Assessing the Cost of Energy Independence

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***Abstract*—Battery management strategies that reserve a certain capacity for power outages are able to increase the energy independence of a smart home. However, such strategies come at a certain cost, since these storage strategies are less flexible and energy from the grid may have to be bought at a high price, even though locally produced energy is still available in the battery, but reserved for power outage periods.**

This paper evaluates the cost of energy independence in smart homes with local energy generation, local storage, stochastic grid outages and seasonal demand and production profiles. As case study we use a house with matching demand and production. We provide a seasonal dependent battery management strategy, that reduces the costs of surviving grid outages. Compared to a system that maximizes self-use, the costs to achieve a survivability of 99.999% are approximately 41 € per year for 1 MWh demand.

***Index Terms*—Batteries, energy management, distributed power generation, resilience, smart grids, stochastic models.**

I. Introduction

Over the last decade, a decrease in costs for photovoltaic panels and other forms of distributed energy generation (e.g., residual heat and biomass CHP), together with governmental subsidies, have lead to an enormous increase of distributed energy generation. Although these developments provide a positive contribution to the generation of renewable energy, they have as drawback that they lead to production peaks (or even grid instabilities), and that production and demand often do not match well. These problems can be overcome through locally storing produced energy either at the level of a house or at the level of a neighborhood. From an operator's point of view, this would allow for peak-shaving, hence, a more stable and balanced grid. From the perspective of a home owner it allows to maximize the so-called *self-use*, that is, the amount of locally produced energy that is also locally used and not fed back into the grid. At the same time, investing in local storage facilities potentially increases the energy independence of smart homes, since the local storage can provide back-up power to isolated units in case of grid outages. Commercial systems with such functionalities, i.e., increasing local usage and providing back-up power, are starting to enter the market (e.g., NEDAP's Power Router).

Recently, we started to evaluate the so-called energy resilience of such smart energy systems in [1], where we combine deterministic demand [2] and production profiles [3], with an abstract battery model for a single house. By introducing stochastic grid outages, we used existing algorithms [4] to analyze the impact of such outages, i.e., to compute the probability that the effective energy supply in the neighborhood is not interrupted by the grid outage (the so-called *survivability* [5]). Note that this probability not only depends on the demand and production profile, but also on the capacity and state-of-charge of the battery at the moment the outage occurs, as well as on the outage duration (distribution) and the employed battery management strategy.

In [1] we introduced and evaluated three different battery management strategies, of which the so-called *smart* strategy proved to be most efficient. This strategy always reserves a certain percentage of the battery capacity as back-up capacity, that is only used in case of a grid outage. However, when battery capacity is reserved for back-up the amount of battery capacity that is available for self-use is decreased accordingly.

The current paper investigates this trade-off between *survivability* and *self-use*. By (i) computing how much local storage is needed to survive grid outages with a certain (high) probability and (ii) introducing a notion of cost by including the prices for buying (selling) from (to) the grid, we are able to (iii) quantify the cost of survivability, i.e., the costs of reserving battery capacity, with respect to a setting, where all battery capacity is used to maximize the self-use. This is achieved by first computing the minimum amount of battery capacity that is necessary as back-up to guarantee the required level of survivability in the case of a grid failure with the model and techniques proposed in [1]. Subsequently, a discrete-event simulator is used to investigate the energy streams (and the induced cost) between the demand, generation and the grid during a full year, taking into account seasonal production and demand patterns for different battery capacities.

Related work [6], [7] also discusses the costs of PV-battery systems. [6] concludes that investment costs and kWh prices need to drop before battery storage becomes economically attractive. [7] is able to show for certain settings a battery may be “useful“, however, currently the economical optimum

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lies at having no battery at all. While economical aspects are clearly important, we discuss the *energy resilience* of a house that may result from added battery storage, if the right battery management strategy is chosen. Hence, we work with a stochastic model, with random repair times. With respect to the cost analysis we show the trade off between cost and survivability, which in a way shows the cost of "autonomy". The end user may use this analysis in his decision process when choosing the size of a battery storage for the smart home.

II. Background

In [1] we presented a Hybrid Petri Net (HPN) model [8] that allows to analyse the effect of different battery management strategies on the resilience of a smart house. Different battery management strategies were considered: the most flexible strategy, i.e., *Greedy*, maximizes the *self-use* and drains the battery whenever the demand exceeds the production. In contrast, the strategy *Smart* reserves a certain percentage of the battery that is only used in case of a power outage. Note that the third strategy presented in [1], i.e., *Conservative*, is not considered any more in the current paper, since it results in faster degradation of the battery.

The model can be analysed with techniques for Hybrid Petri Nets that allow for one stochastic variable in the model. This stochastic variable is used to model the time the grid needs to become operational again after an outage. In the following, we will quickly recall the main parts of the model. For details we refer to [1]. Figure 1 shows an abstraction of the HPN model of a smart house; it consists of three parts (from top to bottom): (i) the battery management system, (ii) the model of the battery together with production and demand, and (iii) the model for the status of the grid.

The battery is modelled as a continuous place with overall capacity B, its current state of charge changes, with the *time-dependent* production $prod(t)$ and demand $demand(t)$, which represent the deterministic production and demand profiles during the day. When the local generation exceeds the demand and the storage capacity, the surplus is forwarded to the grid; similarly, energy is taken from the grid into the house when there is not enough local energy available. The interaction between the battery and the grid is represented by a bidirectional continuous arc. However, this interaction is only possible when the grid is operational. When the grid fails (modelled by the deterministic transition T_e at time a) the token is moved to place *Off* and the house is practically isolated from the grid. This allows to analyse the impact of different times of failure on the survivability. The grid returns from its failure according to a stochastic repair distribution that can be chosen freely.

The *Battery Management unit* controls the flow of power between the local generation, the battery, the house and the grid, depending on the battery management strategy. The model distinguishes between three states of the battery, it can either be *full*, *good* or *empty*. In the state *empty* the battery cannot be discharged, although there might be still energy available which is reserved as back-up in case of grid failures.

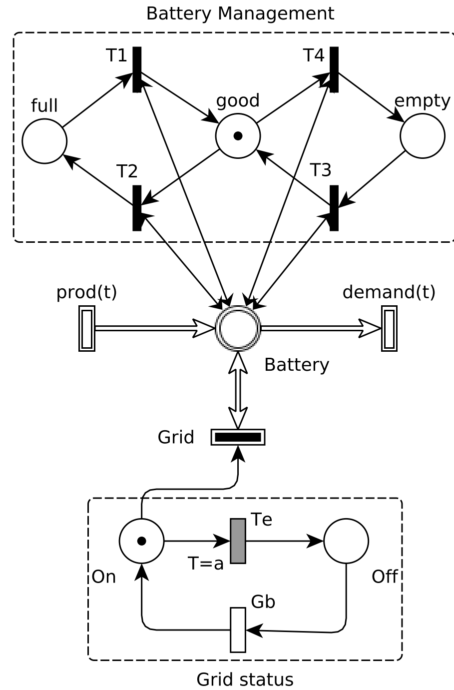

Fig. 1. HPN model of a resilient house.

The transitions T_i for $i \in \{1, 2, 3, 4\}$ coordinate the change of state via test arcs that enable the firing of transition T_i according to some threshold that is compared to the available capacity of the battery. Further details can be found in [1].

III. Set-up and measures of interest

Section III-A discusses the general parameter choices of the presented case study, Section III-B introduces the main measures of interest, and Section III-C refines the parameter setting for the specific measure of interest.

A. Setting

We consider a scenario in which the yearly production is equal to the yearly demand; both have been set to 1 MWh. For the demand, we use a standard profile provided by EDSN [2]. EDSN provides different standard profiles for the Dutch market. We use the E1a profile, for a connection smaller than $3 \times 25A$ with a single meter. The profile gives the demand for a full year at a 15 minute granularity.

The production profile for the PV-panels is obtained from the internet tool PVWatts by the National Renewable Energy Laboratory [3]. This tool provides a full year of PV-production based on the characteristics of the PV-installation, such as size, orientation and system losses. Actual weather data of weather stations around the world is used to generate the a year production profile, with 1 hour granularity. We have used the weather data from the Amsterdam station.

In the analyses, we use the *Smart* strategy for the battery management system [1]. For the battery we consider only the usable capacity, which depends on the used battery technology.

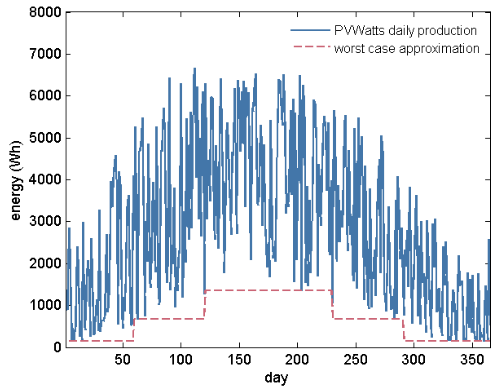

Fig. 2. Energy produced per day according to the PVWatts profile, and an indication of the worst case level.

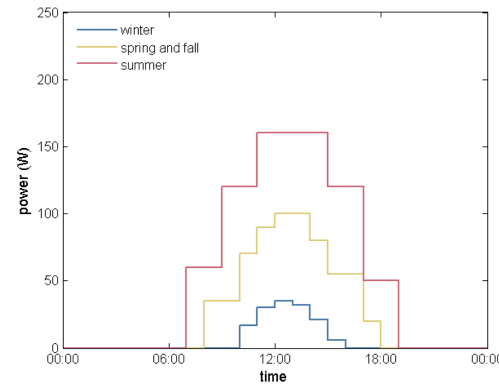

Fig. 3. Approximation of the worst case production profiles for a day in the three periods: winter, spring-fall and summer.

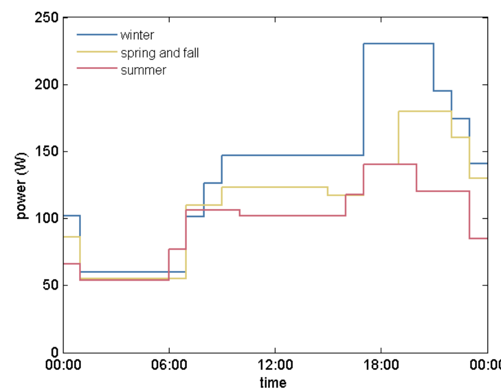

Fig. 4. Approximation of the EDSN demand profiles for a day in the three periods: winter, spring-fall and summer.

In order to extend the battery cycle-life, i.e., the number of charge-discharge cycles until the battery is depleted, lead-acid batteries have a usable capacity of only 50% of the nominal capacity, whereas Li-ion batteries have a usable capacity of 70 to 80%.

Since the battery is only discharged partially, the non-linear properties such as the rate-capacity effect and recovery effect [9] have little impact. Therefore, we can approximate the battery with an ideal energy storage system.

B. Survivability

One of the main measures of interest that is analyzed in this paper is the probability to survive a grid failure, the so-called *survivability*, which is specified in the following for so-called *Given the Occurrence Of Disaster* (GOOD) models [5], where a failure (the power outage) is assumed to occur at a certain time a, specified in STL [4]:

$$\texttt{survivability} = \texttt{battery\_up}\ \mathcal{U}^{[\mathsf{a},\mathsf{a}+\mathsf{t}]}\texttt{grid\_on}.$$

The above logical STL expression specifies that power is available from the battery continuously until the grid is repaired within t time units. For finite values of t, efficient algorithms for validating such formulae are available [4], [10].

The time of failure a is parametrized to consider the impact of different failure times during the day. The repair time of the grid is distributed according to a folded normal distribution with parameters $\mu = 0.5$ and $\sigma = 1$. Although power outage times are monitored and reported by the Council of European Energy Regulators (CEER), providing numbers on average outage times, we did not manage to obtain about individual outage times, that is, per outage event, let alone distributional information on these, even though we contacted several grid operators directly about this. The time bound t is chosen to be very large (equals the maximum time considered in the analysis), since the house can be powered as long as the property `battery_up` holds and the repair of the grid is not the main concern of the home owner.

C. Settings for the survivability model

The overall survivability of the system is determined by the minimum survivability level throughout the year. Therefore, we run the model in Figure 1 with the production profile of the day with the lowest total production. Figure 2 shows the daily production for a whole year, starting from January 1st. We see that the minimum obtained daily production varies considerably throughout the year. Hence, we divide the year in three periods: (i) *Winter* contains days 1-59 and 291-365, (ii) *Spring&fall* contains days 60-120 and 230-290 and (iii) *Summer* contains days 121-229. For each period we take the worst case production profile, shown in Figure 3, and a typical demand profile based on a day from the EDSN profiles in that period, represented in Figure 4. These profiles are then used as input for the smart house model.

IV. Trade-off between survivability and self-use

This paper aims at better understanding the trade-off between a flexible battery use and reserving a certain amount of battery capacity to survive grid failures (as done by the smart strategy). Clearly the latter comes at a certain cost, since the back-up capacity can in general not be used for intermediate

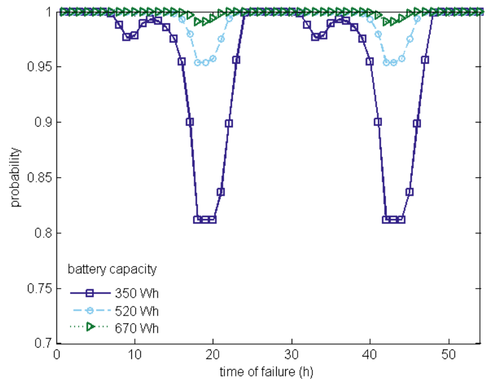

Fig. 5. The probability of surviving a grid failure as a function of the time that the failure occurs for the winter production and demand profiles.

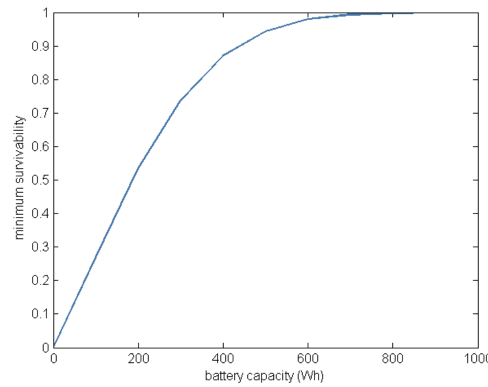

Fig. 6. The minimum of the survivability level as a function of the back-up capacity for the winter scenarios.

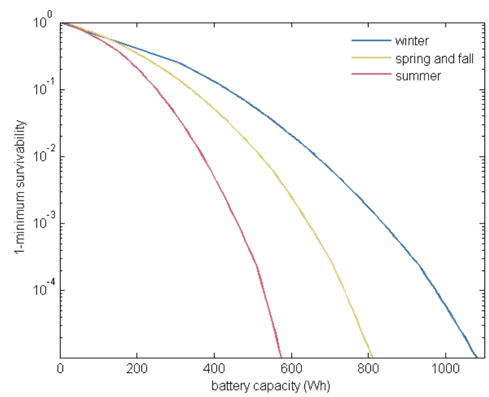

Fig. 7. (1 - the minimum of the survivability level) as a function of the back-up capacity for the three season scenarios.

storage of locally produced energy for self-use, but enforces to buy (potentially) more expensive energy from the grid.

First, in Section IV-A we perform a large number of survivability analyses, where we compute what battery capacity is needed to obtain a given survivability level for all possible failure times. Then, in Section IV-B simulations are performed for specific settings, where the yearly costs of reserving capacity as back-up are computed and compared to a system that maximizes self-use.

The results from the survivability analysis are subsequently used as input for the simulations. The advantage of this two-step approach lies in its efficiency, since analytical results can be obtained more quickly than simulation results.

A. Survivability

The probability to survive a grid failure highly depends on the type of day, clouded or sunny, and on the time of day at which the failure takes place [1]. The survivability of the system is determined by the worst case scenario, a clouded winter day. This worst-case scenario then determines the battery capacity needed to achieve a given survivability level.

First, we compute the survivability as a function of the failure time for different battery capacities that are fully reserved as back-up for different seasons. The level of survivability that can be guaranteed with such a setting is defined by the minimum of the resulting values for the different failure times. Figure 5 shows in an exemplary way the resulting survivability for different battery capacities as a function of the failure time during winter. We see, e.g., that a battery capacity of 350 Wh is just enough to ensure a minimum survivability of 80%. A capacity of 520 Wh guarantees a survivability level of 95% and a capacity of 670 Wh brings the minimum survivability level up to 99%.

This computation is repeated iteratively for different battery capacities and Figure 6 shows the resulting minimum survivability level that can be achieved in winter, when the full battery is used as back-up. We see that in the beginning the survivability grows linearly with the dedicated backup capacity. Then gradually more and more backup capacity is needed to achieve higher survivability levels. To better visualize this limiting behavior, Figure 7 shows on a logarithmic scale how the complementary probability approaches zero for increasing back-up capacities in all seasons, when the complete battery is used as back-up. We see that the difference between the survivability levels that can be achieved with the same amount of backup capacity in different seasons becomes increasingly large for growing backup capacities.

In the following we consider to use the smart strategy with a different amount of backup-capacity in different seasons, in order to guarantee a certain level of survivability all year round. The remaining battery capacity can then be used flexibly for self-use.

Figures 8 and 9 show the survivability level that can be achieved during spring-fall and summer, respectively, when different percentages of the battery are reserved as backup for varying battery sizes. These curves thus allow to chose different backup levels in spring-fall and in summer that ensure that a predefined survivability level is ensured.

Typically, one would chose a minimum battery size from

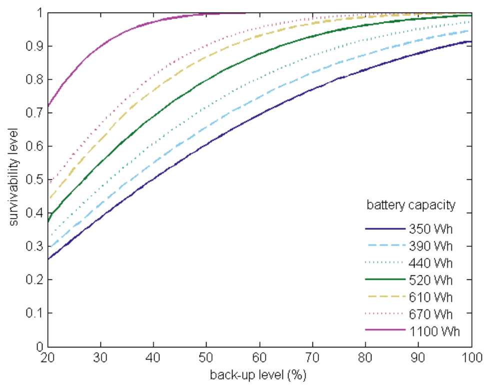

Fig. 8. Achievable survivability level for different battery sizes as a function of the backup level in spring-fall.

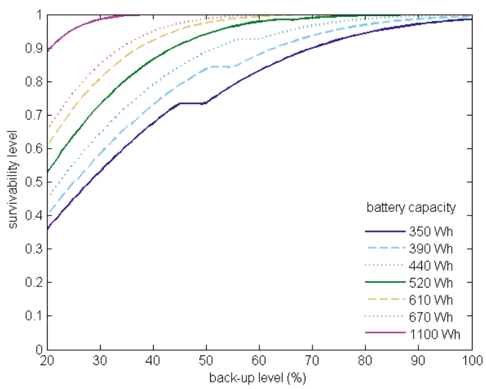

Fig. 9. Achievable survivability level for different battery sizes as a function of the backup level in summer.

Figure 6 that ensures the desired survivability level in winter when the complete battery is dedicated for backup. For the chosen battery capacity one can then pick the resulting thresholds also for the other seasons, and so ensure that the maximum possible battery capacity is left for self-use.

We see that while Figure 8 is smooth, the plots for lower battery sizes in summer, as shown in Figure 9, each contain a plateau, where for a certain range of backup capacity the resulting survivability level does not increase. This can be explained as follows.

For all backup levels that are smaller than the plateau the difference between the battery size and the backup level is too large to be fully loaded on a worst case day. Hence, increasing the backup level results in a larger state of charge at the moment a failure occurs. Thus the survivability increases until the beginning of such a plateau, where the point is reached that the battery is fully loaded even during a worst case day. However, at the worst case time of failure, the state of charge is still larger than the backup level. Increasing the backup level then does not result in a change of the survivability until it is increased to the point that it matches the state of charge at the time of failure which leads to the minimum survivability. Hence, for all larger backup levels, increasing the backup level directly leads to a higher amount of backup energy at the time of a failure and thus to a higher survivability.

Note that even though the plateaus are only visible in the summer setting for low battery capacities, the reasoning holds for all settings. For larger battery capacities in the summer period, the plateaus shift to the right and become less visible. In the spring-fall period theses plateaus are not visible, since the production is lower than the demand and the battery will never be fully charged.

The above figures help to chose not only the right battery capacity but also the backup level which ensures the desired level of survivability all year round. It is important to not chose a backup level which lies on one of the plateaus, since such a setting wastes battery capacity without a return in survivability.

B. *Simulation of cost*

In order to get an indication of the costs of survivability, we compute how much energy is flowing from and to the grid in one year with a Matlab-based simulation. For this, we use the EDSN and PV-Watts profiles, as described in III-A.

The battery is used according to the *Smart* management strategy. Here, we use the results from the survivability analysis (of Section IV-A) to set the back-up levels. For all three periods of the year, the back-up levels are chosen such that a given survivability level is ensured.

We analyze the costs of 7 survivability levels: 80%, 85%, 90%, 95% 98%, 99% and 99.999%. For each level we vary the battery capacity and compute the self-use rate and the costs of the 1 MWh energy that is used. The self-use rate is defined as the portion of produced energy that is used locally.

For the cost analysis we use the same assumptions as in [6]. We assume a system lifetime of 20 year. The feed-in tariff is set to 0.12€/kWh. This is the current feed-in tariff for Germany. We assume this tariff is kept for the full period. The mean grid electricity price is set to 0.34€/kWh. This is based on the current price, including taxes, of 0.28€/kWh, and the assumption of a 2% price increase per year.

The results of the self-use and costs analysis are given in Figure 10 and 11, respectively. We compare the results for the survivable systems to the *Greedy* strategy with no backup, which maximizes the self-use but does not provide any survivability.

The graphs for the different survivability levels start at the battery capacity at which the the survivability is obtained by having 100% back-up in the winter. At lower capacities the survivability level cannot be achieved throughout the year.

The figures clearly show the trade off between optimizing the self-use and reducing the energy bill on one side, and increasing the survivability on the other side.

When one has invested in a system with a battery, a higher survivability can be obtained at the cost of lower self-use and a higher energy bill. Figure 11 shows the additional costs of obtaining a survivability level for a system with a 1100 Wh battery. The additional costs are moderate for survivability levels in the range from 80% up to 90%, being 0.29 € per year per percentage point. A further increase of the survivability

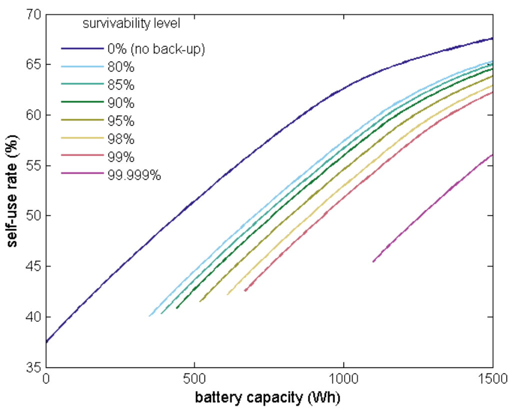

Fig. 10. Self use rate as function of the installed battery capacity for different survivability levels.

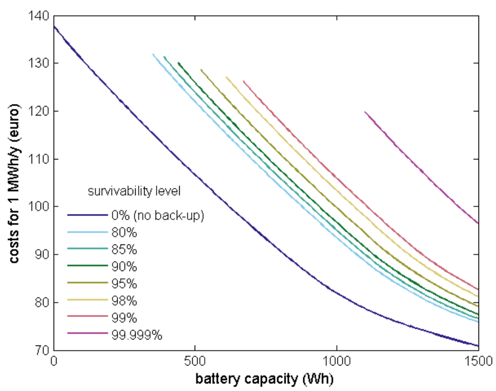

Fig. 11. Costs for 1 MWh/y electricity as function of the installed battery capacity for different survivability levels.

comes at an increasing price. The final percentage, from 99% to 99.999%, will cost 20 € per year for a demand of 1 Mwh/year.

The results can easily be scaled to any demand. For example, for a household with an average demand of 3500 kWh/year, and corresponding 3500 kWh/year production, a $3.5 \times 1100 = 3850$ Wh battery is needed to be able to obtain 99.999% survivability. The costs of being 99.999% survivable compared to using the battery fully for self-use are then: $3.5 \times 41.15 = 144$ € per year.

V. Conclusion

We compare for different battery sizes the cost of using different backup levels to ensure a certain minimum survivability all year round. As has been shown in [1] achieving a certain minimum survivability is especially difficult in winter, since the production is too low to regularly refill the battery. In contrast to this the battery recharges regularly back to its full capacity in summer. Hence, we recommend to use different backup levels for different seasons. We furthermore investigate the cost of survivability, since an increased level of survivability reduces the amount of battery capacity which

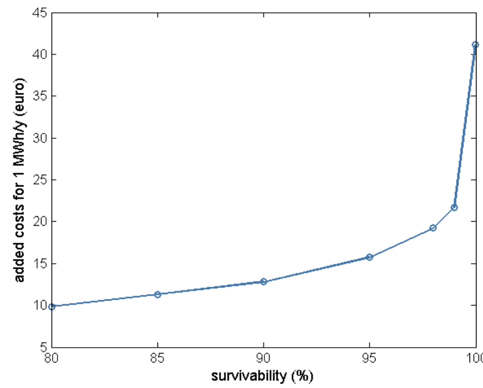

Fig. 12. The additional costs to obtain a given survivability level compared to the situation with no back-up capacity for a 1100 Wh battery.

can be used for self-use. We abstract from investment cost for both solar panels and a storage system and purely consider the additional costs which stem from reserving battery capacity for survivability. To achieve a very high survivability of 99.999% throughout the year we need a large battery with 1100 Wh and this survivability level comes with an added cost of around 41 € per year. Lower survivability levels are considerably cheaper.

While the presented paper considers the case of matching production and demand, further work will investigate a wider range of ratios between demand and production.

References

[1] H. Ghasemieh, B. R. Haverkort, M. R. Jongerden, and A. Remke, "Energy resilience modelling for smart houses," in *Proceedings of the 45th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN 2015)*, 2015, pp. 275–286.

[2] EDSN, "EDSN demand profiles," accessed December 1, 2015. [Online]. Available: http://www.edsn.nl/verbruiksprofielen/

[3] NREL, "PVWatts," accessed December 1, 2015. [Online]. Available: http://pvwatts.nrel.gov/index.php

[4] H. Ghasemieh, A. Remke, and B. R. Haverkort, "Survivability evaluation of fluid critical infrastructures using Hybrid Petri nets," in *Proceedings of the IEEE 19th Pacific Rim International Symposium on Dependable Computing (PRDC 2013)*, 2013, pp. 152–161.

[5] A. Avritzer, L. Carnevali, H. Ghasemieh, L. Happe, B. R. Haverkort, A. Koziolek, D. Menasche, A. Remke, S. S. Sarvestani, and E. Vicario, "Suvivability evaluation of gas, water and electricity infrastructure," in *Proceedings of 7th International Workshop on Practical Applications of Stochastic Modelling (PASM 2014)*. Elsevier, 2014, pp. 1–20.

[6] J. Weniger, T. Tjaden, and V. Quaschning, "Sizing of residential PV battery systems," *Energy Procedia*, vol. 46, pp. 78 – 87, 2014, 8th International Renewable Energy Storage Conference and Exhibition (IRES 2013).

[7] J. Weniger, J. Bergner, T. Tjaden, and V. Quaschning, "Economics of residential PV battery systems in the self-consumption age," in *29th European Photovoltaic Solar Energy Conference and Exhibition, Amsterdam*, 2014.

[8] M. Gribaudo and A. Remke, "Hybrid Petri nets with general one-shot transitions for dependability evaluation of fluid critical infrastructures," in *Proceedings of the 12th IEEE International High Assurance Systems Engineering Symposium (HASE 2010)*, November 2010, pp. 84–93.

[9] M. R. Jongerden and B. R. Haverkort, "Which battery model to use?" *IET Software*, vol. 3, no. 6, pp. 445–457, 2009.

[10] B. F. Postema, A. Remke, B. R. Haverkort, and H. Ghasemieh, "Fluid Survival Tool: A Model Checker for Hybrid Petri Nets," in *Proceedings of MMB/DFT 2014*. Springer, 2014, pp. 255–259.