# Self-Forecasting Energy-load Stakeholders

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***Abstract*—The emergence of the Smart Grid brings new opportunities and challenges for all involved stakeholders. Integration of distributed energy resources, in particular renewables, introduces uncertainties in traditional load forecasting which is pivotal towards capitalizing upon the Smart Grid opportunities. This calls for an active contribution of the grid stakeholders and involvement of many locally available assets that can help achieving such goals. However, resources that can actively contribute to reduce the load uncertainties also need to be measurable and therefore predictable. This works presents a system that enables the realisation of Self-Forecasting EneRgy-load Stakeholders (SFERS) that can achieve highly-predictable loads on its own and report them as such to external parties. Accuracy in self-forecast is achieved by absorbing their unpredictability within locally available assets. We investigate the key performance indicators of such systems and the capability of electric vehicles residing on SFERS premises to absorb the forecasting errors. A detailed assessment of various operational conditions is realised by utilizing real-world data and simulating the main system components.**

***Index Terms*—Smart Grid, Electric Vehicles, Self-Forecasting, Demand-Response**

## I. Motivation

The emergence of Smart Grid and the integration of more Renewable Energy Sources (RES) brings the promise of a more effective grid infrastructure [1]. Their intermittent and unpredictable behaviour however, brings more challenges within the distribution complexity and load balancing [2]. Significant efforts to make a step forward are already done through numerous research and demonstration projects carried out in last years [3]. Many business opportunities are expected to emerge [4] and new stakeholders will be enabled to contribute to increased reliability in future Smart Grid [5]. To fully capitalize on the opportunities presented, all resources willing to contribute need to be reliable and measurable [6]; thus high forecasting accuracy and effective management of their energy signature is needed. If sufficient forecast accuracy can be achieved by a stakeholder many Smart Grid benefits can be considered e.g. participating in demand response (DR) programs [7], [8] and automated energy trading [9].

Forecasting is a key part of efficient energy management, and if it is reliable, improvements in planning of energy relevant processes can be realised [10]. Already today RES utilize static storage solutions to balance the effects of their unpredictable and intermittent behaviour [11], or, if technically possible, by controlling (e.g. starting/stopping/rescheduling) heavyweight energy processes. The latter requires deep knowledge of processes, assets and full-understanding of interdependencies, which is a highly complex endeavour. Hence, the first approach, which is largely agnostic to such extended requirements, simplifies absorption of load uncertainties in power grids [11] and due to its efficiency is considered in this work. As such the traditionally passive stakeholders can use their locally available assets to enable themselves to perform accurate load forecasts, a capability that opens opportunities in new energy related revenues [7].

The nature of storage, if we look at it from the perspective of many different stakeholders, is changing. The increased penetration of electric vehicles (EVs) and the potential coordinated usage of their storage capacity [12], poses them as attractive alternatives to traditional static storage. They become even more attractive if one considers the still high cost of the static storage solutions [13]. The non-utilized storage capacities owned and present at stakeholder's premise, such as the storage capabilities of EVs, can be considered as "wasted" resources. As organizations strive towards fully utilizing their resources, in order to achieve higher efficiency and return of investment (ROI), new solutions can be realized [8]. A system that will use stakeholder's assets and couple them with the state of the art analytics and forecasting capabilities (to enable their active contribution in power networks) is needed [2].

We have already proposed a system for enabling facility management to achieve predictable, or in other words deterministic, energy behaviour [14]. In this work we focus on a subset of that proposal, where we use the electric vehicles of a stakeholder to compose so called Variable Energy Storage (VES) to achieve stakeholder's predictability. These stakeholders are here by a referred to as Self-Forecasting EneRgy-load Stakeholders (SFERS) [5] and the system components are proposed in higher details in this work, as well as its evaluation and identification of its key performance indicators. It is envisioned that such a system will fully utilize the capabilities of Smart Grid and modern IT systems including smart metering, EV integration, energy load reporting, real-time forecasting and management etc. Preliminary experimental results show that such a system has a promising potential for real world applications.

## II. The SFERS system

The system is expected to be utilized by a stakeholder (e.g. managing a commercial building), or a cluster of stakeholders (e.g. active in a residential neighbourhood), where the system can access metering data, business data, and energy management agreements [14]. It constitutes an extension of some parts of a more general architecture [14] proposed for holistic energy management. Sophisticated forecast can be applied in real-time by the Energy Load Forecasting (ELF) component. Decisions are made by the Energy Manager (EM) component, while the exact management of both dynamic storage and static storage is done by the VES unit [15]. Figure 1 depicts the detailed view on architecture extension of [14]. The main focus in this paper is to evaluate the proposed architecture as a running system. The key components used here are the Energy Load Forecasting (ELF), responsible for forecasting the energy needed at each interval, and the VES, responsible for unifying the energy storage units into one (virtual) unit of storage. Both static and dynamic units (such as EV batteries), are considered here.

Although the system runs autonomously, the operator can interact with it via a facility management cockpit where strategy selections are made. Additionally we consider that external services can be integrated by the SFERS in order to enhance its capability on the larger vision and interworking [14], while also it can provide input to other services e.g. a load reporting service of a DSM/DR stakeholder.

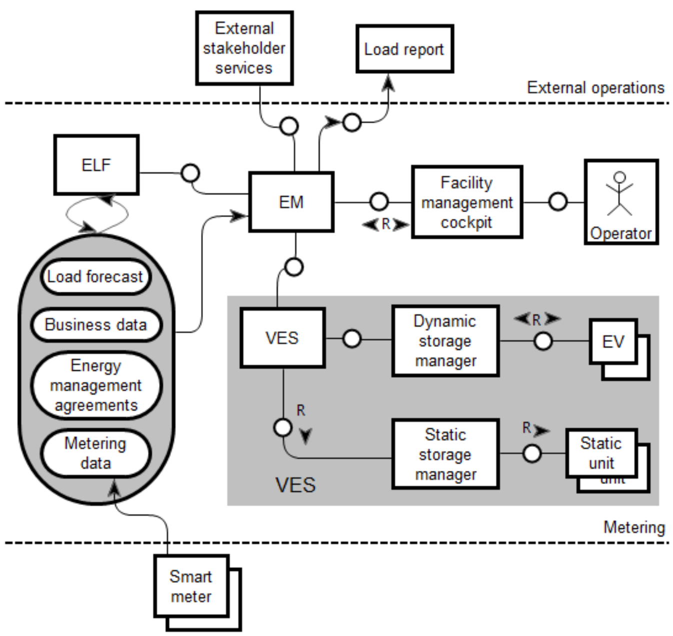


Figure 1. SFERS system view

### A. Operational Context

To clarify the operational aspects of the system, the context and issues it addresses are here described in greater details. The forecast horizon $h$ is the future number of intervals for which a demand forecast is generated. If an energy load $y[n]$ is forecasted from time series and is executed at interval $n_0$, the return forecast series $\widehat{y}[n]$ are for all $n \in [n_0+1, n_0+h]$. Greater horizons are expected to result in higher errors, which however converge [16]. Even though a forecast can be observed by Mean Absolute Percentage Error (MAPE), the mean observation from the intervals in a horizon hides the actual error of the different intervals. As an example, the forecast at $n_0$ is expected to result to much higher absolute percentage error at $n_0+h$ than the one at $n_0+1$, but MAPE in overall will hide it. Nevertheless, the internal system components as VES are expected to benefit from the continuous update of $\widehat{y}$, as scheduling algorithms may use it to better address the errors of ELF [14].

Since the SFERS system will report the energy load in the same fashion as a smart meter with an offset [5], a new parameter is introduced. The offset is observed as time, and is linked to the metering resolution, thus it is observed via $\Delta \in \mathbb{N}_1$ i.e. at end of an interval $n_0$ the load forecast for $n_0+\Delta$ will be reported as $\dot{y}$. As an example, at resolution $T = 15$ minutes, the five hours offset will have $\Delta = 5hours/15min = 20$. In this way all the intervals reported will suffer from the error an offset introduces. The smaller the offset, the greater is the accuracy that can be achieved. Furthermore, having greater errors at intervals will also affect the capacity required by the VES to absorb them [15]. Hence the forecast will be $\dot{y}_{\Delta}$, such that $|\dot{y}_{\Delta_1}[n] - y[n]| < |\dot{y}_{\Delta_2}[n] - y[n]|$ is expected (but not necessarily resulting) for $\Delta_1 < \Delta_2$. Figure 2 demonstrates the effect of $\Delta$ on intraday intervals on a real-world example.

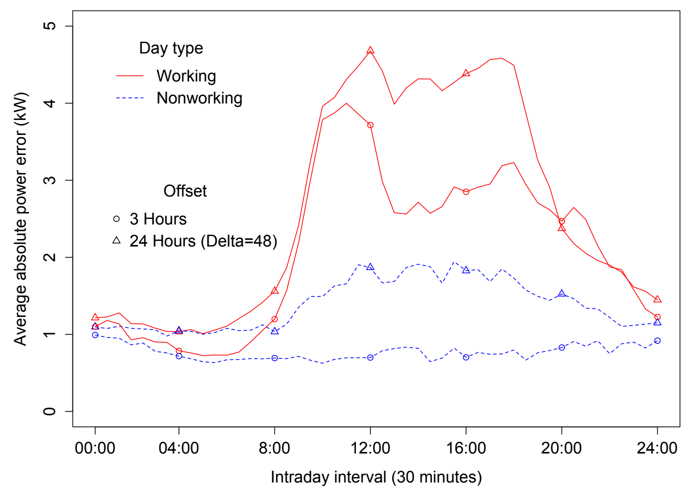


Figure 2. Impact of different $\Delta$ on forecast accuracy over intraday intervals

### B. VES Controller

The management of VES is inevitable for a live system [15], in particular when a dynamic unit of VES is disconnected and connected with its individual state of charge (SOC). The evaluation shown in section III addresses this issue by simulating individual units. For the actual management of VES, a controller for charging/discharging connected storage units and storage load adjustment (required to keep the SFERS system reliable) are required.

Since a SFERS is highly dependent on VES, charging schedules of EVs have a significant impact. In this work the individual SOC of a unit is considered through entire period of the evaluation, where error from reported load $\dot{y} - y$ is changing the state of VES; thus an algorithm has the goal to keep it reliable. In order to achieve such goal, algorithm 1 is utilized, where maximum charge (positive) and discharge (negative) are the steps of change for a unit. Although better solutions may exist, algorithm 1 distributes the SOC equally such that theoretical assessment for SFERS can be made. Further investigations on improving the proposed algorithm, such as by driver requirements, are expected in future work (as noted in section IV).

```
Data: Connected storage units
Result: Remaining energy imbalance
while imbalance > 0 do
    get storage unit with min(SOC);
    if stored energy = unit capacity then
        exit;
    else
        charge min(imbalance, maximum charge);
        update energy imbalance;
    end
end
while imbalance < 0 do
    get storage unit with max(SOC);
    if stored energy = 0 then
        exit;
    else
        discharge max(imbalance, maximum discharge);
        update energy imbalance;
    end
end
```

**Algorithm 1:** A SOC-based control algorithm for VES

As VES absorbs the forecast errors of $\dot{y}$, its SOC is affected. Furthermore, every individual storage unit which is part of the VES, has its targeted SOC, independently if it is static or dynamic. Hence, to keep the system in balance through the entire period of the evaluation (e.g. one year), every report $\dot{y}$ need to be adjusted on requirements of the VES. In this work, the SOC-based adjustment of $\dot{y}$ is made for any offset value $\Delta$. The load requested by VES is based on the current SOC of storage units that are available at $n_0+\Delta$. The $n_0+\Delta$ interval takes an equal fraction over $\Delta$ for the forecast adjustment, and in this case in order to set the SOC to 50%. The adjustment controller is mathematically described as:

$$\dot{y}[n] = \widehat{y}_{\Delta}[n] - \frac{1}{\Delta}\left(\bar{c}[n]\cdot\overline{SOC}_n[n-\Delta] - \frac{\bar{c}[n]}{2}\right), \quad (1)$$

where $\bar{c}[n]$ is the available capacity at $n$, e.g. coming from connected cars, and $\overline{SOC}_n[n-\Delta]$ is the SOC at $n-\Delta$ of all units available at interval $n$. This controller resulted in good performance, however more sophisticated controlling methods could be applied [10] and need to be considered in future work.

### C. Runtime Simulation

To assess the potential of the proposed system, all parts of it are simulated using the real data. In SFERS system, calculating $\widehat{y}$ or $\dot{y}$, the forecasting at $n_0$ will depend only on the actual load $y[n]$ for $n \le n_0$. From the signal description, an interval forecast $\dot{y}[n_0+\Delta]$ needs to be reported once the sample at $n_0-1$ is available. As such, a forecasting algorithm would be executed 48 times to produce $\dot{y}$ for a day in intervals of 30 minutes. As a result, excessive times may be needed and computation requirement of sophisticated forecasting algorithms [17] may heavily impact the system performance. Hence, we decided to execute forecast on preselected offsets $\Delta$ and use them in the simulation environment. The reported energy is calculated as indicated in Equation 1, which is considered as production unit. The consumer of the simulator is the measured energy consumed by the stakeholder in evaluation. The imbalance produced is to be absorbed by VES (from the following section) or will result as an overall system imbalance – used for depicting the graphs in section III.

For the variable storage, the actual disconnection/reconnection of uniquely identifiable units is critical [15]. A dynamic storage unit is only available within VES once it is on-premise and it holds its own SOC. In this work this is simulated on different scales of company EV fleets, that are based on real world data and charge during business hours. The data from five “Mercedes-Benz A-Class E-Cell” (used as pool vehicles with battery capacity of 36 kWh) is collected from 5 January 2012 to 10 August 2013 (585 days). Both individual employee and pool vehicles are considered, where pool EVs were not directly assigned to individual employees and different mobility pattern may be expected [18]. The storage shapes used for the evaluation are presented in Figure 3.

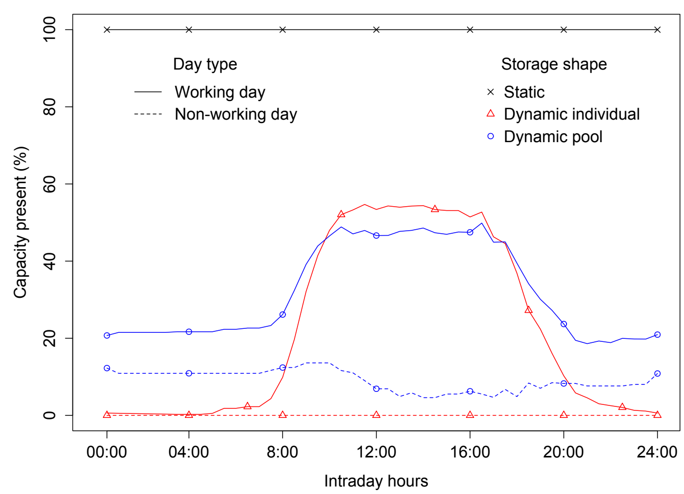


Figure 3. Intraday presence of static and dynamic storage (from pool and individual vehicles)

As it can be seen, the static storage units are not disconnected, while the dynamic part is composed based on data from working and non-working days. Illustrated presence curves are built from few yearly schedules of 100 different units ($\approx$ 800 charging sessions on-premise). In a continuous evaluation, these individual EVs will assist us towards producing more realistic experimental results. However, has to be pointed out that several abstractions are undertaken that may be considered

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as limitations. For instance, round-trip efficiency of the batteries is equal to 1. It is also assumed that all batteries allow discharging down to a SOC of 0%.

## III. Evaluation

The parametrization of SFERS has an impact on its performance; hence we demonstrate in practice how it can be used and the impact on the results it yields. We experiment with a commercial building (with offices occupied by approx. 100 employees) and assess it over the entire year 2011. Its consumption in 2011 was 234.4 MWh with an average daily power consumption of 29 kW for working and 20 kW for non-working days. This building is mainly used on working days, which are responsible for 80% of its yearly consumption. Although working hours (08:00–17:00) cover less than 26% time of a year, they are responsible for 37.8% of energy used and 50.8% of all the forecasting errors. The system is simulated on 30 minute resolution ($T = 30$) over time frame of an entire year, where different offset parameters $\Delta$ and configurations of VES units are evaluated.

### A. Assessing Metric Impact

Using the methodology proposed in subsection II-C, the offset effect on system efficiency is evaluated. Few standard forecasting algorithms were utilized to measure how an offset affects MAPE of the stakeholder in evaluation. Tests were made with Holt-Winters (HW) and seasonal ARIMA (SARIMA) models for weekly season, while SARIMA was also evaluated with the extra daily seasoning (also used by others [16]). In order to enable a direct comparison with evaluations of others, the offsets selected are $\Delta \in [3, 6, 12, 24, 48]$. Finally, the measured energy load from previous 4 weeks was used to train the forecast model of each interval. The experimental results acquired, for both horizon and offset forecasting, can be seen in Figure 4.

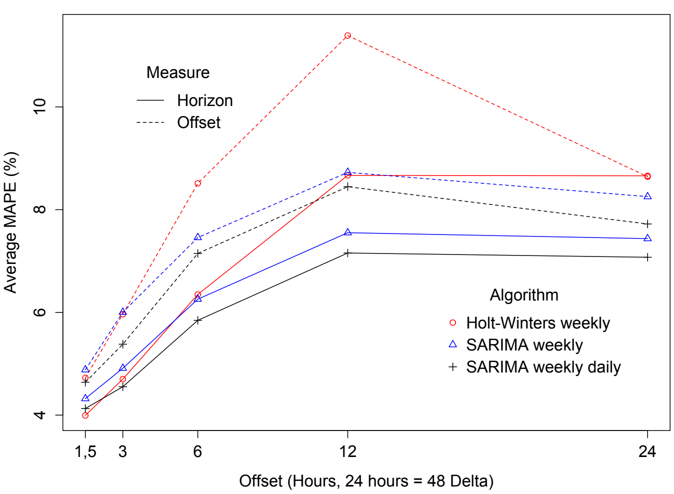


Figure 4. Impact on stakeholder's forecast accuracy by horizon and offset forecasting

It is noted that the average MAPE of the SARIMA models resulted to lower $\Delta$. For HW one can clearly notice significant growth of MAPE for $\Delta = 24$, or 12 hours offset, while for $\Delta = 48$ the results significantly improve. Although it is not easy to identify the reasons behind the performance degradation, one may hypothesize that it is due to the daily seasonality of the data (while only weekly seasoning is considered). Since the SARIMA resulted in better performance, SARIMA weekly was selected for the subsequent experiments with VES.

For comparison with work of others [16], Figure 4 also depicts the forecast accuracy over horizons for all $\Delta$. In other words, the MAPE resulting of $\widehat{y}[n]$ for all intervals $n$ forecasted from $n_0$, thus for $\Delta = 24$ the MAPE for horizon would be the mean of the set $\{\widehat{y}[n_0+1], \widehat{y}[n_0+2], \ldots, \widehat{y}[n_0+24]\}$. As such, when the mean value is observed, the forecasted intervals closer to $n_0$ will improve the overall accuracy. As we can see, function $\dot{y}[n]$ on average resulted to higher errors than from $\widehat{y}[n]$, what was also mentioned in operation part of subsection II-A.

### B. Absorbing Errors with a Static Storage

To improve the forecast accuracy of SFERS, experiments were conducted during which the total capacity $c$ of VES (that is owned by a SFERS) will be increased. As depicted in Figure 3, the shape of static storage solutions is constant, thus capacity growth is linear. Figure 5 presents the forecast accuracy achieved for all offsets already evaluated in Figure 4. It is important to notice that 1% of the horizontal axis represents the capacity of $\frac{234.4\text{MWh}}{365} \cdot 1\% = 6.42$ kWh for this stakeholder.

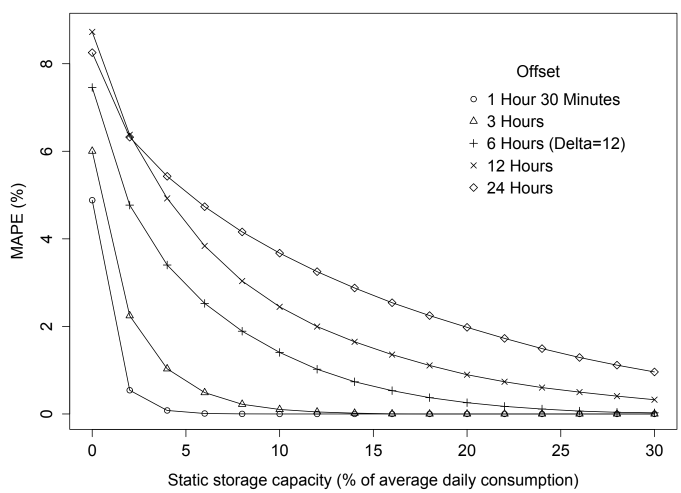


Figure 5. Absorbing forecast errors with a static storage

The significant difference in accuracy progress on different $\Delta$ can be noticed. Interestingly, Figure 4 suggests that $\Delta = 24$ has worse MAPE than $\Delta = 48$ for the selected algorithm, while greater improve rate can be noticed. If observed through numbers, for $\Delta = 48$ at $c = 20\%$ an error of $\approx 2\%$ was measured, while for $\Delta = 24$ the same accuracy was already achieved at $c \approx 12\%$. Since MAPE for $\dot{y}$ approximates for both $\Delta$, the VES controller was identified to be of critical importance. Of course, the controller at $\Delta = 24$ has only half the delay of $\Delta = 48$, but the capacity measured for MAPE $\approx 2\%$ is almost half as well. For all the other offsets, the VES charge adjustment (from Equation 1) brought better performance, such that SFERS in real world implementations can reach a sufficient accuracy with an extremely low $c$ within VES.

### C. Absorbing Errors with Dynamic Storage Units

Assessment done for static storage in the previous experiment, is done here for a dynamic storage composed from both, pool and individual vehicles. In Figure 3 the average presence of pool vehicles corresponds to only 24% of the static one, while the individual one is way lower. Still, this capacity is generally considered to be available "for free" and should not be omitted. As analysed in [15], the availability of the dynamic capacity of both vehicle types is correlated with the source of imbalances and hence good-enough to address the stakeholder's forecast errors depicted in Figure 2. The results of Figure 6 show evaluation for both individual and pool vehicles using batteries of 36 kWh (or 5.6% of average daily consumption). Same as in [15], one can immediately notice how low presence fleets tend to MAPE $> 0\%$. It is important to note that horizontal axis represents the total capacity of the fleet and not only the present part nor its average.

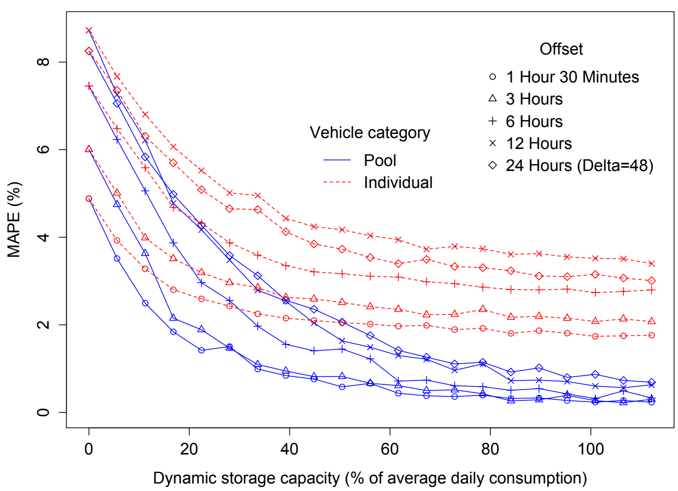


Figure 6. Absorbing forecast errors with a dynamic storage

Understanding the relevance of results in Figure 6 to the consumption pattern of the stakeholder is important. The office has a relative fixed number of employees which corresponds to a stable number of EV cars. At some point the number of EVs may result to dynamic storage capacity that can go beyond the 100% of stakeholder's daily consumption. As shown in Figure 6, depending of the vehicle category, one can rapidly achieve the desired accuracy levels. As an example, in [19] the capacity estimated was around 12% (approx. 181 kWh), which corresponds to the capacity of only 5 EVs for the 183 households in evaluation. That work used the daily Seasonal Naïve algorithm, thus the offset is already $\Delta = 48$.

### D. Enabling a Real World Stakeholder

As the stakeholder in evaluation is the building where authors are located, it was decided to evaluate the real world case of their offices. The location has 100 employees and average presence of company vehicles on-premise was measured at 27 for peak hours on working days. According to the presence curves shown in Figure 3, the total fleet size equals to 46 vehicles, which is the reference point for evaluation in this section. These vehicles, however, suffer from zero presence for non-working hours and non-working days (74% of the time). In [15] similar cases converged to $MAPE > 0\%$ and such accuracy may not be acceptable for the SFERS system. With that in mind, the overall VES will contain a certain number of dedicated individual EVs (within the entire fleet), that will be complemented with a static storage solution. Figure 7 shows how different compositions of VES with individual EVs and different sizing of the static storage, have resulted to enhanced system reliability.

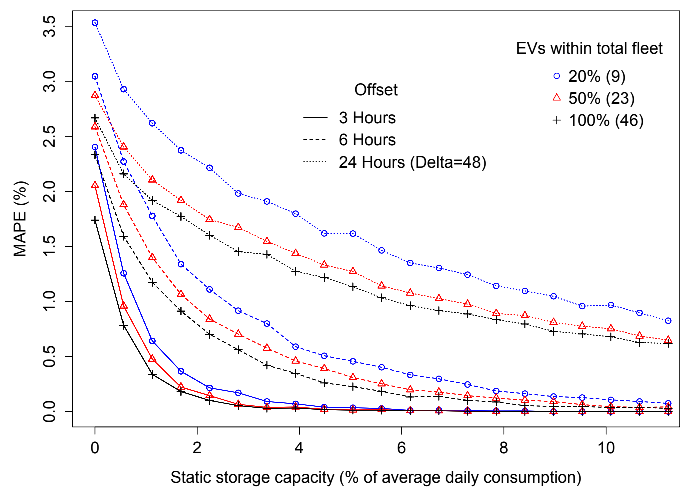


Figure 7. Addressing low presence of individual EVs by adding static storage capacity to VES

One needs to note that Figure 7 indicates the convergence of system without static storage to $MAPE > 0\%$. However, this accuracy is significantly higher than those of Figure 5. Positioned as such, one can immediately notice that only small fraction of the static solution is required. As an example, at $\Delta = 48$ with 20% of EVs in the fleet, accuracy of 1% is already achieved at 10% (64.2 kWh), while static solution on its own achieves it around 28%. This significant difference already justifies the relevance of considering the company EVs on-premise, rather than using costly static solutions [13].

An additional experiment, where individual EVs are replaced by pool EVs (such that the total number of vehicles stays the same), has been realised. In Figure 8, the assessment is depicted and the obvious impact of non-working time presence of pool vehicles can be noticed for all the evaluated cases. One should immediately notice that there is a really small initial difference if 50% and 100% of the total fleet are EVs of individuals. This is due the already fast convergence depicted on Figure 6, where there are enough cars to address all the error produced within working hours. Now, depending on the case, if pool vehicles replace the individual ones, significant impact can be already seen.

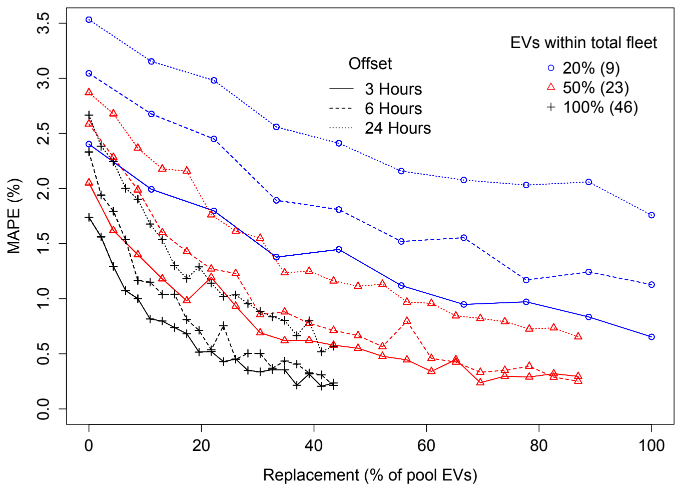


Figure 8. Addressing low presence of individual EVs by their replacement with pool EVs

What is important here to note is that there is no management system behind the pool vehicles. If properly managed, their presence on-premise at non-working hours can be more robust by not releasing all the vehicles to employees. In this particular case, as Figure 5 suggests, if only one vehicle of 36kWh is present at the location, the accuracy of 1.5% can be already achieved for the case of 20% EVs in the fleet (and not $\approx 3.2\%$ from Figure 6). If two pool vehicles are properly managed, this case goes to $\approx$ 1%, and so on. Therefore management is to be considered as important as usage of the static storage and, as one can imagine, already via software for booking the pool vehicles.

## IV. Discussion

If a company utilizes an EV fleet as a storage solution, the system has to make sure that individual and global constraints are met e.g. that each car will be charged for its next trip. To ensure the latter, mitigation actions need to be planned e.g. adding more cars than the minimum needed. In this way each unit can provide a certain percentage of the battery capacity to the variable storage and still can guarantee that the EV is ready whenever the user needs it. As an example, if a desired SOC for SFERS featuring a static storage solution would be at 50%, the clustered available storage from EVs would have to be also at that level. However this does not necessarily mean 50% SOC for the individual EVs as this might conflict with the owner's goals which are e.g. to be at least 80% in order to cover his travel plans. Such constraints are not considered in this assessment, and are left as future work.

Simulation results have shown that KPIs are the offset of reporting the energy load, as well as SOC adjustment of a VES. To achieve the same accuracy, the VES load adjustment required 2% and 20% of capacity, for an offset of 3 and 24 hours respectively. Even though the initial forecast accuracy for the 24 hour offset had MAPE of 8%, the accuracy of a retailer could be achieved with storage of energy capacity between 5 and 15% of his daily energy consumption. If the fleet of pool EVs was used (instead of a static storage), the achieved accuracy of a retailer is reached already at 40% (7 vehicles for 100 employees) of daily consumption. If only traditional vehicles were used as EVs for 20% (9) of the current fleet size (46), the accuracy already approached the one of a retailer. If enhanced with a static storage solution, for only 2% of daily consumption, a significant improvement in performance can be achieved. Smaller forecast offsets resulted to a significantly greater efficiency. Although these preliminary results are promising, larger scale trials need to be carried out, with more heterogeneous fleets as well as a better understanding to the usage of EVs and their availability pattern needs to be researched.

A limitation of this work is that no actual technical aspects dealing with the EV charging are considered. Today, charging or discharging sessions might not be as flexible as assumed in this work, and EV constraints may enforce specific behaviours e.g. once connected charge at least 20% of the capacity per session etc. Additionally, often charging/discharging may have a significant impact on the EV battery charging cycles and degradation might occur [20] which may result in financial costs. These aspects are explicitly left out from this evaluation as we did not want to link the results to a (currently available) technology, but rather to evaluate the concept from a more theoretical/general point of view. However, in the future, for commercial implementations, one needs to investigate what technologies may be considered and their impact.

There is an added value if deterministic systems are operational and would assist towards informed and automated decision-making processes in domain of power networks [5]. The realization of a stakeholder becoming the SFERS however, will need to be assessed and fine-tuned in real-world trials once the required Smart Grid services are in place.

## V. Conclusion

The changes emerging with the wide-spread introduction of the Smart Grid, have implications in traditional solutions e.g. those aiming at better energy management and tackling of incurred imbalances. This work demonstrated how the EV available collective storage can be a real alternative to the traditional static storage energy solutions available. The SFERS system was presented and assessed for various configurations and the illustrated results lead to the conclusion that the errors incurred can be effectively addressed with dynamic storage of EVs residing on-premise.

However, several considerations are also raised as the detailed aspects of the system need to be further investigated both technically and financially. It is also clear that an one-size-fits-all solution might not be available and customization needs to be done depending on the real-world case constraints. As shown, various combinations for desired forecast accuracy can be realised, but every stakeholder should be individually assessed depending on his assets and their usage, before the actual deployment of the SFERS system. In addition to the energy related revenue, benefits are expected to extend in the operation and planing of energy infrastructures as better decision making processes for many stakeholders involved in grid operations can be realized.


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