Characterization of heat-pump, PV and battery demonstrator technologies using a coherent energy assessment

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Abstract. Battery, PV and heat-pump technologies were characterized using a Coherent Energy Demonstrator Assessment (CEDA) approach. In all cases the calibrated simulation models closely matched the measured data; however it is not possible to conclusively say that models, based on a single demonstrator, represent all existing and future cases of a technology. A possible solution would require additional operators to characterize and report the performance of a given technology, in a standardized way, and the resulting data could then contribute to an evolving set of representative CEDA archetypes to be used in studies of energy systems.

1. Introduction

This paper details a collaborative effort to harmonize the description of six energy research demonstrators installed across Switzerland. A set of Coherent Energy Demonstrator Assessment (CEDA) archetypes have been specified for twenty-seven energy technologies that are installed at six demonstrator facilities. The technologies cover a broad range of types ranging from methanation plants to electrical power converters. The first milestone was achieved by reaching an agreement on a common set of indicators for each demonstrator technology. These indicators form the foundation of the CEDA archetypes, providing a common basis for the energy-systemic assessment of the storage and conversion technologies. At the next level, it also includes defining and cataloging mutually consistent operational characteristics of the studied technologies, along with methods to estimate how their performance scales in larger installations. The dissimilarity between energy conversion and storage technologies means that assessments by teams with different backgrounds, such as process engineering, power systems, building physics etc, may not be directly comparable. The resulting subtle differences in the depth and angle of the investigation often make it impossible to directly compare results. The use of CEDA archetypes aims to eradicate this problem by abstracting energy devices into so called technology archetypes: a set of techno-economic characteristics, describing a technology precisely enough for use in long-term energy system simulation models. Such models, used in short and long-term strategic planning of energy systems, feature time-steps well in excess of one minute (typically 15 or 60 minutes) and time-horizons ranging from several days to several decades into the future. As a prerequisite and a core idea of CEDA, those characteristics must depend solely on the technology used by the device, not the energy systemic context it is in. This allows transposing results established in the context of one demonstrator to that of another, or the virtual context of energy system simulators and optimizers.

The work in this paper details, the characterization of batteries, photovoltaic panels and a heat-pump installed at the NEST demonstrator [1] using the CEDA approach. The NEST demonstrator is composed of multiple individual energy systems, resembling a small scale district energy system. These systems are subject to varying control implementations. These alter the behaviour of the systems. Measurements of the buildings states are stored every minute on a SQL-Database, where data has been stored since the beginning of 2017.

1.1. Modelling of Energy Systems

One of the implications of the Swiss Energy Strategy 2050 will be increased installations of renewable and alternative fuel supplies as nuclear energy is phased-out. The transition to a cleaner energy system requires consideration of the entire system including electricity, heat, cooling, fuels and transport. These 'multi-energy systems' can be analyzed from various perspectives; the diversity and complexity of such problems have created the need for advanced modelling techniques and tools [2]. To enable this paradigm shift, a process was outlined to identify the optimal solutions at district scale [3]. In all cases, models of energy generation, conversion and demand are required; thus creating a need for a standardized approach to populate, connect and compare the performance of individual technologies that make up the energy system. The CEDA archetypes are designed to meet this requirement and provide a starting point for anyone wishing to assess the performance of a system that incorporates any of the demonstrator technologies.

1.2. Application of CEDA Archetypes

One particular application where CEDA archetypes will be deployed is Energy Hub modelling. An Energy Hub is a conceptual or physical unit where multiple energy carriers can be converted, conditioned and stored [4]. The modelling of Energy Hubs can capture the synergies between the input fuel types and conversion technologies, where all can be characterized by cost and associated emissions. In the Energy Hub model the conversion technologies are defined using a steady-state power flow model, which includes conversion and transmission of a number of arbitrary energy carriers [5]. The Energy Hubs can then be optimized across multiple objective functions subjective to a set of specified constraints [6]. A similar approach was taken to optimize the supply chains of a biomass boiler, considering both natural gas and biomass [7]. A network of Energy Hubs was also used to model frequency control using clusters of plug-in vehicles and household appliances [8]. The Energy Hub concept does not only apply to the large scale but has also been used to optimize the energy supply of an individual house [9]. The assessment of energy systems can also be applied to micro-grids, one such study investigated the use of electric vehicles to increase the financial and environmental viability of renewables [10]. From this review, it is clear that there is a varied number of cases that could benefit from using CEDA archetypes. The data for such cases is not always available or can be difficult to obtain. The CEDA archetypes will provide a set of generalized parameters that have been populated for each demonstrator technology. These default values can then be changed if the user has more detailed information for a given case.

2. Methodology

The CEDA process has three distinct stages that apply to the developed archetypes: specification, characterization and implementation.

Table 1. The parameters and inputs used to model the performance of the archetypes

	PV	Battery	Heat Pump
Sub-technologies characterized	Mono-facial, Bi-facial	Lithium Ion, Molten Salt	Ground Source
Inputs	Diffuse & direct irradiation, ambient temperature	Charge and discharge schedule	Compressor power, source temperature, sink temperature
Parameters	Capacity, angle, bifaciality, orientation, azimuth, efficiency	Charging and discharging efficiency, capacity	Installed capacity, nominal COP, nominal evaporator & condenser temperature, nominal evaporator & condenser pressure drop
Scaling Parameter	Capacity	Capacity	Compressor Power

2.1. Archetype Specification
The outcome of a collaborative effort between nine research groups was a database specification template. This template was used to define the standard properties for each archetype and its sub-technologies. Each archetype has its own specification containing the specific properties that define its operation and a flow-diagram detailing the full technical and logical specification of each flow signal and the necessary constraints (such as ramp-up rates or mandatory start-up / warm-up sequences), as well as techno-economic data.

2.2. Archetype Characterization
The data collection and population of each sub-technology, covered by each archetype record, involves calibration against monitored performance. The main purpose of this stage was to extract enough parameters to differentiate between the different sub-technologies covered by the archetype. For example, a battery archetype would need to include enough parameters to distinguish between different types of battery, such as molten salt and lithium ion technologies. At the most fundamental level, a battery is a storage device whose state-of-charge (SOC) changes in proportion to its charge and discharge flow. CEDA goes beyond this by calibrating against monitored data to account for differences in operation between the technology types covered by each archetype. The purpose is to consider behaviour that may not be captured by using a pure data-sheet model. The third layer of a CEDA model is the scaling layer, which contains scaling factors that are tied to the properties of the archetype. This is typically values that could be analyzed in an objective function, such as cost or embodied emissions. The parameters identified for each technology are shown in Table 1. In this study, the components are characterized in Modelica, an object-oriented modelling language designed to simulate physical models of complex systems. It effectively handles flows between components and there is an extensive number of component libraries available to build upon. In this study the monitored data is calibrated against components based on the PV, Battery and Heat Pump components of the LBNL Buildings Library [11].

2.3. Archetype Implementation
Modelica is primarily a simulation language; however it can be combined with optimization programs that read the input and outputs from the simulation. GenOpt is a generic optimization program that was developed specifically for the purpose of building energy simulation [12]. Language extensions also enable the formulation of dynamic optimization problems [13] and a framework has been proposed to design and optimize 4th generation district heating systems that contain integrated renewable energy sources [14]. Although the CEDA archetypes are designed to be agnostic in their implementation, Modelica offers a suitable platform to connect, simulate and optimize systems of archetype models. To demonstrate this, the PV and battery archetypes have been connected to evaluate the optimum fraction to sell to the grid or store in

the battery, given a spot price forecast. In this model a Particle Swarm Optimization (PSO) algorithm, which has shown good performance when handling non-linear constraints present in power flows [15], was applied. A 5-day sample time series of spot market price was downloaded from EEX (www.eex.com). An 80MWp PV array was connected to a 60000Ah battery. The constraints were that the battery has a constant discharge power, the battery cannot charge and discharge simultaneously and energy cannot be discharged below 15% SOC. This is an example implementation to demonstrate the use of the archetype. It is recommended that all archetypes are provided with a simple working implementation as illustrated in Figure 3.

3. Results and Discussion

3.1. Battery Archetype Characterization

There was good agreement between the monitored and simulated SOC; however, there was a slight deviation in the profiles. To investigate this deviation, further analysis of the monitored data was carried out to calibrate and derive additional performance parameters for the simulation. Experimentally controlled conditions were defined to derive parameters such as standing losses and power-dependent charging/discharging efficiencies. This involved measuring the response of the battery at varying loads and levels of SOC, and measuring the losses during a period of no use. A setpoint table was constructed to investigate under the different operating conditions; however no power dependence of charging and discharging was measured. As the charging efficiencies were also not reported in the datasheets, these values had to be assumed for each technology to fit the data. A comparison of the integral of SOC for the uncalibrated and calibrated against the monitored SOC was 2.27% and 0.45% when using a charging efficiency of 1 and 0.98 respectively, see Figure 1.

3.2. Photovoltaic Archetype Characterization

Power generation from PV is dependent on uncontrolled environmental variables such as solar irradiation. As we cannot control these variables, they need to be monitored accurately. The only available monitored data from the site was global horizontal irradiation and the diffuse and direct components were not measured. A weather file from Zürich was analysed to determine a ratio between global horizontal irradiation and the normal and diffuse components. Using a conditional expression, it was assumed that a greater portion of the global irradiation was diffuse at low levels of global irradiance. Through using this adjustment, it was possible to close the gap between the monitored and simulated values, however there was still a large difference in the aggregated values, see Figure 2. This highlights the importance of including both the direct and diffuse irradiation components as inputs when characterizing and simulating PV systems.

3.3. Heat Pump Archetype Characterization

A 28kW heat pump was characterized using the flow temperatures and a nominal COP of 4.5 specified in the technical datasheets. The efficiency of the heat pump was scaled based on the Carnot Efficiency. Figure 4 shows a good agreement between the measurement and the simulation.

3.4. Example Implementation

It was assumed that without a battery, all the electricity from the PV system would be sold at spot price to the market. When a battery is connected to the system, it enables the option to store energy to sell at a later time when the spot price is more favourable. Using GenOpt with Particle Swarm Optimization, the fraction of energy directed to the battery system was optimized. The objective function was set to maximize revenue, calculated as the energy exported multiplied by the spot price. With no PV the revenue was €6939, the optimal

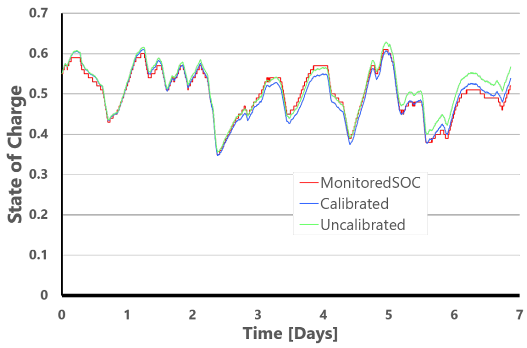

Figure 1. Comparison of SOC for the lithium ion battery.

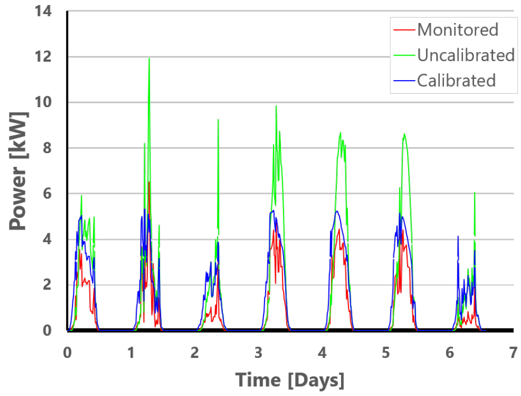

Figure 2. Comparison of SOC for the bifacial PV.

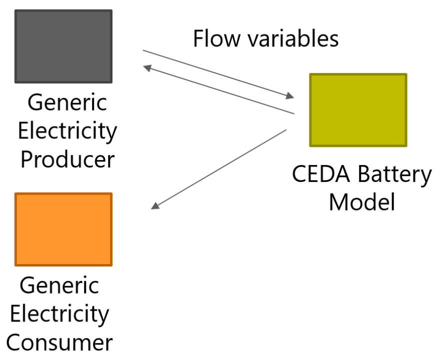

Figure 3. Example of a generic case study for demonstrating a usage case of the archetype.

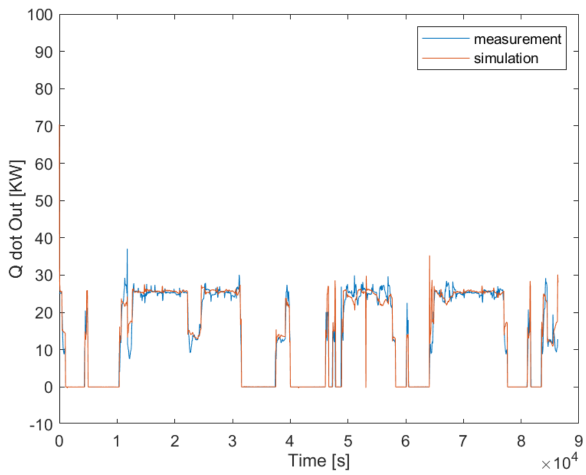

Figure 4. Simulating the output of a heat pump

solution was €7993, a 15% improvement. Figure 5 clearly shows the shifting of export to times of favourable spot price. This is a simple case to demonstrate implementation, but further optimization could also consider the system sizing and capital investment.

4. Conclusions

This paper has described the process of specifying and characterizing technology archetypes to be used in the analysis of energy systems. A unique standardized approach for characterizing the archetypes based on monitored data from energy demonstrators is presented. Despite the characterization having a good match between simulated and measured results, comparison and cross validation using data from other installations is required to create a generalized model both in terms of technological performance, financial aspects and scaling. It is not possible to conclude that the characterization of one demonstrator technology is representative of all other installations of that technology. The sharing of data sources to build a database of archetypes will come with its own challenges, but it is believed that, if the data is processed correctly and anonymously, this will lead to archetypes that are more representative than using a single technology. Nevertheless, standardization of the process of specifying and characterizing

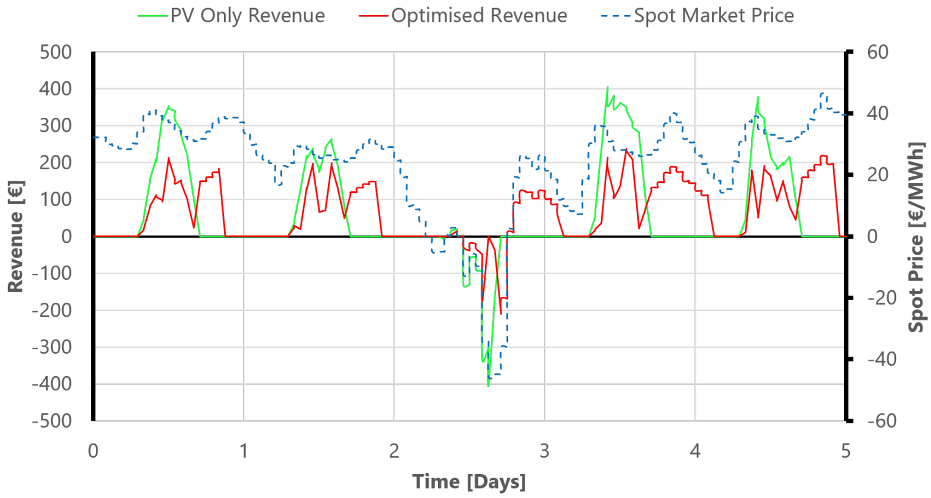

Figure 5. Optimized solution to shift the export of electricity using battery storage

archetypes using demonstrators, as detailed in this report, is a vital starting point.

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