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Final Report

User-Centric Simulation of Demand Response Optimization

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Acknowledgments

> It is not because things are difficult that we do not dare, it is because we do not dare that things are difficult.
>
> *Seneca*

If it had not been for the love and support of my girlfriend, Magdalena, and that of my friends and family, I would never have been able to pursue research abroad. Thank you very much for your understanding and care throughout the years!

Special thanks belong to both, Dominik, my supervisor at Salzburg University of Applied Sciences and Rob, my supervisor at Bowling Green State University. Without you two, this whole exchange would have never happened and I had missed some great experiences! Thank you for your help and input.

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Thank you all!

Abstract

This final report is a shortened version of the master's thesis *User-Centric Simulation of Demand Response Optimization*[1] [14], which was written during the research stay at Bowling Green State University in 2014. Demand response (DR) is a crucial and necessary aspect of the smart grid, particularly when considering the optimization of both, power consumption and generation. This report simulates various use cases with Okeanos, a fundamental, game theoretic, Java-based, multi-agent software framework for DR simulation that is capable of investigating the effect of optimizing multiple electric appliances by utilizing game theoretic algorithms. Results show that by shifting the switch-on time of three household appliances, savings of up to 6% can be reached. Further evaluation involving plug in electric vehicles (PEVs) demonstrates that with an increasing penetration of PEVs and feed-in tariffs the costs per household per month decrease.

[1]Parts of this master's thesis and, thus, this report, were submitted as a conference paper to *IEEE Innovative Smart Grid Technologies 2015* and as a journal paper to Elsevier *International Journal of Electrical Power & Energy Systems*.

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CHAPTER I

Introduction

> During the last century, the United States quietly underwent a change with profound implications. Electricity went from a novelty to a convenience to an advantage to an absolute necessity. Despite the headlines about our addiction to oil, we are even more dependent on electricity. We need it every day, all day. We need it for our most important functions. And we need more and more and more of it, with no end in sight.
>
> *Berst et al.* [11, p. 12]

After the nuclear catastrophe of Fukushima Daiichi in 2011, people began to change their mind about nuclear energy. As the long proclaimed safety of nuclear energy was not taken for granted anymore, renewable energy steadily began to gain popularity among the man on the street. With Germany declaring phasing out nuclear energy by 2022, the topic gained additional momentum. It was also at that time that the author of this report got interested in what he could do to help working towards that change. However, with the increasing pervasiveness of renewable energy, new challenges have arisen: Energy is no longer exclusively produced in large power plants, but also in the homes of ordinary people. Eventually, this development leads to a paradigm shift. That is, away from the traditional hierarchical top-down oriented system with a limited number of large scale power plants, to a more decentralized structure with volatile renewable energy sources, such as wind turbines, photovoltaic cells and plug in electric vehicles (PEV) [3], [8].

This new development offers immense possibilities, as an example, the peak-period demand could be met with this energy. Additionally, coordinating household appliances or charging electric vehicles off-peak could result in cheaper electricity prices. With respect to coordination, *demand response management* could pose an ideal solution to this problem [1], [6], [7].

Demand response management (DRM) refers to "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [13, p. 21].
Chen and authors describe two fundamental strategies for DRM in [5]: Match the supply in case the power supply is inelastic or shape the demand where the power supply is elastic. In essence, the aim is to reach optimum usage for the local distribution system. This is especially hard if supply and demand characteristics show high volatility, e.g., if both, photovoltaic and e-mobility, are used by a large number of users in the local distribution system. As the large number of publications in this area show, taking into account all of these factors is a complex endeavor and there is currently no silver bullet to cope with this complexity [6].
Therefore, this report simulates various use cases with Okeanos, a fundamental, game theoretic, Java-based, multi-agent software framework for DR simulation that is capable of investigating the effect of optimizing multiple electric appliances to bring more insight into this complexity.
The following results are based on the devices listed in Table 1.1. The data for implementing drivers for clothes washer, clothes dryer and dishwasher is taken from [4]. The data for the PEV is based on the specifications of the Tesla Model S [10]. Additionally, a household load profile is used, which is based on the H0 load profile provided by the Bundesverband der Energie- und Wasserwirtschaft (Federal Association of the Energy and Water Industry) [12]. This H0 load profile is a standardized profile used to approximate the consumption of customers that cannot be measured otherwise. Finally, the real-time pricing costs are taken from [15].
In order to draw a sound conclusion, all the consecutively mentioned experiments were repeated at least 100 times and reported results are average values. A single household with a 30 kWh load profile is used as a base case.
The rest of the report is structured as follows.

Chapter 2: Simulation of Single Load-shifting Device

Okeanos' optimization algorithm is checked for proper operation with a fundamental proof of concept that only comprises one dishwasher in Chapter 2.

Chapter 3: Simulation of Load-shifting Devices of One Household

Gradually increasing complexity, Chapter 3 deals with the simulation of one

Appliance	Model	Rating
Household	Standard load profile	Scaled to 25-35kWh
Clothes washer	LG WM2016CW	120V, 60Hz, 5A
Clothes dryer	LG DLE2516W	120/240V, 60Hz, 26A
Dishwasher	Kenmore 665.13242K900	120V, 60Hz, 9.6A
PEV	Tesla Model S	120/240V, 85kW

Table 1.1: Overview of drivers used for evaluation. Data from [12], [4], [10].

household with three different load shifting devices, a dishwasher, a washing machine and a clothes dryer.

Chapter 4: Simulation of Multiple Households with Load-shifting Devices

In Chapter 4, the interaction of multiple households and their load-shifting devices is investigated. Therefore, the load profile and costs per household per month for a different number of households are compared.

Chapter 5: Evaluation of Okeanos with Plug In Electric Vehicles

The penultimate chapter analyzes the impact of plug in electric vehicles on the costs per household. Use cases in this chapter are based on PEVs that can exclusively be used by Okeanos to lower the costs.

Chapter 6: Conclusion

Finally, a summary of the report is given, the outcome described and possible future directions outlined.

CHAPTER 2

Simulation of Single Load-shifting Device

To prove that Okeanos and particularly the optimization algorithm are working correctly, a fundamental use case is constructed: only one dishwasher in the whole system is optimized.

Naturally, the best position for starting the dishwasher is where the price is lowest during the day. Indeed, this is exactly what Okeanos does. Figure 2.1 shows that the dishwasher is started during the low price periods of the day.

While, the length between the start and end is too long for one run, the results are valid, as aforementioned, the chart is the result of several runs. This means that on average the dishwasher will run during those times with the denoted consumption.

Since one device within a whole system is not really near any real world use cases, the following sections will gradually improve this scenario.

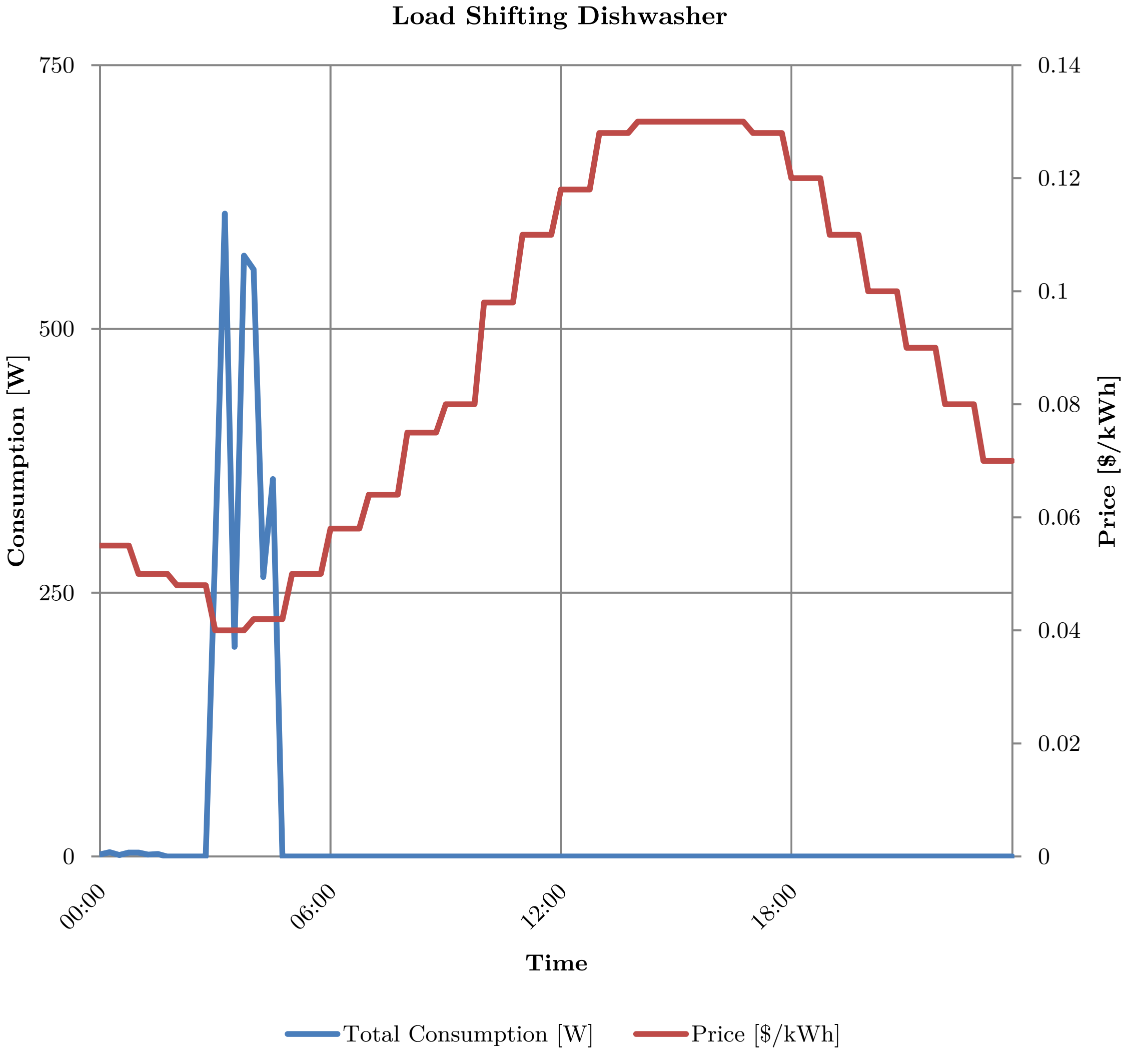

Figure 2.1: Optimizing the schedule of one dishwasher results in it being scheduled at the point in time with the cheapest price.

CHAPTER 3

Simulation of Load-shifting Devices of One Household

As a starting point, multiple devices within a single household are simulated and the interaction between the devices is tested. The devices run on each simulated day with a 33% probability. To make the simulation more realistic and to take the consumption patterns of different households into account, the H0 load profile is shifted 0, ±1h or ±3h. Similar to the previous use case, devices search for the point in time which minimizes the electricity costs for that device.

The impact of shifting the load profile of a household is depicted in Figure 3.1 and 3.2. The major result of this simulation is that the more the regular households differ in their consumption patterns, the more the total load curve evens out. With all households using the standardized H0 load profile, several peaks are present, most notably those at 1 p.m. and 8 p.m. Considering the price per kWh, it is preferable, especially, at those hours to reduce the energy consumption.

The major difference between Figure 3.1 and 3.2 is the peak in the morning, when all the load shifting devices are switched on. This difference is due to the fact that the devices run only with a 33% probability for every day and, therefore, on average, the consumption at that point should be one third of that when they are switched on every day.

It can be seen in Table 3.1 that the effect of varying the load profile of households is negligible. This is valid throughout all compared categories.

Actual savings, according to the outcomes (see Table 3.1), can be noticed between a regular 30kWh household and when load shifting is in place. The average savings is around 4.1%, if load shifting with the dishwasher, the washing machine and the clothes dryer is in place.

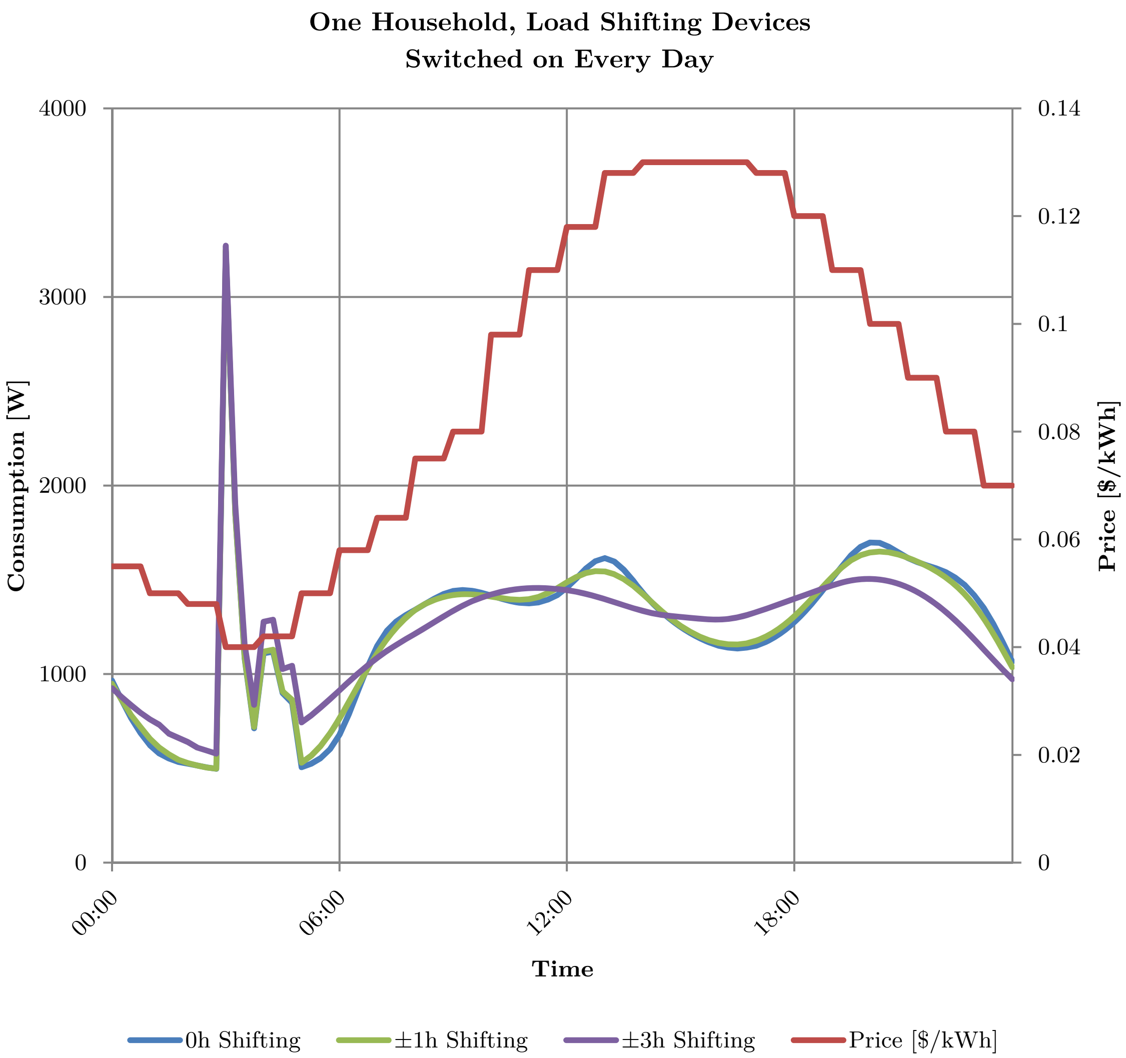

Figure 3.1: Optimizing the schedule of one 28kWh/day household with dishwasher, washing machine and clothes washer running. Devices run every day. Comparison between 0h, ±1h and ±3h shifting of the household's load profile.

	Regular 30kWh Household	28kWh household with 2kWh load shifted devices	
		Run daily	Run with a 33% chance
0h shifting	$85.80	$82.25 (4.14%)	$80.71 (5.93%)
±1h shifting	$85.72	$82.17 (4.14%)	$80.66 (5.90%)
±3h shifting	$85.10	$81.60 (4.11%)	$80.11 (5.86%)

Table 3.1: Comparison of costs with load shifting in relation to shifted household load profiles. The costs per month per household with the savings for using load shifting compared to a regular 30kWh household is given.

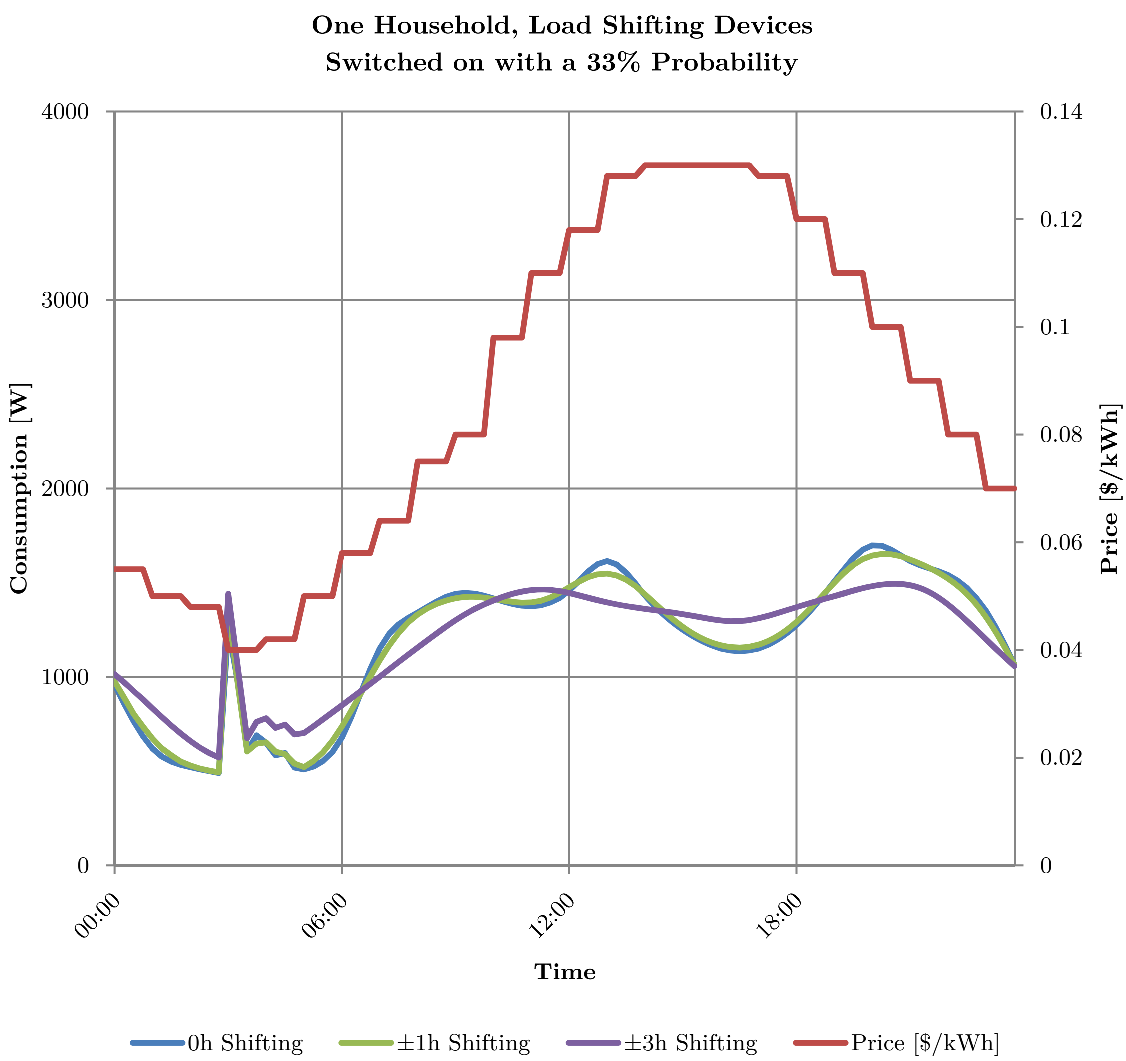

Figure 3.2: Optimizing the schedule of one 28kWh/day household with dishwasher, washing machine and clothes washer running. Devices run with a 33% chance. Comparison between 0h, ±1h and ±3h shifting of the household's load profile.

Naturally, the savings of a household with its devices running only with a 33% chance needs to be higher compared to a household with devices running every day. The savings compared to a regular household with no load shifting is 5.9%.

CHAPTER 4

Simulation of Multiple Households with Load-shifting Devices

The next logical step is to increase the number of households involved. That is, this section studies the impact of a rising number of households on the costs per household per month.

Not every household is alike, therefore, the load profile for every household is randomly scaled to either 25, 28, 30, 33 or 35kWh per day. Additionally, it is randomly shifted between ±1h of its regular time. Finally, dishwashers, washing machines and clothes dryers run with a 33% chance again. This configuration is chosen to account for different habits and usage patterns of customers.

As illustrated in Table 4.1 and Figure 4.1, altering the number of households does not change the outcome. It, however, can be seen that the peaks are getting more extreme the more households are involved.

At least two explanations should be considered when interpreting this results. On the one hand, there are too few devices that can be shifted. Due to this and because the load profiles of households have a minimum at the point in time when energy is cheapest, devices hardly have any other choice but to be switched on at that time. Further, because the average consumption of households is mostly the same, the energy consumption keeps stacking up and, as aforementioned, load shifting devices cannot smoothen the peaks.

On the other hand, the convex cost function at every point in time could need its parameters readjusted. This, however, is not very likely, as the devices that respond to costs, already run at the cheapest points in time. Households, however, do not react to different costs, which explains the peaks and the stacking of load profiles.

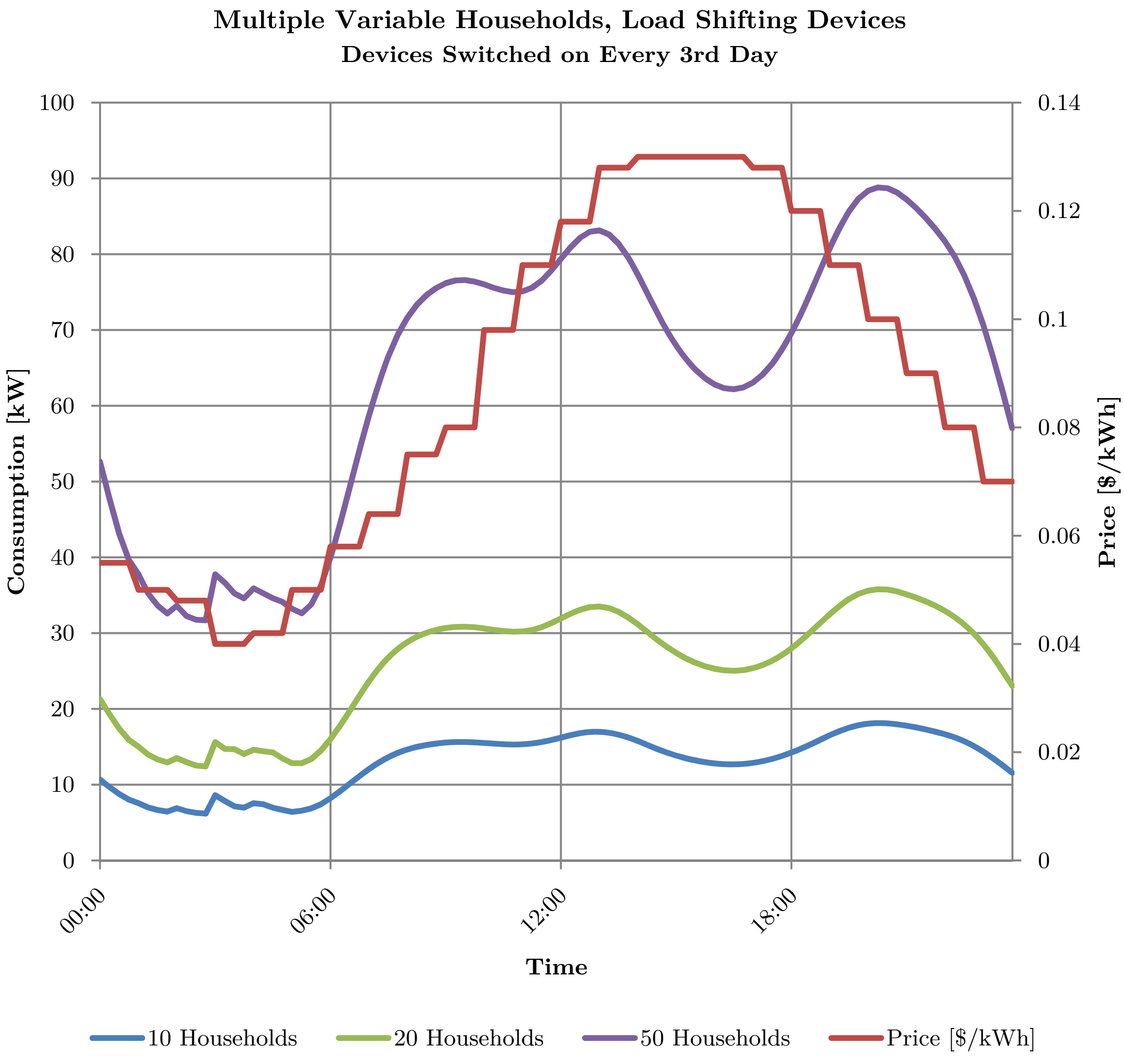

Figure 4.1: Comparison between the impact of a varying number of households on the load profile. Each household comprises one dishwasher, one washing machine and one clothes washer that run with a 33% chance. Households' load profiles are shifted ±1h.

	10 Households	20 Households	50 Households
Costs per month per household	$88.57	$86.84	$90.23

Table 4.1: Comparison of costs per household per month with an increasing number of households.

According to Table 4.1, the costs per household per month do not show a significant difference when the number of participating households is increased. The reason for this is the same as described before: The load profiles are stacked.

CHAPTER 5

Evaluation of Okeanos with Plug In Electric Vehicles

Finally, the last use case is the integration of electric vehicles in the previous use cases. As electric vehicles are all about storing energy, this is an extension to the implemented game theoretic algorithm [2], which proposes an energy consumption scheduling game. The original game was never designed for storage.
The micro-storage management game described in [9] is contrary to that, it only proposes storage devices and does not do any load shifting.
Although, Okeanos does not give a proof, unlike the aforementioned games, this contribution, nevertheless, can be considered valid as the results make sense. However, due to the use of PSO and the fact that PSO is a meta-heuristic, an optimal solution can not be guaranteed.

5.1 Impact of Penetration of Plug In Electric Vehicles on Costs Per Household

The first use case in the category of PEVs is the impact of different penetrations of PEV on the total consumption. This simulation is based on 20 households, with either 0, 25, 50, 75 or 100% of them owning one PEV. Owning really means having it standing around and not actively using it for transportation as for what it is made. In this configuration it acts like a rechargeable battery.
Furthermore, it uses a feed-in tariff of 50%. This means that if any device sells back energy to the grid, it will get 50% of the money it would cost the device to buy the same amount of energy. Additionally, as in the previous sections, load shifting devices are switched on with a 33% chance.

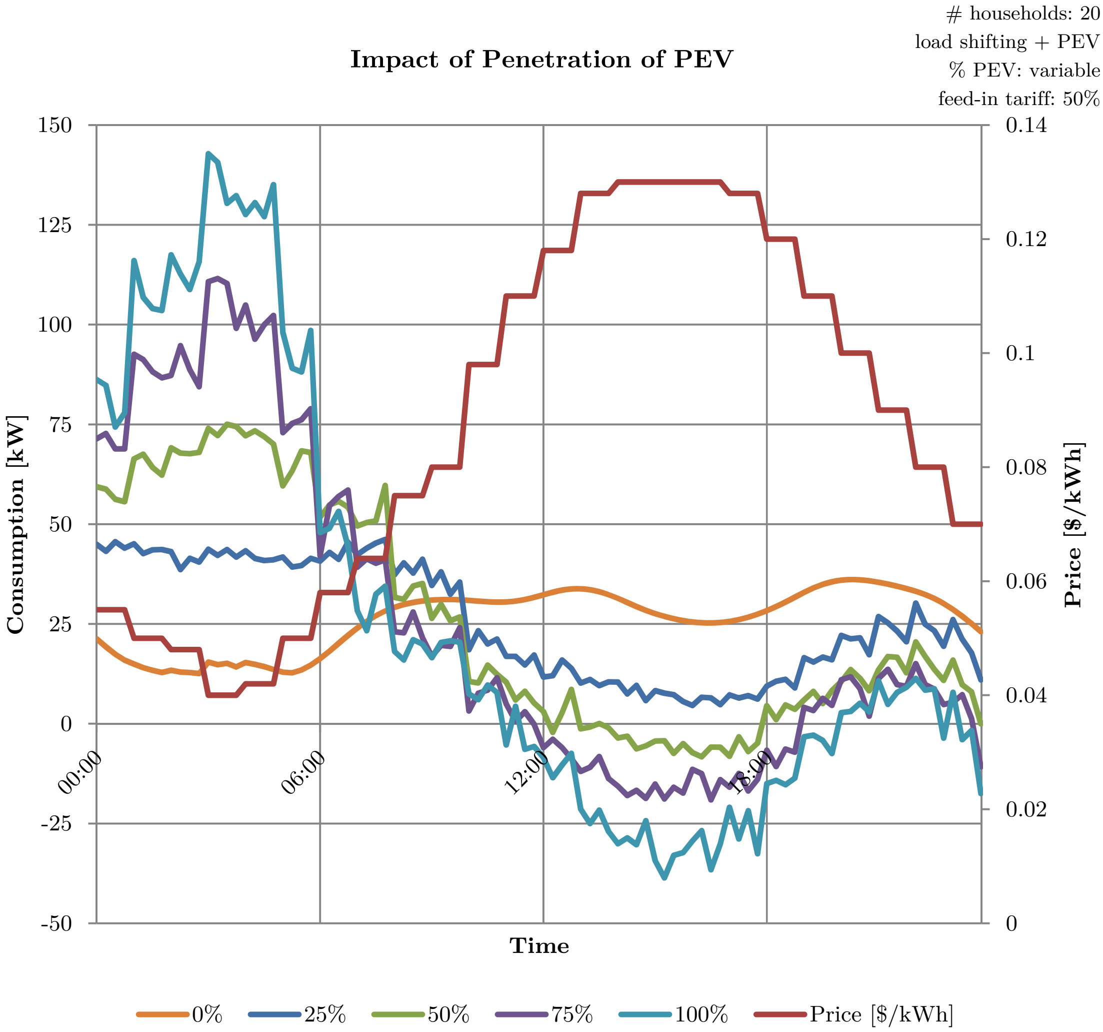

Figure 5.1: Comparison between the impact of different penetrations of households with PEVs on the optimized schedule of 20 households. Each household comprises one dishwasher, one washing machine and one clothes washer that run with a 33% chance, as well as one PEV. Households' load profiles are shifted ±1h.

	Penetration of PEVs				
	0%	25%	50%	75%	100%
Costs per month per household	$88.20	$65.98	$52.27	$40.36	$27.50

Table 5.1: Comparison of costs per household per month with an increasing number of households owning PEVs with a 50% feed-in tariff.

As Figure 5.1 shows, if only five of the 20 households, i.e., 25%, have a PEV, they completely change the load profile of households, overriding it with their own consumption pattern. This pattern, ultimately, is derived from the price function. As can be seen, PEVs charge themselves at the beginning of the day where the price for energy is cheap and use this energy later in the day to prevent the household from having to pay the peak price.

An interesting phenomenon can be noticed at the end of the day at around 11 p.m. Devices start to discharge their remaining energy. This is due to the limited planing horizon, which currently is 24h. Because devices cannot plan more than that, they want to sell the remaining energy to get the most out of the day.

The change of the load profile can be either wanted or unwanted. Even with a 25% penetration of PEVs, the peak consumption is nearly at 40kW, compared to roughly 30kW if there are no PEVs present. For higher penetrations, there is an even higher peak at the low-cost periods. This could be another unwanted peak as the grid needs to be prepared for that. If the grid is capable of transporting that amount of energy, this could be valuable to the utility company, because it sells cheap energy to customers and gets expensive energy for a cheap price, e.g., with a 50% feed-in tariff, which can be sold to other utility companies. Customers, despite the low feed-in tariff, still profit from selling energy back.

If the grid is not capable of handling that amount of energy, a possible countermeasure would be to adjust the cost function. The base price could either be changed or the factor, the costs per kWh at a point in time rise, could be adjusted as well. The latter countermeasure potentially has higher prospects of success, as it particularly penalizes high uses of energy, which, eventually, leads to a flatter load profile.

Table 5.1 compares the average costs per month for a household for a different penetration of PEVs with a 50% feed-in tariff. Most notably, the more households use PEVs the cheaper the average price for all households. Finally, when all households own a PEV and do not use it for anything else beside from participating in load scheduling, households can cut down electricity costs to approximately one fourth compared to not using PEVs at all.

This, however, is very unlikely to happen outside of simulation, as the simulation does not take a wide range of factors into account. Especially, (i) households own PEVs to use them and not let it them stand in the garage at the charging station and (ii) the wear of batteries, etc. is not taken into account.

The simulation, though, respects the maximum capacity, the minimum capacity, the maximum charge at a time and is also capable of "unplugging" a PEV, which means that the vehicle is currently in use and cannot be used for load scheduling. Furthermore, if a PEV is used, it also loses some charge, which can be expressed by the software as well.

5.2 Cross Comparison of Impact of Feed-in Tariff and Penetration of Plug In Electric Vehicles on Costs Per Household

This use case is based on the previous use case, however, greatly expands the changed parameters. A parameter study of the feed-in tariff and the penetration with PEVs is done, unlike the previous use case that assumed a fixed feed-in tariff of 50%.

Figure 5.2 illustrates the load profile when changing the feed-in tariffs. It clearly shows that the higher the incentive, i.e., the higher the feed-in tariff, the higher the likelihood that PEVs will charge during low-cost periods and discharge at high cost periods. Again, this is very similar to previous findings and is the result of trying to minimize the occurring costs for each device.

More interesting, however, is Table 5.2 and Figure 5.3, which illustrates, respectively gives the exact numbers of the costs per household per month depending on the feed-in tariffs and the penetration with PEVs.

As previously pointed out, the costs per household per month decrease the more incentive is given (=a higher feed-in tariff) or the more PEVs are available in the simulation. This effect results in households earning money at the end of the month when there are both, a high incentive and a high number of PEVs available.

The reason that the costs are decreasing with an increasing number of PEVs even with a 0% feed-in tariff is that the PEVs in that case are not actually selling the energy back

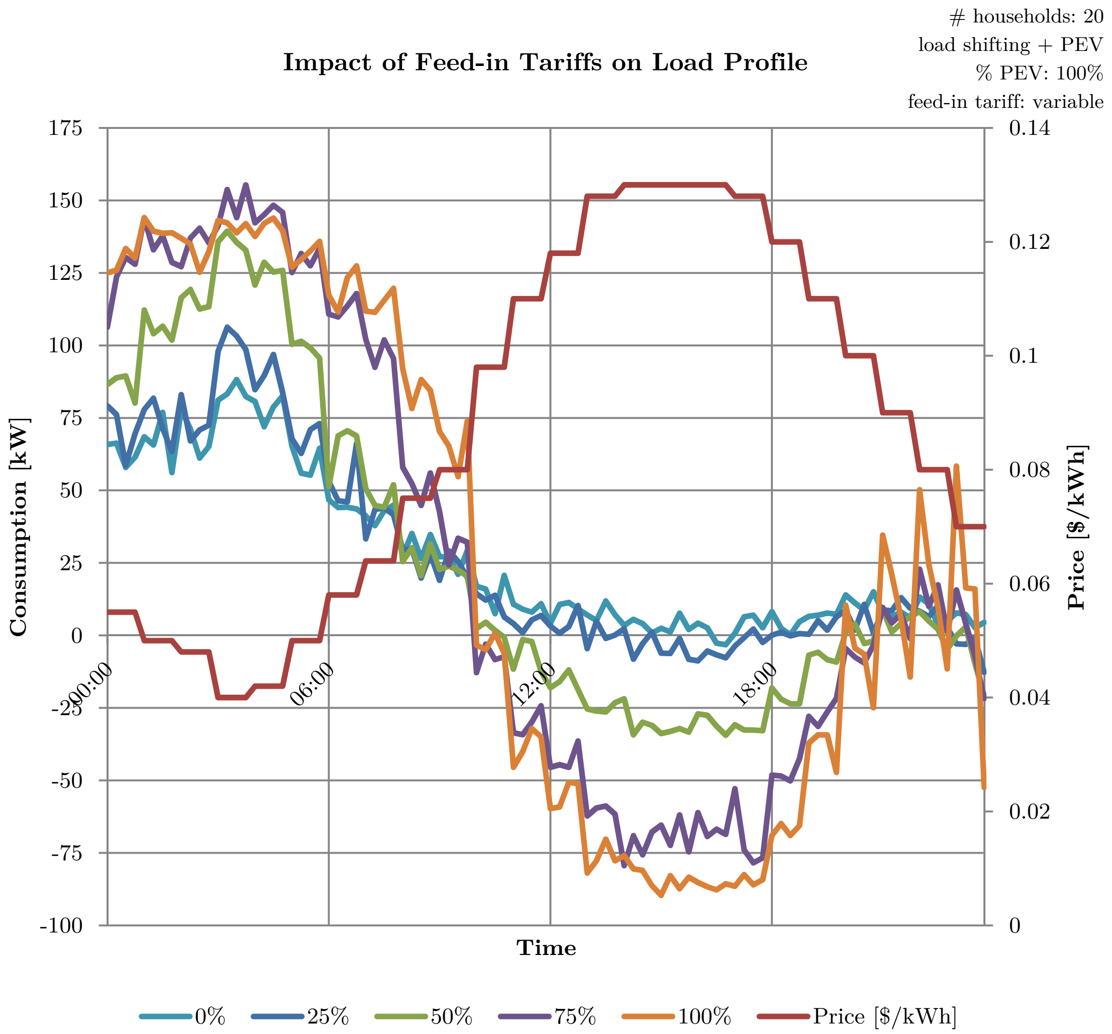

Figure 5.2: Comparison between the impact of different feed-in tariffs on the optimized schedule of 20 households. Each household comprises one dishwasher, one washing machine and one clothes washer that run with a 33% chance, as well as one PEV. Households' load profiles are shifted ±1h.

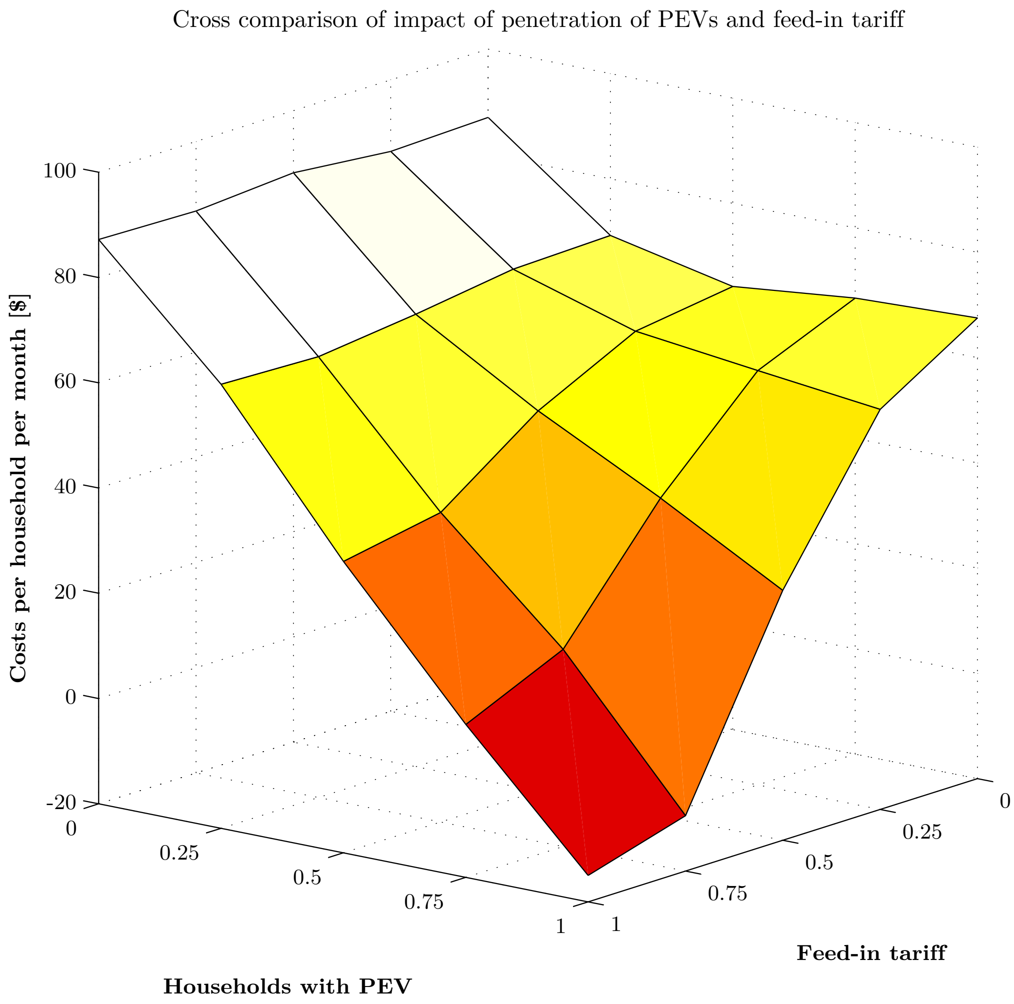

Figure 5.3: Cross comparison on the impact of different feed-in tariffs and penetration of PEVs on the costs per household per month.

Households with PEVs	Feed-in tariff 0%	25%	50%	75%	100%
0%	$87.01	$86.41	$88.20	$86.78	$87.24
25%	$69.25	$68.70	$65.98	$63.77	$64.37
50%	$64.21	$61.55	$52.27	$38.81	$35.36
75%	$66.65	$58.73	$40.36	$17.47	$9.05
100%	$67.52	$56.01	$27.50	-$9.50	-$14.98

Table 5.2: Comparison of costs per household per month with different feed-in tariffs and a different penetration of PEVs.

to the grid, but provide it to other devices. Obviously, in total, this leads to a lower price, as PEVs provide energy during the high-cost periods.
However, earning money through the use of PEVs seems unlikely as [9] simulated the impact of storage devices as well, with the result that in the UK 38% is ideal number of households owning a 4kWh storage device, when the savings of up to 13% is at its maximum. These savings, definitely, do not result in the households earning money at the end of the month. What can be done to make it more realistic is to adjust the aforementioned factor by which the costs per kWh rises.
Further, it can be noted that increasing the feed-in tariff from 75% to 100% has a significantly smaller impact than increasing it from 50% to 75%. One reason could be that the PEVs already use their whole available capacity when the 75% feed-in tariff is offered. Similarly, increasing the percentage of PEVs from 75% to 100% does only have a big impact with high feed-in tariffs.
There does not seem to be a particular parameter combination that is ideal for every case. The decision on the feed-in tariff has to be made by the utility company for every specific situation. Obviously, the number of PEVs in a grid need to be taken into account for that decision.

CHAPTER 6

Conclusion

In the course of this report real-world use cases were evaluated and simulated. A detailed description of Okeanos, the simulation platform used to simulate the aforementioned use cases, is given in the master's thesis *User-Centric Simulation of Demand Response Optimization* [14].

Beginning with validating Okeanos with easy to understand use cases, more elaborate use cases were simulated step-by-step. The first scenario is a proof of concept that only comprised one dishwasher to check for proper operation of the platform. Gradually increasing complexity, the dishwasher was complemented by a washing machine and clothes dryer to comprise a complete household. Table 3.1 summarizes the findings that Okeanos is capable of saving 4% if devices are switched on daily, 5.9%, respectively, if devices are switched on with a 33% chance, on energy costs for a single household.

The next step was to simulate the interaction of multiple households and their load-shifting devices. Therefore, the load profile and costs per household per month for a different number of households were compared. It turned out that increasing the number of households has no significant impact on the costs per household, mainly due to the small number of shiftable devices.

Further, the impact of plug in electric vehicles on the costs per household was investigated. It turned out that the more PEVs in a simulation, the cheaper it gets for every household. Starting with \$88.20 per household per month, the costs decreased down to \$27.50 per household per month. The last value, however, will most likely never be reached in a real world environment due to different parameters, such as battery wear, not taken into account.

As there are more parameters than just the number of households owning PEVs, a comparison evaluating the impact of different feed-in tariffs and different numbers of households owning PEVs on the costs per household was carried out. The general

outcome was that the more PEVs in use and the higher the feed-in tariff, the smaller the costs per household. Further, there is no "best" combination, the decision, which feed-in tariff to use, always needs to be made for every situation again.
Finally, as this report shows, the combination of existing game theoretic concepts and agent-based simulation can adequately reproduce user behavior in demand response scenarios and help working towards the future smart grid. That is, Okeanos can reproduce existing physical systems and carry out simulations, which allow for a more detailed understanding of the involved components. Conclusions drawn from these results can lead to improvements to the simulated system.

Future Developments

Okeanos is only a proof of concept and, therefore, there are countless ways to improve the software. Beginning with a greater number of drivers allowing for a more accurate simulation of households, future developments could also focus on aspects like comparing the performance of different game theoretic algorithms. Other areas of interest also include the evaluation of more optimization algorithms other than PSO and adapt interfaces to allow for a more fine-grained control over devices, e.g., by considering more constraints.
In the future, additional input data like the weather can be integrated as well. This helps improve forecast and, thus, leads to a better and more precise planning.
Furthermore, a graphical user interface that gives an overview of all important information, as well as easily allows for changing of simulation parameters, add and remove agents and devices from the currently running simulation, thus, managing simulation without having to recompile a module is another way to improve the software.
Moreover, an innovative extension would be the integration of locational data into the system. That way, it would be possible to visualize households, visualize the interaction and flow of energy between households and comfortably group households among many other things.
Finally, Okeanos currently lacks a real-time component. That is, the current status, i.e., charge and estimated consumption or production, cannot be retrieved. This is, however, not necessary for the purpose Okeanos was originally developed, which is to optimize the schedule in advance. In the future, though, Okeanos could also be used to react to deviations from the planned schedule.

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