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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, 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 the 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 deployed physical prototype with 191 luminaries over a horizon of six months, based on the monitoring data collected by the proposed controller.

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, briefly named *E + grid*. The proposed system architecture exploits all of the four possible approaches defined in Ref. [1] 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. To the best of our knowledge, the proposed system is the first in the literature to integrate all these technologies in a single street lighting system.

This paper 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

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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 Ref. [2]. The potential approaches to reducing the energy consumption of street lighting systems, such as 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 Refs. [1,3]. These trends and the applicable technological solutions are review in detail below.

Adaptive lighting, i.e., the adjusting of the intensity and the distribution of light to the environmental conditions and user behavior, received significant attention recently, due to the favorable dimming performance of LED light sources. An optimization approach to balancing light quality and energy efficiency in color turnable adaptive lighting systems is proposed in Refs. [4], whereas the psychological effects of adaptive lighting have been studied by Haans and de Kort [5]. Pizzuti et al. [6] 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.

Various authors investigated the application of adaptive lighting in indoor applications as well, with the objective of improving the perceived quality of light and saving energy at the same time. Parise and Martirano [7,8] suggest the integrated design of electric light and natural daylight systems, with the application of advanced sensor and information technologies. Petrov et al. [9] presents an approach to dynamically adjust the color temperature and illumination levels in an indoor lighting system to the observed natural outdoor light conditions using the DALI protocol and dedicated microcontrollers.

The basic services of a *remote monitoring and control system* for street lighting have been defined and a software architecture has been proposed in Ref. [10]. A three-layer control architecture, consisting of a backend server, multiple centralized controllers, as well as node controllers on individual luminaries, is proposed for intelligent street lighting in Ref. [11]. Formal graph models and a rule-based approach to controlling a complex adaptive lighting system are proposed in Ref. [12]. An intelligent communication and control system for street lighting, integrated into an experimental microgrid, is presented in Refs. [13,14]. proposes a controller architecture for individual, adaptive lighting points powered by PV panels mounted on the light pole, for off-grid applications.

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 Ref. [15]. A thorough assessment of the effects of PV generation on the overall European electricity system, as well as recommendations for quantifying the full cost of PV generation are presented in Ref. [16]. An alternative methodology for the assessment of the economic value of PV generation is proposed in Refs. [17], where the calculation of the true market value, considering the temporal variability and geographical particularities of both PV generation and electricity demand, as well as time-of-use energy tariffs, is put forward, instead of the often used grid parity metric.

An important means for improving the yield of PV systems is the *maximum power point (MPP) tracking* algorithm in the power converter (inverter), which addresses the dynamic regulation of the operating voltage and current to maximize the power output. Recent improvements of the conventional *perturb and observe* (P&O) algorithm, often implemented in commercial systems, address the reduction of the oscillation around the MPP and the risk of divergence from the MPP [18,19]. The performance of the P&O and the incremental conductance (IC) algorithms is compared in Ref. [20]. In the experiments, IC yielded marginally better efficiency than P&O, but it was considerably more sensitive to parameter settings.

Energy management in microgrids 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 microgrid 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 [21]. While the prediction of grid load has been a widely studied problem [22], 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 [23]. Methods for forecasting PV production on a short-term horizon include ANNs [24], time series models based on dynamic harmonic regression [25], or time series for spatial-temporal forecasts [26]. The adaptive aggregation of different time series models was investigated in Ref. [27].

Approaches to computing the *optimal control* based on given, deterministic or stochastic forecasts include [21], who introduced mixed-integer linear programming models for energy management in a microgrid, assuming non-cooperative users autonomously managing their own electricity demand, as well as for cooperative users targeting at a common objective. Elsied et al. [28] proposed a nonlinear optimization model for controlling distributed generators and storage systems. Provata et al. [29] introduced a genetic algorithm for minimizing the operating cost of a community microgrid, considering production and consumption forecasts generated using ANNs. Clastres et al. [30] proposed a two-step approach, in which the schedule of buying and selling electricity is computed first on a horizon of 24 h 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. [31] propose an on-line stochastic optimization approach, applying model predictive control and a weather forecasting model. In Refs. [32], 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 [33] 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.

[34] present a scenario-based stochastic program to compute Pareto-optimal solutions for minimizing cost and emission.

The *E + grid intelligent street lighting system*, presented in this paper, combines and integrates the above technologies into an adaptive LED lighting system running on solar energy, with a positive energy balance over a one-year time horizon. The authors are not aware of any earlier works in the literature that *combined the five essential building blocks* (adaptive lighting, communication between luminaries, remote monitoring and control, PV energy generation, active energy management) in a single street lighting system. Special focus will be given to the central controller of the system, which was the crucial element for the successful integration of the different technologies, and performs the remote monitoring and control of the overall system, ensures its adaptive behavior, and optimizes its energy management to minimize the cost of the consumed energy subject to the applicable variable energy tariff.

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 system must be built from *commercial*, *market-ready hardware components*, integrated under a custom developed controller software, to enable commercialization in the very near future.
5. 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.
6. 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.
7. The CC of the lighting system must deliver the expected *smart city services* via a web-based GUI to all stakeholders with appropriate access rights, including the control and monitoring of the overall lighting and energy system.
8. *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 1–5), and partly by the CC (5–8).

3.2. System architecture

In response to the above requirements, the E + grid system (see Fig. 1) 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 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

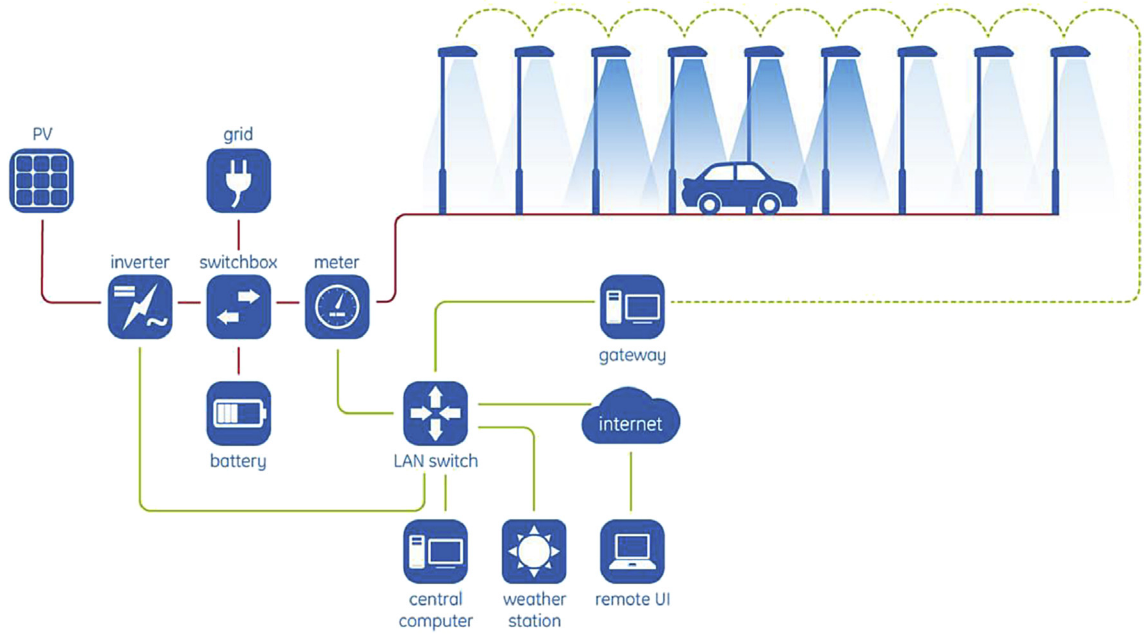

Fig. 1. Architecture of the E + grid system. Red lines indicate power flow, green connectors correspond to information flow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 min 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).
- 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. 5, in the next section, 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 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 min, and they are stored in the CC

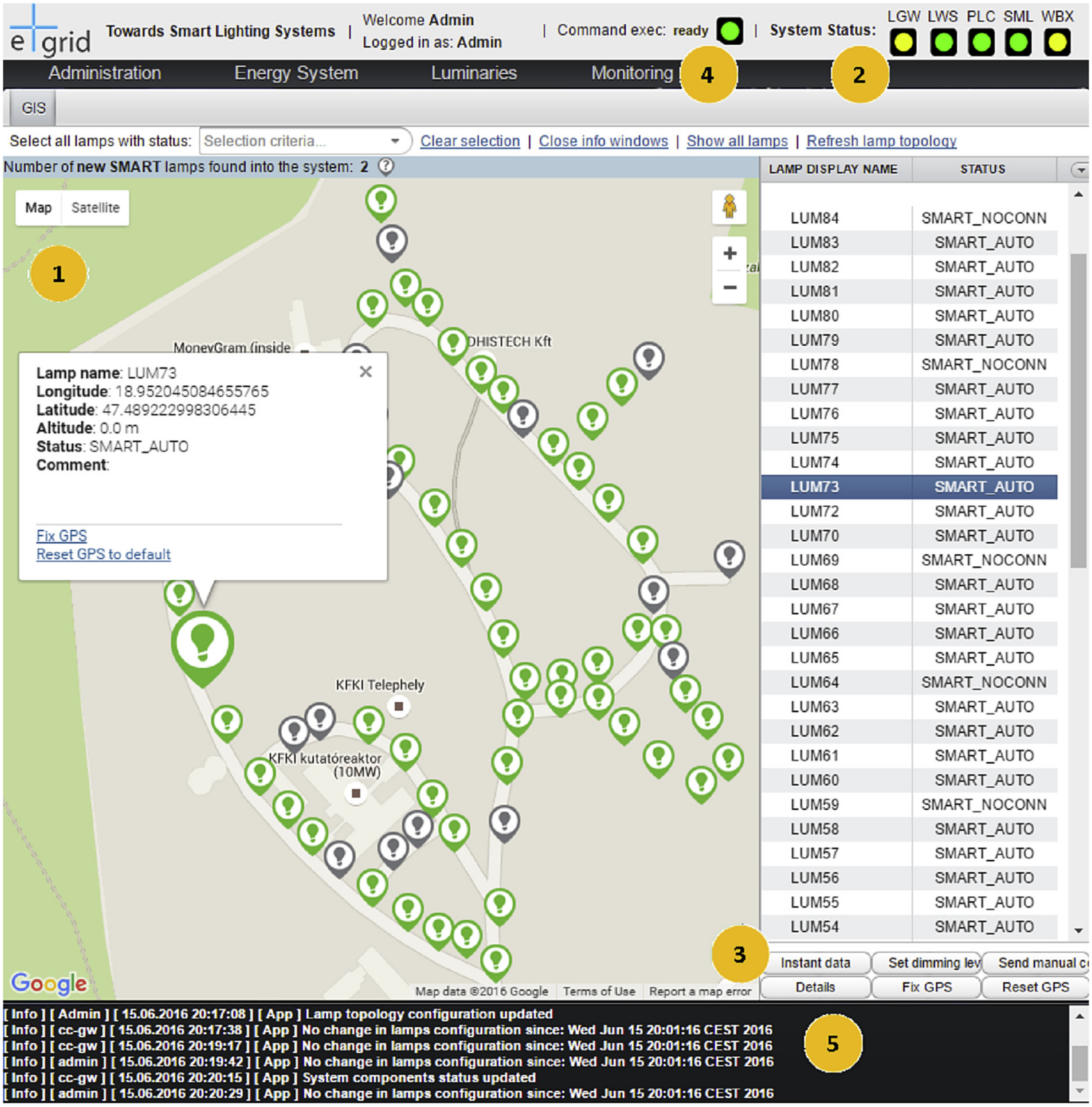

Fig. 2. The main page of the central controller GUI.

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 energy tariff, in order to minimize the total cost of the energy consumed. In order to do so, the CC must forecast future energy production and consumption, prepare a plan on how to charge or discharge its batteries in the close future, and execute the planned actions on the physical system. This section proposes a receding horizon controller, which, during each of its period runs (once an hour in the current implementation), generates forecasts and plans on a short-term horizon (one day, with hourly time units in the implementation). The first action of the plan is executed on the physical system, whereas the tail of the plan provides the foresight necessary for achieving a close-to-optimal control. This tail of the plan will be revised during the next periodic run.

An overview of the procedure is given in Fig. 4. Each periodic run

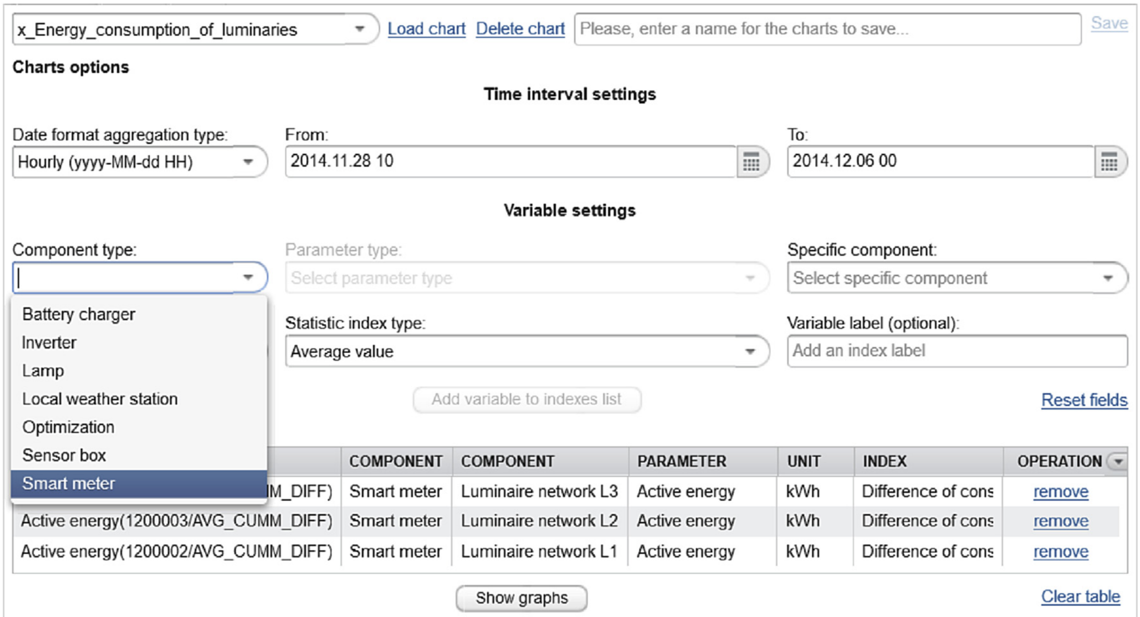

Fig. 3. Parametrization of charts for the visualization of monitoring data.

of the algorithm starts with acquiring up-to-date energy production and consumption data from the smart meters of the system, as well as historic data from the database. Separate time series models are fitted to this data to generate production and consumption forecasts and confidence bounds, which serve as the basis for calculating the plan for charging/discharging the batteries. In this section we first (i) discuss how energy production and consumption are forecasted, then (ii) describe how the energy flow is optimized based on these forecasts.

5.1. *Forecasting energy production and consumption*

Stochastic time series models of energy production and consumption are estimated by *system identification* techniques [35]. 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 nonlinear stochastic models, including Box-Jenkins, Hammerstein-Wiener, ANN (multilayer perceptron), support vector regression and wavelet type models [27,36]. Although nonlinear 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 nonlinear models; (ii) they were easy to interpret and analyze in contrast to nonlinear 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 [35]. 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 [27,36] that AR processes provide only poor performance. It is mainly because they are not flexible enough to model the periodic nature of these

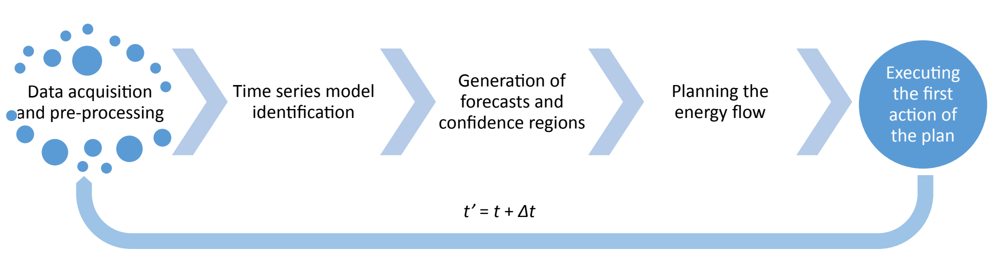

Fig. 4. Overview of the proposed algorithm for predicting and optimizing the energy flow.

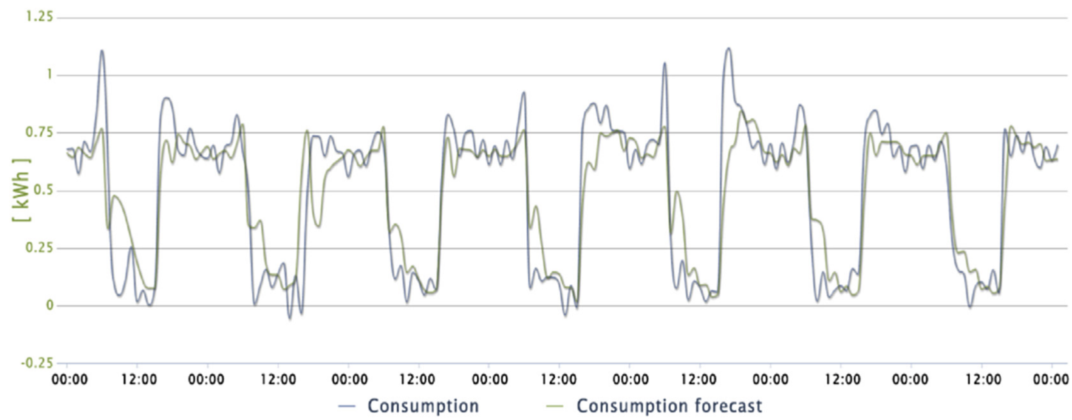

Fig. 5. Comparison of the predicted (green) and the realized (blue) consumption on the GUI of the controller over a one-week time horizon. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 [27,36].

It is noted that the forecasts computed by the proposed time series models, in their raw form, do not necessarily reflect the technical limitations of the physical system. This may occasionally result in unreasonable (e.g., negative or overly high) forecast values. This was handled by thresholding the forecasts in a post-processing step, using 0 as a lower bound (both for production and for consumption) and the nominal PV power as an upper bound (for production only). No upper bound was applied for energy consumption due to the diversity of consumers in the system.

In the implemented system, the overall procedure described above (including pre-processing, parameter identification, forecast generation and post-processing) was executed in each periodic, hourly run of the forecaster. The orders of the ARX models which provided the best performance were $(p = 5, q = 4)$ in the production case and $(p = 7, q = 5)$ for consumption data, whereas parameters $\{a_i^*\}$ and $\{b_i^*\}$ varied hour-by-hour, according to the results of parameter identification. Fig. 5 illustrates a typical consumption forecast along with the later observed real consumption process, showing the efficiency of the proposed approach. The detailed evaluation of the performance of the proposed forecasting methods is given in Refs. [27,36].

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 [36]. 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 Ref. [36].

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

6.1. Configuration of the prototype system

The physical prototype of the E + grid system, comprising 191 intelligent LED luminaries (133 roadway lights and 58 pedestrian walkway lights, with a total nominal power of 6.4 kW) 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 new intelligent LED luminaries were developed from a commercial LED luminary product of the consortium partner, by extending it with smart controllers, as well as with the required sensor and communication devices. The luminaries were designed, manufactured and tested according to the Electromagnetic Compatibility (EMC) Directive 2004/108/EC [37], which ensures electromagnetic compatibility with the utility grid and other electronic devices.

In order to enable a long-term performance evaluation of different PV technologies, the roof-mounted PV system, with a total peak power of 21 kWp, is composed of three different subsystem: monocrystalline cells (3.50 kWp), as well as thin-film (3.46 kWp) and polycrystalline (13.51 kWp) panels from three different manufacturers. The design of the PV system and the estimation of the yield was performed using the PV* SOL software application. Analogously, three different batteries are used on the three electric phases: a top-class industrial lead-acid battery pack with 8 kWh nominal capacity, and two different Lithium-ion batteries with capacities of 5.5 kWh and 5 kWh. During the design process and the selection of the purchased hardware components, special attention was paid to the sustainability aspect, based on life-cycle assessment (LCA) data available from the manufacturers [38–40].

The complete system has been working in its near-final configuration for ca. 8 months at the time of writing this paper, which included a half-a-year period between the summer and the winter solstices. Hence, the gathered data allows drawing conclusions about the natural, yearly operation cycle of the lighting system as well.

6.2. 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. 6).
- 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 6043 kWh per year. The energy balance in the system was positive until mid-October, see Fig. 7. It is noted that this surplus may or may not result in a positive financial balance on the electricity bill, depending on the applicable tariff and the control of the energy flow.
- The typical intra-day behavior of the energy system is shown for a summer day in Fig. 8 and for a winter day in Fig. 9. In either season, the system is a net producer of energy during the day, and a net consumer during the night. Production dominates consumption regarding both volume and duration in summer, with an opposite relation in winter. The batteries are charged to (nearly) full capacity at the time of switching on the luminaries, and discharged gradually during the night. However, battery capacity is insufficient to cover the energy demand of the luminaries even on long sunny days.
- Adaptive lighting resulted in a 55.71% reduction in energy consumption, compared to the calculated consumption assuming non-adaptive LED luminaries, at a site where the peak traffic intensity was 98 vehicles and 54 pedestrians per hour for a single luminary in the afternoon, and there was hardly any traffic during the night.
- 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.

6.3. 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 experiments were performed on real energy production and consumption data, gathered from the physical prototype system during the half-a-year period indicated above, and extended to a whole year by duplication. The experiments addressed computing the of energy balance (difference of the total energy fed into the grid and purchased from the grid over the one-year horizon) and the financial balance (difference of the total cost of electricity purchased from the grid and the income achieved by feeding electricity into the grid, c.f. eq. (2)), subject to different energy tariffs taken from various distribution system operators around the world. Since the goal of the experiment was the evaluation of the different control strategies on the given, completely specified prototype system, the investment cost, maintenance, amortization, etc. was disregarded. Three different energy management strategies were compared:

- 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. 10. 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

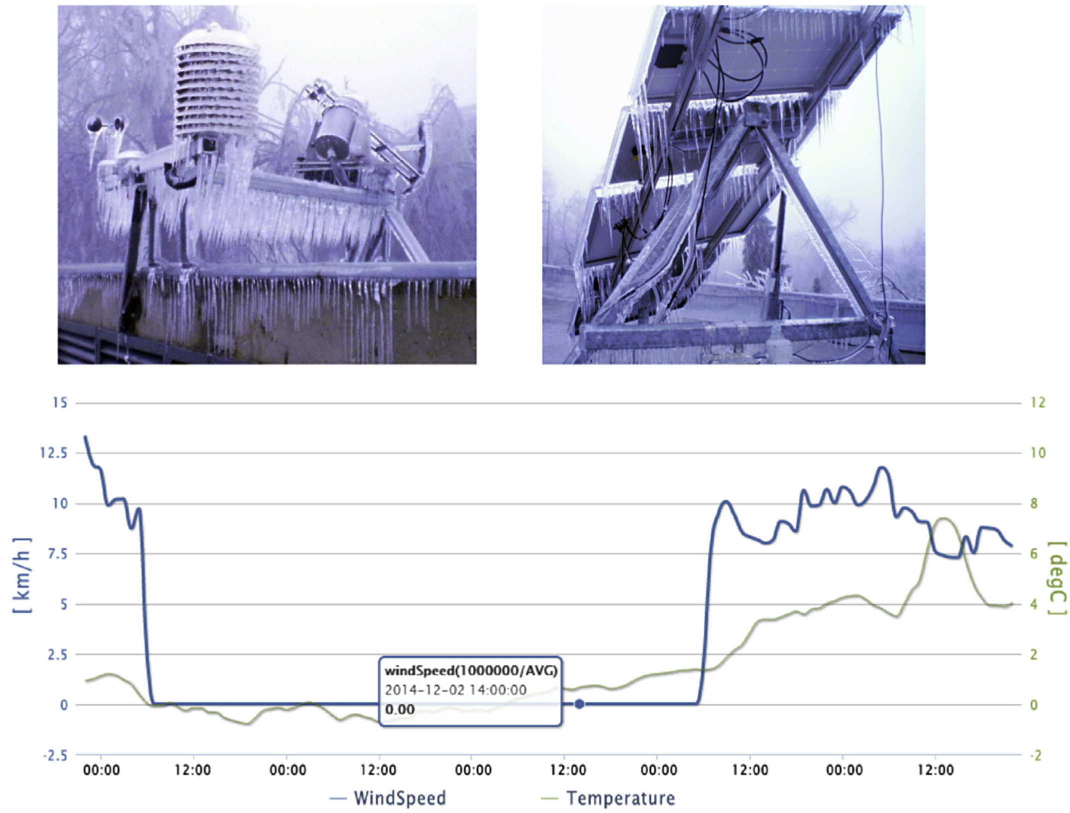

Fig. 6. Local weather station (top left) and PV solar tracker (top right) frozen in ice in the severe winter weather conditions. Wind speed (blue) and temperature (green) data registered by the weather station during the same time period (bottom). False wind speed data was registered due to the frozen anemometer. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

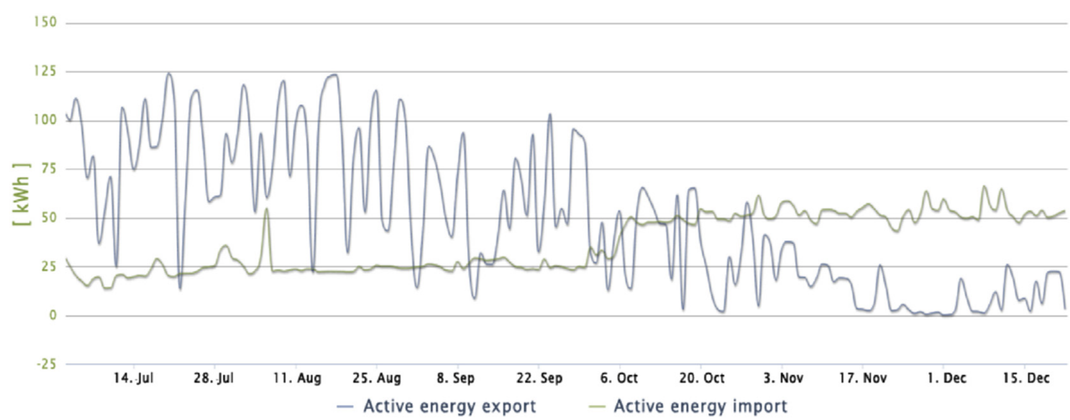

Fig. 7. Comparison of daily energy export (blue) and energy import (green) over a half-a-year horizon. The daily energy balance was typically positive until mid-October. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 losses on the battery. In the case of the 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, significantly increasing the realized profit. 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. Discussion and 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 a computational cloud, ensures the adaptation of the system to the environmental conditions, and

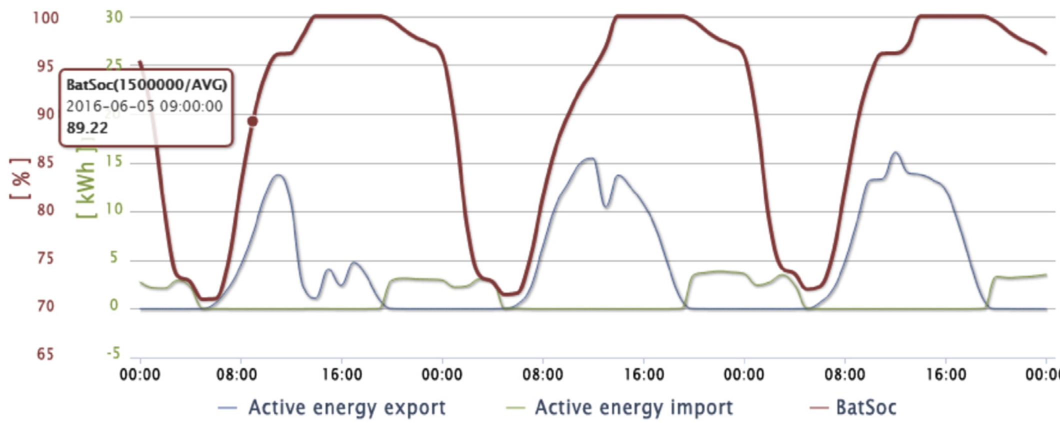

Fig. 8. Typical behavior of the energy system on a summer day: energy export (kW, blue), energy import (kW, green), and battery state-of-charge (%, red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

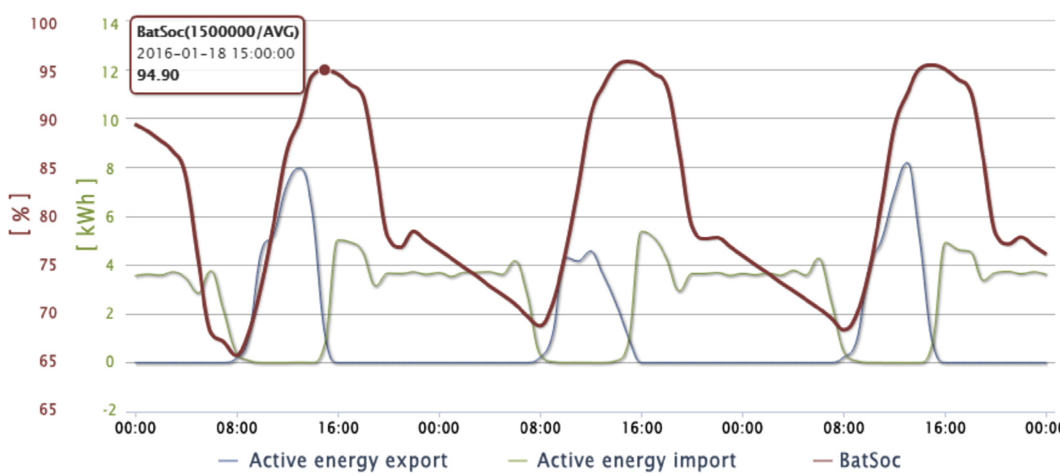

Fig. 9. Typical behavior of the energy system on a winter day: energy export (kW, blue), energy import (kW, green), and battery state-of-charge (%, red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

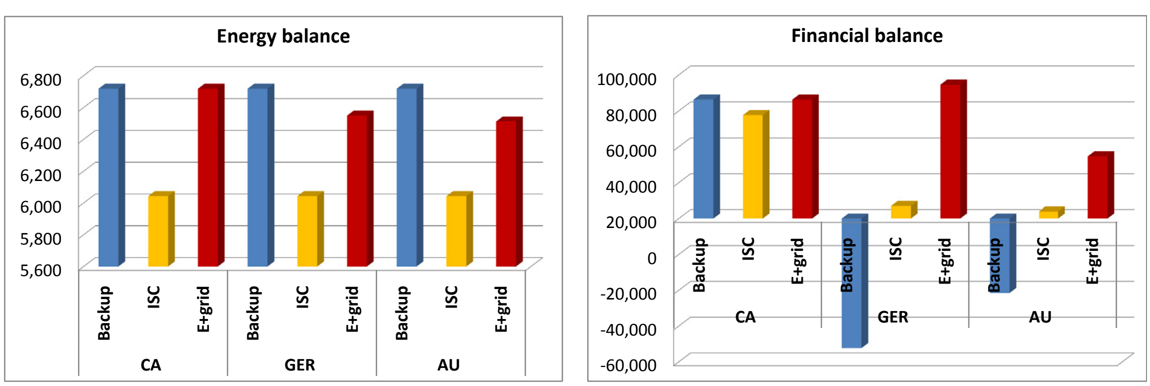

Fig. 10. Energy and financial balance for different tariffs and different energy management strategies.

provides smart city services to its end users. A functionality of crucial significance is the optimization of the energy management of the system, which requires precise forecasts of energy production and consumption, as well as solving the resulting robust optimization problem. While preliminary experiments investigated various advanced 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.

Although this paper focused mostly on the controller, the assessment of the *application potential* of the overall E + grid system is of interest. It must be emphasized that the potential benefits and the desirable configuration of an intelligent lighting system depend heavily on the particular application scenario, with special regard to the traffic and meteorological conditions, as well as to the applicable energy tariff. Adaptive lighting based on motion sensor data can bring considerable reduction of energy consumption in low-traffic environments (55.71% was measured on the particular prototype system), such as rural or residential areas. On the other hand, the reduction can be negligible (or, in theory, even an increased consumption is possible due to the overhead in the equipment) along major roadways with high traffic even at night. It should be noted that the standards applicable to intelligent street lighting vary country by country, and international legislation saw positive changes only recently, see Ref. [41].

A similar *dependence on environmental conditions* holds also for the energetic components of E + grid. The application of batteries is economically viable only in case of a significant variation of the energy tariff over time, or a considerable difference between the feed-in and purchase prices. Alternatively, the island mode capability provided by batteries may also represent a considerable added value in areas exposed to frequent power outages. Moreover, in various applications, such as industrial parks or supermarket parking lots, it can be worthwhile to apply a complex building energy system, rather than an energy system separately for lighting purposes. Therefore, E + grid must be regarded as a modular system, which can be flexibly configured for the specific application case.

A detailed analysis of the *return on investment* (ROI) achievable by E + grid, when retrofitting earlier CMH lamps, is presented in Ref. [42]. The estimated ROI was 4.97 years, assuming a time-of-use energy tariff varying between 0.16 and 0.78 USD/kWh, considering purely the financial aspect. However, additional benefits, such as smart city services, the possibility of remote monitoring and control, or island mode operation must also be emphasized.

A promising direction for *future research and development* is the integration of further sensor types into the luminaries, including air pollution, weather, noise and vibration sensors, as well as a microwave radar for advanced traffic monitoring. The objective is to provide smart city services along the urban road network, such as a publicly available map-based visualization of the current and past levels of different environmental stressors, predictions on future conditions, and alerts when a stressor is likely to reach a specified threshold, e.g., smog or traffic jam alerts. Luminaries are ideal locations for the deployment of a smart city sensor network from the point of view of their strategic location, as well as the availability of power supply and communication infrastructure. However, it should be noted that, according to current standards in continental Europe, the power supply of street lights is cut off during the day. This implies that the daytime operation of the sensor network is manageable only after a change in the standards or by installing batteries in individual luminaries at considerable extra cost.

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References

[1] Boyce PR, Fotios S, Richards M. Road lighting and energy saving. Light Res Technol 2009;41:245–60.
[2] de Almeida A, Santos B, Bertoldi P, Quicheron M. Solid state lighting review—Potential and challenges in Europe. Renew Sustain Energy Rev 2014;34:30–48.
[3] Radulovic D, Skok S, Kirincic V. Energy efficiency public lighting management in the cities. Energy 2011;36:1908–15.
[4] Afshari S, Mishra S, Julius A, Lizarralde F, Wason JD, Wen JT. Modeling and control of color tunable lighting systems. Energy Build 2014;68:242–53.
[5] Haans A, de Kort YAW. Light distribution in dynamic street lighting: two experimental studies on its effects on perceived safety, prospect, concealment, and escape. J Environ Psychol 2012;32:342–52.
[6] Pizzuti S, Annunziato M, Moretti F. Smart street lighting management. Energy Effic 2013;6(3):607–16.
[7] Parise G, Martirano L. Combined electric light and daylight systems ecodesign. IEEE Trans Industry Appl 2013;49(3):1062–70.
[8] Parise G, Martirano L. Daylight impact on energy performance of internal lighting. IEEE Trans Industry Appl 2013;49(1):242–9.
[9] Petrov O, Dimitrov M, Ruseva V. A specialised system for dynamic control and adjustment of the colour temperature and illumination of a lighting system. In: Environment and electrical engineering (eeeic), 2011 10th international Conference on; 2011.
[10] da Fonseca CC, Pantoni RP, Brandao D. Public street lighting remote operation and supervision system. Comput Stand Interfaces 2015;38:25–34.
[11] Rong J. The design of intelligent street lighting control system. In: Construction and urban planning, vol. 671 of advanced Materials research. Trans Tech Publications; 2013. p. 2941–5.
[12] Wojnicki I, Ernst S, Kotulski L, Se,dziwy A. Advanced street lighting control. Expert Syst Appl 2014;41:999–1005.
[13] Shahidehpour M, Bartucci C, Patel N, Hulsebosch T, Burgess P, Buch N. Streetlights are getting smarter: integrating an intelligent communications and control system to the current infrastructure. IEEE Power Energy Mag 2015;13(3):67–80.
[14] Visconti P, Zizzari G, Romanello D, Cavalera G. Electronic board for driving of HID and LED lamps with auxiliary power supply from solar panel and presence detector. In: Environment and electrical engineering (eeeic), 2011 10th international Conference on; 2011. p. 430–3.
[15] Liu G. Sustainable feasibility of solar photovoltaic powered street lighting systems. Electr Power Energy Syst 2014;56:168–74.
[16] Pudjianto D, Djapic P, Dragovic J, Strbac G. Direct costs analysis related to grid impacts of photovoltaics. Tech. rep., Imperial College London; 2013.
[17] Hirth L. The market value of solar power: is photovoltaics cost-competitive? IET Renew Power Gener 2015;9(1):37–45.
[18] Ahmed J, Salam Z. An improved perturb and observe (P&O) maximum power point tracking (MPPT) algorithm for higher efficiency. Appl Energy 2015;150:97–108.
[19] Liu Y, Li M, Ji X, Luo X, Wang M, Zhang Y. A comparative study of the maximum power point tracking methods for PV systems. Energy Convers Manag 2014;85:809–16.
[20] Ishaque K, Salam Z, Lauss G. The performance of perturb and observe and incremental conductance maximum power point tracking method under dynamic weather conditions. Appl Energy 2014;119:228–36.
[21] Barbato A, Capone A, Carello G, Delfanti M, Falabretti D, Merlo M. A framework for home energy management and its experimental validation. Energy Effic 2014;7(6):1013–52.
[22] Macedo MNQ, Galo JJM, de Almeida LAL, de C. Lima AC. Demand side management using artificial neural networks in a smart grid environment. Renew Sustain Energy Rev 2015;41:128–33.
[23] Myers DR. Solar radiation: practical modeling for renewable energy applications. CRC Press; 2013.
[24] Paoli C, Voyant C, Muselli M, Nivet M-L. Forecasting of preprocessed daily solar radiation time series using neural networks. Sol Energy 2010;84(12):2146–60.
[25] Trapero JR, Kourentzes N, Martin A. Short-term solar irradiation forecasting based on dynamic harmonic regression. Energy 2015;84:289–95.
[26] Boland J. Spatial-temporal forecasting of solar radiation. Renew Energy 2015;75:607–16.
[27] Csáji BC, Kovács A, Váncza J. Adaptive aggregated predictions for renewable energy systems. In: Proceedings of the 2014 IEEE symposium on adaptive dynamic programming and reinforcement learning (ADPRL), Orlando, USA; 2014. p. 132–9.
[28] Elsied M, Oukaour A, Gualous H, Hassan R. Energy management and optimization in microgrid system based on green energy. Energy 2015;84:139–51.
[29] Provata E, Kolokotsa D, Papantoniou S, Pietrini M, Giovannelli A, Romiti G. Development of optimization algorithms for the Leaf Community microgrid. Renew Energy 2015;74:782–95.
[30] Clastres C, Ha Pham TT, Wurtz F, Bacha S. Ancillary services and optimal household energy management with photovoltaic production. Energy 2010;35(1):55–64.
[31] Zavala VM, Constantinescu EM, Krause T, Anitescu M. Weather forecast-based optimization of integrated energy systems. Tech. rep., Argonne National Laboratory; 2009.
[32] Constantinescu EM, Zavala VM, Rocklin M, Lee S, Anitescu M. A computational framework for uncertainty quantification and stochastic optimization in unit commitment with wind power generation. IEEE Trans Power Syst 2011;26(1):431–41.

[33] Livengood D, Larson R. The energy box: locally automated optimal control of residential electricity usage. Serv Sci 2009;1(1):1–16.
[34] Niknam T, Azizipanah-Abarghooee R, Narimani MR. An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation. Appl Energy 2012;99:455–70.
[35] Ljung L. System identification: theory for the user. second ed. Prentice-Hall; 1999.
[36] Csáji BC, Kovács A, Váncza J. Prediction and robust control of energy flow in renewable energy systems. In: Proceedings of the 19th IFAC world Congress, Cape town, South Africa; 2014. p. 3663–9.
[37] European Commission. Electromagnetic compatibility (EMC) directive 2004/108/EC. 2004. https://ec.europa.eu/growth/single-market/european-standards/harmonised-standards/electromagnetic-compatibility_en.
[38] Trina Solar Ltd. Sustainability. 2016. http://www.trinasolar.com/au/about-us/Sustainability.html.
[39] Saft Groupe S.A. Environmental responsibility. 2016. http://www.saftbatteries.com/group/sustainability/environnemental-responsibility.
[40] SMA Solar Technology AG. SMA's corporate citizenship. 2016. http://www.sma.de/en/company/corporate-social-responsibility/overview.html.
[41] International Commission on Illumination. Standard CIE 115 – lighting of roads for motor and pedestrian traffic. second ed. 2010.
[42] General Electric. E+grid – network inteconnectivity for a sustainable, better managed future. 2016. http://www.luminspiration.com/i/606957-the-energy-positive-adaptive-outdoor-lighting.