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# Energy Management System for Peak Shaving in an Experimental Microgrid Employing MILP Optimization

Mojtaba Moghimi, Domagoj Leskarac, Chirag Panchal, Junwei Lu, Sascha Stegen
Griffith School of Engineering, Griffith University, Brisbane, QLD 4111, Australia

***Abstract—This paper presents an Energy Management System (EMS) for an experimental commercial Microgrid at Griffith University. Microgrids, as the solution for modern power grids face challenges from both generation and load side. One of the main challenges on the generation side is the intermittency of renewable energies (e.g. PV). Employing Battery Energy Storage (BES) with renewable energies is one of the solutions to integrate more renewable into the power grid. On the load side of Microgrids, the main effort is to minimize the cost by reducing the energy volume and shaving the peak demand. To properly operate the BES with renewable energies and achieve objectives of cost reduction, a Mixed Integer Linear Programming (MILP) optimization is implemented in the EMS. Different sections of EMS are explained and results are presented and analyzed. The results show that the EMS is capable of reducing the energy consumption and shaving the peak by optimally scheduling the BES, charging in off-hours and discharging during peak hours.***

***Index Terms*—Peak shaving, cost minimization, MILP optimization, Microgrids, Battery Energy Storage.**

## I. INTRODUCTION

The increasing penetration of renewable energies raises new challenges to electrical grid at different levels. One of the main challenges is the integration of Renewable Energy Sources (RESs) at the distribution level. To integrate RESs into the distribution networks, Microgrids can play an important role. Microgrids as the building blocks of future grids, provide new solutions to the challenges in distribution networks [1]. Microgrids provide an environment to combine various RESs with Battery Energy Storage Systems (BESS) alongside the Energy Management Systems (EMS) to effectively benefit from capabilities of Smart grids[2]. Solar photovoltaic systems (PV) and wind turbines as the major generation sources in Microgrids, bring intermittency problems to the grid [3]. One of the solutions to overcome intermittency of RESs is to utilize BESS along with a scheduling system that reduces the uncertainties of RESs [4]. To manage the RESs and BESS cooperatively, an EMS is required in the Microgrid [5], which includes a forecasting system, scheduling system, and optimization algorithm.

There are different optimization methods applied in literature to handle the energy management in Microgrids [3]. Authors in [4, 6] have investigated a management system, based on rule-based heuristic and Neural Network approaches. The management system considered in [7-9] applies a Model Predictive Control (MPC) approach to minimize the operational costs in the Microgrid. A Particle Swarm Optimization (PSO) method has been employed by [10, 11] to control the power flow in Microgrids. Stochastic approaches in order to optimize the benefits of energy management of Microgrids have been promising [12-15]. Dynamic programming as the solution for the energy management problem have been presented in the past [16, 17]. Mixed-integer Linear Programming (MILP) has been proposed in some simulation related articles in regards to distribution LV networks [18-21]. Comparing the mentioned optimization methods, MILP takes less computational efforts to solve the problems than dynamic programming or mixed methods like MPC-MILP [21]. On the other hand, the advantage of MILP over heuristic methods is its capability to consider the uncertainty of a system. Furthermore, MILP is suitable for real-time operation whereas PSO and heuristic methods are not intended to optimize the system in this condition [9].

In this paper, an EMS for the experimental Microgrid is proposed and tested and the MILP is applied as the optimization approach of the EMS. Different elements of the EMS such as the forecasting and scheduling system are developed to provide the inputs to the optimization operation. The main objectives of the EMS, peak shaving and cost reduction, are investigated and results have been analyzed. In order to run the EMS, real data is obtained from the experimental Microgrid at Griffith University. The subsequent sections of the paper are organized as follows. Section 2 discusses the methodology employed for the EMS, and section 3 presents an analysis of results. The paper concludes with section 4.

## II. METHODOLOGY

### A. Overview

To run an EMS in a Microgrid, all different elements need to work as one integrated platform. The forecasting system, peak shaving algorithm, scheduling system, and optimization algorithm are the elements of this proposed EMS. The data for PV generation and building load consumption are collected from the experimental Microgrid to operate the EMS. The main purpose of the EMS in this study is to minimize the cost of the Microgrid by optimizing energy storage scheduling and shaving the peak demand.

### *B. Microgrid Energy Management System*

The EMS in the Microgrid has the task of control and management of load and generation while maximizing the benefits via the optimization routine. The EMS consists of different sections such as a forecasting system, peak shaving algorithm, battery-scheduling system and an optimization function. The optimization function in the EMS is designed to reduce the peak demand and minimize the costs. To achieve the objectives of EMS, the forecasting system and the scheduling system provide the required information to the optimization function. In the EMS, scheduling system schedules the charging and discharging of battery and forecasting system predicts the PV and load data for the next day. The Time of Use (TOU) tariff is received from the grid and the compiled information allows the optimization function to determine the decisions to minimize the cost of the Microgrid. The EMS is illustrated in Fig. 1.

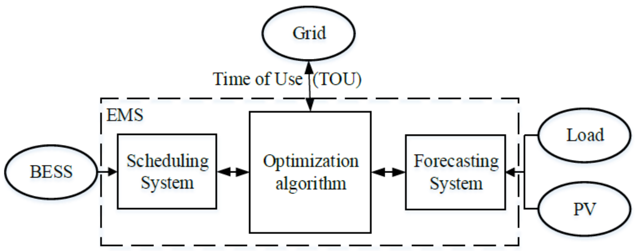


**Fig.1. EMS Structure**

### *C. Forecasting System*

The main purpose of forecasting system is to decrease the level of uncertainty coming from intermittent PV generation as well as load consumption. The forecasting system deploys the predicted information to the optimization system to achieve a more accurate scheduling of BESS. The predicted information is utilized to set the initial schedule for the next day [6, 22]. In this study, the load forecast model is applied to a commercial load profile and solar PV generation data. Base on the model in [23], autoregressive moving average (ARMA) for average load forecast model is shown as:

$$\hat{y}_t = \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \hat{\varepsilon}_t + \varepsilon_t \qquad (1)$$

Where  is load at time t,  is the load forecast,  is the y-intercept and  is the coefficient for time lag i. There are time lags,  is the forecast error and  is the error forecast for time . First, the forecast system predicts the peak load and then forecasts the load profile  $LPF$ of the current day. After predicting the peaks and load profile, the model manipulates the  $LPF$ to adjust it to match the peak load forecast. The final step of the forecast system deals with the error adjustment, i.e. adds the historical error forecast to the load profile forecast.

### *D. Peak Shaving Algorithm*

The EMS is designed to manage the energy in a way that the costs of energy consumption are minimized. There are two major cost contributors in a Microgrid, which are in the form of demand and volume charges. As the utility charges the Microgrids energy consumption relative to the load peak occurring within a given month, a peak shaving algorithm is required to reduce the demand charges. The peak shaving algorithm reduces the peak power based on the proposed algorithm by considering the energy available within the BESS [24]. The modified peak shaving algorithm is summarized in the following main steps as illustrated in Fig. 2:

Step 1: The battery scheduling system sets the discharge level and the available capacity of battery for peak shaving,

Step 2: The battery scheduling system finds the peak load and reduces the peak demand to the discharge level,

Step 3: If there is still energy available to reduce the peak, peak shaving continues to the point that no energy remains for peak demand shaving.

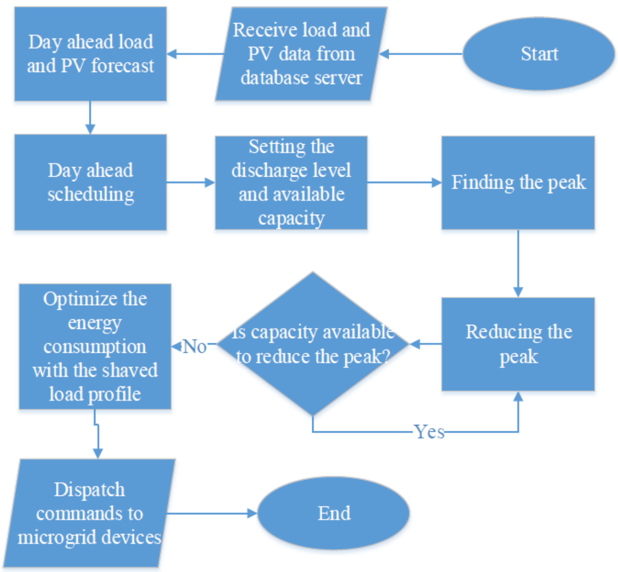


**Fig.2. Scheduling System Including Peak Shaving Algorithm**

### *E. MILP Optimization*

Optimization algorithm, as a part of EMS is employed to minimize the costs of the system and maximize the benefits in the EMS. In other words, EMS utilizes the optimization algorithm to reduce the consumed energy and load demand. To define the optimization algorithm, modeling of system components, an objective function and constraints are required. The main component to model is the BESS and its charging and discharging behavior. The battery energy storage is modeled to charge and discharge as follows:

$$E(t) = E(t-T) + \eta_c P_{BESS,ch}(t-T)T - \frac{P_{BESS,disch}(t-T)}{\eta_d} T \qquad (2)$$

where $E(t)$ is the energy of battery (kWh), $P_{BESS,ch}(t)$ is the charging power of battery (kW), $P_{BESS,disch}(t)$ is the discharging power of battery, $\eta_c$ is the battery charging efficiency, $\eta_d$ is battery discharge efficiency and $T$ is the scheduling time step, which is set to 15 min.

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Volume 7, Issue 7, January 2018

The objective function is chosen in a way that it maximizes the benefits of utilizing the battery and minimizes the costs in the Microgrid. The objective function is expressed in (3):

$$J = \min \sum_{t=t_0}^{t_f} \{C_p P_{grid}(t) + C_{op}(P_{BESS,ch} + P_{BESS,disch}) + C_{peak} P_{peak}\} \quad (3)$$

where $P_{grid}(t)$ is the purchased power from the grid, the $C_p$ is the cost coefficient of power purchased from grid (TOU tariffs), $C_{op}$ is the operation cost of battery for charging and discharging, $P_{peak}(t)$ is the peak power of load in Microgrid, $C_{peak}$ represents the cost coefficient of peak demand, and $t_f$ is the final time of the simulation period which is one day.

There are constraints to meet which are defined according to the requirements of the EMS.

Power balance:

$$P_{Load}(t) = P_{grid}(t) + P_{PV}(t) + P_{BESS,disch}(t) - P_{BESS,ch}(t)$$

BESS constraints:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (5)$$

$$P_{BESS,ch}(t) - P_{ch,max}\beta \leq 0 \quad (6)$$

$$P_{BESS,disch}(t) + P_{disch,max}\beta \leq P_{disch,max} \quad (7)$$

$$E_{BESS,min} \leq E(t) \leq E_{BESS,max} \quad (8)$$

$$0 \leq P_{BESS,ch}(t) \leq P_{ch,max} \quad (9)$$

$$0 \leq P_{BESS,disch}(t) \leq P_{disch,max} \quad (10)$$

Peak shaving:

$$0 \leq P_{grid}(t) \leq P_{grid,max} \quad (11)$$

Where β is the binary decision variable to charge or discharge the battery. Because of β in the objective function, the optimization problem turns into an MILP problem.

## III. RESULTS

The EMS performance is tested on an experimental Microgrid with commercial load characteristics. The data is collected from the experimental Microgrid located at Griffith University, Nathan campus. The relevant TOU tariffs for N44 are presented in Table I.

**Table I: Time of Use (TOU) tariffs**

| **TOU tariffs (Volume)** | **Price** | **Time** |
|---|---|---|
| Peak | 9.7 c/kWh | 7 am – 8 pm |
| Off-peak | 6.6 c/kWh | 8 pm – 7 am |
| **TOU tariffs (Demand)** | **Price** | **Time** |
| Peak | 24.14 $/kW | Whole day |

The experimental Microgrid at Griffith University is designed and implemented to test different RESs, power conversion components, and algorithms and compare their performance. The distributed generation in the Microgrid is in form of solar PV arrays with the total capacity of 16 kW power generation. The solar cells, via DC/DC converters, are connected to a DC bus, which connects the DC components to the Statcom converter and energy storage. The energy storage in the Microgrid is in the form of 80 kWh of Lithium-ion batteries.

A 30-kVA three-phase and three 10kVA single-phase Statcoms are employed to connect the DC bus to the AC bus alongside adding voltage and power control capabilities to the Microgrid. The Microgrid load is the university building with commercial load characteristics [25]. In this commercial load, the peak occurs during midday, which is compatible with a standard PV generation pattern. For the optimization, CPLEX optimization solver is employed and MATLAB software is utilized to simulate the Microgrid and apply the real data of building and solar PV to the EMS to minimize the energy cost. The structure of experimental Microgrid is shown in Fig. 3.

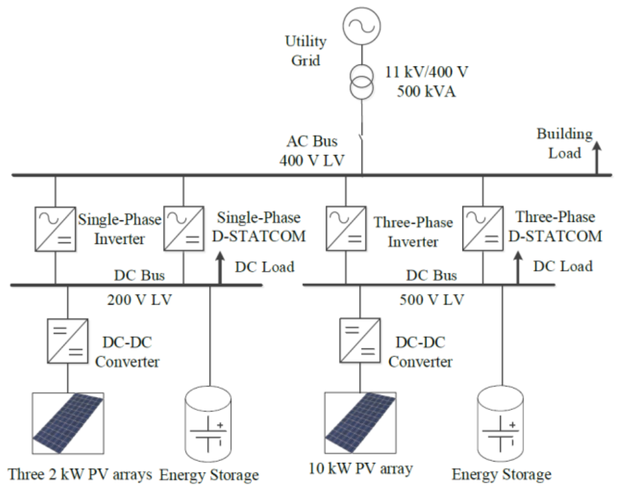


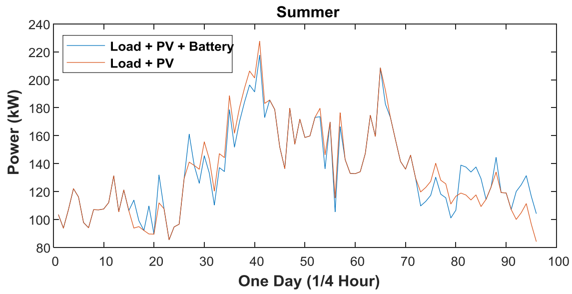

**Fig.3. Experimental Microgrid Structure**

### A. *EMS Performance without Peak Shaving Algorithm*

#### 1) *Energy Reduction*

The EMS performance is examined concentrating on the reduction of energy purchase from grid via battery scheduling. In this scenario, the battery is scheduled to charge at off-peak hours and discharge during peak hours regardless of the peak values within the one-day cycle.

A normal day in summer (December) and winter (July) 2016 is chosen to test the performance of EMS while peak shaving algorithm is not applied. The scheduling system receives the building load data, the information from the battery, and the data from the forecasting system and schedules the battery charging and discharging to minimize the purchased energy from the grid. The MILP optimization system is applied to minimize the costs. To run the MILP optimizer, the code is written in MATLAB and program uses CPLEX software to solve the problem.



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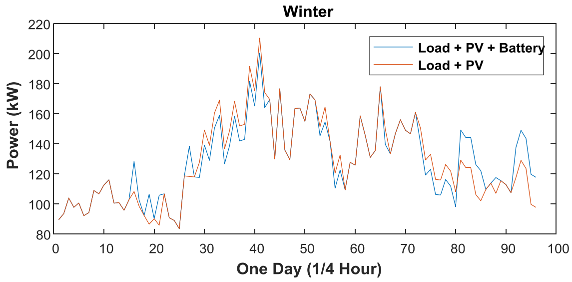



**Fig.4. Energy Reduction Employing MILP Optimization Routine**

As seen in Fig. 4, the system is charging and discharging according to TOU the tariffs table, Table 1. In other words, scheduling system charges the battery early in the morning and late in the afternoon, which are off peak hours and discharges the battery during peak hours. The total saved value by minimizing the energy is $ 272.04 within one-day cycle. As the tariffs are the same in summer and winter, the savings would be similar throughout the whole year, depending on solar PV production and load characteristics. If there were different tariffs for different seasons, then there would have been specific scheduling system for each season.

*2) Battery Performance*

The performance of the battery is indicated in Fig. 5. The total available energy of the battery is 70 kWh and initial energy of the battery is set to 50 kWh. At the end of the one-day cycle, the battery is charged to the same level of initial energy.

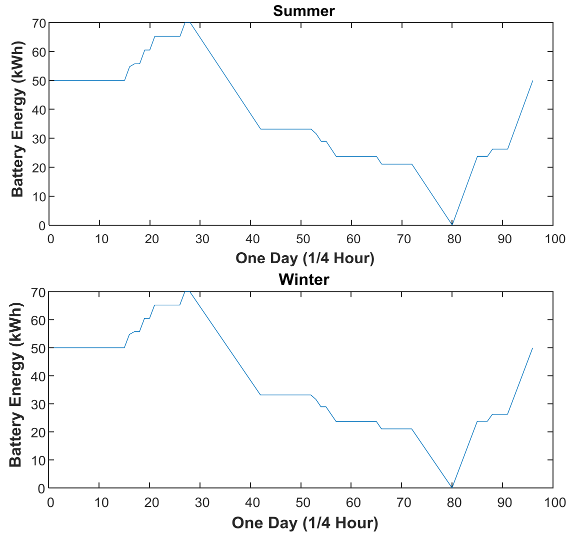



**Fig.5. BESS Charge/Discharge in One-day Cycle**

As it is illustrated in Fig. 5, the MILP optimizer defines the discharge routine. The point here is that peak shaving is not considered, so the peaks are not necessarily reduced but just the total energy purchased from the grid is reduced employing the energy storage.

### *B. EMS Performance with Peak Shaving Algorithm*

*1) Demand Reduction*

A major contributor to cost of a commercial Microgrid is from the charges for peak power. Thus, a primary objective of the EMS is to reduce the peak demand, which results in fewer demand charges from the grid. The demand charges are set as the monthly highest peak of the day. In order to test the extreme performance of the developed EMS in regards to its peak shaving algorithm, the peak day of summer and winter 2016 is selected. The scheduling system applies the peak shaving routine to reduce the peak, followed by reducing the energy consumption with the remaining energy in the battery.

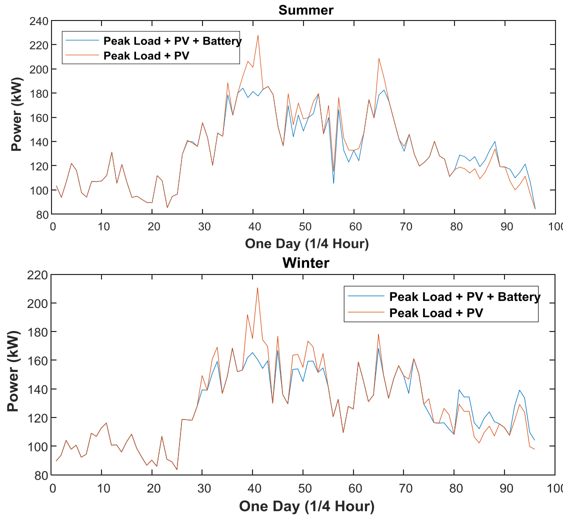


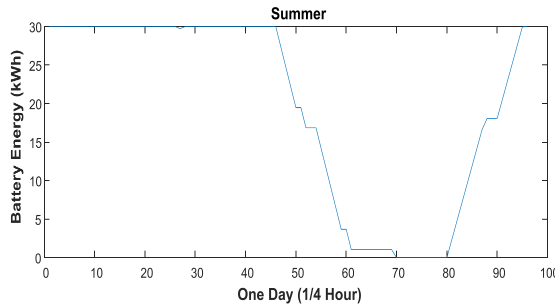

**Fig.6. EMS Employing MILP Optimization Routine with Peak Shaving Algorithm**

Consequently, seen in Fig. 6, the overall peak demand on the supplier grid is reduced and thus the overall energy cost are abridged to $ 4315.64 in summer and $ 4412.43 in winter.

*2) Battery Performance*

The performance of the battery is illustrated in Fig. 7. A percentage of the energy in the battery is specified to the peak shaving and the rest to energy reduction. The reason for not specifying all the available energy in the battery to the peak shaving is that the EMS would not be functional in case peak does not appear. Therefore, there should always be a percentage specified to the energy base line usage reduction. As the utility charges for peak demand is much higher than charges for energy (Table I), the majority of BESS is specified to the peak shaving. In this study, 60 % of available energy in BESS is specified to peak shaving and 40 % to the energy reduction.

As it is shown in Fig. 7, after achieving peak shaving, the rest of the remaining energy in the BESS is used to reduce the energy charges of the Microgrid. The MILP optimizer discharges the battery to reduce the load purchased from the grid and charges the battery when the prices are low in order to supply the initial energy of the battery for the next cycle.



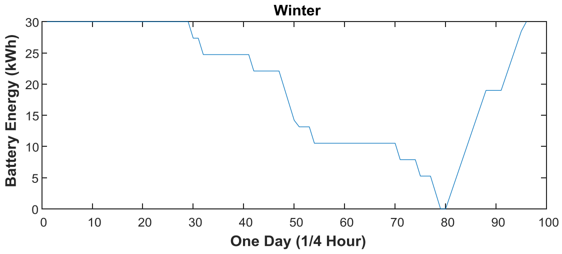



**Fig.7. BESS Charge/Discharge after Peak Shaving**

## IV. CONCLUSION

In this paper, the performance of an EMS employing MILP optimization in an experimental commercial Microgrid is investigated. The peak shaving algorithm is applied to the system and results are analyzed. The MILP optimization algorithm is utilized to minimize the two main sources of costs in the Microgrid. As Microgrids are turning into a major part of the modern power grid, the role of the control system and energy management of these systems is more critical. By employing EMS in conjunction with BESS in Microgrids containing RES, a substantial benefit to the load profile of a commercial building can be achieved. The results show a substantial improvement to the energy profile of the building, optimized to minimize costs via the tariff system. Further work will include achieving a semi-dynamic usage between peak shaving and base line energy usage reduction of the battery storage.

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## AUTHOR BIOGRAPHY

**Mojtaba Moghimi** (IEEE S'15) received the B.Sc. and M.Sc. degrees in electrical engineering from University of Tehran, Iran and RWTH Aachen University, Germany, in 2011 and 2014, respectively. He is currently pursuing his Ph.D. in electrical engineering at Griffith University, Australia.

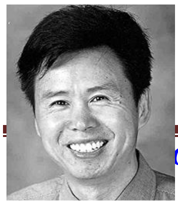
His research interests include scheduling of energy systems, control, management and optimization of energy management systems in Microgrids.

**Domagoj Leskarac** (IEEE S'13) received a BEng with First Class Honors in sustainable energy systems from Griffith University, Australia in 2012. He is currently undertaking Ph.D. studies in power and energy systems engineering, also at Griffith University, Australia.

His research interests include grid integration of energy storage, renewable energy sources, static-synchronous compensators and plug-in electric vehicles along with peak demand management on distribution networks and the Microgrid concept.

**Chirag Panchal** (IEEE S'13) received the B.E. and M.E. degree in Electronics and Communication engineering from Bhavnagar University, India and Griffith University, Australia, in 2006 and 2009, respectively. He is currently pursuing the Ph.D. in electrical & electronics engineering at Griffith University, Australia.

His research interests include wireless charging system for electric vehicles (EVs), EMC compatibility, Magnetic components design and Vehicle to Grid (V2G).



**Prof. Junwei Lu** (IEEE Senior Member and ICS Board Member) received the degree in electrical engineering from Xian Jiaotong University, China and the M.Eng. Degree in electronic and computer engineering from the National Toyama University, Japan, the Ph.D. degree in electrical and computer engineering from the National Kanazawa University, Japan, in 1991.

From 1976 to 1984, he worked with the electrical power industry (now is called State Grid) in China, where he was involved in the various national research projects for electrical power industry. In 1985, his academic study and research was in the area of computational electromagnetics at the laboratory of electrical communication engineering at Toyama University, Japan. In 1988, he worked on the applied computational electromagnetics and was involved in the development of magnetic devices with the Laboratory of Electrical Energy Conversion, Kanazawa University. He joined the School of Microelectronic Engineering, Griffith University, Brisbane, Australia, in 1992, and moved to Gold Coast campus to establish Electrical and Electronic Engineering as a Foundation Professor since 2011. His fields of interest are computational electromagnetics, EMC computer modeling and simulation, smart mobile terminal antennas and RF/MW devices and circuits, and high-frequency magnetics for power electronics and renewable energy system. His current research interests include smart transformer and V2G with built-in statcom inverter, smart hybrid AC/DC Microgrid. He has published over 250 journal and conference papers and two coauthored books in the area of EMC and V2G, and holds over 10 international patents related smart antennas and high frequency transformers.

**Sascha Stegen** studied electrical engineering at the University of Applied Sciences Düsseldorf, Germany and at the University of Wuppertal in Germany. He received his PhD in electrical Engineering from Griffith University in Brisbane, Australia in 2012. Since 2012, he has been a Lecturer at the Griffith School of Engineering for electronic and energy. Furthermore, he is research theme leader, IEEE board member QLD section as well as Author of over twenty peer-reviewed publications. His major research interests include renewable energy sources, Smart-and Micro-grids, simulation techniques in regards to power related applications, e-mobility, energy storage, Distribution and transmission.