

Analysis of Battery Storage Usage of Heuristic Energy Flow Controllers

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Abstract—Due to the increasing usage of renewable energy sources like photovoltaic (PV) systems in the private sector and their fluctuations in production, energy management systems (EMS) are becoming more and more important. As such system use the produced energy as efficiently as possible, they also have an influence on a battery storage which is often installed together with the PV system. Nowadays batteries are already durable and cost efficient, but the possible negative effects an EMS might have on its usage and lifetime still need to be taken into account and be aware of. This is why this work analyses the battery usage of heuristic energy management controllers in detail and compares them to two existing energy management systems. It is shown that the heuristic energy management controllers are able to reduce the number of used battery cycles and therefore also the charged and discharged energy remarkable compared to the rule-based self-consumption optimization and the linear MPC, which also leads to a prolongation of the battery lifetime.

Keywords: Energy Management System, Genetic Programming, Symbolic Regression.

1. INTRODUCTION

During the last years, the usage of renewable energy sources is increasing also in the private sector. Due to their fluctuations in production, energy management systems (EMS) are currently becoming more and more important and therefore also more prominent in research. Such systems should use, store and distribute the produced renewable energy as efficiently as possible in order to minimize the energy costs of buildings or to support the grid stability as good as possible.

Especially when combining a PV system with a battery storage, such EMS become important due to multiple components that need to be controlled. And although batteries are nowadays cost efficient and durable, it is also important to be aware of possible negative effects such energy management systems might have on their usage and lifetime.

Because of that, this work optimizes a residential building with a PV system and a battery for its energy costs using genetic programming to solve it as a symbolic regression problem. This energy cost minimization causes an increase in the amount of self-consumed energy and less interactions with the energy grid in general, which should also result in an optimized battery usage by causing less consumed battery cycles and therefore also an extended lifetime.

The trained heuristic controllers are therefore analysed in detail for their battery usage and lifetime influence by taking a closer look on the used battery cycles per year and the course of the state of charge during the year. The results of these heuristic controllers are also compared to two existing and well known energy management systems, a rule-based self-consumption optimization and a linear model predictive controller, in order to get a better and more profound analysis result.

The remaining work is structured as follows: Chapter 2 gives an overview of existing EMS technologies, followed by a detailed description of the developed methodology and the used data basis in chapters 3 and 4. Chapters 5 and 6 describe the evaluation and its results, while chapter 7 contains the conclusions.

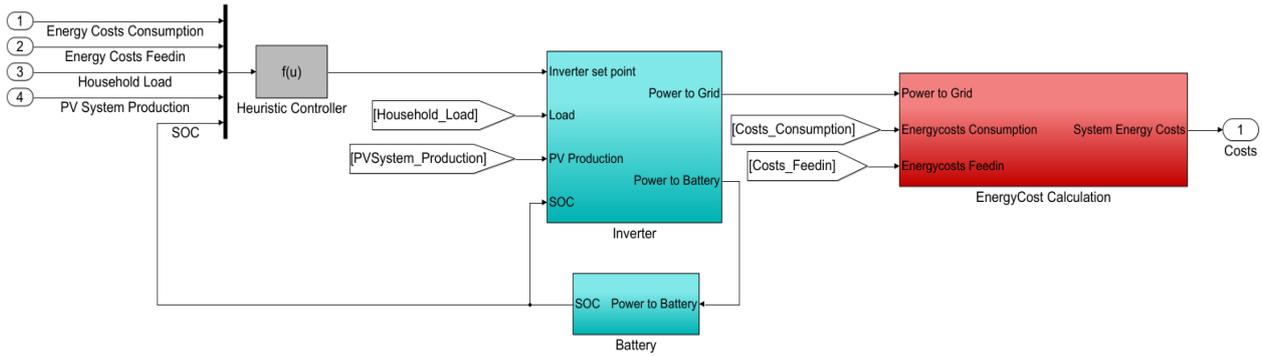


Figure 1 The simulation model used for the optimization of the residential system. Using the provided input data, the heuristic controller calculates the grid set point for the inverter which in turn then calculates how much energy should be fed into the battery or as surplus into the grid to fulfil this set point. Finally, the energy costs caused by the system are calculated in the red block.

2. RELATED WORK

For the optimization of residential energy flows, four main trends can be identified, which all briefly are explained below: Rule-based control systems, model predictive controls, mixed integer linear programming approaches and also meta-heuristic optimization algorithms as they are used in this work.

2.1. Rule-based Energy Management Systems

Rule-based energy management systems are one of the simplest ways to optimize the energy flows of a building. For that, the rules for the system are created by an expert and represented as a tree with the rules as simple either-or decisions in the branches and the respective actions in the leaf nodes. This makes the approach fast, easy to create and also good-working for simple systems. However, optimizing complex systems with this rule-based approach requires a lot of development effort and expert knowledge to achieve acceptable results and might be prone to unwanted side effects that are hard to detect and eliminate. But despite that, during execution rule-based EMS are very performant and can control also larger systems in realtime. Three examples for rule-based energy management systems were presented by De Coninck et al. in 2014 [1], Salpakari and Lund in 2016 [2] and by Alimohammadisagvand et al. in 2018 [3].

2.2. Model Predictive Controls

Another widely used energy flow optimization technique are model predictive controls (MPCs), which are linear or quadratic optimization programs. They calculate the optimal control values for the next timestep using the current system values to predict the future system behaviour. With these forecasts, the control commands for the next timestep are calculated by the optimization algorithm and sent to the system to be executed [4]. Because MPCs use a detailed simulation

model representing the system to be optimized together with forecasts that are as accurate as possible, they achieve almost optimal optimization results. Two recent works were presented in 2018 by Godina et al. [4] and in 2020 by Seal et al. [5]. Godina et al. developed an MPC that optimizes and controls the air conditioning of a room within a house with a PV system [4], while Seal et al. implemented a centralized MPC for a zone based comfort and energy management in a residential building with a PV system, a battery and an integrated heat pump [5].

2.3. Mixed Integer Linear Programming based Energy Management Systems

Mixed integer linear programming (MILP) algorithms aim at optimizing the value of a linear quality function under given constraints. They are a further development or refinement of linear programming algorithms where the defined variables may also take on continuous values like real numbers [6]. Three papers that use a mixed integer linear programming approach to optimize or control energy flows were presented in 2013 by De Angelis et al. [7], in 2015 by Kaczmarczyk [8] and in 2020 by Foroozandeh et al.[9].

2.4. Heuristic Optimization based Energy Management Systems

One of the more recent approaches for energy management systems is to use meta-heuristic algorithms, which is also done in this work. So far, mostly Particle Swarm Optimization (PSO) algorithms are used besides genetic algorithms. Such algorithms (randomly) create a certain number of solution candidates, which are referred to as "particles" that form a "swarm" that moves through the solution space to find the best solution for the given problem [10]. As examples, Pedrasa et al. use an improved PSO algorithm to optimize the schedule of energy services for net benefits [10] while Eseye et al. optimize an energy management system for an isolated industrial micro grid for minimal energy costs and

maximum economic benefit using a modified particle swarm optimization algorithm [11].

Genetic algorithms are able to find almost optimal solutions by having the natural, biological selection process as paradigm. Based on a parent generation and by using crossover and random mutation, these algorithms generate new solution candidates, which are transferred to the next generation after a (quality) selection. In the course of multiple generations, very good to optimal solutions can be found in that way [12]. In 2009, Morganti et al. [13] and in 2017, Soares et al. [14] published their works on using genetic algorithms for the optimization or management of energy sources and loads.

3. METHOD

With a further development [15] of the model-based heuristic optimization approach presented by Kefer et al. [16] the energy costs of a household with PV system, battery storage and a variable energy tariff are minimized. There, the optimization framework HeuristicLab [17] first initiates the C-code generation from a MATLAB Simulink model (Fehler! Verweisquelle konnte nicht gefunden werden.), extends this code with additionally needed functionality and then compiles the code into a Dynamic Linked Library (DLL). This DLL is then used for the actual training process, where HeuristicLab uses genetic algorithms to solve this symbolic regression optimization problem. For that, HeuristicLab first creates an initially random population of solution candidates. From these parent solution candidates, some are chosen for “mating” where crossover and mutation is applied so that new children solution candidates are generated. These children solution candidates are then evaluated for their quality by injecting them into the DLL, simulating the model and extracting the resulting energy costs again from the DLL. The energy costs are then used as the quality measure that should be minimized and based on which the best solution candidates are selected for the next generation, where again some of them are selected for the children solution candidate creation [15]. The model used for this optimization (shown in Figure 1) was developed by Kirchsteiger et al. [18] and was only slightly adapted for this work as described in [16].

Using this approach, two different genetic algorithms are used to each train five controllers with each of the three training datasets described in chapter 4, which results in 30 controllers to be compared. The first genetic algorithm is the Offspring Selection Genetic Algorithm (OSGA) by Affenzeller et al. [19]. It is a single-objective optimization algorithm, which has the sole goal to minimize the energy costs of the system. As parameters, a population size of 500 with 1000 selected parents, a maximum of 100 generations and 50 000 evaluated solutions, a mutation probability of 15% and a maximum

selection pressure of 100 are used. Despite that, a Gender Specific Selector [20] with a proportional selector as female and a random selector as male selector is used.

The second one is the Non-Dominated Sorting Genetic Algorithm (NSGA-II) by Deb et al.[21]. This multi-objective genetic algorithm not only minimizes the energy costs but also aims at minimizing the complexity of the controllers by assigning different complexity values to the different mathematical operations, e.g. lower complexities for the basic arithmetic operations and higher complexities for e.g. exponential or logarithmic operators. Similar to the parameters of the OSGA, a population size of 500 with 1000 selected parents, a mutation probability of 15% and 100 generations are used for the NSGA-II. As selector, a Crowded Tournament Selector [22] with a group size of six is used.

4. DATA BASIS

Three years of measured data (2016 - 2019) from a single-family household in Upper Austria is used as data basis for this work. It includes the household load in a resolution of five seconds, the energy production of the PV system in a five minutes resolution and variable energy tariffs in a one hour resolution. The tariff for the energy consumption from the grid varies every hour, whereas the feed-in tariff varies monthly. This data was pre-processed by eliminating possibly missing data using linear interpolation. From this basis, three different datasets were then created based on findings from a previous work [15] and which hold the data from the whole March 2016, the 3rd quarter of 2016 and the whole year 2016. As evaluation datasets, the two following years 2017 and 2018 are used and split up into the two separate years.

5. EVALUATION

The 30 heuristic controllers trained with the approach described in chapter 3, are evaluated in simulation with the same model and parameters that were also used for the training of the controllers: a simulation interval of 30 seconds, a total battery capacity of 6kWh with 5kW maximum charging and discharging power and an initial state of charge of the battery of 30%. As evaluation timespans, the two evaluation datasets holding the data of the years 2017 and 2018 are used. For the evaluation, the following data is recorded during the simulation and saved for later analysis: the power charged and discharged into and from the battery and the state of charge of the battery for every simulation step. With this data and a battery capacity of $capacity_{Ws} = 6000Wh * 3600s$, the number of full cycles is calculated as shown in equations 1 to 3. In these equations, N is the total number of time steps the simulation should run while t denotes the current time

step. In the model, charging the battery is represented with negative values while discharging it produces positive values. This is why for the calculation of $cycles_{charging}$, the multiplication factor -1 is introduced.

$$chargedPower_{\frac{W}{30s}} = \sum_{t=1}^N P_{Batt}(t) \text{ where } P_{Batt}(t) < 0 \quad (1)$$

$$dischargedPower_{\frac{W}{30s}} = \sum_{t=1}^N P_{Batt}(t) \text{ where } P_{Batt}(t) > 0 \quad (2)$$

$$cycles_{charging} = \frac{chargedPower_{\frac{W}{30s}} * (-1) * 30}{capacity_{Ws}}$$

$$cycles_{discharging} = \frac{dischargedPower_{\frac{W}{30s}} * 30}{capacity_{Ws}} \quad (3)$$

6. RESULTS

In general, it was found that most of the heuristic controllers are able to reduce the used battery cycles and therefore of course also the charged and discharged energy compared to the two reference EMS. The detailed results are shown in tables 1 and 2 and are presented below.

Table 1 The number of charging, discharging and full battery cycles with their standard deviations in the brackets below consumed by the heuristic controllers (average of the five controllers trained with each algorithm) and the two reference EMS during the whole year 2017.

Controller		Charging Cycles	Discharging Cycles	Total Cycles
SCO		163.14	159.54	322.68
MPC		276.13	270.54	546.67
March 2016	NSGA	162.75	147.27	310.02
	-II	(14.01)	(12.65)	(22.79)
	OSGA	179.57	138.28	317.84
		(15.22)	(4.39)	(10.83)

Q3 2016	NSGA	147.83	138.38	286.21
	-II	(13.26)	(4.99)	(16.70)
2016	OSGA	144.08	140.67	284.75
		(0.62)	(0.55)	(1.17)
2016	NSGA	162.21	150.16	312.27
	-II	(18.88)	(9.18)	(27.88)
2016	OSGA	144.48	140.83	285.31
		(1.00)	(0.81)	(1.79)

Table 2 The number of charging, discharging and full battery cycles with their standard deviations in the brackets below consumed by the heuristic controllers (average of the five controllers trained with each algorithm) and the two reference EMS during the whole year 2018.

Controller		Charging Cycles	Discharging Cycles	Total Cycles
SCO		191.05	186.92	377.97
MPC		284.06	279.04	563.10
March 2016	NSGA	194.79	179.67	374.46
	-II	(15.80)	(15.70)	(28.39)
2016	OSGA	211.05	168.75	379.80
		(16.92)	(5.29)	(11.63)
Q3 2016	NSGA	178.61	168.98	347.59
	-II	(13.50)	(5.63)	(17.53)
2016	OSGA	179.14	167.99	347.13
		(6.04)	(7.45)	(2.60)
2016	NSGA	192.64	179.92	372.56
	-II	(16.26)	(7.14)	(23.09)
2016	OSGA	175.88	171.78	347.66
		(1.02)	(0.88)	(1.90)

6.1. Battery Cycles

On average, the heuristic controllers trained with the NSGA-II and March 2016 reduce the total battery cycles for the year 2017 by 4.63% compared to the Fronius SCO and even by 77.26% compared to the linear MPC. The controllers trained with the OSGA achieve reductions of 1.63% on average compared to the Fronius SCO and 72.18% compared to the linear MPC. For 2018, the results are worse for all heuristic controllers with the NSGA-II trained controllers saving 1.45% of the total battery cycles, but the OSGA controllers needing on average 0.39% more cycles than the Fronius SCO. Compared to the linear MPC, they are still able to reduce the cycles by 51.19% when trained with the NSGA-II, respectively 48.39% when trained with the OSGA.

Taking a closer look on the controllers trained with the data of the third quarter of 2016, the results look much more promising. For 2017, the heuristic controllers were

able to save on average 13.22% cycles compared to the Fronius SCO and 91.82% compared to the linear MPC. Similar to the results of the controllers trained with March 2016, the results for 2018 are worse compared to 2017. Nevertheless, the NSGA-II trained controllers achieve on average cycle reductions of 9.02% and the OSGA trained controllers of 8.89% compared to the Fronius SCO. Compared to the linear MPC, these percentages rise again to 62.42% respectively 62.23% for the NSGA-II and OSGA trained controllers.

For the controllers trained with the data of the whole year 2016, the results are worse than the ones achieved with the third quarter 2016 as training data, but still a lot better than for the ones trained with only March 2016. Especially the OSGA trained controllers achieve very good results by reducing the overall needed battery cycles by 13.10% respectively 8.72% compared to the Fronius SCO for 2017 and 2018 and 91.62% respectively 61.97% compared to the linear MPC for 2017 and 2018. The NSGA-II trained controllers are only able to reduce the cycles by 4.09% in 2017, respectively 1.83% in 2018 compared to the Fronius SCO. However, compared to the linear MPC, they still achieve reductions of 76.35% respectively 51.70% for 2017 respectively 2018.

Taking a closer look on the standard deviations of the heuristic controllers as shown in tables 1 and 2, it becomes obvious that the controllers trained with the OSGA have much smaller standard deviations than the ones trained with the NSGA-II algorithm. This indicates that the training of those controllers is much more stable and produces more similar results. The smallest standard deviations are achieved by the controllers trained with the data of the third quarter of 2016, which also achieve the best overall results at reducing the battery cycles

6.2. Battery Usage

In addition to the detailed mathematical analysis of the battery usage, it is also evaluated to which times of the year which energy management systems uses the battery most by taking a closer look on the state of charge of the battery during the whole year. As shown in figures 2 and 3, the Fronius SCO as well as all the heuristic controllers mainly use the battery storage during the summer months, which makes sense due to more energy produced by the PV system and therefore more surplus energy that can be stored in it. However, the linear MPC shows a different behaviour by using the battery storage mainly during the colder times of the year and less during the summer months. This is caused by the way that the linear MPC works: it tries to mainly take advantage from the varying energy tariffs. As the load is higher during the winter times and as the tariff variations are also higher during this time, the linear MPC then often charges the battery from the grid when it expects the tariffs to be low and then discharges the cheaply bought energy during high tariff times. This behaviour might also be one of the

reasons why the linear MPC needs much more battery cycles compared to the heuristic controllers and also the Fronius SCO.

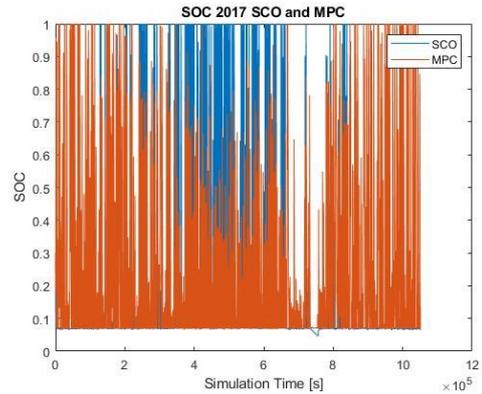


Figure 2 The state of charge of the battery for the whole year 2017 by the Fronius SCO and the linear MPC.

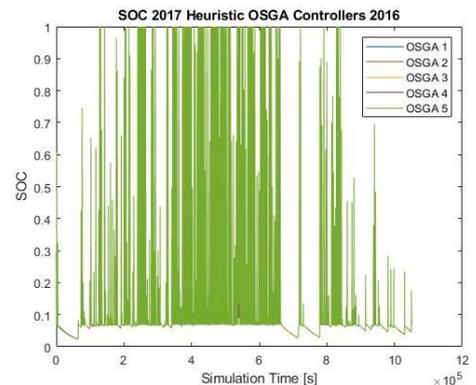
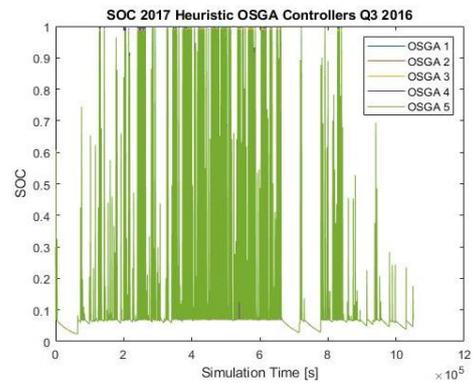
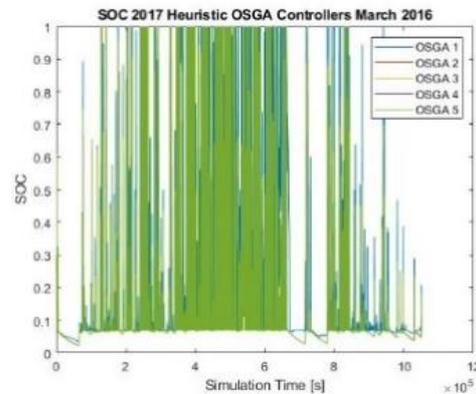


Figure 3 The state of charge of the battery for the whole year 2017 by heuristic controllers trained with the OSGA.



7. CONCLUSIONS

This work focuses on the analysis of the battery usage of heuristic energy management controllers. The controllers are trained using a model-based optimization approach where genetic programming is used to solve a symbolic regression problem with the goal to minimize the energy costs of the system. As simulation model, a MATLAB Simulink model of the electrical system of a residential building with a PV system and a battery storage is used. With this approach, measured data from a real-world single-family household split up into three different datasets and two genetic algorithms, 30 heuristic controllers are trained. They are evaluated in detail with two years of evaluation data for their influence on the battery behaviour, including the amount of charged and discharged energy as well as the used battery cycles and the battery's state of charge. For better performance estimation, the results are also compared to two existing energy management systems, a rule-based self-consumption optimization and a linear model predictive controller.

It is shown that the heuristic controllers are able to reduce the amount of used battery cycles on average by 3.69% per year compared to the self-consumption optimization and even by 64.99% on average per year compared to the linear MPC. As the battery cycles and the amount of charged and discharged energy are closely correlated, similar values can also be found for those evaluation measures.

Despite that, it is found that the heuristic controllers, similarly to the self-consumption optimization, use the battery preferably during the warmer months of the year. The linear MPC uses it mainly during the colder months where the tariff variations and the load is higher, because it actively charges the battery from the grid when the tariffs are expected to be low and discharges it during the high tariff times.

Despite not being trained for the optimal usage of the battery but solely for minimizing the energy costs of the system, the heuristic controllers proved to relieve the battery by using more of the produced energy directly for supplying the loads and buffering less in the battery.

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