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Intelligent control for energy-positive street lighting

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Abstract The paper investigates the application of solar energy in public lighting for realizing a street lighting sub-grid with positive yearly energy balance. The focus is given to the central controller of the system, which ensures the adaptive behavior of the overall system and provides smart city services to the end users via its web-based user interface. A functionality of the controller of special interest is the optimization of the energy management of the system, i.e., determining when to sell and buy electricity to/from the grid, in order to minimize the cost of electricity (or to maximize profit) subject to a given, time-of-use variable energy tariff. This requires precise forecasts of the energy produced and consumed, as well as appropriate robust optimization techniques that guarantee that the system bridges potential power outages of moderate duration in island mode. The algorithms implemented in the controller are presented in detail, together with the evaluation of the operation of a physical prototype with 191 luminaries over a horizon of six months, based on the monitoring data collected by the proposed controller.

Keywords Street lighting · photovoltaics · energy management · smart cities

1 Introduction

This research has been motivated by the application of solar energy in public lighting with the intention to achieve an energy-positive street lighting sub-grid,

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briefly named *E+grid*. The proposed system architecture exploits all of the four possible approaches defined in (Boyce et al, 2009) to minimize the energy consumption and the operating costs of the lighting system: advances in technology (i) by applying energy-efficient *LED luminaries*, *photovoltaic* (PV) panels for energy production, and *batteries* for intermediate energy storage; changes in use patterns (ii) by adjusting the daily switch on/off times to current *meteorological conditions*; modification in the basis of design (iii) by applying *adaptive lighting* that concentrates the lighting service to locations and times with vehicle or pedestrian traffic; and finally, changes in contracts (iv) by *optimizing the energy management* of the system subject to a *time-of-use variable energy tariff*. Hence, the proposed system can fully unfold its benefits if deployed in areas with low traffic during the night, such as residential areas, industrial parks, or supermarket car parks.

This paper mainly focuses on the *central controller* (CC) of the E+grid system that ensures the adaptation of the lighting system to the actual environmental conditions and user requirements, including the control of the daily switch on/off times and the dimming levels of the luminaries. Special attention is given to the energy management of the system: battery storage, bi-directional grid connection and intelligent control enable the system to buy and sell electricity when it is the most profitable, taking into account forecasted energy production and consumption, as well as a variable, time-of-use energy tariff. The controller is also responsible for delivering smart city services to end users by means of its web-based graphical user interface (GUI), such as the visualization of the current status and historical operational data, which are crucial for the efficient operation and maintenance of the overall system.

The physical prototype of the E+grid system has been developed and deployed recently by an industry-academy consortium formed by General Electric Hungary, the Budapest University of Technology and Economics, the Institute for Technical Physics and Materials Science and the Institute for Computer Science and Control of the Hungarian Academy of Sciences.

This paper content is organized as follows. First, a review of the recent literature on intelligent, energy-efficient street lighting and on renewable energy management systems is given. Then, Section 3 formulates the objectives that led to the specification of the proposed controller, and it also presents the architecture of the overall E+grid system. Section 4 gives a detailed account on the services of the CC. The algorithms for forecasting and optimizing the flow of energy are discussed separately in Section 5. Finally, the lessons learnt during a half-a-year operation of the physical prototype are summarized (Section 6) and conclusions are drawn (Section 7).

2 Literature review

A recent review on the opportunities and challenges in solid-state lighting, including technological development, policy options, environmental impact, as well as future trends, is presented in (de Almeida et al, 2014). Since LEDs offer favorable dimming performance, an important direction in improving the energy efficiency of street lighting is the application of adaptive lighting, i.e., adjusting the dimming levels and the light distribution to the environmental conditions and user behavior. An optimization approach to balancing light quality and energy efficiency in color turnable adaptive lighting systems is proposed in (Afshari et al, 2014), whereas the psychological effects of adaptive lighting have been studied by Haans and de Kort (2012). The basic services of a remote monitoring and control system for street lighting have been defined and a software architecture has been proposed in (da Fonseca et al, 2015). Formal graph models and a rule-based approach to controlling a complex adaptive lighting system are proposed in (Wojnicki et al, 2014).

The current trends in reducing the energy consumption of street lighting systems, including changes in technology (e.g., light sources), in use patterns (e.g., applying a twilight switch and remote dimming), and changes to standards and design criteria have been investigated in (Boyce et al, 2009; Radulovic et al, 2011). Pizzuti et al (2013) proposed reducing the energy consumption of street lighting by adjusting the dimming levels to the forecasted traffic intensity, and using an ensemble of artificial neural networks (ANNs) to derive such a forecast. The potential of PV assisted street lighting in off-grid and grid-connected systems is analyzed from the economic, ecologic, and energetic point of view using a simulation model in (Liu, 2014).

Energy management in micro-grids addresses finding the optimal matching of power demand to power supply, potentially via intermediate storage, in such a way that the operating cost of the micro-grid is minimized (or analogously, the profit is maximized) subject to a variable energy tariff. The integration of the capabilities to forecast power demand and supply, as well as to control loads, generators and storage in a single system is of utmost importance (Barbato et al, 2014; Álvarez-Bel et al, 2013). While the prediction of grid load has been a widely studied problem (Macedo et al, 2015), PV production forecasts became of interest with the spreading use of renewable energy. Typical approaches combine dynamic time series methods with astronomic models, such as clear-sky approaches that estimate PV production under the assumption of a cloudless sky, based on the solar elevation angle and site altitude (Myers, 2013). Methods for forecasting PV production on a short-term horizon include ANNs (Paoli et al, 2010), multi-model time series (Wu et al, 2014), or time series for spatial-temporal forecasts (Boland, 2015). The adaptive aggregation of different time series models was investigated in (Csáji et al, 2014a).

Approaches to computing the optimal control based on given, deterministic or stochastic forecasts include (Álvarez-Bel et al, 2013), who apply an economic dispatch algorithm to match partly controllable demand to power supply from the grid and from the generators within the micro-grid. Barbato et al (2014) introduced mixed-integer linear programming models for energy management in a micro-grid, assuming non-cooperative users autonomously managing their own electricity demand, as well as for cooperative users targeting at a common objective. Elsied et al (2015) proposed a nonlinear optimization model for controlling distributed generators and storage systems. Provata et al (2015) introduced a genetic algorithm for minimizing the operating cost of a community micro-grid, considering production and consumption forecasts generated using ANNs. Clastres et al (2010) proposed a two-step approach, in which the schedule of buying and selling electricity is computed first on a horizon of 24 hours with the objective of maximizing the profit. The resulting active power bid is submitted to the distribution system operator. The second step is the real-time adjustment of the plan to the realization, with the objective of fulfilling the bid.

To cope with imperfect predictions, various papers investigate the application of probabilistic forecasts and stochastic optimization. Zavala et al (2009) propose an on-line stochastic optimization approach, applying model predictive control and a weather forecasting model. In (Constantinescu et al, 2011), a similar approach is taken to the problem of controlling the production/distribution of a set of thermal power plants in order to compensate for the uncertain production of wind farms. Livengood and Larson (2009) assume probabilistic weather and tariff forecast and apply stochastic dynamic programming to compute an optimal energy management policy in a residential or small office environment. Niknam et al (2012) present a scenario-based stochastic program to compute Pareto-optimal solutions for minimizing cost and emission.

3 Overview of the lighting system

3.1 Objectives and requirements

Below we review the general design objectives set for the overall E+grid system, which defined the system architecture and determined the requirements on the CC as well.

1. An *energy efficient* street lighting system has to be developed that minimizes energy consumption by applying adaptive LED luminaries.
2. Despite the variation of dimming levels, participants of traffic should *perceive the standard, customary level of lighting.* Hence, detected motion must imply that a series of nearby luminaries dim up along the path of the vehicle or the pedestrian.
3. The system is expected to achieve a *positive energy balance* over a yearly horizon by adopting PV energy production.
4. The lighting system must be able to *bridge power outages* of moderate, predefined length in island mode by using the energy stored in its batteries.
5. The system should be able to *minimize its operating cost* by optimizing its energy management with respect to the applicable energy tariff. In this way, the lighting system also contributes to the stability of the grid by shifting its consumption into off-peak periods.
6. The CC of the lighting system must deliver the expected *smart city services* via a web-based GUI to all stakeholders with appropriate permissions, including the control and monitoring of the overall lighting and energy system.
7. *Dependable and scalable control* is a must, which can be achieved by applying a combination of distributed control on the level of individual luminaries (for real-time control and for critical functionalities, such as dimming the luminaries) and central control (e.g., for delivering information services to users and for functionalities involving large amounts of data on the overall system). Deploying the CC in a *computational cloud* ensures scalability and contributes to further reducing energy consumption.

The above requirements must be satisfied partly by an appropriate system architecture and the sizing of the components (requirements 1-4), and partly ensured by the CC (4-7).

3.2 System architecture

In response to the above requirements, the E+grid system provides adaptive, energy-efficient lighting service by applying dimmable LED luminaries, which modulate their light intensity according to the current traffic and environmental conditions. Infrared motion sensors, mounted into the lighting fixtures on each pole, measure the speed and the direction of the motion in the proximity of the luminaries. Smart controllers, in turn, classify these motion signals as vehicle traffic, pedestrian traffic, or no traffic, and adjust their dimming levels to the detected scenario. However, luminaries are not isolated; they inform their neighbors about the detected traffic scenario via wireless communication, enabling the long-range adaptation of the lighting service despite the fact that the motion sensors are dependable only in a shorter range (e.g., 10 neighbors are switched to full intensity in case of vehicle traffic, 4 neighbors in case of pedestrian traffic). Hence, real-time control of the lighting system is achieved by distributed intelligence, eliminating the dependence on communication with the CC.

The energy management system comprises PV panels and inverters for energy generation, batteries for energy storage, as well as the appropriate measurement and control instruments. PV panels have been sized to achieve positive energy balance over a yearly horizon, whereas batteries to ensure island mode operation for at least three hours in case of power outages, considering the environmental, meteorological, and traffic conditions of the deployment site. Power flow in the system is monitored by smart meters and the CC. The latter also decides when to buy or sell electricity from/to the grid, with the objective of minimizing the costs of energy (or equivalently, maximizing profit) subject to the applied variable energy tariff.

The local weather station of the system measures six different weather parameters, which can be correlated to energy production and consumption data in order to evaluate and predict system performance. The signals of the twilight switch in the weather station are used to determine the daily switch on/off times of the luminaries.

The central controller of the E+grid system is in charge of controlling and monitoring the lighting and the energy management system, and it is also responsible for delivering smart city information services to the various stakeholders. Technically, it is a web-based software application, hosted on a virtual server in a computational cloud. Such a deployment approach revealed measurable advantages compared to deployment on traditional, physical servers, mainly with respect to augmented scalability and configurability, redundancy of the hardware resources and hence increased dependability, as well as lower energy consumption and investment cost. The architecture of the overall E+grid system is shown in Fig. 1, where the red lines indicate power flow, while green connectors correspond to information flow.

4 Services of the central controller

The CC has a dual role in the architecture of the E+grid system. On the one hand, the IT services provided to the end users are delivered via its web-based GUI. On the other hand, the CC is fundamental to the adaptive behavior of the

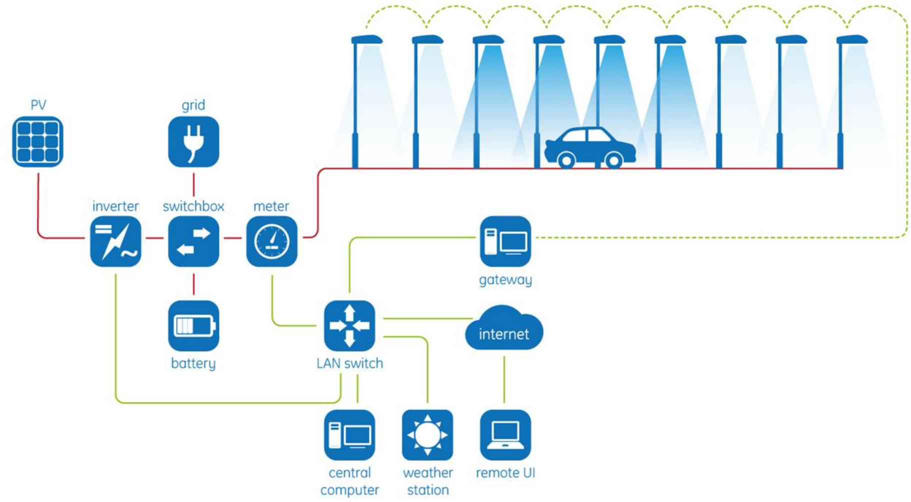

Fig. 1 Architecture of the E+grid system. Red lines indicate power flow, green connectors correspond to information flow.

lighting system and the associated energy management system. These services are presented in detail below.

4.1 User-driven services of the controller

The web-based GUI provides the user with a friendly access to all functionalities of the CC, as listed below. The elements of the GUI associated to the referenced functions are highlighted in Fig. 2 using yellow circular labels.

- The layout of the luminary network and the current state of each luminary are visualized in a Geographic Information System (GIS) based on Google Maps (area 1 in Fig. 2). The layout of the luminary network can be defined and the parameters of individual luminaries can be edited in the *Luminaries* menu item (area 4).
- A quick overview of the status of each individual system component is presented on a series of color-coded icons in the upper right corner of the page (area 2). Statuses are updated in real-time for active components, and every 5 minutes for passive ones.
- Users can control and poll the luminaries: they can set custom dimming levels on any selected subset of the luminaries, request instant data from a luminary controller, or, as a support for developers working on the prototype system, send any textual command to the luminary controllers (command buttons in area 3). Luminary statuses on the screens of concurrent users are updated instantaneously.
- Administration of users, system configuration, and background processes can be performed, and detailed system logs can be accessed with advanced filtering options in the *Administration* menu (area 4).

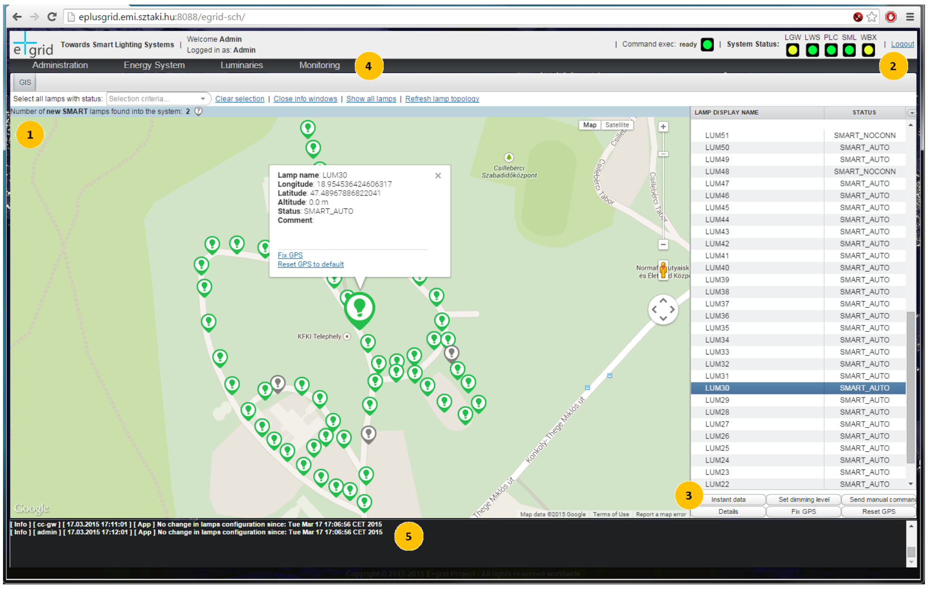

Fig. 2 The main page of the central controller GUI.

– The GUI supports the analysis of the system behavior by graphical visualization of historic data, including monitoring data and computed data (e.g., forecasted energy production and consumption). Charts provide rich parameterizations opportunities, and data from various sources can be combined together and displayed in graphical or tabular format (see Fig 3). Finally, charts can be printed, saved within the CC, or exported into MS Excel or CSV format (*Monitoring* menu in area 4). Fig. 4 presents the graphical visualization of the forecasted energy consumption.
– The user is notified in real-time about all events occurring in the system via text messages appearing in the system console (area 5).

Access to system functionalities is regulated according to user roles, ranging from a *guest* role (allows displaying components statuses and monitoring data, but prohibits any changes in the configuration and behavior of the system), passing to *operator* (can modify the state of luminaries), then to *supervisor* (can manage the layout and configuration of the luminary network or other components), finally up to *administrator* (unlimited access to all functionalities).

4.2 Background processes in the controller

Background processes running 24/7 in the CC aim at assuring the adaptation of the system to the environmental conditions and collect detailed data about the behavior of the system. The main functionalities provided by such processes are the following:

– *Calculation of lighting times*, by combining the signal of the twilight switch located in the weather station and the astronomical calendar. Fault tolerance

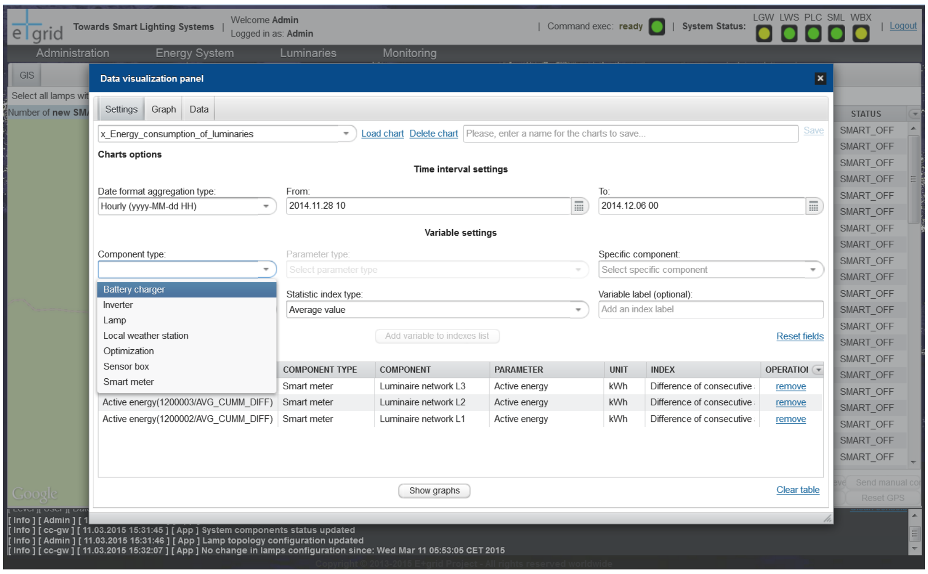

Fig. 3 Parameterization of charts for the visualization of monitoring data.

w.r.t. defects of the twilight switch is achieved by imposing an upper bound on the deviation from the astronomical calendar, whereas communication problems are managed by a PLC (Programmable Logic Controller) that takes control of the main switch whenever it loses connection with the CC, and guarantees a default behavior according to the calendar. Nevertheless, users with proper permissions can control the daily switch on/off times by adjusting the calendar or by editing the parameters of the corresponding process. It is noted that adaptive dimming of the individual luminaries based on motion sensor signals is managed real-time by the controllers of the luminaries, independently of the CC;

– *Optimization of energy management in the system* (see Section 5 for details);
– *Monitoring* the behavior of the lighting and the energy management system by collecting 77 different parameters, including status information, electronic measurements, weather parameters, etc. from each relevant component. Detailed monitoring data are queried every 15 minutes, and they are stored in the CC database. The data acquired on the prototype system not only enables the efficient operation and maintenance of the particular system instance, but it also supports future design decisions related to the next generation of public lighting systems.

Technically, each of the above functionalities is realized through an independent job, including separate, dedicated jobs for monitoring each individual high-level system component. Life cycle management of the jobs is delegated to a scheduler, with parameters (including periodicity) editable by users with appropriate permissions. The interoperability between the E+grid system components is undertaken by a dedicated layer in the CC, responsible both for handling connections and for validating and interpreting application semantics formalized in JSON (JavaScript Object Notation) communication messages.

5 Predicting and optimizing the energy flow

One of the core objectives of the CC is to optimize the energy flow in the system subject to a given variable, time-of-use energy tariff. In order to do so, it is necessary to forecast future energy production and consumption. In this section we first (i) discuss how the energy production and consumption are forecasted, then (ii) we describe how the energy flow is optimized based on these forecasts.

5.1 Forecasting energy production and consumption

To produce forecasts, first (i) time series data are gathered with the help of smart meters; then, (ii) stochastic models are estimated; finally, (iii) the forecasts are constructed, also accompanied by confidence regions generated by Monte Carlo methods, using these models.

The models are estimated by system identification (Ljung, 1999) techniques. System identification is a subfield of control theory and statistics which aims at building models of dynamical systems based on experimental data, typically given as time series. Experiments have been performed with various linear and non-linear stochastic models, including Box-Jenkins, Hammerstein-Wiener, ANN (multilayer perceptron), support vector regression and wavelet type models (Csáji et al, 2014b,a). Although non-linear models (e.g., support vector regression based ones) achieved the best forecast precision, a decision has been made to apply linear autoregressive exogenous (ARX) models in the system, as (i) their performance was comparable to the performance of the non-linear models; (ii) they were easy to interpret and analyze in contrast to non-linear models; (iii) they performed uniformly well in both cases (production and consumption); and finally (iv) they were dependable from a software development viewpoint, e.g., they did not require specialized libraries. ARX models can be formalized as follows:

$$X_t \triangleq \sum_{i=1}^{p} a_i^* X_{t-i} + \sum_{i=0}^{q-1} b_i^* U_{t-i} + N_t, \tag{1}$$

where X_t, U_t and N_t denote the output, the input and the noise at time t, respectively. Constants $\{a_i^*\}$ and $\{b_i^*\}$ are the "true" parameters that we aim at identifying (estimating), while p and q are referred to as the orders of the system. It is known that ARX systems can be estimated by the least-squares (LS) method which is strongly consistent and asymptotically Gaussian in the ARX case (Ljung, 1999). The LS estimate can be found by solving a system of linear equations (the "normal" equations), which can be done by a wide-range of methods readily available in most standard libraries.

The time-step of the time series was one hour. Standard pre-processing was applied, such as removing outliers, as well as centering and scaling the data. Two ARX models were used: one for production and another one for consumption; the corresponding data were treated as the output, $\{X_t\}$. The inputs, $\{U_t\}$, are also very important to get efficient models. Though, theoretically there is an option to leave them out from the model, which leads to simple AR (autoregressive) systems, our experiments showed (Csáji et al, 2014b,a) that AR processes provide only poor performance. It is mainly because they are not flexible enough to model

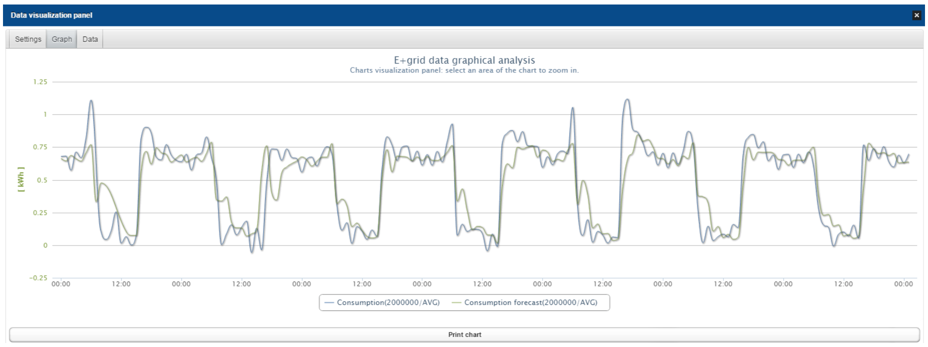

Fig. 4 Comparison of the predicted (green) and the actual (blue) consumption on the GUI of the controller.

the periodic nature of these processes. On the other hand, possible periodicities can be taken into account in the exogenous part of the ARX model. Particularly, typical (based on historical data) consumption pattern w.r.t. a given hour of the day was used as the input signal when estimating energy consumption; and clear-sky estimate was treated as the input for the case of production (Csáji et al, 2014b,a). The orders of ARX models which provided the best performance were $(p = 5, q = 4)$ in the production case and $(p = 7, q = 5)$ for consumption data. Fig. 4 illustrates a typical consumption forecast along with the later observed real consumption process, showing the efficiency of the proposed approach.

5.2 Controlling the energy flow

This section presents a receding horizon controller, which in each step computes an open-loop control sequence for a given horizon T. The environmental feedback is incorporated by recalculating the control, taking new forecasts into account after each iteration. The procedure for computing a finite-horizon control sequence in one iteration of the approach is discussed below.

The control sequence is obtained as the solution of an optimization problem. The input contains the expected future energy production, $\{C_t^+\}$ and consumption $\{C_t^-\}$, as well as stochastically guaranteed lower confidence bounds on production $\{\underline{C}_t^+\}$ and upper confidence bounds on consumption $\{\overline{C}_t^-\}$, generated by Monte Carlo methods (Csáji et al, 2014b). The control policy must be *robust* in the sense that it must guarantee island mode operation for a given amount of time for a single power cut arising at any point in time, even in the worst-case scenario defined by $\{\underline{C}_t^+\}$ and $\{\overline{C}_t^-\}$. This requirement can be fulfilled by maintaining the appropriate state of charge, $\{\underline{B}_t\}$, in the battery. The battery is characterized by its capacity $\overline{B}$, maximum charge and discharge rates R^+ and R^-, the initial state of charge b_0 and the efficiency of charging β. A method for computing $\{\underline{B}_t\}$ from $\{\underline{C}_t^+\}$ and $\{\overline{C}_t^-\}$, together with the detailed assumptions, is presented in (Csáji et al, 2014b).

Then, a control sequence defining the optimal electricity purchase rate x_t^+, grid feed-in rate x_t^-, battery charge rate r_t^+, discharge rate r_t^-, and state of charge b_t is sought for each time period t that minimize the total energy cost subject to time-varying electricity purchase and feed-in prices Q_t^+ and Q_t^-. A linear programming (LP) formulation of the problem is

$$\text{minimize} \quad \sum_{t=1}^{T} \left(Q_t^+ x_t^+ - Q_t^- x_t^- \right) \tag{2}$$

subject to

$$C_t^+ - C_t^- + x_t^+ - x_t^- = r_t^+ - r_t^- \quad \forall\, t \tag{3}$$

$$\beta\, r_t^+ - r_t^- = b_t - b_{t-1} \quad \forall\, t \tag{4}$$

$$\underline{B}_t \le b_t \le \overline{B} \quad \forall\, t \tag{5}$$

$$0 \le r_t^+ \le R^+ \quad \forall\, t \tag{6}$$

$$0 \le r_t^- \le R^- \quad \forall\, t \tag{7}$$

$$0 \le x_t^+, x_t^- \quad \forall\, t \tag{8}$$

The objective (2) encodes minimizing the total cost of energy; constraint (3) ensures that the energy balance in the system is maintained; equality (4) defines the state of charge in the battery based on the charge and discharge rates; finally, box constraints (5-8) define the range of the variables. Such an LP problem can be solved by standard libraries.

6 Evaluation of the physical prototype

The physical prototype of the E+grid system, comprising 191 intelligent LED luminaries and 152.5 m^2 of active PV surface area, has been deployed at a research campus of the Hungarian Academy of Sciences in Budapest (near latitude N47), in a typical industrial park environment. The complete system has been working in its near-final configuration for ca. 8 months at the time of writing this paper. Since this includes a half-a-year period between the summer and the winter solstices in 2014, the gathered data allows drawing conclusions about the natural, yearly operation cycle of the lighting system as well.

6.1 Analysis of monitoring data

- In the investigated time interval, each individual component of the system evidenced an availability over 95% (with the exception of a few problematic luminaries and a faulty Li-ion battery). In particular, the availability of the central controller was 99.48%, where the main source of loss of availability was software updates. These availability values were achieved despite the harsh weather conditions experienced in various periods of the year (see Fig. 5).
- The yearly energy import of the system is 13 061 kWh, its energy export is 19 104 kWh, resulting in a massively positive energy balance of 6 043 kWh per year. The energy balance in the system was positive until mid-October, see Fig. 6. It is noted that this surplus may or may not result in a positive

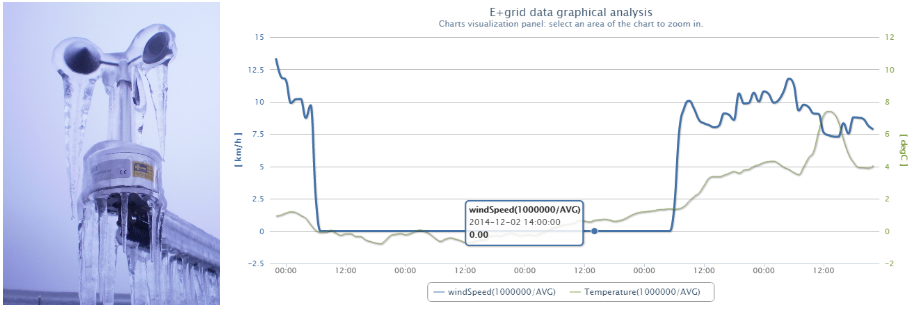

Fig. 5 Anemometer of the local weather station in severe weather conditions in December (left). Wind speed (blue) and temperature (green) data registered by the weather station during the same time period (right).

financial balance on the electricity bill, depending on the applicable tariff and the control of the energy flow.
- Energy consumption of the luminary network strongly depends on the period of the year (daily consumption ca. 2.5 times higher in winter than in summer) and on the hour of the day as well, with consumption peaks occurring before switching off the luminaries in the morning, and after switching them on in the evening on workdays in winter. This variation follows the natural expectations based on the length of nights within a year and the traffic within a day.
- The consumption reported by individual luminary controllers follows the variation of the consumption of the overall network. The maximum of the daily average consumption and traffic is 0.276 kWh and 115 vehicles at the main entrance of the industrial park, whereas the minimum is 0.152 kWh and 4.89 vehicles on a road section with very low traffic intensity.

6.2 Simulation for assessing energy management

In order to investigate the efficiency of the proposed energy management approach, the operation of the system was investigated on a yearly horizon. Simulation ex-

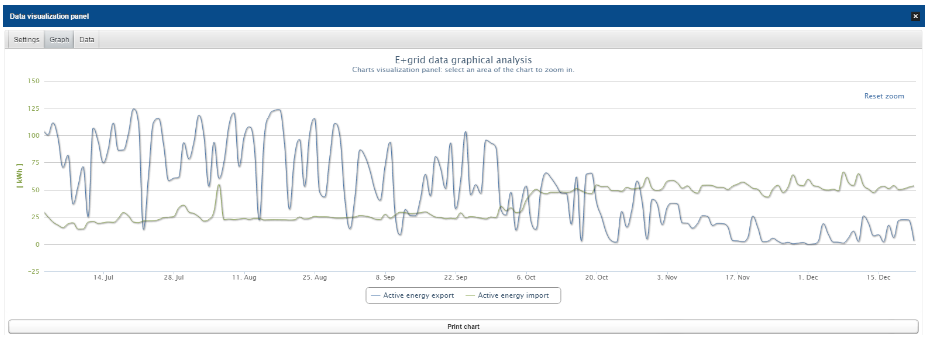

Fig. 6 Comparison of daily energy export (blue) and energy import (green) over a half-a-year horizon. The daily energy balance was typically positive until mid-October.

periments were performed on real production and consumption data, gathered during the half-a-year period indicated above, and extended to a whole year by duplication. The experiments addressed computing the of energy and financial balance in the system, using three different energy management strategies, subject to different energy tariffs taken from various distribution system operators around the world. The three strategies can be summarised as follows:

- A baseline approach that employs the battery only as a backup, without actively using it. This approach is denoted as *Backup*.
- The energy management algorithm implemented in the deployed battery chargers, called *increase self-consumption (ISC)* mode. At times when the system is a net producer, it charges the battery until it reaches its full capacity, then it sells the surplus to the grid. On the other hand, if the system becomes a net consumer, the required energy is supplied from the battery until it reaches a specified minimum charge level, 40% in the experiments; then, it purchases electricity from the grid.
- Finally, the optimization approach developed for the E+grid system, denoted as *E+grid*, minimizes the operating cost (or alternatively, maximizes the profit) that can be achieved subject to a specific energy tariff.

The three energy tariffs considered in the experiments included a so-called *net surplus* tariff from California (CA), where the settlement of the accounts is purely based on the yearly net production of a renewable energy system; a *flat* tariff from Germany (GER) with purchase prices 2.2 times higher than feed-in prices; and a *time-of-use* variable tariff from Australia (AU) with purchase prices 2–3.5 times higher than feed-in prices.

The resulting financial and energy balance are displayed in two diagrams in Fig. 7. The energy balance of the system is massively positive in all cases, and it is only slightly decreased (by 10% for *ISC* and by 2.5–3.1% for *E+grid*) by the active energy management approaches due to losses on charging and discharging the batteries. On the other hand, the financial balance achieved strongly depends on the tariff and the energy management approach adopted. In the case of the net surplus CA tariff, the optimal strategy is using the batteries only as backup, and hence, *Backup* and *E+grid* coincide. *ISC* achieved somewhat worse energy and financial balance due to the battery losses. In the case of GER and AU tariffs, the baseline *Backup* strategy evidenced negative financial balance, due to the asymmetry in the tariffs between the two directions of energy flow. The simple *ISC* strategy was sufficient for turning this balance into positive, since it allowed to partly shift the consumption peaks into a late night period with lower electricity prices. In contrast, the optimization approach applied in *E+grid* could efficiently exploit the variation of the electricity prices, increasing the realized profit by a factor of 2–3.5. In addition to the financial gain, *E+grid* also guarantees a higher level of service by storing always the required amount of energy in the batteries to bridge eventual power outages.

7 Conclusions

The paper proposed an intelligent controller for energy-positive solar street lighting. The central controller, which is a web-based software application running in

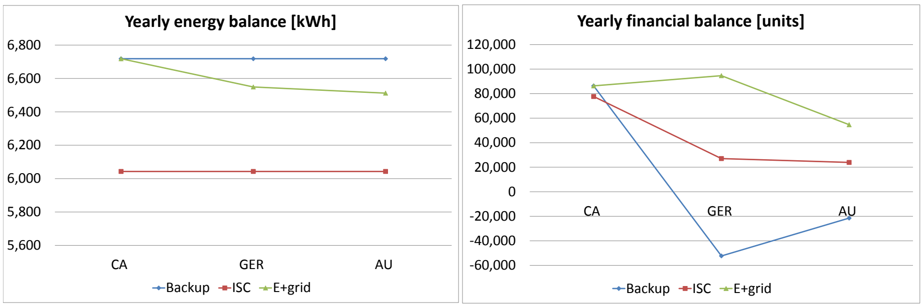

Fig. 7 Energy and financial balance for different tariffs and different energy management strategies.

a computational cloud, ensures the adaptation of the system to the environmental conditions, and provides smart city services to its end users. A functionality of crucial significance is optimizing the energy management of the system, which required precise forecasts of energy production and consumption, as well as solving the resulting robust optimization problem. While preliminary experiments investigated various stochastic time series models, a relatively simple ARX model has been applied in the deployed software, due to its adequate precision and dependability in a completely automated process. The operation of the physical prototype of the E+grid system has been evaluated based on monitoring data collected during a period of six months. It has been shown that the system design guarantees positive energy balance over a yearly horizon, but the algorithms implemented in the controller are decisive in the corresponding financial balance.

Future research will focus on the integration of further sensor types into the luminaries, including air pollution, noise and vibration, weather sensors, as well as a microwave radar for advanced traffic monitoring. The objective is to develop smart city services along with the urban road network, based on the readily available street lighting infrastructure, with additional functionalities such as map-based visualization of the current and past levels of different environmental stressors, predictions on future conditions, and alerts in case a stressor is likely to reach a specified threshold level in the close future, such as a probable smog alert or traffic jam.

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