Minimizing Grid Interaction of Solar Generation and DHW Loads in nZEBs using Model-free Reinforcement Learning

Adhra Ali¹ and Hussain Kazmi²

¹ Adhra Ali, Technical University of Delft, Jaffalaan 5, 2628BX, Delft, The Netherlands

² Hussain Kazmi, Enervalis, Greenville Campus, Centrum Zuid 1111, Houthalen-Helchteren, Belgium

Abstract. This study applies model-free reinforcement learning (RL) on a case study based in Utrecht province in the Netherlands to optimize for on-site renewable energy. This aims at reducing the interaction of net zero-energy buildings with the grid as a result of an increase of heat pump installations and renewable energy systems (RES) integration. It is believed that this will become increasingly more important since the regulations regarding 2020 and beyond ascribe significant increase in energy efficiency of the built environment. On-site RES self-consumption is therefore a central lead in this research. The project data comprise air source heat pump and solar energy data of 6 different households for the months June to November 2016. The RL algorithm is applied to the different data sets to derive an optimized individual and generalized control strategy. Simulations were carried on, to acquire the resulting energy consumption, self-consumption, and self-sufficiency. The results show an increase of individual self-consumption between 17% and 348% and self-sufficiency between 18% and 72%. This results in an additional monetary benefit for the occupants based on the transition proposals of 2020 for the renewable energy generation net-metering abolishment in the Netherlands. Furthermore, reducing the grid interaction implies benefits for the grid operators in terms of investments required for grid reinforcement.

Keywords: nZEB, Demand Response, Smart Grid, Reinforcement Learning, Solar Power, Heat Pumps, Self-consumption, Self-sufficiency.

1 Introduction

Improvements of the energy efficiency of the built environment in the Netherlands is planned partly to be achieved by increasing the number of nZEB concepts by building new nZEBs as well as refurbishing existing buildings [1]. An nZEB is a nearly zero energy building which consumes very little energy over the course of a year (and preferably meets most of this using renewable energy). Residential nZEBs are dominantly provided by heat pumps (HP) for HVAC and DHW operation to disconnect from the gas network while solar panels are used to generate the required energy to meet the local energy demand. This setup increases the interaction of the residential built environment with the electricity grid as a result of solar power injection and also increased power consumption as a result of the HP load.

This could be addressed by integrating more storage facilities and reinforcing the grid components such as the transformers and cables which, given the required RES goals of 2020 and beyond, implies significant investments. The weak link in this area of renewable energy generation is the lack of large scale storage capacity due to its relatively high cost. Increasing the size of the grid components is a similarly costly procedure. However, it is believed that the necessity for a costly reform of the energy infrastructure could be reduced and substantially spread over a larger period of time if the variety of decentralized actors could be centrally monitored and managed [2]. The need for centrally monitoring and managing the variety of power sources and sinks in the grid has introduced the concept of Smart Grids [2]. Smart Grids are required to facilitate real-time monitoring and steering tools so as to allow the distribution and transportation capacity of the grid to progress in a more flexible fashion. In the traditional top-down approach of the energy system, the Distribution Systems Operators (DSO) are primarily responsible for the operation and maintenance of the distribution system. However, the need for Smart Grids imposes the need for a change in this role to a more pro-active grid management. This introduces new service opportunities for grid operators. Connecting a large number of nZEB buildings with fluctuating individual energy generation is one such example of locally generated energy that adds to the volatility of the grid power for which grid operators could monitor and manage[3].

Research in this area ranges from fully automated building energy discarding occupant behavior, to smart metering objectives aiming at increasing occupants' energy performance awareness, and control strategies based on electricity prices signals etc [4], [5], [6], [7]. A large part of this research applies rule-based control (RBC) and model-predictive control (MPC) methodologies [7], [8], [10], [11], [12]. Generally, MPC performs significantly better than RBC as a result of accurate modelling of the system physics [12]. Both methodologies have benefits and drawbacks related to their application with the model complexity being the main central technical difference [12]. Although both methods have proved to reduce the grid interaction on building level to a certain extent, both methods lack generalizability potential [9]. Hence, when applied on a large scale the system parameters have to be adjusted from system to system. To solve this problem, a learning based methodology is proposed in this paper.

This study, therefore, applies model-free reinforcement learning (RL) to optimize for the self-consumption and self-generation of the DHW load of the HP installation in six different households of a refurbishment project in the Netherlands conducted by a housing corporation. "De Stroomversnelling" project is implemented to refurbish low performing dwellings into nZEB concepts [13]. This is done by applying a high performing façade to the existing one and supplying the houses with solar panels. The houses are fully disconnected from the gas network and operate therefore only on electricity.

2 Methods

2.1 System setup and data

An air source heat pump (ASHP) is installed to supply the hot water and special heating. The ASHP has a COP ranging between 3 and 5 for a temperature range of 45 °C and 51.5 °C, depending on the outside temperature. Secondly, a hot water storage vessel of 200 liters is installed in the dwellings which is only used for DHW purposes. The third system component is an array of solar panels. The data is measured in 5 minute uniform intervals in the form of three different sensors each measuring a different parameter:

1. A hot water flow rate meter
2. A smart meter registering the power consumption of the heat pump at different modes and the power delivered by the PV panels
3. A temperature sensor in the storage vessel.

The data is measured and sent to a central repository in which the baseline control and/or the optimization algorithm is embedded. The individual control action is calculated based on the embedded control strategy and subsequently sent as an action signal to the corresponding ASHP per house.

2.2 Baseline control and comfort standards

The default control strategy is a simple rule-based control algorithm given by eq. 1 [9]:

$$\mathbf{a}_t = \begin{cases} 1, & \text{if } T_m < T_{th} \\ 0, & \text{if } T_m \geq T_{th} \end{cases} \quad (1)$$

In which $\mathbf{a}_t$ is the action taken by the heat pump: 1 when it is heating and 0 when it is off. Considering the temperature in the vessel, T_m is the temperature measured by the midway sensor in the vessel and T_{th} is the threshold temperature set point [9]. The comfort standards usually dictate that if T_{th} is lower than 45 °C, the ASHP initiates a reheat cycle. Additionally, the upper limit for T_m was set threshold of 51.5 °C to which T_m increases during a reheat cycle. Additional comfort standards determine the water content of the vessel containing the threshold temperatures. A minimum of 50 liters with temperature T_m of at least 45 °C, was defined as a minimum requirement to maintain occupant comfort. The PV output is not considered in the default control strategy as the main goal of that control strategy is to comply to the comfort standards. The solar energy delivered is only considered for compensating the energy required from the grid in order to comply to the nZEB concept on annual basis [13].

2.3 Optimization objectives

The main objective for this study is to shift the DHW energy consumption towards high solar energy production hours in order to reduce the energy required during low production hours. It is also important to maintain a balanced ASHP consumption to not

affect the nZEB concept by either violating the occupant comfort or a large rise in the energy consumption. Two main optimization indicators for this objective, are defined as the relative change in self-consumption and self-sufficiency compared to the baseline conditions. Self-consumption is defined as the energy of the load that was covered by the solar energy expressed in either in kWh in absolute terms or as a percentage of the total generated energy. Self-sufficiency on the other hand, is defined as this same energy covered by the solar energy expressed either in kWh in absolute terms or a percentage of the total load. The following figure illustrates the two concepts:

Fig. 1. Schematic overview of the daily net load (A+C), net generation (B+C), and absolute self-consumption (C) [14]

2.4 Application to case study

The control algorithm that is aimed at in this study, is an algorithm that optimized for onsite solar energy consumption. The aim is therefore to utilize the hot water storage vessel similarly to a storage capacity for the PV energy. Hence, it is important to use as much PV energy as possible during the high solar energy production hours of the day. To achieve this, a SARSA(λ) algorithm is applied with a reward function that takes several parameters regulating the vessel state into consideration according to:

$$Q_{(s_t, a_t)} \leftarrow (1 - \alpha)Q_{(s_t, a_t)} + \alpha[r_{t+1} + \gamma Q_{(s_{t+1}, a_{t+1})}] \quad (2)$$

Here, $Q_{(s_t, a_t)}$ represents the state-action value showing how good it is to take action a when being in state s . α represents the step-size parameter which functions as the exponentially moving average parameter. It is especially useful for non-stationary environments for weighting recent rewards more heavily than long-past ones. If α is a number smaller than one for non-stationary environments which indicates that recent updates weight more than previous ones. This transition happens after every nonterminal state. The $Q_{(s_{t+1}, a_{t+1})}$ of every terminal state are defined as zero. Hence, every terminal state has an update value of 0. Once the correct modes and their corresponding variables have been filtered, the episodes are simulated accordingly. Each episode

consists of the states during which the mode was 0 and ends with the state at which action 1 was taken. From this data, the features needed for the SARSA(λ) code are compiled.

The reward function applied in this algorithm is presented in a flowchart fashion in figure 2. This reward will be appended to each action 0 to be taken. Action 1 leads to a terminal state which will lead by definition to a standard update of 0 as described previously. Consequently, if the Q-value of taking action 0 is higher than 0, action 0 is more favorable than taking action 1 and vice versa. A drawback to the binary action-space, is that action 1 could not be punished or rewarded. However, this is solved by amplifying the negative or positive reward for not reheating (action 0) instead.

To prevent the vessel from constantly reheating when there is high generation of solar energy, a temperature of 2 °C below T_{start} is defined as the threshold temperature for the ASHP to reheat the vessel. This is equal to 49.5 °C when T_{start} is set to 51.5 °C such as in the case in the default strategy. Therefore, two main scenarios are created this way, one describing a midpoint temperature of higher than 49.5 °C and one lower. Temperatures higher than 49.5°C receive a constant high reward of 25 points to ensure an idle state. On the other hand, to fully exploit the solar energy when available, if the temperature falls below this threshold and the solar energy available is higher than that is needed for rising the temperature of the vessel to 51.5 °C again, negative rewards are favoured to enhance reheating.

Fig. 2. Flowchart of reward function

When the temperature falls below 49.5 °C and the solar energy available is higher than what is needed to increase T_m by 2°C, the algorithm will append an increasingly negative reward to temperatures below 49.5 °C which depend on the amount of water consumed. For this purpose, the water consumption threshold is set according to the comfort standards already defined. If the water consumed at time t is higher than this threshold L_{max} , a reward as a function of both T_m and the water consumption is appended according to:

$$R = (T_{next} - T_{min}) - \left(\frac{L_{next}}{100}\right) - \left(\frac{Sol}{100}\right) \quad (3)$$

In which L_{next} represents the cumulative volume of water consumed and T_{min} represents the minimum midpoint temperature for that scenario. The solar and water parameters are divided by 100 to be normalized to the temperature range.

In each of the scenarios, the agent is punished to a different extent by adjusting T_{min} so as to create a linear decrease in the reward for decreasing temperatures and increasing solar energy and DHW consumption. Also, in case of high solar energy generation in combination with a high DHW consumption, the weight of the solar parameter is increased to enhance reheating for these scenarios. Hence, reheat cycles are preferred when there is a sufficient amount of solar energy and T_m is more than 2 °C below T_{start} . In the scenario of temperatures above 49.5 °C, the appended reward is always positive. This reward function is then applied to SARSA(λ) update which results in state-action pair values determining how favourable it is to reach a certain state at a particular action. The derived optimized control strategy is then applied to the vessel state model learned by the study of [9].

The comparison between the baseline control output and the optimized control output will be based on the same solar energy and water consumption profile derived from the data of June to September 2016 for the houses. This serves to compare the potential of reducing grid interaction with the Sarsa(λ) control in the same context.

3 Results

3.1 Q-value analysis

The Q-value function (indicating how good action ‘0’ is) for the summer months for a house are shown in figure 3. A negative value (blue) suggests the start of a reheat cycle whereas a positive (green/orange) value favors the idle state. It is evident from the figure that temperatures higher than 51.5 °C always favor the idle state. Temperatures between 45 °C and 51.5 °C favor the idle state when there is no to low solar energy production and decreases in value as a function of the total water consumed and the solar energy produced.

The most negative Q_0 values (most left corner) represent the least favorable states for the idle state. This shows that the algorithm learns to favor reheating when there is high solar energy generation. This effect is amplified when there is DHW consumption in the dwelling that causes the temperature to drop significantly. The Q-values in the right-most corner of the plot show the most stable states which represent the states with high temperatures above 51.5°C. The influence of the reward is visible this plot as the Q-values follow the strategy set in the reward function. Deriving from these results, it can

be concluded that the algorithm learns the desired behavior to enhance the heating cycles during high solar energy generation events while considering the occupant DHW use.

Fig. 3. 3D representation of the Q_0 values of house 1 summer months' data

3.2 Linear model analysis

The reward function built in the algorithm is based on a linear function which suggests that the output of the algorithm should vary accordingly. Therefore, linear regression is applied to approximate the function of the algorithm. The same features as the algorithm were taken as the variables of the linear function. The comparison between the Sarsa Q -values and the linear Q -values are shown in figure 4. The clearest differences lay in the transition from positive to negative values. The values of the Sarsa algorithm show sharp incline and decline in certain points in time whereas the transition of the linear model progresses in a smoother fashion. This explains the increase of the difference shown, as an example, in the encircled area in figure 4 in which it clear that when the algorithm's output declined sharply, the linear output continued to increase steadily following the increase in solar energy production. Additionally, the fluctuations due to the solar energy fluctuation are damped significantly in comparison with the algorithm. This results also in a slight delay in the transition to negative values. However, this does not pose a drawback to the model as the delay remains in the comfort level temperatures of higher than 45°C. In fact, the damping effect of the model could be considered as an improvement to the algorithm since it is less responsive to sudden fluctuations in the solar energy production.

Fig. 4. Sarsa Q-values vs. linearly approximated Q-values

3.3 Optimization results

The results of the energy consumption and the average daily number of reheat cycles for the six houses are shown in table 1.

Table 1. Complete numerical results of the optimization control strategy for Jun-Sep

2 House nr.	Baseline total energy consumption (kWh)	Δ Times turned on	Δ Total energy withdrawn from grid (kWh)	Δ Self-consumption (kWh)	Self-sufficiency baseline and optimized (%)	Δ Comfort violation (nr of times)
1	133	162 (+36%)	-24 (-63%)	16 17%	71% 89%	-363 (-88%)
2	94	19 (+6%)	-33 (-82%)	17 31%	58% 91%	-45 (-53%)
3	124	123 (+28%)	-37 (-70%)	20 28%	58% 85%	-287 (-84%)
4	44	44 (+23%)	-11 (-73%)	10 35%	67% 91%	-13 (-72%)
5	53	135 (+67%)	-38 (-99%)	51 348%	28% 100%	-132 (-70%)
6	91	217 (+74%)	-37 (-67%)	32 89%	39% 79%	-164 (-73%)

The interaction of the ASHP load with the grid decreases significantly as a result of the optimization control strategy. Overall, it is evident from the results, that the energy withdrawn from the grid is reduced primarily due to the optimized timing of the reheat cycles during high energy generation hours. The total energy injected to the grid by the

solar panels (indicated by the self-consumption column) is therefore reduced accordingly. The highest increase in self-consumed energy is 348% larger than for the baseline control strategy for house number 5 and the lowest for 15% for house number 1. This supports the significance of the consumption pattern of the building occupant on the optimization potential furthermore.

The combined total amount of enhanced onsite solar energy consumption for these houses accounts for 165 kWh in the period of June to September. This would have alternatively been injected to the grid causing large peaks in the grid during high generation hours. Moreover, the number of comfort violations (T_m lower than 45°C and water consumption is greater than 0L) is decreased significantly as a result of the optimization for all houses. This could be attributed to significant rise in the number of reheat cycles in order to maintain vessel midpoint temperatures of higher 49.5 °C during high generation hours as set in the reward function. Therefore, the reduction of the comfort violation is considered to account for part of the increase in total average daily required energy.

Perhaps the most notable effect of the optimization is visible in the self-sufficiency parameter. The optimization resulted in a remarkable increase in the self-sufficiency for all houses. House 5 even reached an increase of 70% in self-sufficiency to reach a total self-sufficiency of 99% of the load. The lowest increase is evident for house number 1 with an increase of 17% which resulted in a total self-sufficiency of 89%. The large difference could partly be explained by the high baseline self-sufficiency of house number 1 of 71% against that of only 28% for house 5. Intuitively, the lower the initial self-sufficiency, the larger the potential for optimization. Secondly, house 1 has significantly higher DHW consumption than the other houses which depletes the DHW storage tank much faster forcing it to reheat additionally during the low energy generation hours.

4 Discussion

4.1 Generalizability

The cluster of houses of this case-study comprise identical refurbished social housing dwellings. Therefore, the system size and parameters are all identical which will naturally result in similar control behavior. The only highly divergent variable on daily basis is the occupant behavior. Nevertheless, the algorithm learns the corresponding control strategy based on the individual data input. Therefore, this control strategy could also be applied to clusters with different and also divergent system parameters provided that the features used in this case study are available. In other words, the algorithm is generalizable and could be applied to any system that could provide these three parameters. The optimization potential will vary from one system to another based on the system parameters such as the insulation and the size of the water vessel, solar energy generation, type of dwelling, and the number of occupants of the dwelling.

4.2 Implications for the occupants

The current Dutch net metering compensation scheme means selling excess solar energy is beneficial in all cases before 2020. Power sold to the grid is compensated against the total consumed power on annual basis. The excess power sold to the grid beyond the range of the total consumed power, is also compensated for a fair price determined by the DSO. This scheme is therefore stimulating consumers to invest in solar energy. As a result, consumers do not have to pay tax on their energy bill. This tax is estimated to account for 40 million Euros annually [15] which is funded by the Dutch tax system. It is therefore argued that this tax is paid for by tax-payers without solar panels [15]. Moreover, the scheme is not beneficial for grid operators on a long-term scale as a result of the need for grid reinforcement. It is therefore planned to diminish this scheme by 2020.

All of this means that while currently reducing the power injected to the grid is not beneficial, it will become so according to the plans for the transition plan in 2020 [16]. Two main transition proposals are stated in the report state a reduced value for the excess sold power to the grid. The first proposal states a buying value of €0.22/kWh against a selling value of €0.06/kWh. The second proposal includes an additional feed-in tariff of €0.075 to the selling price. In both cases, on-site solar energy consumption will become more beneficial than selling to the grid. It is estimated by [16] that the monthly cost for nZEBs will increase, as a result of diminishing the net-metering scheme, by €40 given the current prices of solar technology and heat pumps and €30 considering the expected price reduction of these installations. Table 2 presents the total reduction of the summed energy injection and uptake for all six houses in the period of June to December, against the monetary value in both scenario 1 and 2 of the proposal of [16]. Deducting the money missed due to the reduction of solar energy selling from the gained money due to the reduction of electricity uptake, results in a total benefit between € 4 - 24 in the first scenario and €1 - 9 in the second for the six houses for the period of June to December.

Table 2. Overview of reduction of energy uptake and injection and the corresponding monetary benefit for the two scenarios proposed in [16] to replace the net-metering policy in the Netherlands in 2020

House nr	Total reduced injection (kWh)	Total reduced uptake (kWh)	Δ Monetary benefit scenario 1 (€)	Δ Monetary benefit scenario 2 (€)
1	79	89	14.84	8.915
2	98	118	20.08	12.73
3	102	137	24.02	16.37
4	37	30	4.38	1.605
5	164	104	13.04	0.74
6	115	108	16.86	8.235

4.3 Implications for grid operators

The optimization results discussed in the previous sections show a decrease of energy injection to the grid of a maximum of 25 kWh on average for the houses in summer and a minimum of 10 kWh for the period of September to December. The reduction of injected power to the grid translates directly to a reduction in the necessary cost for grid reinforcement. The required grid reinforcement cost comes from the size of the transformers and cables required to accommodate a large increase solar energy generation due to an increase in nZEB concepts. Additional benefits for the grid operators relate to the real-time grid monitoring and steering role of the grid operators.

4.4 Learning mechanism of RL

The main argument to use RL for this optimization is the learning aspect and generalizability of the method. The constantly changing solar and occupant behavior patterns create a disadvantage for fixed optimization approaches such as MPCs and rule-based control methodologies. To test and proof the learning mechanism of the RL algorithm used, average occupant behavior and monthly solar energy profiles were created from the individual profiles of the six houses. These profiles were then applied to the algorithm to simulate the results for each of the houses. The number of reheat cycles as a result of the averaged profiles optimization show remarkable results for being substantially amplified for houses with a low energy consumption profile. The large difference of the number of heating cycles between the individual and averaged profiles indicates the strong influence of the individual occupant behavior on the performance of the algorithm. This emphasizes the significance of the learning behavior of the algorithm as opposed to rigid approach of rule-based control optimization algorithms.

5 Conclusions and recommendations

Deriving from the results and discussion, using RL could provide means for improving the performance of nZEB to comply to the label standards and in the same time reduce the pressure on the grid as a result of the increasing electrification of the built environment without posing a threat to the occupant comfort. Providing these means for the utility grid not only reduces the need / cost for grid reinforcement, but allows for more renewable energy technologies to be deployed in the residential built environment. The results show an increase of individual self-consumption between 17% and 348% and self-sufficiency between 18% and 72% by applying DHW load shifting. This indicates a significant potential to reduce grid interaction to boost the implementation of RES in the residential built environment for the sake of increasing the share of renewables and also to improve the efficiency of the built environment by implementing more nZEBs. Additionally, considering the planned abolishment of the net-metering policy for solar power in 2020 in the Netherlands, reducing the grid interaction increases the monetary benefit for the residents. Moreover, this approach improves the monitoring potential of grid operators to avoid grid curtailment as a result of the increased electrification of the building loads and locally generated renewable energy. However, if the

transient grid stability is aimed at as a main factor by the DSO, then the instantaneous power injection should be included as an additional variable and prioritized in the algorithm.

6 References

1. Rijksoverheid website, Onderzoeken Energie Gebouwde Omgeving. <https://www.rijksoverheid.nl/onderwerpen/onderzoeken-over-bouwen-wonen-en-leefomgeving/onderzoeken-energie-gebouwde-omgeving>, last Accessed: 2017/04/07.
2. Van den Oosterkamp, P., Koutstaal, O., van der Welle, A., de Joode, J., Lenstra, J., van Hussen, K., Haffner, R. The role of DSOs in a Smart Grid environment. ECORYS, Amsterdam/Rotterdam (2014).
3. Lawrence, T.M., Boudreau, M., Helsen, L., Henze, G., Mohammadpour, J., Noonan, D., Pateeuw, D., Pless, S., Watson, R.T. Ten questions concerning integration smart buildings into the smart grid. In: Building and Environment, Vol. 108, pp. 273 -283, Elsevier (2016).
4. Yang, R., Wang, L. Multi-objective optimization for decision-making of energy management in building automation and control. In: Sustainable Cities and Society, Vol. 2, pp. 1-7. Elsevier (2012)
5. Klein, L., Kwak, J., Kavulya, G., Jazizadeh, F., Becerik-Gerber, B., Varakantham, P., Tambe, M. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. In: Automation in Constructions, Vol. 22, pp. 525-526. Elsevier (2012).
6. Lund, P., Lindgren, J., Mikkola, J., Salpakari, J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. In: Renewable and Sustainable Energy Reviews, Vol. 45, pp. 785-807, Elsevier (2015).
7. Sossan, F., Kosek, A.M., Martinenas, S., Marinelli, M., Bindner, H.W. Scheduling of domestic water heater power demand for maximizing PV self-consumption using model predictive control. Technical university of Denmark, Lyngby (2013).
8. Arteconi, A., Hewitt, N.J., Polonara, F., Domestic demand-side management (DSM): Role of heat pumps and thermal energy storage (TES) systems. In: Applied Thermal Engineering, Vol. 51 (1–2), pp. 155-165. Elsevier (2013).
9. Kazmi, H., D'Oca, S., Delmastro C., Lodeweyckx, S., Corgnati, S.P. Generalizable occupant-driven optimization model for domestic hot water production in NZEB. In: Applied Energy, Vol. 175, pp. 1 – 15, Elsevier (2016).
10. Ijaz Dar, U., Sartori, I., Georges, L., Novakovic, V. Advanced control of heat pumps for improved flexibility of Net-ZEB towards the grid. In: Energy and Buildings, Vol 69, pp. 74 – 84, Elsevier (2014).
11. De Coninck, R., Baetens, D., Saelens, D., Woyte, A., Helsen, L. Rule-based demand side management of domestic hot water production with heat pumps in zero energy neighborhoods. In: Journal of Building Performance Simulation. Vol. 7, pp. 271 – 288, (2014).
12. Ruelens, F. Residential Demand Response Using Reinforcement Learning. Arenberg Doctoral School, Faculty of engineering science, KU Leuven, Leuven (2016).
13. Portaal homepage. <http://www.portaal.nl/stroomversnellingsoesterberg.aspx>, last Accessed: 2016/07/02
14. Pruissen, O.P., Kamphuis, I.G. Grote concentraties warmtepompen in een woonwijk en gevolgen elektriciteitsnetwerk. Energy research Centre of the Netherlands (ECN), Petten (2010)

15. Rijksdienst voor Ondernemend Nederland, Saldering, zelflevering en tariefkorting.
<http://www.rvo.nl/onderwerpen/duurzaam-ondernemen/duurzame-energie-opwekken/duurzame-energie/saldering-en-zelflevering>, last Accessed 2016/06/26
16. Merosch, de effecten van en oplossingen voor aanpassing van salderingsregeling op NOM-woningen in 2020.
<http://www.merosch.nl/download/CAwdEAwUUkBFXw==&inline=0>.