with real-world data. Our data source is the region of Alginet near Valencia in Spain, where an extensive trial of the NOBEL project [7, 8] has taken place for several months. Both generation datasets for wind and PV as well as the consumption of electricity correspond to this dataset.

An overview of the microgrid dataset that reflects wind & PV average daily generation as well as the average daily consumption is depicted in Figure 1. In the evaluated time frame the total kWh of production is equal to the total kWh of consumption; for this case 100%. To calculate the energy production from the wind data, we used the model for the "Tornado 1 kW" turbine. Since the model for wind starts producing energy at a wind speed of 5 m/s, we multiplied the wind speed with a constant factor, so that the average wind speed results to approx. 4.76 m/s. According to [9] there are regions in Spain where the mean wind speed lies between 4 and 5 m/s such as the region close to the NOBEL trial from where the data has been obtained. In case of PV we assumed that the production scales linearly with the solar radiation.

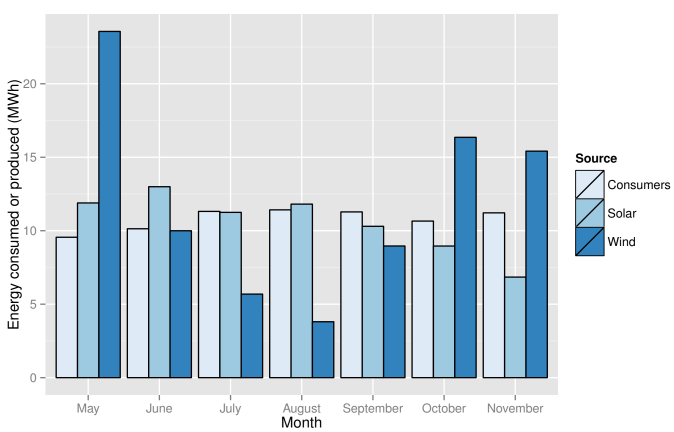

Figure 1. Overview of the microgrid average daily generation (wind & solar) and average daily consumption for seven months

Both storage systems (static and dynamic) behaviours are simulated over a time frame of 6 months (7th May– 7th Nov) with time granularity of 5 minutes. In each time step the simulator calculates the overall imbalance between consumption and production aggregated over all households. This incurred imbalance is then addressed by the storage actively (by flexibly charging or discharging). The negative imbalance that still remains after utilizing the storage, is subsequently measured for each step and summed up for the entire time frame in order to calculate the self-consumption.

In order to ease the comparative analysis between the two scenarios, the storage size was chosen to be the equivalent to 10%, 20%, 50%, 100% and 200% of the consumer's own electric vehicle storage capability. Therefore, in both scenarios the storage is scaled in units of 19 kWh, as this battery capacity is later used for dynamic storage units. Hence, when an acquisition of a static storage unit for 50% of the consumers is bought, its storage size is $1046 \cdot 0.5 \cdot 19kWh = 9937kWh$. The first storage system that is analysed to maximize self-consumption, will be the static storage.

III. Use Case: Static Storage

Using the dataset and approach depicted in section II, we first investigate the impact of static storage. The first simulations show the behaviour of the self-consumption factor for different storage sizes, when we increase the production from 0% to 500% of the total consumption of the consumers for the entire time frame of the evaluation. For wind energy this is visualized in Figure 2 and for solar energy in Figure 3 for the same setup.

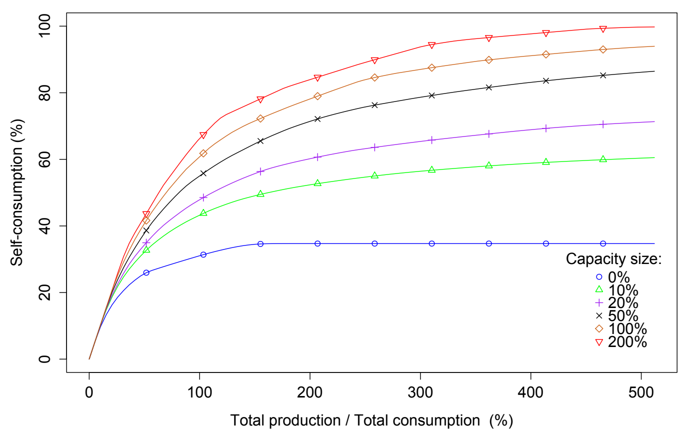

Figure 2. Self-Consumption factor for different static storage sizes for wind production

In both graphs we can see that the curves increase almost linearly at the beginning until 100% production is reached, and then they continue with a smaller gradient until they approach an asymptotic value. For the wind energy the asymptote is 35% without any storage, whilst by adding 10% this value almost doubles to 60%. It increases even further by scaling the storage higher, until it reaches almost 100% with the storage of 200%. With the solar production we have an even higher rate. Without any storage the scenario reaches 54% self-consumption. By adding 10% static units the asymptote of the self-consumption reaches 73%. By scaling the storage higher the asymptote increases until it reaches almost 100% with the storage of 200%.

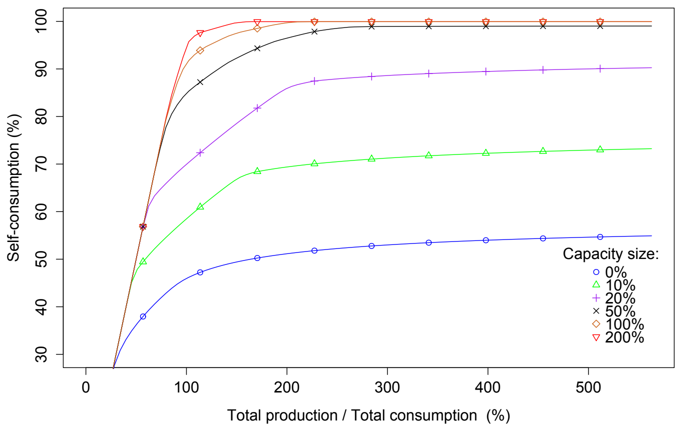

Figure 3. Self-Consumption factor for different static storage sizes for solar production

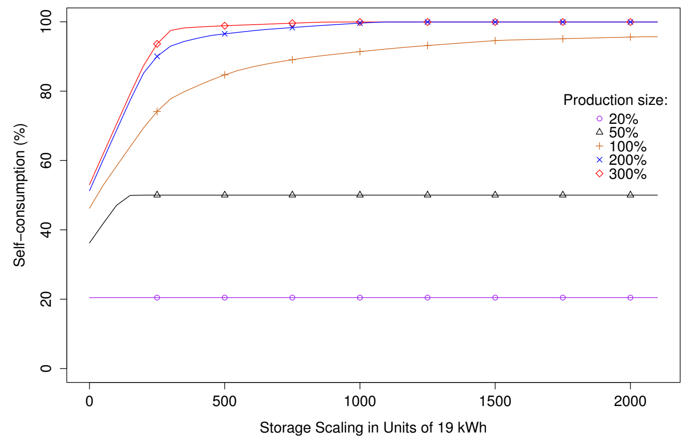

Figure 5. Self-consumption factor for 20, 50, 100, 200, 300% solar production, by scaling the static storage from 0 to 2100 storage units

The difference in the performance of both productions may be explained as followed: While the wind speed is more irregular and it can happen that there is no production for a longer time frame even during the day, solar is more reliable and predictable. Additionally, the PVs production of energy timely maps the higher needs for consumption during that time. Hence, the solar energy only has to be stored to meet the lower consumption during the night. The simulations we conducted run trough measure period of the NOBEL project, which means summer until autumn, and in these months there is lot of radiation in Spain, which also explains the high production rate.

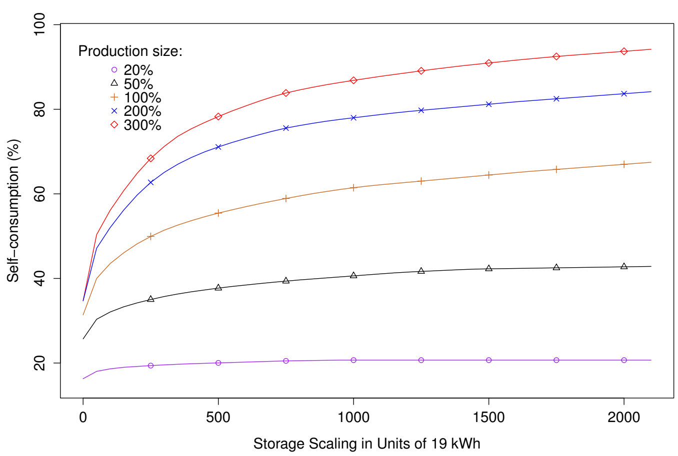

Figure 4. Self-consumption factor for 20, 50, 100, 200, 300% wind production, by scaling the static storage from 0 to 2100 storage units

Figure 4 shows the self-consumption factor for 20, 50, 100, 200, 300% production of wind energy of the total consumption of the households, when we scale the storage units from 0 to 2100. The curves show a similar form as the self-consumption by production scaling. All lines start with a certain self-consumption even without any storage and they convert to an asymptotic value. This value increases with the production up to 94% for 300% production.

Figure 5 shows the self-consumption factor for 20, 50, 100, 200, 300% production of solar energy of the total consumption of the households, when we scale the storage units from 0 to 2100. In the case of 20% production it shows that the line is constant at 20%, which means that the storage has no impact for the amount of solar produced energy; in other words that amount of energy is always anyway consumed and there is no excess left to store. For 50% production the storage shows a little impact and increases the self-consumption, while at around 200 storage units the curve stays at a constant value of 50%. The behaviour of these two curves shows that the production is in total consumed by the households and only a little amount can be stored in the battery.

The other three curves show a similar form as the wind curves but with a better performance. All lines start with a certain self-consumption and they convert to an asymptotic value, that increases with the production up to 100% for 300% production. The curves for 200% and 300% convert really fast to 100%. This also shows that for solar production a large storage scaling for more than 200 storage units has almost no effect to increase the self-consumption factor.

IV. Use Case: Dynamic Storage of EVs

A. *EV usage pattern*

As there is no publicly available large scale data on EV usage, we have used the dataset of the 2008 mobility study in Germany [10] to analyse the characteristics of the presence curve of privately used vehicles and the distances for each journey. From these patterns, we only used journeys that were done by car owners as drivers, while trips longer than one day and journeys with a distance longer than 160 km were removed from the dataset, as these are generally not feasible for the majority of EVs today without recharging. This results in an average daily distance of approximately 39 km. We consider here typical city EVs such as Volkswagen e-up [11] and BMW i3 [12] that have a battery capacity of approx. 19kWh and an average range of 120–160 km. Furthermore we used a dataset that shows a presence curve which is sparsely below the one from the real data set to show that our results are still valid when the users behave slightly different than in average.

To create the dataset for six months the raised journeys were first classified by week days. Then we randomly selected vehicles with the journeys that this car took on this week day with start time, end time and distance. Following this process, we created a dataset of 2100 cars for six months starting on the 7th of May, in order to temporally align it with the consumer, PV and wind datasets.This way we can scale the number of cars from 0 EVs up to a scenario with 2 EVs per household.

The presence curve of the dataset is shown in Figure 6. We see that for work days almost 100% of the cars are present at night. In the early morning the curve drops until it reaches a minimum of 88% at about 08:00. During the middle of the day the curve increases to over 90%. In the afternoon it decreases again to a minimum of 88% at 16:00. After that it rises again until we reach almost 100% during the night. On the weekend the presence curve has its minimum during the middle of the day. In the morning and in the evening we have a very high presence of almost 100%.

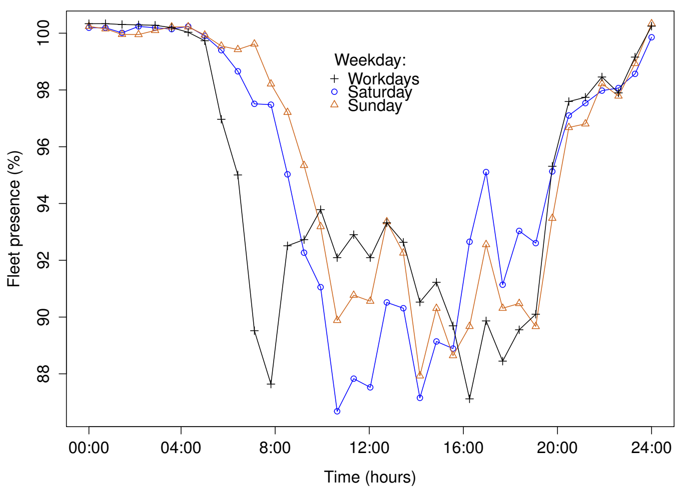

Figure 6. EV presence curve for the used dataset

Although this is an indirect way of creating a dataset for EV usage, that is derived from a real-world empirically measured study [10] in Germany, and then applied in Spain, we consider that this is largely realistic while also acknowledging its potential limitations. Significant deviations in the EV usage vs. conventional car usage, as well as potential country-specific impacts on the pattern identified and used, may have an impact on the results. However, we still consider that the point we make is still valid and the assumptions made do not bias the proof of concept presented in this work. Similar presence curves were identified by others [13].

B. Assessing dynamic storage

Next step is to specify the technical data which were used to describe the cars. City EVs such as Volkswagen e-up [11] and BMW i3 [12] have a battery capacity of 19 kWh and an average range of 120-160 km, while the consumption is 12.9 kWh per 100 km. Since the consumption can vary due to different factors, we used a slightly worse approximation and set the consumption to 13.9 kWh/100 km.

In this scenario it can appear that a car is not charged enough for its next trip. In this case the missing energy is addressed as consumed energy of the car. This affects the self-consumption factor in a negative way by adding this to the negative imbalance. This work assumes that the EVs are always connected to the grid when they are not used, thus are available to be utilized as dynamic storage. Complex algorithms optimizing the charging of cars under set constraints e.g. considering car and battery needs exist [14, 15], but this is not the main focus of this investigation. We follow a simpler approach, with the goal to keep the units in balance so that all of them have the same state of charge (SoC). Therefore the main principle followed is to charge always the car with the lowest SoC until the imbalance is absorbed completely. Similarly in the case of discharging, the EV with the highest SoC is discharged first. An overview of this logic is depicted in algorithm 1. Note: An overview of this logic will be added in the full paper. It is assumed that all cars can be charged and discharged to the battery limit, and for this investigation other parameters as well as secondary losses [16] are not considered.

```
Data: List of connected EVs
Start with the list of connected EVs;
Set EnergyUnit;
while EnergyImbalance >0 do
    get EV with min(SoC);
    if StoredEnergy = Capacity then
        exit;
    else
        charge min(EnergyImbalance, EnergyUnit,
        Capacity-Stored Energy);
        update EnergyImbalance;
    end
end
while EnergyImbalance <0 do
    get EV with max(SoC);
    if StoredEnergy = 0 then
        exit;
    else
        discharge max(EnergyImbalance, -EnergyUnit,
        -Stored Energy);
        update EnergyImbalance;
    end
end
```

Algorithm 1: A simple EV charging algorithm

The simulations were conducted in the same manner as the static storage scenario. While the static storage is always available to be charged or discharged, the EV as dynamic storage units are only available as dictated by the presence curve. The self-consumption factor for increasing wind production with dynamic storage shows a similar behaviour as the static storage. There is only a small decrease in performance of less than 1% (for equal capacities) than the respective curves in the static storage utilisation scenario. The same result is witnessed for the PV production. This may be explained by the high presence of the EVs. In addition when there is overproduction, it appears to be present for a longer timeframe than most trips take to conclude. As such, first the cars that are connected get charged, and later when the other cars arrive they will be charged, when there is still overproduction. For the wind case, the most overproduction is during the night when the consumption is low and almost 100% of the cars are connected.

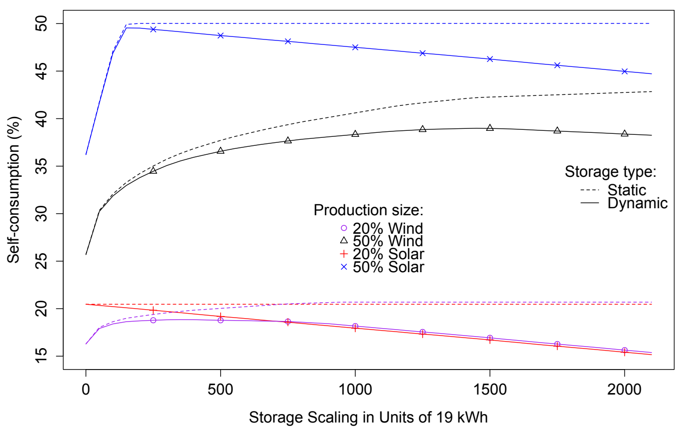

Figure 7. Dynamic storage with 20% & 50%of the households having an EV

Figure 7 shows the self-consumption factor for 20 and 50% production of wind and solar energy of the total consumption of the consumers, when we scale the EVs from 0 up to 2100. One noticeable difference is that for a production of 20% the curve slowly decreases when we add more EVs. This may be explained by the increased energy consumption that occurs when the cars are used, and hence an increase in the EV population will have an impact on the overall consumption. Therefore the line for the solar production is no more constant. This is shown also for the 50% production case, where the curve increases at first when adding cars, and subsequently starts to decrease linearly with the number of cars.

For wind production in Figure 7 , the self-consumption factor decreases more slowly for 20% production than in the solar case, and when 50% is reached, the consumption factor stays almost constant despite of the fact that the EV population increases. For the other three cases the factor increases at the beginning and then the gradient slows down. This exemplifies that in this setup, the first cars added to the system have a bigger impact, and at a certain point (around the mark of 200 EVs) the additional EVs have less impact to the maximization of the self-consumption factor.

V. Business Analysis

We have already shown from a technical perspective that the utilization of dynamic storage is similar to the static storage, and hence the question that needs to be tackled is if this utilization is cost efficient and what can be done to give incentives to the potential EV owners. We will approach this aspect by investigating the total cost of ownership (TCO) which includes the direct and indirect costs, and look closer to potential actions such as providing a lump sum to potential EV buyers or offering price discounts.

The cost-effectiveness of static energy storage systems in form of batteries is mainly determined by the investment costs and by the projected cycle stability of the battery storage technology [17]. The TCO can be calculated as $TCO = I + (A + M) \cdot S$. In this formula I refers to the investment costs, which in our case are determined mostly by battery price, inverter, installation costs and charge management . The administration cost involved A and maintenance costs M have to be considered with the factor for the projected lifetime of the asset. Finally the S refers to the cost that appears by the projected cycle stability of the battery storage technology. In terms of technological maturity and cycle stability, Lithium-ion (Li-ion) batteries may be classified as established battery technology.

In favour of simplicity some assumptions are made for the calculation of TCO. It is assumed that there is no replacement of the converter because the projected lifetime of an inverter has a high variance. Although the world is not risk-neutral, in our abstract calculations we assume that we operate in perfect markets with no taxes and zero interest rates. Finally, we adopted the kWh prices at 0,25€ of today, although potential inflation and price variations may occur in future.

Battery prices are steadily decreasing due to scale effects and standardization especially caused by the automotive industry and PV storage systems [18]. Prices for battery packages are projected to decrease steadily from a level of 400 €/kWh for Lithium-ion batteries to a level of 220 €/kWh by 2020. The TCO for 1kWh calculation is depicted in Table I. Battery technologies have a lifetime cycle capacity in the range of about 5000 cycles which is equivalent to an average lifetime of 13 years for at least one daily load cycle. Projected technology improvements double cycle capacities up to 2020 [19].

Table I
Lithium-ion TCO per kWh

	2014	2020
Initial Investment Costs		
Battery price	400	190
Inverter	200	150
Installation costs	120	68
Change management	included	included
Running Costs		
Maintenance	140	160
TCO	860	570
TCO per Year	66	22

Instead of implementing a static battery storage solution, owners of electric vehicles could be compensated for connecting their EV to the grid using the car's battery as energy storage, hence effectively building up a clustered variable storage. To investigate this, we consider the equivalent static storage capacity and two compensation scenarios i.e. (i) a bonus payment model and (ii) an electricity price discount model.

By using the TCO calculated for a static storage system, one can calculate the lump sum bonus that could be given to potential EV owners in order to incentivise them to buy an EV and integrate it in the variable storage. A view of the calculations is depicted in Table II. The lump sum bonus per EV is assumed to be an one-time event and also compensate for all other inconveniences that may occur e.g. battery degradation etc.

Table II
COMPENSATION SCENARIO: BONUS PAYMENT

Number of cars	Total storage (in kWh)	TCO for equivalent static storage in € (Mio.)		Lump Sum Bonus per EV in €	
		2014	2020	2014	2020
105	1995	1.7	1.1	16348	10775
209	3971	3.4	2.3	16348	10775
523	9937	8.5	5.6	16348	10775
1046	19874	17.0	11.3	16348	10775
2092	39748	34.2	22.5	16348	10775

An alternative scenario is the electricity price discount model which targets mostly existing EV owners looking e.g. for free kWh per month. The relation for TCO per month for a static storage and the costs for charging the equivalent number of EVs yields the results depicted in Table III.

Table III
COMPENSATION SCENARIO: ELECTRICITY PRICE DISCOUNT

Number of cars (19 kWh battery)	Discount in € per kWh	TCO per month for equivalent static storage in €		Free amount of kWh/month per EV	
		2014	2020	2014	2020
105	0,25	10.961	3.612	419	138
209	0,25	21.923	7.225	419	138
523	0,25	54.806	18.062	419	138
1046	0,25	109.613	36.125	419	138
2092	0,25	219.226	72.250	419	138

As it can be seen, the dynamic storage can be an alternative solution also from the business side. We have shown that the TCO corresponding to the static storage can be effectively used to incentivise EV acquisition and usage scenarios in as part of the envisioned variable storage. The examples are indicative, and of course similar ones will depend on the marketing strategies as well as the stakeholders involved and service-level agreements among them. Nevertheless, the sharing of resources and view of the microgrid in from a system point of view may lead to win-win situations for all participants.

VI. CONCLUSION AND FUTURE WORK

We have demonstrated that the clustering of EV batteries can be used to form a variable storage that can be effectively used to increase self-consumption in microgrids. The dynamic storage behaviour is similar to the static one, but much more flexible and at lower cost. We have also provided a business view on how the static storage TCO can be used to properly incentivise EV potential buyers and owners to participate in variable storage driven approaches in the future.

This work serves as a proof of concept and hence several assumptions have been made as already indicated. These limitations should be seen as starting points for future investigations, such as the applicability to other world regions. More research needs to be done in order to more accurately simulate the EV and user behaviour and fully satisfy the multiple constraints set by the EV owners, the electric mobility provider, the grid infrastructure etc. To that end more sophisticated algorithms can be used for EV charging. We have also assumed full control and 100% availability of the EV battery for charging/discharging which in reality may again be limited by the EV owner, or other conditions. Furthermore charging/discharging produces secondary losses and might as well affect the EV battery charging cycles [16]. As the lump-sum is large enough, such degradation may be considered already as included, but this may not be the case for other scenarios with lower compensation such as the free amount of kWh per month as depicted in the electric price discount scenario. Even with these limitations, it is clear that the utilization of EVs is very promising as a replacement of the traditional static solutions.

The Smart Grid brings innovative cooperation scenarios that could provide benefits to all of the stakeholders. The realisation of these does not lie only on the technical feasibility, but also on social and the marketing side. Advanced cross-disciplinary investigations are therefore asked, which may lead us to the more eco-friendly smart cities of the future.

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REFERENCES

[1] European Commission, "SmartGrids SRA 2035 – strategic research agenda: Update of the smartgrids SRA 2007 for the needs by the year 2035," European Technology Platform SmartGrids, European Commission, Tech. Rep., Mar. 2012. [Online]. Available: http://www.smartgrids.eu/documents/sra2035.pdf

[2] S. Karnouskos, "Demand side management via prosumer interactions in a smart city energy marketplace," in *IEEE International Conference on Innovative Smart Grid Technologies (ISGT 2011), Manchester, UK*, Dec. 5–7 2011.

[3] V. Giordano, A. Meletiou, C. F. Covrig, A. Mengolini, M. Ardelean, G. Fulli, M. S. Jiménez, and C. Filiou, "Smart Grid projects in Europe: Lessons learned and current developments 2012 update," Joint Research Center of the European Commission, JRC79219, 2013.

[4] K. Divya and J. Ostergaard, "Battery energy storage technology for power systems - an overview," *Electric*

Power Systems Research, vol. 79, no. 4, pp. 511–520, 2009.

[5] D. Ilić, S. Karnouskos, P. Goncalves Da Silva, and S. Detzler, "A system for enabling facility management to achieve deterministic energy behaviour in the smart grid era," in *3rd International Conference on Smart Grids and Green IT Systems (SmartGreens), Barcelona, Spain*, 3–4 Apr. 2014.

[6] S. Karnouskos, D. Ilić, and P. Goncalves Da Silva, "Using flexible energy infrastructures for demand response in a smart grid city," in *The third IEEE PES Innovative Smart Grid Technologies (ISGT) Europe, Berlin, Germany*, 14–17 Oct. 2012.

[7] A. Marqués, M. Serrano, S. Karnouskos, P. J. Marrón, R. Sauter, E. Bekiaris, E. Kesidou, and J. Höglund, "NOBEL – a neighborhood oriented brokerage electricity and monitoring system," in *1st International ICST Conference on E-Energy, 14-15 October 2010 Athens Greece*. Springer, Oct. 2010.

[8] S. Karnouskos, M. Serrano, A. Marqués, and P. J. Marrón, "Prosumer interactions for efficient energy management in smartgrid neighborhoods," in *2nd Workshop on eeBuildings Data Models, CIB Conference W078-W012, Sophia Antipolis, France*. European Commission, Oct. 26–28 2011, pp. 243–250.

[9] M. Gastón, E. Pascal, L. Frías, I. Martí, U. Irigoyen, E. Cantero, S. Lozano, and Y. Loureiro, "Wind resources map of spain at mesoscale. methodology and validation," in *Proceedings of European Wind Energy Conference*, 2008.

[10] R. Follmer, D. Gruschwitz, B. Jesske, S. Quandt, B. Lenz, C. Nobis, K. Köhler, and M. Mehlin, "Mobilität in Deutschland 2008: Ergebnisbericht Struktur – Aufkommen – Emissionen – Trends," Federal Ministry for Transport, Building and Urban Development, Germany, Tech. Rep., Feb. 2010. [Online]. Available: http://www.mobilitaet-in-deutschland.de/pdf/MiD2008_Abschlussbericht_I.pdf

[11] Volkswagen. (2014, Oct.) E-up electric car specifications. [Online]. Available: http://www.volkswagen.de/de/models/up/varianten.s9_trimlevel_detail.suffix.html/e-up~2Fe-up/tab=TECHDATA.html

[12] BMW. (2014, Oct.) I3 electric car specifications. [Online]. Available: http://www.bmw.com/com/en/newvehicles/i/i3/2013/showroom/technical_data.html

[13] M. Dogru, M. Andrews, J. Hobby, , Y. Jin, and G. Tucci, "Modeling and optimization for electric vehicle charging infrastructure," in *24th annual POM conference Denver, Colorado, USA*, 2013.

[14] C. Ahn, C.-T. Li, and H. Peng, "Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid," *Journal of Power Sources*, vol. 196, no. 23, pp. 10 369–10 379, 2011.

[15] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, "An optimized EV charging model considering TOU price and SOC curve," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 388–393, Mar. 2012.

[16] S. B. Peterson, "Plug-in hybrid electric vehicles: battery degradation, grid support, emissions, and battery size tradeoffs," Ph.D. dissertation, Carnegie Mellon University, May 2012.

[17] A. Thielmann, A. Sauer, R. Isenmann, M. Wietschel, and P. Plötz, "Produkt-Roadmap Lithium-Ionen-Batterien 2030," Fraunhofer ISI, Tech. Rep., 2012. [Online]. Available: http://www.isi.fraunhofer.de/isi-media/docs/v/de/publikationen/PRM-LIB2030.pdf

[18] T. Schlick, B. Hagemann, M. Kramer, J. Garrelfs, and A. R. Studie, "Zukunftsfeld Energiespeicher: Marktpotenziale standardisierter Lithium-Ionen-Batteriesysteme," German Engineering Federation (VDMA) and Roland Berger Strategy Consultants, Tech. Rep., Oct. 2012. [Online]. Available: http://www.rolandberger.de/media/pdf/Roland_Berger_Zukunftsfeld_Energiespeicher_20120912.pdf

[19] D. U. Sauer, "Marktanreizprogramm für dezentrale Speicher insbesondere für PV-Strom," Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety, Germany, Tech. Rep., Mar. 2013. [Online]. Available: http://www.erneuerbare-energien.de/fileadmin/Daten_EE/Dokumente__PDFs_/kurzgutachten_marktanreizprogramm_bf.pdf