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Energy Management for Buildings and Microgrids

Petr Stluka, Datta Godbole, and Tariq Samad

Abstract — **Intelligent consumer energy management systems will become important elements at the delivery points of the smart grid inside homes, buildings, and industrial plants. The end users will be able to better monitor and manage their energy consumption, while utilities will gain more flexible mechanisms for management of peak demands that will extend beyond demand response initiatives as they are implemented today. With a broader use of distributed generation many buildings and campuses will become microgrids interconnecting multiple generation, storage, and consumption devices of one or several end users. We discuss how energy management and control for such facilities can be viewed as a large-scale optimization problem. Specific supply-side and demand-side aspects include on-site renewable generation, storage technologies, electric cars, dynamic pricing, and load management. Technical challenges related to the optimization formulation are noted – in general, mixed-integer, nonlinear, constrained optimization is needed. We also describe an implementation of optimization-based energy management solution for a hospital in the Netherlands, providing economic details and an analysis of the savings achieved.**

I. Introduction

WITH the increased focus on energy efficiency, deployment of renewable energy sources, and smart grid technologies, a growing number of buildings and multi-building facilities will become more active participants in the electricity market. From the system point of view, such next-generation facilities will be autonomous microgrids with capabilities to sell or buy electricity from the power network and flexibly shift or reduce electrical loads when needed. Modern building systems organized in microgrids will enable improved efficiency of overall energy consumption, reduction of emissions, and integration of green power from renewables. In the context of smart grid initiatives, microgrids are usually considered as small-scale versions of the centralized electricity system [1]. However, in its essence, a microgrid system of a building or campus can include any type of local energy generation, distribution, consumption, and storage elements. Frequently, a central combined heat and power (CHP) plant represents a key generation element of the microgrid and this means that a heat distribution network – and possibly also thermal storage – must be considered in addition to the electricity network [2]. Microgrid management can be seen as an optimization problem, as shown in Fig. 1, which illustrates an electricity network interconnecting various energy generation elements (supply side) with energy consumption elements (demand side) and storage devices.

P. Stluka is with the Honeywell Prague Laboratory, V Parku 2326/18, 148 00 Prague 4, Czech Republic (phone: +420-234-625-934; fax: +420-234-625-900; e-mail: petr.stluka@honeywell.com).

D. Godbole is with Honeywell ACS Labs, Golden Valley, MN 55422 USA. (e-mail: datta.godbole@honeywell.com).

T. Samad is with Honeywell ACS Labs, Golden Valley, MN 55422 USA (e-mail: tariq.samad@honeywell.com).

A. Supply Side

The supply side feeds the microgrid with electricity that is generated locally by a variety of distributed generation elements. These can range from complex cogeneration (CHP) units to stand-alone generation units (wind turbines, photovoltaics, etc.) that utilize conventional or renewable sources of energy. Supply to the microgrid also still comes from the electricity distribution network, which is operated by the respective system operator. This connection can also serve for selling locally generated excess or green energy back to the main electricity network.

B. Demand Side

The demand side aggregates all energy-consuming devices. These aggregated loads represent various building systems such as lighting or heating, ventilation, and air conditioning (HVAC). From the demand management perspective the loads can be categorized as follows:

1) Critical loads must be met at all times. These are typically power supplies to essential processes.

2) Curtailable loads can be temporarily lowered. Air conditioning systems are a classical example.

3) Reschedulable loads can be flexibly shifted in time to avoid penalties associated with peak demand or overloading of the grid. Rescheduling means that some energy-intensive activities can be moved forwards or backwards in time. For instance, pre-cooling of a building can be done in the early morning – before actual cooling demand.

C. Energy storage and electric cars

Energy storage is an important element that adds more flexibility to the microgrid, but it also increases the grid's operational complexity. Energy storage elements can bring significant advantages particularly when the microgrid includes intermittent renewable generation sources. In the future, when electric cars are widely used, their storage capacity could be exploited in a similar way to smoothen energy consumption profiles.

D. Supervisory control and optimization for the microgrid

The safe, reliable, and cost-effective operation of the microgrid requires coordinating and dispatching these

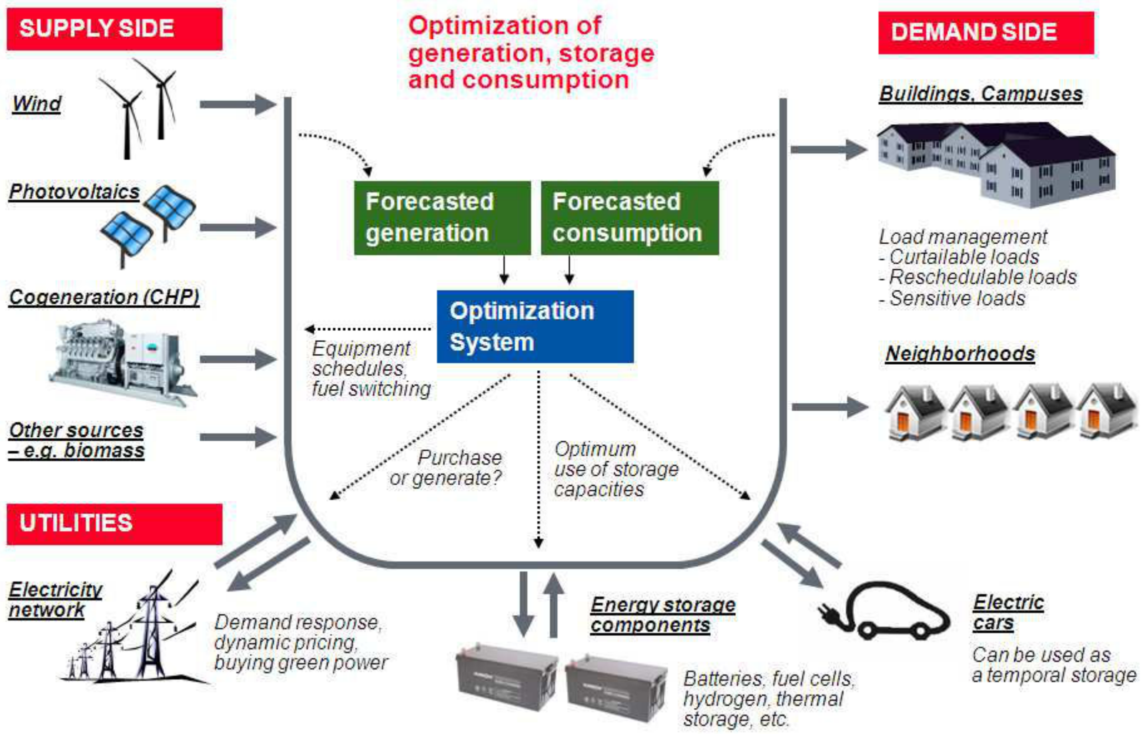

Fig. 1. Schematic representation of the microgrid

multiple generation, consumption, and storage devices connected to the grid. The associated optimization problem is a difficult one for several reasons. First, the optimizer needs to collect and process information from individual components about their past, current, and predicted future states. Second, a significant portion of the optimized variables are symbolic, indicating operational modes for equipment (including binary variables indicating whether a specific piece of equipment should be running or not). Third, the optimization task has to span a reasonably long future time interval (e.g., 24 hours) to assure consistency of operation [3]. Finally, the context within which the microgrid operates is uncertain because of the limited predictability of renewable generation, future energy demands, and dynamic prices. The optimization objective is to minimize the total energy bill within the operational, safety, reliability, and environmental constraints of the microgrid.

We note that microgrid operation also involves fast electrical control of the phase, frequency, and voltage of individual elements. A special functionality that integrates both electrical control and system coordination relates to *management of emergency situations* in the grid [4]. There can be a need to isolate feeder faults and enable healthy sections of the microgrid to continue operating during a fault, or transition to an islanding mode where the microgrid can operate independently of the main grid. In this paper we assume that these high-speed controllers are available and we focus on system-level optimization of the microgrid.

In the rest of this paper, we first discuss a number of aspects of microgrid energy management, highlighting the several complexities that must be considered in optimization and control schemes. Next, in Sections III and IV, we present optimization formulations for supply-side and demand-side problems respectively. Section V discusses a microgrid optimization solution and its application to a hospital facility in the Netherlands. We conclude by noting some areas for future work.

II. ASPECTS OF MICROGRID ENERGY MANAGEMENT

Depending on the types of devices connected to the microgrid, the energy management problem can cover optimization of the microgrid's supply side or demand side, or optimization of the whole system.

Supply side optimization. The basic supply side configuration includes CHP and other conventional generation devices. The system is connected to a public electricity grid with two-way energy flows. All demand side loads are considered critical and must always be met. The energy management decisions then consist in the dispatching of individual energy supplies, switching among various types of fuel, and optimizing the time for purchasing electricity or selling excess electricity back to the grid.

Integration of renewable generation sources. Adding renewable generation sources makes the energy management tasks more complicated. Renewable sources bring more uncertainty as their operation depends on hardly predictable environmental conditions such as wind speed or sun irradiation. Then the objective is to balance different forms

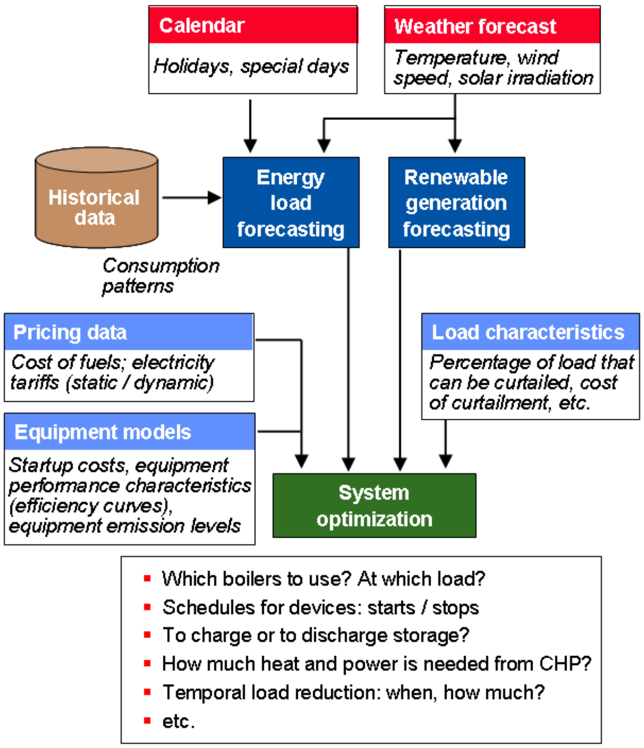

Fig. 2. Input data and preparation steps for microgrid optimization

of supplies: renewables, conventional sources and direct imports from the main grid.

Optimal use of energy storage. Energy storage devices are used to improve the generation – consumption balance of the microgrid by temporarily storing the surplus energy. This may be particularly advantageous for systems with renewable energy sources, which are highly intermittent. To optimally use the storage capacity it is necessary to determine optimal charging and discharging schemes for each device that will take into account the dynamic environment.

Demand-side optimization. When all loads are considered to be critical, there is no opportunity to optimize the demand side of the microgrid. Otherwise, the optimization will include lowering or rescheduling some of the loads. In current practice, the optimal control of building systems, such as HVAC, is frequently addressed as a stand-alone problem, not necessarily connected to load management. Model predictive control (MPC) techniques have been recently studied in this context [5],[6].

The optimal operation of the microgrid as a whole can be achieved when both supply and demand sides are optimized simultaneously, which however also increases complexity of the energy management problem in mathematical terms. Before starting any system optimization task, specific input data needs to be collected and several pre-processing steps executed as illustrated in the workflow in Fig. 2. For reaching the optimum or near-optimum solution over a given horizon of interest (e.g., 1 day) it is important to consider forecasts of future electricity production from renewable sources on the supply side [7],[8], as well as forecasts of future energy consumption on the demand side. Both forecasts are primarily influenced by future environmental conditions that can be available in the form of weather forecast. Energy load forecasts also strongly depend on behavioral patterns, which are tightly linked to calendar data. The other inputs to the system optimization algorithm include pricing data, equipment models, and characteristics of the curtailable or reschedulable loads.

Load forecasting. Modeling and forecasting of the energy consumed on the demand side of the microgrid usually leads to implementation of forecasting models for commercial or residential buildings and other types of facilities. Each building has a specific energy consumption pattern that is composed from daily, weekly, and seasonal cycles [9]. Models are run to predict future demand for the interval of interest, typically one day ahead.

Renewable generation forecasting. Forecasting of renewable power production is a significantly more difficult task than energy load forecasting due to the immediate impact of fluctuating primary factors – wind or cloudiness.

a) *Wind power forecasting* techniques range from quite simple ones to rather complex [10]. The simplest methods are based on climatology or averages of past production values. The advanced approaches for short-term (4-6 hours) wind power forecasting require predictions of wind speed, which allows prediction of the produced electricity through the so-called power curve, provided by the manufacturer or inferred from historical production data.

b) *Solar power forecasting* is mostly based on short-term forecasting of cloudiness [11]. While motion patterns for "stable" clouds are relatively predictable, a major challenge is with convective events of "unstable" clouds. The forecasting methods work with digitized cloud masks whose motion vectors are identified and projected to the future.

In both cases the forecast accuracy is inevitably limited and prediction errors achieved by the best forecasting solutions are usually in the range of 5-15%.

Equipment models should be reasonably simple but realistic to assure the optimization results are meaningful. Typically, each piece of energy generation equipment can be characterized by an efficiency curve, which can be obtained from the equipment manufacturer or estimated from historical data. Other characteristics can include ramp-up and ramp-down rates, start-up costs, normal running costs, or minimal/maximal required up and down times. Energy storage devices are usually characterized by maximum storage capacity and by charging and discharging rates.

Pricing data is needed to allow comparison between energy costs from self-generation and utility purchase. In addition to electricity, cost details of natural gas, heating oil, and other fuels must be known as well. Electricity prices can follow either the traditional static tariffs, or dynamic pricing mechanisms such as real-time pricing (RTP).

Load characteristics come into play in cases of demand side optimization, known also as load management. Curtailment characteristics can include the percentage of load that can be curtailed, the cost of curtailment, the length of time for which the load can be curtailed, and the maximum frequency of curtailments. Reschedulable loads can be characterized by maximum acceptable time to reschedule, cost of rescheduling, lead time needed before rescheduling can take effect, etc.

III. Formulating the Supply-Side Problem

Microgrid supply side optimization problems are quite similar to the traditional problems known from the domain of bulk power generation. This is true primarily for the problems of unit commitment and economic dispatch – two short-term optimization tasks that need to be solved to minimize the total fuel cost or to maximize the total profit. These problems are typically considered from a utility perspective but they apply also to microgrid configurations. In either case, the responsible party must ensure that the total generation must equal the forecasted demand. Unit commitment is the process of deciding when and which generating assets to start-up and shut-down. Economic dispatch is the process of deciding what the individual power outputs of the scheduled generating assets should be at each time-point. Both unit commitment and economic dispatch problems are interdependent and should be solved simultaneously, although a possible solution strategy may of course apply decomposition ideas [12][13]. Note that renewable generation sources are not considered in the following problem formulations because, in principle, the renewable power production cannot be scheduled.

A. Economic Dispatch

The basic problem of economic dispatch of the simplest configuration of N parallel energy generation units can be described mathematically as a cost minimization problem:

$$\text{Minimize } F = \sum_{i=1}^{N} f_i(P_i) \tag{1}$$

The minimization is over the energy generated in the units, P_1 ... P_N. F is the total cost and $f_i(P_i)$ is the cost function of the i-th unit. The function characterizes the dependence of operation costs ($) on the generated energy P (kW or MW) and includes energy conversion efficiency. The minimization is subject to the following constraints:

$$\sum_{i=1}^{N} P_i = D \tag{2}$$

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{3}$$

Where D is the energy demand that must be met. As we are focused on local generation and microgrids, transmission losses are not considered in equation (2). The optimization problem is formulated for one instant of time. For many applications it is reasonable to assume that the cost functions are convex. In this case, the objective function F is also convex. Since all constraints are linear and the feasible region is closed, bounded and convex, the problem has a global minimum (possibly non-unique) solution and can be solved using a suitable numerical method of convex mathematical programming.

B. Unit Commitment

The economic dispatch problem presented above for one instant of time is based on the assumption that all parallel generation units $i = 1, ..., N$ are running. Let us assume that the system consists of N generating units working in a parallel configuration. Decisions on which of them to run are the outcomes of the unit commitment problem, which introduces binary decision variables $X_{t,i}$ for each unit i. $X_{t,i} = 1$ if unit i is ON at time t, and $X_{t,i} = 0$ if unit i is OFF. Then a combined formulation of both the economic dispatch and the unit commitment problems is as follows:

Minimize

$$\sum_{t=1}^{T}\left[\sum_{i=1}^{N}\left[X_{t,i}\cdot\left(f_i(P_{t,i})+C_i^{fixed}\right)+C_{t,i}^{start}\max(X_{t,i}-X_{t-1,i},0)\right]+P_{t,u}R_t^{sell}\right] \tag{4}$$

subject to

$$\sum_{i=1}^{N} P_{t,i} + P_{t,u} = D_t \tag{5}$$

$$P_{i,\min} X_{t,i} \le P_{t,i} \le P_{i,\max} X_{t,i} \tag{6}$$

$$P_{u,\min} \le P_{t,u} \le D_t \tag{7}$$

$$X_{t,i} \in \{0,1\} \tag{8}$$

$$X_{0,i} = \overline{X}_{0,i} \tag{9}$$

The problem is now formulated over multiple periods of time $t = 1,\ldots,T$. The objective is to determine for each time interval t optimum values of X_i, P_i, and P_u that will minimize the function (4) over the entire time interval $1,\ldots,T$. Note that solving the optimization problem requires forecasting of future load demands $D_1, \ldots, D_T$.

The objective function (4) consists of, term by term: the operating costs (we have included fixed running costs C_i^{fixed} here), start-up costs $C_{t,i}^{start}$, and also costs associated with purchasing electricity $P_{t,u}$ from the utility at the sell price R_t^{sell} in interval t. Equation (5) represents the demand constraints – i.e. the demand D must be met by a combination of locally produced energy P_i and energy supplied from the main electricity grid P_u. Inequalities (6) and (7) correspond to restrictions on production limits and the amount of purchased electricity that must not exceed the respective demand D_t. Expression (9) specifies initial states of generation units, which can be 0 (unit is OFF) or 1 (unit is ON) as defined in (8). The formulation can be further extended by adding constraints for minimal up and down times, detailing the start-up costs, or including ramp rates.

Differences between optimization of microgrids and bulk power generation. Microgrids are more complex and more flexible in configuration than a simple parallel ordering, which is typical for large power plants. The microgrid frequently requires joint optimization of both electrical and thermal energy. A significant difference between power plants and microgrids is also in how the demand side is handled. While the meeting of demand requirements is a strong constraint for electricity generating plants, in microgrids the demand is more flexible and may represent another degree of freedom for optimization. In the following section, we will formulate the demand side optimization problem including integration of distributed renewable generation sources and storage devices.

IV. Demand-Side Formulation

Active participation of buildings, campuses and other facilities in the smart grid environment assumes a scenario in which the utility provides dynamic prices to these consumers who can then decide how to adapt their usage to minimize their consumption cost. We can start to formulate this decision problem as follows:

$$\text{Minimize } \sum_{t=1}^{T} R_t^{sell} L_t \tag{10}$$

subject to

$$L_t = L_t^{base} + L_t^{ctrl} \tag{11}$$

$$L_t^{ctrl} \geq 0 \tag{12}$$

$$\sum_{t=1}^{T} L_t^{ctrl} = L^{ctrl} \tag{13}$$

Here R_t^{sell} is the electricity price charged for time interval t and L_t is the consumer's load at t. This load is composed of a fixed base amount for each time unit, L_t^{base}, and a non-negative controllable (reschedulable) – amount L_t^{ctrl} (11). The total controllable amount L^{ctrl} over the day is fixed (13).

In this case, the optimization problem is to decide how to spread and/or reduce the load over a planning horizon (e.g. 1 day) so as to minimize the total cost. This requires determining optimal values L_t^{ctrl} over the entire time interval $1,\ldots,T$. The formulation above is simplified as each of the base and controllable loads is actually composed of multiple individual device loads. Also it is important to note some of the other neglected aspects. Firstly, certainty in the load profile is assumed. The controllable part of the load is assumed to be completely fragmentable (over the time horizon), and no part of the load is discretionary. The formulation also assumes a "planning" approach when the prices are communicated in advance and the consumer determines the load profile over a future time window.

Distributed renewable sources. With the ability to generate power locally and to sell any excess production from renewables to the utility, consumers have additional decisions to make. In the absence of storage capability, on-site generation at any time must either be used to power existing loads or sold back to the utility. The updated formulation is as follows.

$$\text{Minimize } \sum_{t=1}^{T} \left(R_t^{sell} P_{t,u} - R_t^{buy} P_{t,LG}^{excess} \right) \tag{10a}$$

subject to

$$L_t = L_t^{base} + L_t^{ctrl} \tag{11}$$

$$\sum_{t=1}^{T} L_t^{ctrl} = L^{ctrl} \tag{13}$$

$$P_{t,u} + P_{t,LG}^{cons} = L_t \tag{14}$$

$$P_{t,LG} = P_{t,LG}^{cons} + P_{t,LG}^{excess} \tag{15}$$

$$L_t^{ctrl}, P_{t,LG}^{cons}, P_{t,LG}^{excess} \geq 0 \tag{16}$$

Here we distinguish between the electricity price charged by the utility R_t^{sell} and the utility's payment for consumer-supplied power R_t^{buy}. The load demand L_t is now covered by a combination of utility-supplied power $P_{t,u}$ and locally

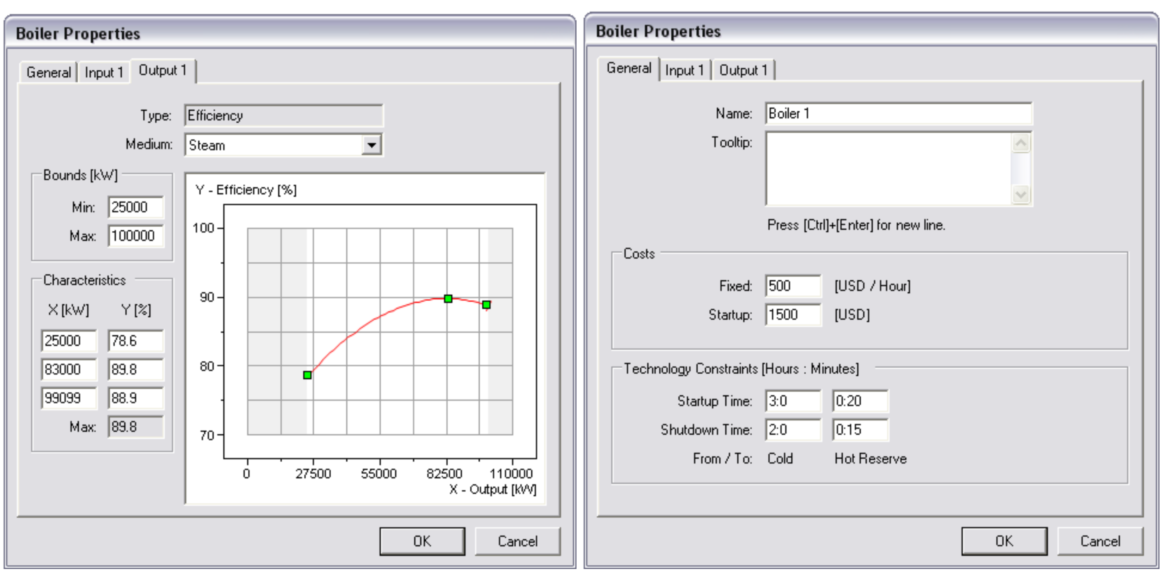

Fig. 3. Model parameters of a boiler

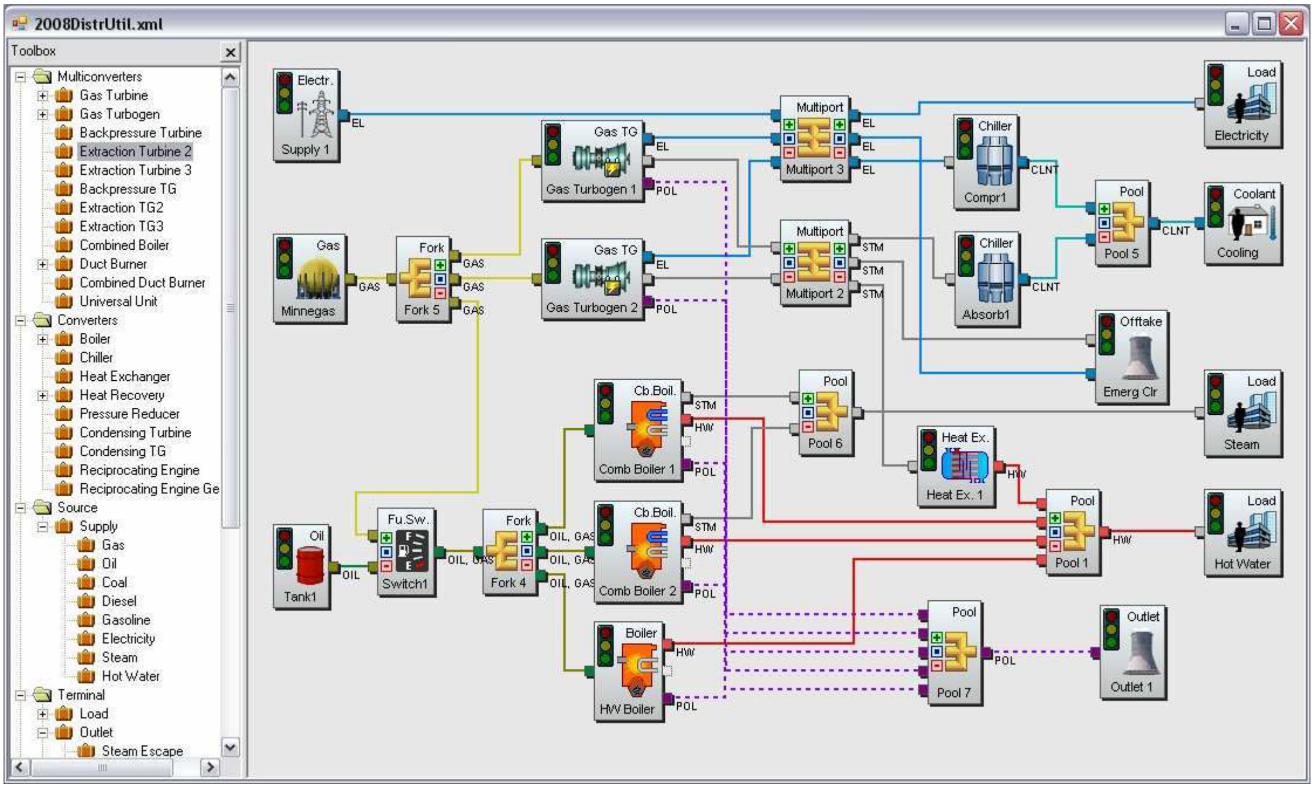

Fig. 4. Building's microgrid system configured in VERA

generated and consumed power $P_{t,LG}^{cons}$ (14). In addition to load management decisions on L_t^{ctrl} (11), other decisions must be made about what proportion $P_{t,LG}^{cons}$ of the on-site generation $P_{t,LG}$ should be consumed and what proportion $P_{t,LG}^{excess}$ should be sold to the grid (15).

Integration of storage. Another important enhancement is the integration of storage devices. This extends the demand-side problem formulation in a way that the load demand L_t can be now covered by a combination of utility-supplied power $P_{t,u}$, locally generated power $P_{t,LG}^{cons}$, and power provided by the storage device $P_{t,s}^{cons}$ (17). We model a storage device as a state of charge S_t (18) that can be affected positively by some amount $P_{t,LG}^{stored}$ of the locally generated power and some amount of utility supplied power $P_{t,u}^{stored}$ and negatively by discharging the storage device to service loads $P_{t,s}^{cons}$ and to provide grid power $P_{t,s}^{grid}$. This leads to the following problem formulation.

$$\text{Minimize} \sum_{t=1}^{T}\left(R_t^{sell}P_{t,u} - R_t^{buy}P_{t,LG}^{excess} - R_t^{buy}P_{t,s}^{grid}\right) \quad (10b)$$

subject to

$$L_t = L_t^{base} + L_t^{ctrl} \quad (11)$$

$$\sum_{t=1}^{T} L_t^{ctrl} = L^{ctrl} \quad (13)$$

$$P_{t,u} + P_{t,LG}^{cons} + P_{t,s}^{cons} = L_t \quad (17)$$

$$S_t = S_{t-1} + \eta^c\left(P_{t,LG}^{stored} + P_{t,u}^{stored}\right) - \left(P_{t,s}^{cons} + P_{t,s}^{grid}\right)/\eta^d \quad (18)$$

$$S_{\min} \le S_t \le S_{\max} \quad (19)$$

$$\left(P_{t,LG}^{stored} + P_{t,u}^{stored} = 0\right) \vee \left(P_{t,s}^{cons} + P_{t,s}^{grid} = 0\right) \quad (20)$$

$$L_t^{ctrl}, P_{t,LG}^{cons}, P_{t,LG}^{excess}, P_{t,LG}^{stored}, P_{t,s}^{cons}, P_{t,s}^{grid} \ge 0 \quad (21)$$

Respective charging and discharging efficiencies η^c and η^d are considered in (18). The state of charge S_t must always be within its lower and upper bounds (19), while constraint (20) ensures that the storage device is not simultaneously being charged and discharged. Additional decision variables are introduced: the amount of local generation $P_{t,LG}^{stored}$ that should be used to charge storage and the amount of stored power $P_{t,s}^{cons}$ that should be used to service loads. Simplifications here include omission of constraints related to maximum and minimum charging and discharging rates and cycling between charging to discharging modes.

V. Versatile Energy Resource Allocation

Versatile Energy Resource Allocation (VERA) is an energy management software solution that is focused on the optimization of microgrids with renewable generation and storage. It is also applicable to other integrated systems that combine various forms of cooling, heating, and power generation, such as CHP plants. Target markets include campuses, military bases, hospitals, office buildings and residential neighborhoods.

VERA can solve a combination of problems including unit commitment, economic dispatch, fuel switching, balancing of local generation with utility purchases, and optimal utilization of the capacity of storage devices. The underlying optimization task is currently formulated as the supply-side problem (Section III) with integrated aspects of renewable generation and storage. VERA finds the most cost-effective setpoint schedules for generation equipment, while attempting to achieve the lowest operation costs. The resulting solution complies with constraints such as meeting all energy demands, equipment capacities, influence of changing weather on equipment efficiency, variable availability of units, and maintenance schedules. VERA also takes into account principal economic aspects: time dependent costs of purchased energy and fuels, penalties for emissions, earnings from selling energy, start-up and shut-down costs of equipment, and fixed costs of operation. Fig. 3 provides an illustration of such parameters for a boiler.

A. Solution elements

Two advanced modules – load forecasting and optimal resource allocation – represent the core of VERA.

Load forecasting. VERA uses methodology known from non-parametric statistics (as locally weighted regression) and machine learning (as memory-based learning). The differentiating feature is that the forecasting algorithm runs on top of a history database, and the local regression models are built on the fly using only a fraction of the most relevant past data points. The regression model $y = f(x_1, x_2, \ldots, x_M)$ represents the correlation between energy consumption y and a number of independent influencing factors $x_1, \ldots, x_M$ – mainly weather conditions, calendar-based variables, and seasonal effects. Ambient temperature usually has the key impact, while the other environmental factors like humidity, wind speed, cloud cover, or sun irradiation can be used for better interpretation and finer modeling of the demand data. Calendar-based variables can help with capturing behavioral patterns. These variables include time of day, which is defined on the closed interval <0h;24h>, and also categorical variables like the day of week and holiday and special day indicators, which enable clustering of similar days into coherent groups. Details of the data-centric forecasting approach used in VERA can be found in [15].

Optimal resource allocation. VERA uses a Sequential Quadratic Programming (SQP) solver for finding a solution of the nonlinear optimization task. The nonlinearity is given by the cost functions f_i of individual units, which usually correspond to the nonlinear efficiency curves (as in Fig. 3). The optimization problem is defined as a dynamic programming problem over the time interval of 24 hours and solved with a solution step ranging typically from 15 to 60 minutes. Obviously, the accuracy and reliability of the optimal solution relies on the accuracy and reliability of the load forecast. This can be partially overcome by running more model scenarios.

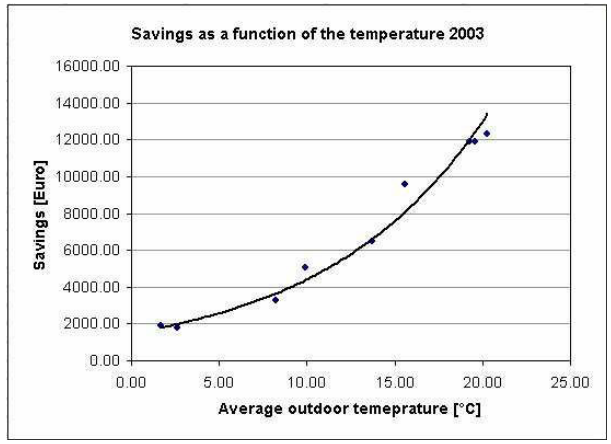

Fig. 5. The relation between monthly savings and outdoor temperature

B. Application – hospital utility optimization

The optimization technology of VERA was implemented in a project for the Atrium Hospital in Heerlen, the Netherlands. It is a 850-bed hospital, which, at the time of project implementation, had an average annual energy consumption of approximately 3.7 million m^3 of natural gas and imported 2.5 GWh of electrical energy from the public grid. This represented a variable energy cost of approximately €1,200,000 per year.

This hospital built a modern and state-of-the-art trigeneration utility system in the late 1990s to feed steam, heat, electricity, and cooling to the hospital's utility networks. The energy generating equipment consists of a hot water boiler, two steam boilers, an electrical and absorption chiller, and two gas engine CHP units. A schematic layout of the hospital utility is shown in Fig. 4. Electricity can be generated using own electricity generators or imported from the public grid, absorption or electrical chillers can be used for cooling purposes, and finally, heat can be generated in the CHP gas turbines or using the steam or hot water boilers.

The operating strategy in the past was based on the fact that fuel prices were low and electricity prices were high. However, later due to various reasons, economical energy management has turned out to be a very difficult task. These reasons include the liberalization and liquidity of the gas and electricity market, environmental taxes, CHP subsidies, the flexibility of configuration of the hospital utility, economic pressures, and the continuously varying energy demands.

To improve the quality of energy management decisions, first generations of load forecasting and optimal resource allocation technologies were installed and configured to optimize the operation within a two-days-ahead period. Evaluation of the new energy management concept was done primarily in years 2003 and 2004 (see [14] for details). The application is operating for eight years and the results are very encouraging. In short, the total gas consumption has decreased and the operation of the cogeneration units and the absorption chiller has become more economical. The electrical import and the use of the electrical chillers have increased as well as the use of the emergency cooler, which was sometimes active during low heat and cooling demand at a high electricity price.

The correlation between monthly savings and average outdoor temperature (Fig. 5) shows that the greatest savings were achieved during summer months when the operation can be improved by optimal coordination of absorption and compressor chillers and gas engines. As prices of electricity and fuels are growing, the savings are more and more significant. The annual savings achieved every year until 2010 varied between 6% and 12% of utility costs. The achieved return of investment was shorter than 1 year.

VI. Conclusions and Future Work

In this paper, an optimization approach is presented to support energy management decisions on both supply and demand sides of building microgrid systems. The documented results of the optimization-based application for the hospital in the Netherlands indicate the promise of this approach. For our future work we are considering the following main directions.

1. Full integration of the supply side and demand side formulations. This is the natural next step, which however may bring new challenges related to the overall solution complexity and dealing with the inherent uncertainty.

a) Need for a cost-effective approach. The microgrid optimization is a complex mathematical problem whose formal description belongs to the category of MINLP problems. For real applications it is necessary to determine the right balance between the level of detail of the mathematical model, time and resources available for calculation, and the complexity of optimization method. At any rate, the total cost of the solution (configuration effort, cost of commercial software and its maintenance, upgrades of communication infrastructure and hardware) must be in relation to its potential benefits (cost savings).

b) Dealing with uncertainty. Uncertainty relates to several operational aspects, including uncertainty of future energy demands, renewable generation, and dynamic prices. To correctly address the uncertainty may require adoption of stochastic optimization methods, such as stochastic SQP, as well as higher-level probabilistic decision-making concepts, such as those based on Bayesian theory.

2. Synchronization of system-level energy management with building controls. The formulations presented in this paper are primarily addressing the problem of optimal dispatching of all building devices. There is a natural opportunity for synchronization between this dispatching problem and the operation of building controls, including thermostats and unitary and plant-level controllers that ensure smooth operation of the respective building systems.

3. *Interactions between system-level energy management and power flow control.* The objective of power flow control units is to transform the raw quality power generated by each local source to grid quality power. This is essential for ensuring smooth transitions among different modes of operation. Although power flow control is a different type of problem than presented in this paper, it makes sense to study possible interactions between both.

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