Run-Time Parameter Selection and Tuning for Energy Optimization Algorithms

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Abstract. Energy Management Systems (EMS) promise a great potential to enable the sustainable and efficient integration of distributed energy generation from renewable sources by optimization of energy flows. In this paper, we present a run-time selection and meta-evolutionary parameter tuning component for optimization algorithms in EMS and an approach for the distributed application of this component. These have been applied to an existing EMS, which uses an Evolutionary Algorithm. Evaluations of the component in realistic scenarios show reduced run-times with similar or even improved solution quality, while the distributed application reduces the risk of over-confidence and over-tuning.

1 Introduction

Today, the integration of distributed generation, mainly from renewable sources, into energy systems is a major challenge. Techniques, which make loads more flexible, seem to be an efficient way to meet this challenge [10]. One of these techniques is the automated management of energy consumption, generation, and storage in buildings [2]. The differing setups of devices, preferences of the user, and dynamically changing environments at the run-time of an *Energy Management System* (EMS) require an adaptive design of the applied optimization algorithm.

The major contribution of this paper is a run-time parameter selection and meta-evolutionary tuning component for optimization algorithms in EMS. These algorithms are confronted with a wide variety of search and solution spaces, due to the varying scenarios as depicted in Section 2: The scenarios cannot be completely known at design-time of the optimization algorithm, what demands for a concept to adapt the algorithms at run-time of the system. The architecture and mechanisms are described in Section 3. Moreover, a distributed application of the component is presented, which enables collaborative parameter tuning and overcomes the obstacles of over-tuning and over-confidence.

Many approaches to energy management use linear or mixed integer linear programming for optimization [6,8,11]. These systems use an *a priori* formulation of the problem instances that have to be solved. It is assumed that building

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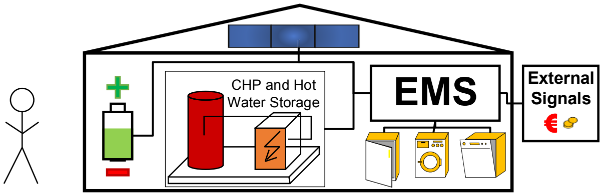


Fig. 1. Smart building scenario with EMS

equipment, user preferences concerning device interaction, and external circumstances form an *a priori* known scheduling problem, which can then be solved by a state-of-the-art system. The broad applicability of EMS in many different buildings is necessary for the integration of distributed energy resources. Thus, the system and its optimization algorithm should be executable on low-power computers with limited system resources. In this context, the running time of the optimization algorithm is crucial, because frequent rescheduling is quite likely. Therefore, the concept of parameter selection and tuning, and its distributed application are applied to an EMS that uses an *Evolutionary Algorithm* (EA) with dynamic formulation of the problem instances at run-time.

Realistic experimental setups for the parameter selection and tuning component and its distributed application are described in Section 4. Results show that problem-specific parameter choices decrease the number of evaluations while keeping or even improving the solution quality in the investigated scenarios.

2 Energy Management Scenario

The focused scenario (see Fig. 1) is the energy management and optimization in smart buildings, which use intelligent energy consuming devices and decentralized energy generation, like photovoltaic systems and combined heat and power plants (CHP). Additionally, batteries or hot water tanks can be installed and controlled, which decouple generation and consumption.

Different devices offer distinct capabilities in terms of influencing the electrical load shape and the overall energy profile of the building. The generators may cause feed-in into the grid or charging of the storage systems. Some energy consuming devices, e.g., household appliances, can be delayed in their operation or interrupted at certain points in their operation cycle. These capabilities allow for a flexible planning of the electrical load by an optimization algorithm.

Load and time variable energy tariffs mirror the external conditions in the grid and on markets. The configuration of the smart building, capabilities of the devices, the variable tariffs as well as goals and preferences of the user form the problem instances in the energy management scenario that the respective optimization algorithm is confronted with. These problem instances are not completely known at the design-time of optimization algorithm. Moreover, all of these aspects vary dynamically over the the run-time of the EMS. These factors call for an adaptive concept for algorithm design.

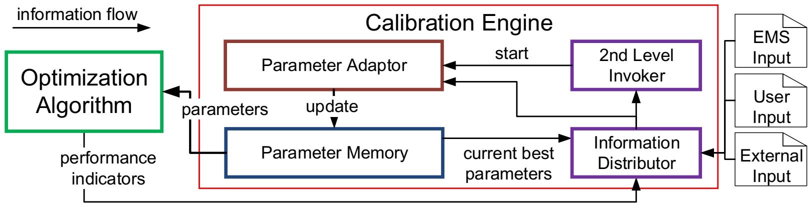


Fig. 2. Calibration Engine: Overview

3 Parameter Selection and Tuning

The *a priori* unknown factors in the energy management scenario may vary the search and solution spaces dramatically. Thus, the configuration of the respective optimization algorithms should be realized at the run-time of the EMS, i.e., after the installation process at the building. This can be realized using an additional component in the EMS.

3.1 Calibration Engine: Architecture

The EMS, which has a configurable *Optimization Algorithm*, is enhanced by an additional component, the *Calibration Engine* (see Fig. 2) that provides the required run-time adaptivity of parameter settings to the algorithm.

The Calibration Engine has two major modules: The first module is the *Parameter Memory* that stores parameter settings for known energy management scenarios. These are stored according to the devices and their respective capabilities in the smart building. Moreover, user's goals and external conditions are part of the storage schema. The second module is the *Parameter Adaptor* that is supposed to find better parameter settings for the concrete problem instances which occur in different scenarios. Additionally, the Calibration Engine has two functionally oriented parts: Firstly, the *Information Distributor* that manages the necessary information, which includes objectives of the user and external signals. Secondly, the *2nd Level Invoker* that determines whether an adaptation of the algorithm's parameters is necessary.

The Optimization Algorithm gets suitable parameter settings at run-time of the EMS by the Parameter Memory. These settings have already been adapted to scenarios that are similar to the current one in terms of the concrete smart building scenario. The 2nd Level Invoker invokes the Parameter Adaptor, when the scenario changes, e.g., due to the installation of new devices or novel user objectives. Then, the Parameter Adaptor systematically tries to find better parameter settings. It therefore uses a *Simulation Model* of the EMS, which is operating in the real-world smart building, to evaluate a parameter setting. By that, the evaluation process does not affect the productive system (comp. Fig. 3). At the end of parameter tuning process, the Parameter Adaptor updates the Parameter Memory with new parameter settings for the current scenario.

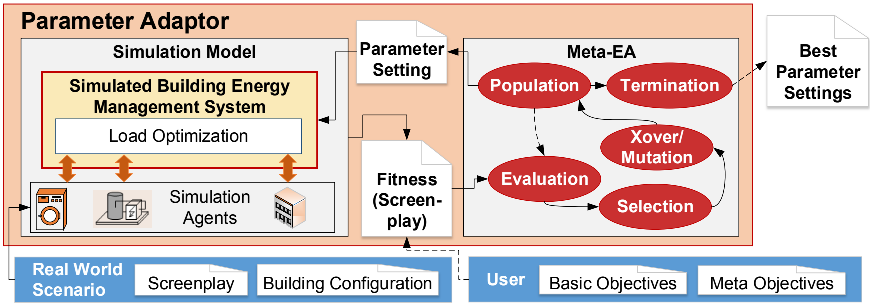


Fig. 3. Structural overview of parameter adaption process and data

3.2 Parameter Adaptor and Process of Parameter Tuning

Parameter tuning requires a systematic selection and evaluation of different parameter settings. It has to be ensured that the search space of different combinations is at the same time explored as already good solutions are exploited by some local search. Several approaches to parameter tuning have already shown good results in improving the solution quality of meta-heuristic algorithms. These include, *Iterated Local Search* algorithms [9], which utilize iterative mechanisms of local search and acceptance criteria, and *Sequential Parameter Optimization* [3], which is based on statistically derived models of the search space.

The mechanism presented hereafter, which is used for the generation of the parameter settings, extends a meta-evolutionary parameter tuning approach by [7] and adapts it to optimization algorithms in EMS. Its main advantage is the simple and flexible structure that allows for a distributed, parallel evaluation of candidate solutions in the domain of energy management. Additionally, the EA can be used twice: If an EA is already used in the load optimization, which has been presented in [1], this EA can be re-used for the parameter tuning. This simplifies the system design of an EMS and reduces its complexity.

Parameter tuning by the Parameter Adaptor (see Fig. 3) for a certain building and situation requires extensive information about the concrete real world scenario and the user objectives. The scenario consists of the *Building Configuration*, i.e., the available devices and their specific capabilities, as well as the *Screenplay* that is the recorded pattern of user behavior and interaction, device usage, and further relevant information. The objectives of the Meta-EA have to mirror the ones in the real system, e.g., overall cost minimization, but can also take additional sub-objectives into account, e.g., reduction of evaluations while keeping a certain solution quality. Candidate parameter settings are represented as real-valued genes of the meta-individuals of an EA. The evaluation of a meta-individual is realized by loading the Simulation Model, which consists of replica of the productive real world EMS, the building and the devices. This model is necessary to simulate the usage of energy and to calculate the fitness of parameter settings. The optimization is applied to a certain Screenplay, which, for comparability reasons, has to be the same for each individual evaluated in the Meta-EA.

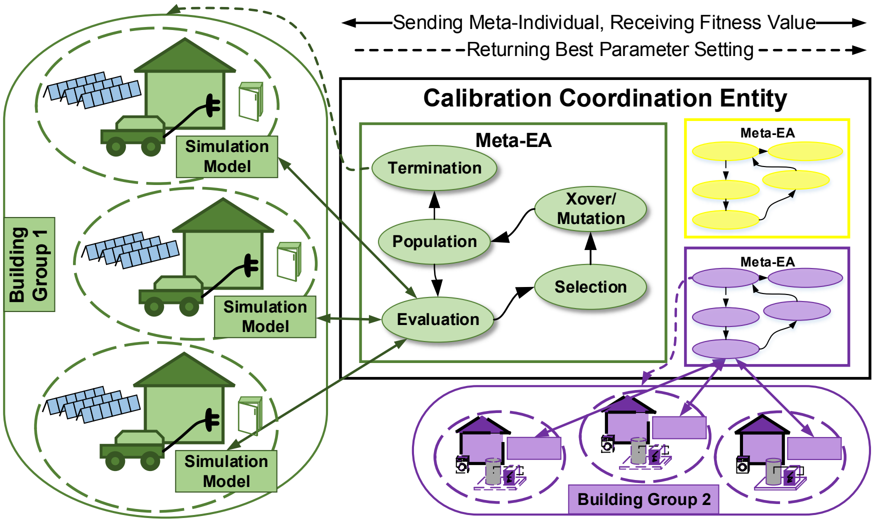


Fig. 4. Calibration Coordination Entity with different groups of buildings

3.3 Distributed Evaluation

As the target platforms of the EMS in real-world scenarios are low-power computers with limited resources, the described parameter tuning process can only be performed in the otherwise idle time of the system. Therefore, the EMS should take advantage of a wider range of information from similar buildings and a distributed evaluation of parameter settings as follows.

The working of the parameter tuning is now enhanced to a distributed approach using multiple buildings. Similar buildings, i.e. similar scenarios, are grouped according to their equipment, objectives, energy consumption, and typical behavior of users. These grouping criteria are called *characteristic parameters*. The *Calibration Coordination Entity* (CCE) shown in Fig. 4 executes a Meta-EA for every group of similar buildings. The evaluation of a parameter setting, which is represented by a meta-individual, is performed in a distributed manner in the EMS of the buildings. There, the simulation model described in the previous section calculates a local fitness by applying the parameter setting from the CCE to the optimization using the locally recorded Screenplay. The resulting fitness is communicated to the CCE, where it is averaged over all buildings of one group. The fitness of a meta-individual is thus the averaged fitness of similar buildings.

At the end of the distributed parameter adaption process, the found parameter settings are more closely adapted to the characteristic parameters than to a specific Screenplay. Therefore, they are better applicable throughout all buildings of their respective group and their typical, not their one-time behavior represented in a single Screenplay. Additionally, this distributed approach is sensitive towards data privacy, since the Screenplays, which reflect very intimate data of the users, do not have to be exchanged with an instance outside of the building.

4 Experimental Setup

In order to investigate the parameter selection and tuning component for optimization algorithms in EMS and the distributed application of this component, they were implemented for an EMS that is already in use in two exemplary smart buildings[1].

This EMS uses EA for optimization purposes [1]. The parameters that have to be selected and tuned for this EA are crossover and mutation probability. Additionally, the ratio of population size and number of generations are investigated to reduce the running time of the algorithm. Thus, it supports the execution of the EMS on low-power computers with limited system resources.

In the following section, the energy management scenarios for the experiments, the *test scenarios*, are described. From these test scenarios, Screenplays were generated, which represent the problem instances occurring in the concrete energy management scenario. Afterward, the experiments are depicted in Section 4.2.

4.1 Test scenarios

There are a few major factors that determine an energy management scenario: First of all, there is the configuration of the smart building concerning the available devices. Furthermore, the capabilities of these devices in terms of influencing the load shape by optimization are distinct.

Five basic appliances and a combined heat and power plant (CHP) with different capabilities form the basis for the test scenarios in this paper (see Tab. 1a). A *non-delayable* device's operation always starts immediately when used and thus does not have to be optimized, though it still has to be considered. In contrast, the operation time of a *delayable* device may be shifted by the optimization, while complying with the user's preferences. Additionally, an *interruptible* device offers the capability to be paused at certain points in its operation cycle.

The capabilities of the CHP, which are both connected to a hot water storage system, are differentiated into *non-controllable* and *controllable* by the EMS. Non-controllable stands for a thermal management of the CHP, meaning that it is switched on and off according only to the thermal demands in the building. In contrast, the controllable CHP can be switched on, whenever capacity is left in the storage. Of course, the thermal demand and local limitations of the storage system, e.g., the minimum threshold temperature, still have to be respected.

Another determining factor of energy management scenarios is the user. On the one hand, the overall goal of the user is cost minimization. On the other hand, the user behavior has to be considered. Her preferences are represented by the electrical demand, e.g., when the appliances are used and how long they may be delayed if possible. The maximum delay is set to eight hours across all test scenarios. The user's thermal demand is modeled as a 5-person-household.

The last determining factors are the external conditions. They are mirrored by a time-variable energy tariff based upon a market simulation as described in [4].

[1] KIT *Energy Smart Home Lab* `http://www.izeus.kit.edu/english/` and FZI *House of Living Labs* `http://www.fzi.de/en/fzi-house-of-living-labs/`

Table 1. Devices and configurations of households used in simulation

(a) Different devices

Name	Device	Capability
D1N	Hob	Non-delayable
D2N	Dishwasher	Non-delayable
D2D	Dishwasher	Delayable
D3N	Oven	Non-delayable
D4N	Dryer	Non-delayable
D4D	Dryer	Delayable
D4I	Dryer	Interruptible
D5N	Washing machine	Non-delayable
D5D	Washing machine	Delayable
CHP0	CHP	Non-controllable
CHP1	CHP	Controllable

(b) Configurations of households

Configuration	Devices
H0	D1N, D2N, D3N, D4N, D5N, CHP0
H1	D1N, D2D, D3N, D4D, D5D, CHP1
H2	D1N, D2D, D4N, D4I, D5D, CHP1
H3	D1N, D2D, D3N, D4D, D5D, CHP0
H4	D1N, D2D, D3N, D4I, D5D, CHP0

The tariff changes every hour and ranges from 3 to $39\,ct/kWh$ with a mean value of $24\,ct/kWh$, respectively. Moreover, a load limit is set to $3\,kW$ across all H0 – H4. When the power limit is violated, the amount of energy consumed above the limit is penalized by a doubling of electricity costs. The decentralized generator, the CHP, produces electrical and thermal energy by the consumption of natural gas. The gas price of $6\,ct/kWh_{th}$[2] is constant. If the electricity generation exceeds the current consumption in the building, the difference is fed into the grid, receiving constant feed-in compensations of $5\,ct/kWh_{el}$.

From the devices above, five configurations for smart buildings had been assembled (see Tab. 1b). These configurations are furthermore referred to as *households* H0 – H4. The problem instances for the parameter tuning process—the Screenplays—were generated according to typical times of use for each household. To reflect differing thermal demands that effect the optimization of the CHP, ten Screenplays per household are located in January (winter) and ten Screenplays are located in July (summer).

4.2 Experiments

The Calibration Engine and its distributed application are confronted with a set of experiments that are based on the test scenarios described in the last section. The reference parameter setting of the EA consists of a crossover probability of 0.7, a mutation probability of 0.1, a binary tournament selection of parents, a single-point-crossover with two offspring and a bit-flip-mutation using an elitist (μ,λ)-strategy with a rank based survivor selection. The stopping criteria is a maximum number of evaluations, determined by varying numbers of generations and individuals. The Meta-EA has been set up as follows: ten generations of 24 individuals, SBXCrossover [5] with a probability of 0.7, and polynomial mutation with a probability of $0.\overline{3}$, both with a distribution index of 20.

The fitness of a certain parameter setting is evaluated by the calculation of the *average electricity costs* (AEC). AEC are given by the average price per kWh

[2] Due to the constant degree of efficiency, the price is non-varying over kWh_{el}, too.

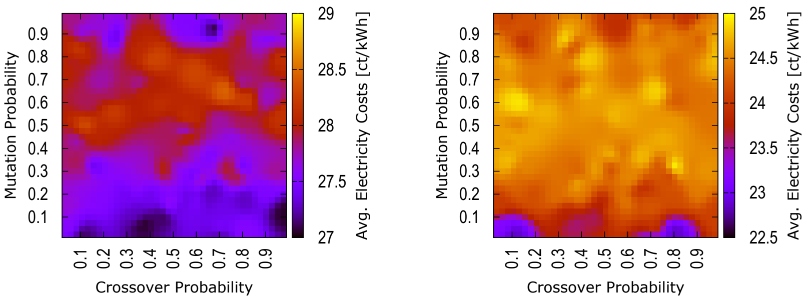
that results from consumption from the grid as well as from the generation by the CHP and its consumption of natural gas.

In the first experiment, the Parameter Adaptor is confronted with one problem instance (Screenplay) per household. Afterward, the found settings are applied to all ten corresponding Screenplays. This proceeding should simulate the usage of the Parameter Memory in a single building with EMS. Moreover, risks of over-tuning and over-confidence should be identifiable. In the second and third experiment, the Calibration Engine is used in the distributed application. The Parameter Adaptor evaluates the fitness of the found parameter setting according to the averaged resulting fitness of three respective five Screenplays per household. Afterward, the parameter settings are applied to all ten corresponding problem instances. This experiment investigates the potential of reduction of the risk of over-tuning and over-confidence by the distributed approach.

5 Results and Discussion

A comparison of two exemplary fitness landscapes in Fig. 5 visualizes the seasonal influences on the parameters, which mainly result from seasonally different device usage and thermal demand. The result of the Meta-EA for the configurations H1 and H2, different maximum number of evaluations and included Screenplays with corresponding outcomes of Avg. EC are shown in Fig. 6. "Average" in this case means that the results of all ten Screenplays of buildings were averaged.

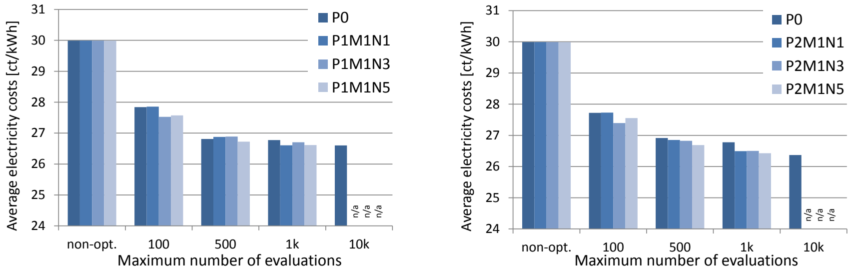
The results show that on the one hand the parameter tuning is able to exploit considerable potentials of optimization. On the other hand, the advantage induced by adapting the parameter settings is remarkable due to the possibility to reduce evaluations, while resulting in the same level of solution quality compared to the run with 10,000 evaluations and the initial parameters. This means that individual parameters can successfully reduce execution time of the EA in the EMS, without worsen its results. Moreover, the results also show



(a) H1, January, 10 individuals, 50 generations

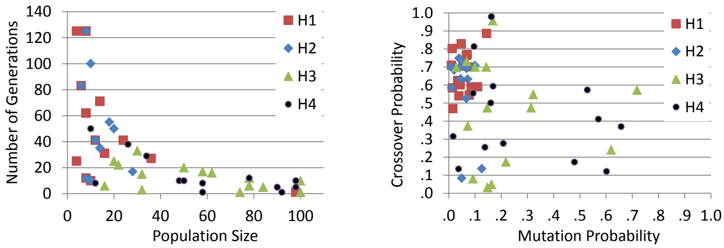
(b) H1, July, 10 individuals, 50 generations

Fig. 5. Fitness landscapes of January and July showing distinct areas of good parameter settings



(a) H1: Avg. EC **(b)** H2: Avg. EC

Fig. 6. Simulation results of H1 and H2 with default (P0) and optimized parameter settings (P1, P2) using N Screenplays in January (M1)



(a) Number of Generations and Population Size **(b)** Mutation Probability and Crossover Probability

Fig. 7. Resulting parameter settings for households H1 – H4

that the distributed optimization approach tends to result in better parameter settings, which are better applicable throughout the ten Screenplays of similar households.

Resulting parameter settings differ across the building configurations. Fig. 7 visualizes optimized parameter settings for all test scenarios H1 – H4. Simulation setups with a controllable CHP (H1 and H2) tend to have lower ratios of population size to number of generations (see Fig. 7a) and more clustered parameter combinations of crossover and mutation probability (see Fig. 7b), whereas setups with a non-controllable CHP (H3 and H4) show a larger spreading.

The potential of parameter tuning has been shown across different experimental setups. The Calibration Engine was able to exploit potentials, although it sometimes produces parameters settings with worse results when applied to all corresponding Screenplays than the initial settings. Nevertheless, the Calibration Coordination Entity was able to tackle this issue by averaging the fitness of parameter settings. This is important, because Screenplays always represent past behavior of households which is likely to never happen exactly the same again. Therefore, a better fitness with Screenplays of other similar households will lead to better results within the same household in a similar future month.

6 Summary and Outlook

This paper presented a run-time parameter selection and tuning component for optimization algorithms in Energy Management Systems and an approach to a distributed application of this component. An implementation for an EMS, which uses a run-time formulation of the problem instances and an EA to optimize them, is presented. In this context, the component has been tested and has shown potential to decrease the average electricity costs while reducing the running time per optimization process. The parameter tuning has reacted sensitively to different configurations of devices, capabilities of devices and user preferences.

It has been shown that parameter tuning in the domain of EMS and thus enhances a broad applicability of EMS at the level of buildings. Future work shall further validate the component, also taking into account more parameters and other optimization algorithms. Moreover, it shall be applied to other real-world implementations of EMS.

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