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Valuing Investments in Multi-Energy Conversion, Storage, and Demand-Side Management Systems Under Uncertainty

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Abstract—In this paper, a financial valuation method for energy hubs with conversion, storage, and demand-side management (DSM) capabilities is proposed. An energy hub is an integrated system of units, e.g., a combined heat and power plant and a heat storage, which allows the conversion and storage of multiple energy carriers. In this paper, an extended energy hub model is presented which additionally takes into account the possibility of performing DSM with the load(s) connected to the hub output. Taking into account the energy hub's flexibility to change its output power(s), its economic value is determined with a method based on Monte Carlo simulation. This method calculates an optimal dispatch of the hub for a large amount of possible price paths of the input and output energy carriers. By means of the proposed energy hub Monte Carlo valuation model, integrated systems of multi-energy conversion and storage devices can be valued together with load management schemes. In doing so, the energy hub's ability to flexibly adapt its output to uncertain and volatile market prices is explicitly considered.

Index Terms—Combined heat and power (CHP), demand-side management (DSM), energy storage, Monte Carlo simulation, multiple energy carriers, power generation investment.

I. INTRODUCTION

THE research project “Vision of Future Energy Networks” (VoFEN) at the Swiss Federal Institute of Technology (ETH) Zurich aims at providing a framework for the systematic analysis of systems involving multiple energy carriers. Distributed generation and technologies that establish a coupling between different energy infrastructures, e.g., combined heat and power (CHP) plants, are of particular importance for the development of this framework. The integrated consideration of multiple energy carriers allows for identifying various untapped potentials for system improvements including the increase of energy efficiency with respect to today's situation. The key concept in the VoFEN project is the energy hub [1]. An energy hub is an integrated system of units which is able to convert and store multiple energy carriers. A generic

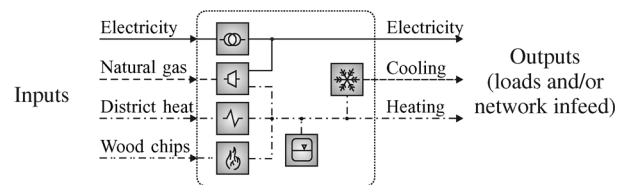


Fig. 1. Example of an energy hub with the following elements: Electric transformer, microturbine fired by natural gas, heat exchanger, wood chips furnace, heat storage, and absorption chiller.

example of an energy hub is shown in Fig. 1. Depending on its configuration, an energy hub can provide a certain output carrier by using several input carriers. The hub in Fig. 1, e.g., can supply its thermal load with heat via the microturbine, the district heating network, and the wood chips furnace. This redundancy together with the possibility to store energy allows us to flexibly adapt the hub's operation and outputs to a changing environment, e.g., to prices or loads. By additionally considering the possibility of actively managing the loads at the output of a hub with a demand-side management (DSM) scheme, the operational flexibility is further increased. This flexibility can be especially beneficial given the increasing share of renewable power sources like photovoltaic or wind power which deliver a fluctuating nondeterministic network infeed. With the prospective introduction of real-time pricing schemes in future electric power systems, an energy hub's flexibility can be particularly important to profit from intra-day price differences.

The aim of this paper is to provide a valuation method that incorporates the above described types of flexibility of an energy hub. A concept that takes into account the flexibility to react to volatile market prices is Monte Carlo simulation [2]. In contrast to deterministic models, Monte Carlo methods use stochastic models to represent those sources of uncertainty that may have a potential impact on the asset value. When using Monte Carlo valuation methods, uncertainty can even represent a positive factor as a driver of value because flexible operation allows for both limiting downside risks and exploiting the upside potential of price volatility. In this paper, an energy hub is considered as a profit-maximizing entity that converts and stores multiple energy carriers depending on prices of input and output carriers and on loads that have to be supplied. It is assumed that loads for which DSM schemes are established can be shifted within given constraints. Using a Monte Carlo simulation method allows for an adequate valuation of an energy hub as a flexible modular system of elements for conversion, storage, and DSM.

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Including the possibility of DSM into the model represents an extension of a previous paper which outlined an investment valuation model for energy hubs with conversion and storage elements [3]. Monte Carlo methods have been applied to electricity generation assets as well as to cogeneration plants [4]–[7]. In this respect, the model presented in this paper represents a generalization of Monte Carlo valuation methods for an arbitrary number of input and output energy carriers.

The remainder of the paper is structured as follows. Section II provides a description of the energy hub model including DSM and the corresponding Monte Carlo valuation method. Section III presents the results of an application example illustrating the valuation method. Section IV concludes the paper.

II. METHODS AND MODELING

In this section, the energy hub model including DSM is described in a first step. Subsequently, it is outlined how the flexible operation of an energy hub can be modeled and valued with a Monte Carlo simulation method.

A. Energy Hub

The energy hub concept is a generic model describing the conversion and storage of multiple energy carriers. Due to its generality, the concept is particularly suitable for the integrated modeling of a number of energy conversion devices like power plants or energy storage devices. Based on the energy hub model, the coordinated operation of different devices can be optimized for example with the objective of minimizing total system costs. The energy hub concept uses an input–output representation of a system’s energy loads, conversion and storage devices, and the fuels or other inputs that are used in order to satisfy a given load.

Formally it is expressed in the following way. Letting $P_1^{\text{in}}, P_2^{\text{in}}, \dots, P_m^{\text{in}}$ denote the different energy carrier inputs (e.g., electricity, gas, biomass, hydrogen), $P_1^{\text{out}}, P_2^{\text{out}}, \dots, P_n^{\text{out}}$ the different energy carrier outputs and the c_{ij} the couplings between them, we can write the basic hub equality

$$\underbrace{\begin{pmatrix} P_1^{\text{out}} \\ P_2^{\text{out}} \\ \vdots \\ P_m^{\text{out}} \end{pmatrix}}_{\mathbf{P}^{\text{out}}} = \underbrace{\begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{pmatrix}}_{\mathbf{C}} \underbrace{\begin{pmatrix} P_1^{\text{in}} \\ P_2^{\text{in}} \\ \vdots \\ P_n^{\text{in}} \end{pmatrix}}_{\mathbf{P}^{\text{in}}}. \quad (1)$$

If there are energy storage devices present in the system, one can additionally define a *storage coupling matrix* \mathbf{S} . The vector \mathbf{E} denotes the contents of the storage devices. $\dot{\mathbf{E}}$ are the corresponding changes in storage content within a time period Δt , i.e., $\dot{\mathbf{E}} = \mathbf{E}(t + \Delta t) - \mathbf{E}(t)$. The vector \mathbf{M} stands for the storage output power flows. With these definitions, the relation between

the changes in storage contents and the storage output flows results as follows:

$$\underbrace{\begin{pmatrix} M_1 \\ M_2 \\ \vdots \\ M_m \end{pmatrix}}_{\mathbf{M}} = \underbrace{\begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1v} \\ s_{21} & s_{22} & \cdots & s_{2v} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mv} \end{pmatrix}}_{\mathbf{S}} \underbrace{\begin{pmatrix} \dot{E}_1 \\ \dot{E}_2 \\ \vdots \\ \dot{E}_v \end{pmatrix}}_{\dot{\mathbf{E}}}. \quad (2)$$

Equation (3) shows the power balance for an energy hub with conversion and storage devices

$$\mathbf{P}^{\text{out}} = (\mathbf{C} \quad \mathbf{S}) \cdot \begin{pmatrix} \mathbf{P}^{\text{in}} \\ \dot{\mathbf{E}} \end{pmatrix}. \quad (3)$$

For a more detailed description of the hub concept, one can refer to [8]. Section II-B will introduce a recent extension to the energy hub model as described in [9].

B. Demand-Side Management

One of the uses of energy storage is the possibility to shift energy availability between times of high prices and times of low prices, which is called load shifting. The storage can be charged when prices are low and discharged when prices are high. Demand response and DSM play a very similar role. If prices at a certain time of the day are high, the consumers or the utility will try to use energy at an earlier or a later time when prices are lower. Formalized to fit the hub’s matrix representation, the coupling matrix \mathbf{D} corresponding to DSM together with the shifted load \mathbf{H} determine the resulting change in the hub’s output power $\Delta \mathbf{P}^{\text{out}}$

$$\underbrace{\begin{pmatrix} \Delta P_1^{\text{out}} \\ \Delta P_2^{\text{out}} \\ \vdots \\ \Delta P_m^{\text{out}} \end{pmatrix}}_{\Delta \mathbf{P}^{\text{out}}} = \underbrace{\begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1r} \\ d_{21} & d_{22} & \cdots & d_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mr} \end{pmatrix}}_{\mathbf{D}} \underbrace{\begin{pmatrix} H_1 \\ H_2 \\ \vdots \\ H_r \end{pmatrix}}_{\mathbf{H}}. \quad (4)$$

Together with the already described energy conversion and storage matrices, the complete power balance equation for an energy hub with DSM becomes

$$\mathbf{P}^{\text{out}} - (\mathbf{C} \quad \mathbf{S} \quad \mathbf{D}) \cdot \begin{pmatrix} \mathbf{P}^{\text{in}} \\ \dot{\mathbf{E}} \\ \mathbf{H} \end{pmatrix} = \mathbf{0}. \quad (5)$$

In the following paragraph, we will provide a simple derivation of the constraints for the example of heat DSM, which will be illustrated in Section III.

Example of Heat Load Management: Depending upon given system conditions, the proposed model can be used for different kinds of DSM or demand response schemes. These schemes can generally concern all energy carriers whose consumption or utilization can be shifted in time. Here, we exemplarily show how to derive the multiperiod conditions for a utility-driven heat load management scheme as classified in [10] from a simple discrete thermodynamic model of the building temperature. The conditions for heat load management are derived for a case where a

prediction of the heat load for the following day is given and the building parameters are known.

We assume the inside temperature T of a building can fluctuate between T_{\min} and T_{\max} . The choice of T_{\min} and T_{\max} directly influences the resulting comfort level. At time step 2, the temperature equals the temperature at the previous time step T_1 decreased by the heat losses through the building hull, and increased by the heating energy received from the building heating system $\dot{Q}_1 \Delta t$. The heat losses depend on the outside temperature $T_{\text{amb},1}$, the inside temperature T_1 , the heat transfer coefficient k , and the surface area of the building hull A . The inside temperature at time step 2 thus results as follows:

$$T_2 = T_1 + (T_{\text{amb},1} - T_1) \frac{kA}{cm} \Delta t + \dot{Q}_1 \frac{1}{cm} \Delta t. \quad (6)$$

In the above equation, the effects of thermal losses and heating power delivered to the building are scaled by the product of the building's thermal mass m , heat capacity c , and the length of the time step Δt . By iteratively inserting the expression for the inside temperature of the current time step into the expression for the next time step, we obtain

$$T_n = T_1(1 - G_1)^{n-1} + G_1 \sum_{t=1}^n T_{\text{amb},t}(1 - G_1)^{n-t} + G_2 \sum_{t=1}^n \dot{Q}_t(1 - G_1)^{n-t} \quad (7)$$

where n is the number of time steps in the total period to be analyzed. The constants G_1 and G_2 are defined as

$$G_1 = \frac{kA}{mc} \Delta t$$

and

$$G_2 = \frac{1}{mc} \Delta t.$$

Combining (7) with the conditions for the upper and lower temperature boundaries

$$T_{\min} \leq T_n \leq T_{\max}$$

we obtain the DSM conditions for the delivered heat

$$H_{\min,n} \leq G_2 \sum_{t=1}^n \dot{Q}_t(1 - G_1)^{n-t} \leq H_{\max,n}. \quad (8)$$

Finally, by setting

$$\dot{Q}_t = \dot{Q}_t^* + H_t$$

where \dot{Q}_t^* stands for the heating power necessary to keep the temperature in the building constant and H_t is the deviation from this power, we obtain the DSM conditions which can be included into the energy hub matrix representation

$$H_{\min,n} \leq G_2 \sum_{t=1}^n H_t(1 - G_1)^{n-t} \leq H_{\max,n} \quad (9)$$

where H_{\min} and H_{\max} correspond to

$$H_{\max,n} = T_{\max} - T_1(1 - G_1)^n - G_1 \sum_{t=1}^n T_{\text{amb},t}(1 - G_1)^{n-t} - G_2 \sum_{t=1}^n \dot{Q}_t^*(1 - G_1)^{n-t}$$

and

$$H_{\min,n} = T_{\min} - T_1(1 - G_1)^n - G_1 \sum_{t=1}^n T_{\text{amb},i}(1 - G_1)^{n-t} - G_2 \sum_{t=1}^n \dot{Q}_t^*(1 - G_1)^{n-t}.$$

Depending upon the total heat delivered until time step n , we can keep the room temperature between designated boundaries by delivering between $H_{\min,n}$ less or $H_{\max,n}$ more heat than required to keep the temperature constant. The above conditions have to hold for each time step and each building. As there is an upper and a lower bound, this results in twice as many conditions as there are buildings. If the resulting number of inequations excessively complicates the optimization problem, a reasonable simplification can be used, where the constants G_1 and G_2 are calculated in an aggregated way for a number of several buildings with similar thermodynamic characteristics.

C. Monte Carlo Valuation Method

Generally speaking, Monte Carlo methods make use of techniques that use probability distributions and the corresponding random numbers to solve problems. Monte Carlo methods represent a class of stochastic algorithms which are often used when a deterministic problem formulation is not appropriate or when the problem cannot be solved analytically.

A common application of Monte Carlo methods is the pricing of derivatives such as options. For such an application, prices of equities in an efficient market are modeled as random variables. Although these prices show causal relationships with fundamental economic processes, they exhibit random characteristics, which makes them very difficult to predict. The same is true for energy prices. They are essentially causal and depend on the balance between supply and demand, but precisely measuring and analyzing the various factors influencing the price formation process is too difficult a task. Although we might be able to forecast some fundamental characteristics of the price development such as the average change in price over a certain period, an exact estimate of the price of an energy carrier one year from today would rely on pure luck. Due to this lack of information with respect to making a more precise forecast, energy prices can be modeled as random variables just like equity prices.

One of the most relevant tools to study stochastic systems is simulation. Simulation is the analysis of a real-world process or a system based on a mathematical model. As a perfect representation of the real world is practically impossible, one always has to make assumptions about the system that is modeled. Simulation methods are generally efficient for models of great complexity that use few assumptions. Thus, they allow for a more accurate representation of the real world.

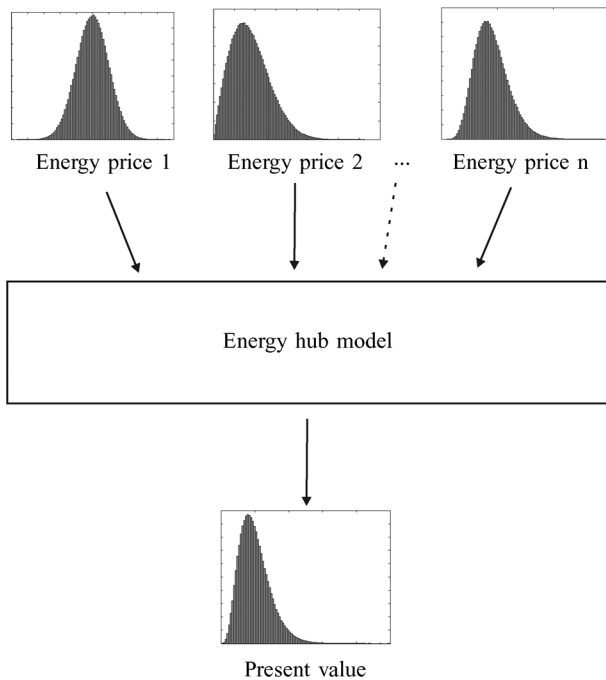


Fig. 2. Schematic showing the underlying principles of the Monte Carlo valuation method for energy hubs.

For the application in this paper, a Monte Carlo method is applied that repeatedly evaluates a deterministic model using sets of random numbers as inputs. Such a method is often used when the model is complex, nonlinear, or involves many uncertain variables. By using random inputs, the deterministic model essentially changes into a stochastic model. Many simulations are carried out to evaluate the model, and the law of large numbers ensures that the model estimate converges to the correct value as the number of simulations increases [11]. The main disadvantage of Monte Carlo methods directly results from the law of large numbers: a significant amount of computing time is often needed for a good approximation of the “true” value.

In view of the adequacy of Monte Carlo methods for complex valuation problems with multiple sources of uncertainty, this method was chosen for valuing energy hubs. Fig. 2 illustrates the underlying principles of the method. The prices of all input and output energy carriers are modeled as random variables. The Monte Carlo technique consists in simulating several thousands of possible price paths for these energy carriers. For that, price process models such as log-of-price mean reversion or the Pilipovic model [12], which assumes a two-factor representation of the price behavior, are assigned to the considered energy carriers. The energy hub is modeled following the concept described in Section II-B. This concept incorporates the ability of an energy hub to flexibly react to volatile prices of input and/or output energy carriers and to adapt its dispatch accordingly. In contrast to deterministic models, where only the most likely outcomes are considered, the Monte Carlo method explicitly takes into account the operational flexibility of an energy hub. Making use of this flexibility, energy hubs are able to profit from the upside potential of price uncertainty while they will not suffer to the same extent from the downside risk. Using the random energy prices as input to the simulation, the profits

obtained by the operation of the energy hub are calculated for each set of price paths. Based on these profits, the energy hub values are calculated for each individual simulation run, discounted to a chosen date, and averaged. In this way, the frequency distribution of the present value (PV) of an energy hub is obtained.

D. Energy Price Modeling

Due to the flexibility of the Monte Carlo method, in principle any price process can be chosen to model the evolution of energy prices. For the purpose of illustrating the energy hub Monte Carlo valuation model, a simple price model, which represents the main characteristics of energy price processes, has been chosen: the log-of-price mean reversion process. With this price model, the natural logarithm of a certain energy carrier can be expressed as follows:

$$dy = \kappa(b - y)dt + \sigma dz \quad (10)$$

where y is the natural logarithm of the energy carrier price π , κ is the mean reversion rate, b is the long-term equilibrium value of y , σ is the price volatility, and dz is a normally distributed random variable with a mean of 1 and a variance of dt . The discrete approximation of (10) is used to generate price paths for the Monte Carlo simulation

$$y_{t+1} = y_t + \kappa(b - y_t)\Delta t + \sigma\epsilon\sqrt{\Delta t} \quad (11)$$

where ϵ is a normally distributed random variable with a mean of 0 and a variance of 1.

Correlations between price paths of different energy carriers are taken into account applying the Cholesky decomposition to the correlation matrix (cf., [13, Appendix A]). By means of this decomposition method, the correlation matrix Ω is factorized

$$\Omega = \mathbf{L}\mathbf{L}^T \quad (12)$$

where \mathbf{L} is a lower triangular matrix. In order to generate a vector ϵ_{corr} with normalized variates being correlated according to the correlation matrix Ω , a vector ϵ of independent normalized variates is generated in a first step. Multiplying this vector ϵ with the matrix \mathbf{L} obtained by Cholesky decomposition yields the vector ϵ_{corr}

$$\epsilon_{\text{corr}} = \mathbf{L}\epsilon \quad (13)$$

where ϵ_{corr} contains one entry per energy carrier. A sample of correlated gas, electricity and heat prices [given in CHF¹ per kilowatt-hour (kWh)] with a daily resolution generated with the method described above is shown in Fig. 3.

For the valuation of energy hubs with storage and DSM, the assumption of a daily price resolution, i.e., only one price per day, is not sufficient. Instead, a finer time resolution, e.g., hourly price profiles, have to be chosen for the price modeling in order to adequately assess the intra-day operation of a storage device. In this case, the variable y in (10) and (11) does not represent the natural logarithm of the price itself, but a scaling factor with a mean value of 1, i.e., $b = 0$. For each day of a run in the Monte Carlo simulation, this scaling factor is calculated and multiplied

¹The abbreviation CHF stands for Swiss franc.

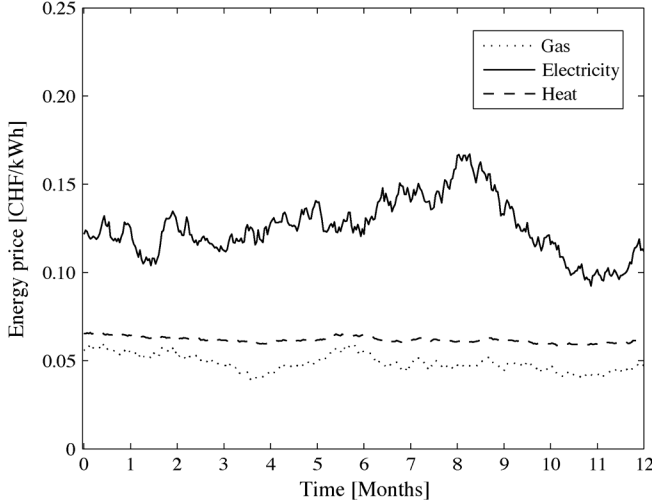


Fig. 3. Correlated gas, electricity, and heat prices ($\Delta t = 24 h$) with volatilities $\sigma_{\text{gas}} = 0.4$, $\sigma_{\text{el}} = 0.5$, and $\sigma_{\text{heat}} = 0.1$, and correlation coefficients $\omega_{\text{gas,el}} = 0.4$, $\omega_{\text{gas,heat}} = 0.8$, and $\omega_{\text{el,heat}} = 0.2$.

with an assumed hourly base price curve of the respective energy carrier. In this way, different price levels within one day due to different supply and demand conditions at different times are taken into account.

E. Optimal Dispatch and Energy Hub Valuation

The basis for the calculation of an energy hub's value is the computation of the daily profits from operation. Depending on the time resolution of the energy price simulation, each day is divided into N_t periods depending on the time horizon of the analysis. With this definition the daily profits F_d for each set of simulated price paths of the input and output energy carriers can be computed

$$F_d = \sum_{t=1}^{N_t} ((\mathbf{P}_t^{\text{out}} \cdot \boldsymbol{\pi}_t^{\text{out}}) - (\mathbf{P}_t^{\text{in}} \cdot \boldsymbol{\pi}_t^{\text{in}})) \quad (14)$$

where $\mathbf{P}_t^{\text{out}}$ and \mathbf{P}_t^{in} are the vectors of the output and input powers at each instant of time t , and $\boldsymbol{\pi}_t^{\text{out}}$ and $\boldsymbol{\pi}_t^{\text{in}}$ are the corresponding prices of input and output energy carriers. This means that the daily profits F_d result as the difference between the revenues obtained by selling output energy carriers and the costs incurred by the procurement of input energy carriers. When external costs such as environmental impacts from CO_2 emissions are internalized, additional cost terms can be included in (14).

The input and output powers are determined by optimizing the dispatch of the energy hub. In the model presented in this paper, optimal operation means maximization of daily profits. The simulated energy prices are used as input to the optimization. For each set of simulated energy prices, i.e., for each day of the simulation, the following optimization problem is solved:

$$\begin{aligned} & \text{Maximize} \\ & f(\mathbf{P}_t^{\text{in}}, \boldsymbol{\nu}_t, \mathbf{E}_t, \mathbf{H}_t) \\ & = \sum_{t=1}^{N_t} ((\mathbf{P}_t^{\text{out}} \cdot \boldsymbol{\pi}_t^{\text{out}}) - (\mathbf{P}_t^{\text{in}} \cdot \boldsymbol{\pi}_t^{\text{in}})) \end{aligned} \quad (15)$$

subject to

$$\mathbf{P}_t^{\text{out}} - \mathbf{C}\mathbf{P}_t^{\text{in}} - \dot{\mathbf{S}}\mathbf{E}_t - \mathbf{D}\mathbf{H}_t = \mathbf{0} \quad (16a)$$

$$\mathbf{E}(t=1) = \mathbf{E}_1 \quad (16b)$$

$$\mathbf{E}(t=N_t) = \mathbf{E}_{N_t} \quad (16c)$$

$$\sum_{t=1}^{t_{\text{DSM}}} \mathbf{H}_t = \mathbf{0} \quad (16d)$$

and

$$\mathbf{P}_{\text{min}}^{\text{out}} \leq \mathbf{P}_t^{\text{out}} \leq \mathbf{P}_{\text{max}}^{\text{out}} \quad (17a)$$

$$\mathbf{E}_{\text{min}} \leq \mathbf{E}_t \leq \mathbf{E}_{\text{max}} \quad (17b)$$

$$\mathbf{H}_{\text{min}} \leq \mathbf{H}_t \leq \mathbf{H}_{\text{max}} \quad (17c)$$

$$0 \leq \boldsymbol{\nu}_t \leq 1. \quad (17d)$$

The objective function is optimized by varying the input powers \mathbf{P}_t^{in} , the dispatch factors $\boldsymbol{\nu}_t$, the storage levels \mathbf{E}_t , and the shifted demand \mathbf{H}_t depending on the energy prices $\boldsymbol{\pi}_t^{\text{out}}$ and $\boldsymbol{\pi}_t^{\text{in}}$.² The equality constraints (16) comprise the power flow balances at the hub output, two sets of equations guaranteeing that the storage devices have the desired level at the beginning and at the end of each optimization period and one set of equations saying that all load shifting actions induced by the DSM have to balance out in the time period t_{DSM} . Equation (17a) ensures that minimum and maximum output limits of the converters are respected. With (17b) the storage content constraints are described and (17c) defines the maximum allowable amount of load shifting in the positive and negative direction. The vector $\boldsymbol{\nu}_t$ in (17d) gathers all dispatch factors which are defined according to the hub configuration and the number of energy carriers that are shared among several devices [8]. At each simulation time step, the value of the objective function $f(\mathbf{P}_t^{\text{in}}, \boldsymbol{\nu}_t, \mathbf{E}_t, \mathbf{H}_t)$ is used to calculate the daily profits F_d according to (14). As the daily profits are determined via an optimal dispatch, the daily profits F_d directly equal the daily payoffs B_d . In a situation where no critical loads have to be supplied in any case, negative profits are excluded by the optimization algorithm and the minimum profit is 0 (energy hub kept idle).³ If another method, which does not inherently exclude negative profit values, is used to calculate the daily profits F_d , the daily payoffs become

$$B_d = \max[F_d; 0]. \quad (18)$$

The daily payoffs on each set of paths of simulated energy prices are discounted and summed up for the whole depreciable life of the plant T to obtain the PV of the energy hub for each individual simulation run

$$B_{\text{run}} = \sum_{t=0}^T (B_{d,t} \cdot e^{-rt}) \quad (19)$$

²The specific size of the optimization problem depends on the complexity of the hub configuration to be analyzed and on the chosen time step resulting in a certain number of time periods N_t per day.

³If there are critical loads that have to be supplied by all means, situations can occur where the energy hub has to be operated although this leads to financial losses.

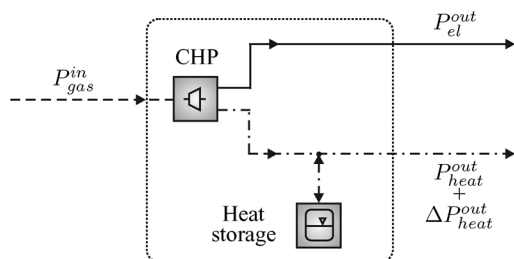


Fig. 4. Energy hub with CHP unit and heat storage. The heat output can be controlled by a DSM scheme.

where r is the continuous risk-adjusted discount rate. Continuous discounting is used because it is an adequate approximation for the actual daily discounting. Furthermore, it facilitates potential model refinements, e.g., the consideration of time-varying discount rates. Eventually, the value of the energy hub is obtained by averaging the payoffs of all N simulation runs

$$V = \sum_{n=1}^N B_{\text{run},n} \cdot \frac{1}{N}. \quad (20)$$

The value V of the energy hub can then be compared with its capital investment costs I . If $V > I$, the investment is profitable given the assumptions made in the modeling process. If $V < I$, the investment costs exceed the value of the energy hub, and one would disregard an investment in this energy hub configuration.⁴

III. APPLICATION EXAMPLE

The following application example demonstrates the proposed investment evaluation method for energy hubs which can flexibly react to uncertain energy prices. Different energy hub configurations are analyzed and compared. For that, we take the viewpoint of a utility that is considering four different investment options to generate electricity and heat:

- 1) CHP unit;
- 2) CHP unit and thermal storage;
- 3) CHP unit and heat DSM scheme;
- 4) CHP unit, heat storage, and heat DSM scheme.

Fig. 4 represents the latter configuration where the hub contains both a CHP unit and a heat storage in the form of a hot-water tank. The possibility of performing heat DSM is expressed by the variable $\Delta P_{\text{heat}}^{\text{out}}$ at the heat output of the hub. Starting with the base configuration, where the energy hub is only equipped with a CHP unit, the four configurations mentioned above are evaluated.

The parameters of the CHP unit and of the hot-water tank are listed in Table I.

The heat generated by the energy hub is supplied via an existing district heating system to an area of 50 000 residents. The total heat consumption of the area is roughly 250 GWh per year. Fig. 5 shows the corresponding heat load curve with its seasonal variations for the 8760 hours of the year.

⁴If further costs in the life cycle of the plant, e.g., deconstruction and disposal costs, are relevant, they have to be considered in addition to the investment costs I .

TABLE I
CHP AND STORAGE PARAMETERS

CHP unit	
Electrical efficiency	$\eta_{CHP,el} = 0.33$
Thermal efficiency	$\eta_{CHP,heat} = 0.57$
Rated electrical capacity	$P_{max}^{out,CHP,el} = 50$ MW
Heat storage	
Min./Max. energy content	0/500 MWh
Min./Max. power	-50/ + 50 MW
Charge/Discharge efficiency	0.98/0.98

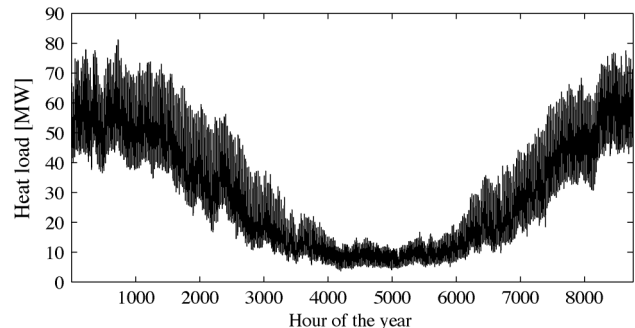


Fig. 5. Heat load curve for one year.

The operation of the energy hub has to be such that its heat output guarantees the supply of the area's heat demand at each point of time. In this application example, half of the heat load participates in the DSM scheme, i.e., 50% of the heat load can be shifted according to the boundary conditions described in Section II-B. From this, it results that $\mathbf{H}_{\min} = 0.5 \cdot \mathbf{L}_t^{\text{heat}}$. From the thermal inertia of the buildings it results that all load shifting actions of the heat DSM scheme have to balance out during one day in order to keep the temperature in the allowable range. With an hourly time resolution, (16d) thus becomes $\sum_{t=1}^{24} \mathbf{H}_t = \mathbf{0}$ for this application example. \mathbf{H}_{\max} is not defined explicitly. However, the maximum amount of positive heat load shifting actions is indirectly limited by (16d) as well as by the output limitations of the CHP unit and the heat storage. It is assumed that the whole electricity output produced by the hub is sold to the market with the aim of profit maximization. The base profiles of the energy prices are shown in Fig. 6.

For the electricity base price, a three-level time-of-use tariff structure is assumed. The base prices for gas and heat are constant over the day. For the investment evaluation, these base price profiles are multiplied with a random scaling factor, which is calculated for each day of a Monte Carlo simulation run according to (11). As this application example involves a storage device as well as a DSM scheme, the variables y_t and y_{t+1} in (11) do not represent the natural logarithms of the energy prices themselves but the natural logarithms of the scaling factors. Therefore, the long-term equilibrium values b_i are equal to 0. The correlated random scaling factors only influence the magnitude of the base price profiles and do not change them in any other way. Thus, the scaling factors establish the price spreads between the different energy prices. As these price spreads determine the operation of storage devices and for the DSM scheme, this relatively simple price model is expected to reflect the main factors influencing the economic

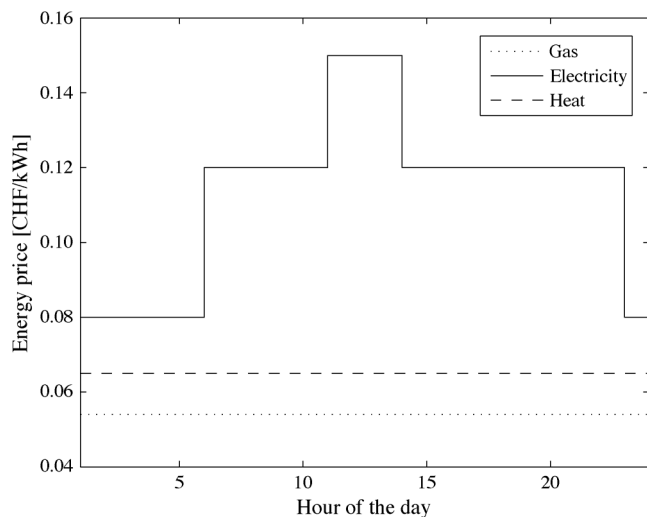


Fig. 6. Base profiles of energy prices with an hourly resolution.

TABLE II
PARAMETERS OF MEAN REVERSION PROCESSES

Price volatilities		
$\sigma_{gas} = 40\%$	$\sigma_{el} = 50\%$	$\sigma_{heat} = 0\%$
Mean reversion rates		
$\kappa_{gas} = 1.69$	$\kappa_{el} = 1.69$	$\kappa_{heat} = 1.69$
Price correlations		
$\rho_{gas,el} = 0.4$	$\rho_{gas,heat} = 0.8$	$\rho_{el,heat} = 0.2$

value of an energy hub. However, the general model formulation allows for the use of any more sophisticated price model if this is required. Instead of assuming a simple three-level time-of-use tariff structure, one could, e.g., simulate the effect of a variable tariff where prices change on an hourly or even quarter-hourly basis. The remaining parameters for the mean reversion processes of the price scaling factors are given in Table II.

The value σ_{heat} being 0% means a constant scaling factor for the heat price, i.e., the heat price does not change from day to day. A mean reversion rate of 1.69 implies that the half-life of the mean reversion process is $t_{1/2} = (\ln 2 / 1.69)$ years ≈ 5 months. The depreciable life of the hubs is assumed to be 20 years. In order to limit simulation times to a reasonable range, i.e., from a couple of hours up to one day with a 2.83-GHz quad-core desktop processor, only one year of operation is simulated and it is assumed that this year is representative for the whole lifetime of the plant. A discount rate r of 7% is used in the analysis.

Following the method proposed in this paper, each of the four considered investment alternatives has been evaluated with Monte Carlo simulations of 2000 runs.⁵ The result for the basic hub configuration with a CHP unit is shown in Fig. 7.

This configuration results in an expected mean PV of 107.2 million CHF at a standard deviation of 32.8 million CHF or 30.6% respectively. As the heat generated by the CHP unit

⁵This number of simulation runs proved to be sufficient for an accurate approximation of the hub value in this application example. No explicit convergence criterion or advanced method to reduce the variance from the Monte Carlo simulation was used. However, the proposed method allows for extending the model in this respect.

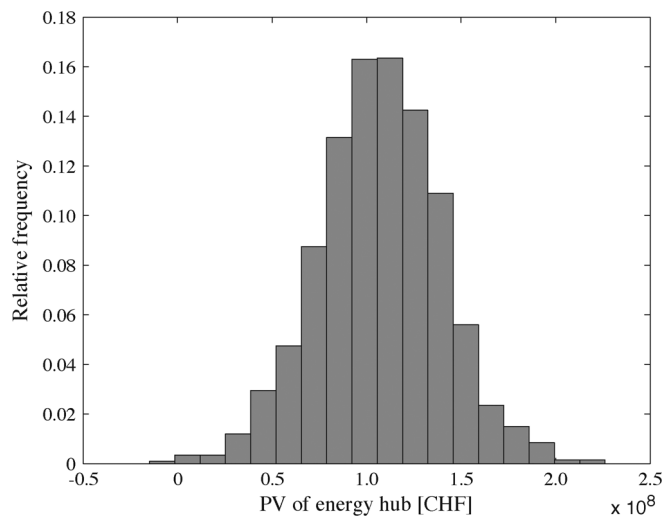


Fig. 7. Distribution of PVs for the energy hub configuration with CHP unit.

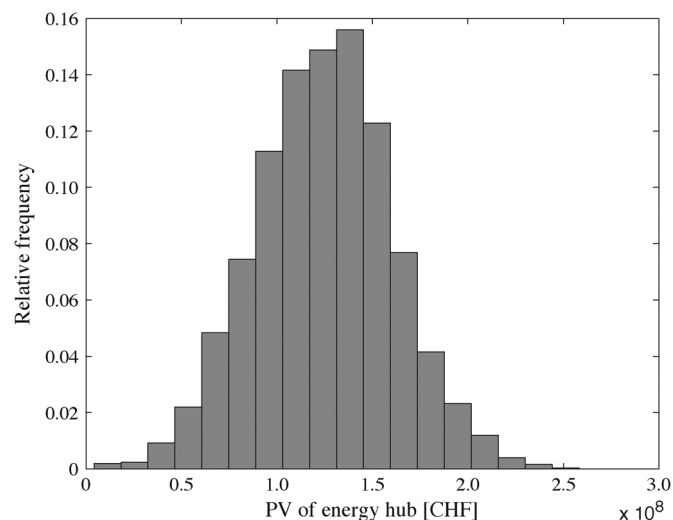


Fig. 8. Distribution of PVs for the energy hub configuration with CHP unit and heat storage.

is the only means to cover the heat demand, the operation of the CHP unit is completely heat-driven. There is no flexibility concerning the adaptation of the output in response to changing gas or electricity prices. The amount and timing of electricity production is indirectly fixed by the demand for heat.⁶

Fig. 8 illustrates the result for the hub configuration with CHP unit and heat storage. In this case, the Monte Carlo simulation yields a mean PV of 124.8 million CHF at a standard deviation of 35.8 million CHF or 28.7%, respectively. Comparing these results with the basic configuration, one can see that the additional hot-water tank allows for significantly increasing the value of the investment while it simultaneously reduces the investment risk measured by the standard deviation. Due to the flexibility provided by the heat storage, the electricity production can be increased at times of high electricity prices. The simultaneously produced heat is stored in the hot-water tank and is supplied to the heat load at a later point of time.

⁶This constraint could be relaxed by allowing for dissipating excess heat. For energy efficiency considerations, we refrained from including such an operational mode in this application example.

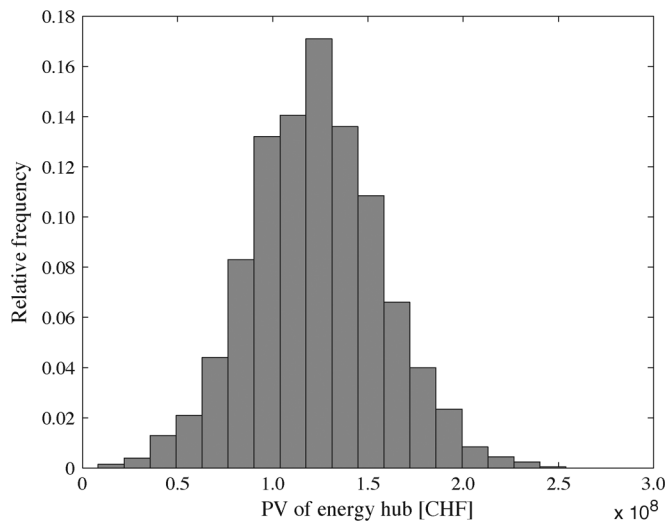


Fig. 9. Distribution of PVs for the energy hub configuration with CHP unit and heat DSM.

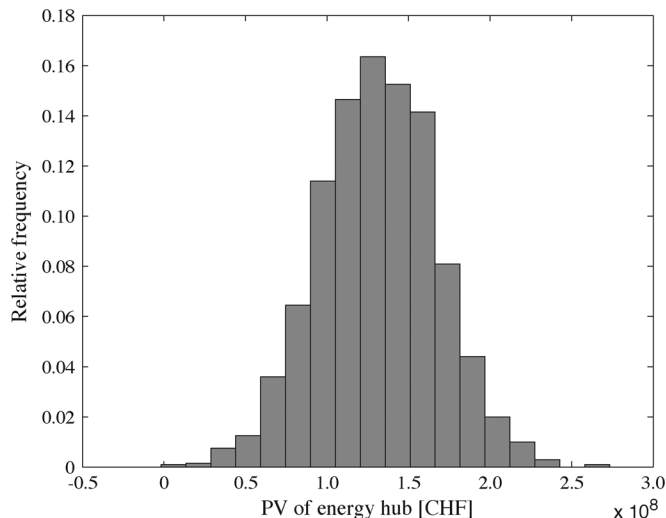


Fig. 10. Distribution of PVs for the energy hub configuration with CHP unit, heat storage, and heat DSM.

The results for the third investment alternative, where the CHP unit is combined with a heat DSM scheme, are represented in Fig. 9. For this configuration, a mean PV of 122.7 million CHF and a standard deviation of 28.3% are obtained. These results are in a similar range as the results for the configuration with CHP unit and heat storage. Analog to the hot-water tank, DSM increases the operational flexibility. The thermal inertia of the buildings participating in the DSM scheme is used as a virtual storage and the corresponding heat load can be shifted within given system limitations.

Finally, the distribution of PVs for the last investment option with CHP unit, heat storage, and DSM are shown in Fig. 10. With a mean PV of 131.2 million CHF and a standard deviation of 27.6%, this configuration provides the highest value and the lowest risk among all investment alternatives. The combination of the heat storage with the DSM scheme provides maximum flexibility. Therefore, this energy hub configuration can react

best to volatile energy prices and allows for maximizing the value of the investment.

In order to derive concrete recommendations for specific investment decisions, the value and risk of different energy hub configurations have to be confronted with the associated costs.

IV. CONCLUSION

The Monte Carlo valuation method for energy hubs presented in this paper represents a generalization of Monte Carlo applications to power generation or CHP units. By using the energy hub approach, it is possible to value integrated modular systems of multi-energy conversion and storage devices together with DSM schemes. By comparing different configurations with storage and/or DSM, the added value of the corresponding investments can be assessed.

Including an optimal dispatch in the valuation method implies relatively high computational efforts. However, as the time horizon of the investments to be valued is at least several years or rather decades, this aspect should not represent a prohibitive barrier.

The Monte Carlo approach takes into account strategic and operational flexibility in the analysis. This characteristic of the model is particularly important given that real time pricing is expected to play a significant role in the operation of future electric power systems. The ability of distributed generation units being possibly combined with storage devices and DSM to react to changing prices is adequately valued with the energy hub Monte Carlo model. The proposed method can thus provide valuable information for investment decisions with regard to flexibly controllable generation, storage and DSM in future energy systems.

Future work may address the issue of adequately including the cost of CO₂ emissions and its uncertainty in the valuation. Furthermore, it could be assessed if offering electric reserve power would be a profitable option for a cluster of distributed flexible energy hubs

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