Optimal and Almost Optimal Strategies for Rational Agents in a Smart Grid

Alexander Wallis
Faculty of Interdisciplinary Studies
University of Applied Sciences Landshut
Landshut, Germany
email: alexander.wallis@haw-landshut.de

Sascha Hauke
Faculty of Interdisciplinary Studies
University of Applied Sciences Landshut
Landshut, Germany
email: sascha.hauke@haw-landshut.de

Konstantin Ziegler
Faculty of Interdisciplinary Studies
University of Applied Sciences Landshut
Landshut, Germany
email: konstantin.ziegler@haw-landshut.de

***Abstract*—The rising tide of single household prosumers leads to a paradigm shift for power grid operators. Those prosumers are characterized by their consumption, production and storage capabilities. Via buying and selling electricity, every prosumer becomes a rational agent in the smart grid, trying to maximize one's utility. The optimal short- and long-term behavior can now be analyzed using methods of game theory. In this paper, we present a game theoretic model for smart grids with rational prosumers. Using real-world data, we equipped every agent with a growing class of strategies and then compute the resulting Nash equilibria. The differences in prosumers' utility between optimal and almost optimal strategy selection is given as the *price if not knowing the future*.**

Keywords*—smart grid; game theory; nash equilibrium; prosumer; battery energy storage system.

NOMENCLATURE

$\mathcal{D}_{\mathrm{C}}^{(a)}$	Daily consumption of agent a.
$\mathcal{D}_{\mathrm{P}}^{(a)}$	Daily production of agent a.
$\ell_{\mathrm{C},t}$	Consumption of agent a at time t.
$\ell_{\mathrm{M},t}$	Market power of agent a at time t.
$\ell_{\mathrm{P},t}$	Production of agent a at time t.
$\ell_{\mathrm{R},t}$	Residual of agent a at time t.
$\mathrm{M}_{\max}$	Maximum price for buying electricity.
M_{HT}	Time interval for high-tariff.
M_{LT}	Time interval for low-tariff.
$m_{\mathrm{buy},t}$	Price for buying at t.
$m_{\mathrm{sell},t}$	Price for selling at t.
$\mathrm{P}_{\max}$	Maximal production power.
$\mathcal{R}_t$	Sum of all agents' residual loads.
$\mathrm{SOC}_{\max}$	Maximal storage capacity.
$\mathrm{S}_{\mathrm{charge}}$	Maximal storage charging power.
$\mathrm{S}_{\mathrm{discharge}}$	Maximal storage discharging power.
$\pi_{\sigma}^{(a)}$	Payoff of agent a for strategy σ.

I. INTRODUCTION

Stable and reliable electricity supply is mandatory for our everyday life. Over the past 100 years, our power grid has been steadily evolving to ensure this supply. Now, with the increasing amounts of electric vehicles and the simultaneous shift of generating process from fossil energy resources to Renewable Energy Resources (RESs), the power grid is facing a Herculean task to maintain this function. The ongoing integration of Distributed Renewable Energy Resourcess (DERs) into the existing power grid, due to its highly volatile behavior, leads to an increase of complexity for network management tasks in terms of stability and security. But not only the power grid is evolving, consumer equipped with production capabilities, e.g., photovoltaic, wind turbine, or diesel generators, are now producer at the same time–so-called *prosumers*.

In [1], we define prosumers, which are capable of producing and storing electricity, as atomic entities in smart holonic micro grids. To achieve stable Smart Grid (SG) operation, especially on low-voltage level, accurate forecasting is necessary to handle the volatile nature of RESs. The increasing capacitiy of battery energy storage systems with the simultaneous decreasing costs, lead to more usage in households may they be residential or commercial. Unfortunately, this introduce more unpredictability into the power grid because every prosumer now has more possible decisions to make. To handle this kind of uncertainty, the study of complex interactions between independent rational actors is needed, which falls in the domain of Game Theory (GT). Therefore, we propose a game of rational prosumers and different kind of electricity markets and give the following contributions:

1) Model for SGs with different kinds of actors represented as rational agents under varying market conditions.
2) Determination of a stable system state by calculating the Nash equilibrium for a finite set of defined strategies.
3) Implementation on a real-world data set and evaluating the game results.

The remaining paper is structured in the following manner. Section II gives an overview of existing research approaches for strategic operation of Battery Energy Storage Systems (BESSs). In Section III, we give a detailed description of the developed model, the agent representation, the different electricity markets, as well as explicit strategy implementations. Afterwards, a game is run on a real-world data set and the system equilibrium is calculated in Section IV. We summarize and discuss the results and conclude with possible improvements and ideas for future works.

II. RELATED WORK

Ensuing from our previous definition of atomic units in a holonic SG, and the need for accurate forecasting models and strategic energy storage operation, we focus on the latter in this paper [1]. Therefore, this section provides an overview of the existing research approaches and their impact on our work. For a clearer description, we break them down into the two main

 ISBN: 978-1-61208-855-6

areas of BESS management in general and GT approaches in particular.

A. BESS Management

The efficient integration of BESSs into the existing power grid is a major research topic [2] [3]. The majority of them focus on solving optimization problems like sizing [4] [5] or scheduling [6]–[9]. The authors in [10] propose a optimization model for microgrids with generation capacities, e.g., diesel generator, wind turbine, and one scenario with additional battery storages. Their results show that BESS can assist microgrids in the power generation sector. In [11], an genetic algorithm (NSGA-II) for multi-objective optimization in terms of minimize generation costs and battery life loss is presented. Simulated on two scenarios, abundant and short renewable resources, their method reduces both objectives. One major application of BESSs is peak shaving to reduce peak demand on a power system. In [12] two optimization methods in combination with load forecasting are presented. Furthermore, the authors in [13] also take different electricity tariffs into account to shave and shift peak consumption and conclude that strategic operation can lead to reasonable pay-back investment times.

B. Game Theoretic Approach

One problem of modeling and simulating strategic behavior of an arbitrary number of actors or players within a SG, is the rational thinking and the variable goals of each individual. To overcome this problem, game theoretic approaches gain more attention in recent years [14]–[16]. Basically, GT approaches can be divided into cooperative [17] and non-cooperative games. In [18], the authors propose a cooperative game for sharing storage capacities and the results show effective influence on the power grid. Furthermore, a distributed solution for coalition formation to reduce households' electricity costs within a SG is offered in [19]. Similar, consumers are trading energy with each other to minimize their own electricity bill formulated as a centralized optimization problem in [20]. Another application is the examination of trading mechanism in energy markets. In [21], a detailed review of GT methods for local energy trading scenarios is given.

The previous mentioned related work influence this paper, specifically, led to the consideration of modeling prosumer as rational agents with strategic behavior. Within the scope of this paper, every rational agent tries to maximize their own payoff and never negotiate with other participants in the SG.

III. Model Description

In this paper, we implement prosumer as rational agents within a multi-agent system. To analyze different strategies for buying and selling electricity and also–if available–for charging and dischargin battery storage systems and their respective outcome under varying market conditions, a game theoretic approach is presented. Therefore, we introduce in this section a game (Section III-A) of an arbitrary number of agents (Section III-B) and one specific electricity market (Section III-C). Following this, we define a set of strategies agents can choose from and the selected utility function to evaluate their respective outcome (Section III-D).

A. Game

We propose a game $\mathcal{G}$ to analyze the interactions between a set of players modeled as rational agents and a specific electricity market: $\mathcal{G} = (\mathcal{A}, \mathcal{M}, \mathcal{S})$. Where every agent $a \in \mathcal{A}$ is able to buy and sell electricity from respectively to the market $\mathcal{M}$ based on their chosen strategy $\sigma \in \mathcal{S}$. Figure 1 depicts the information flow between agents and the electricity market. In every time interval $t \in T$, the market sends the price for buying and selling $1\,\mathrm{kW\,h}$ electricity to every agent a within the game. It can be also seen from Figure 1, that no

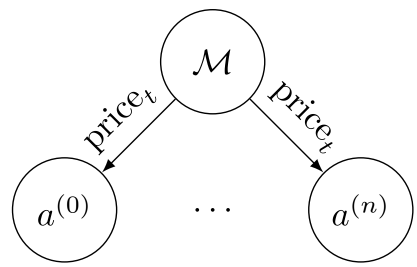

Figure 1. Every agent $a \in \mathcal{A}$ within the game is connected to the same market $\mathcal{M}$ and receive the identical price in every time step t

communication between the agents is allowed. This feature is out of scope of this paper but will be implemented in future work to enable coalition formations between agents. Besides buying and selling electricity, a prosumer+ is also able to charge and discharge their storage unit. To handle this additional behavior, a definition and classification of the used agents based on their available actions is given in the following.

B. Agent

The goal of this paper is to find the optimal battery charge and discharge strategy based on each individual prosumer's rational utilization. Therefore, every player $a \in \mathcal{A}$ in our game is represented by an rational agent. Agents within our game can be classified into consumer, producer, prosumer with or whitout storage. Depending on this classification, the agents have different properties shown in Figure 2. From Figure 2 can be seen, that a prosumer$^+$agent has a consumption, production, and storage. Furthermore, every agent is connected to the power grid. The daily consumption $\mathcal{D}_{\mathrm{C}}^{(a)}$ of an agent a is fixed in our game and is given by the sum of the consumption in every time interval $\ell_{C,t}^{(a)}$. Similar, the daily production $\mathcal{D}_{\mathrm{P}}^{(a)}$ is the sum of the electricity produced $\ell_{\mathrm{P},t}^{(a)}$ in every time interval

$$\mathcal{D}_{\mathrm{C}}^{(a)} = \sum_{t \in T} \ell_{\mathrm{C},t}^{(a)} \tag{1}$$

$$\mathcal{D}_{\mathrm{P}}^{(a)} = \sum_{t \in T} \ell_{\mathrm{P},t}^{(a)}. \tag{2}$$

For the remaining paper, electricity produced by the production unit or discharged from the storage device is represented by

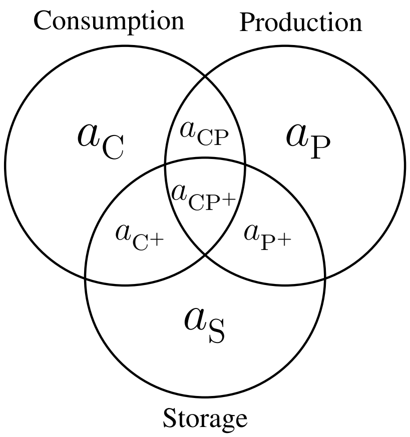

Figure 2. An agent a is composed of at least one of the following properties: Consumption, Production, or Storage

negative values by convention. Therefore, the provided power in kW per time interval by an agent's production unit with maximum power $\mathrm{P}_{\max}$ is given by

$$-\mathrm{P}^{(a)}_{\max} \leq \ell^{(a)}_{\mathrm{P,t}} \leq 0. \tag{3}$$

Additionally to the charge and discharge power constraint in (4), the storage unit has also a maximum capacity $\mathrm{SOC}_{\max}$ in $\mathrm{kW\,h}$ given in (5). Taken all together, this leads to the state-of-charge calculation of the storage in time interval t in (6).

$$\ell^{(a)}_{\mathrm{discharge},t} \leq \ell^{(a)}_{\mathrm{S},t} \leq \ell^{(a)}_{\mathrm{charge},t} \tag{4}$$

$$0 \leq \mathrm{SOC}^{(a)}_{t} \leq \mathrm{SOC}^{(a)}_{\max} \tag{5}$$

$$\mathrm{SOC}^{(a)}_{t} = \mathrm{SOC}^{(a)}_{t-1} + (\ell^{(a)}_{\mathrm{S},t} \times \frac{24\,\mathrm{h}}{T}) \tag{6}$$

The initial daily SOC for every agent is set to the maximum capacity $\mathrm{SOC}^{(a)}_{0} = \mathrm{SOC}^{(a)}_{\max}$. We are fully aware of inverter efficiencies at production and storage units, but for convenience and to keep our model simple, we exclude these factors for the scope of the presented work. Since we are focusing on short-term analysis, battery aging due to calendaric or chemical effects are ignored as well. For long-term investing and operating optimization, these factors will be given thorough considerations in future work. Taken all together leads to the main constraint in (7). In every time interval t, an agent's consumption needs to be covered either by produced electricity, discharged storage, or bought from the connected market.

$$\ell^{(a)}_{\mathrm{C},t} + \ell^{(a)}_{\mathrm{P},t} + \ell^{(a)}_{\mathrm{S},t} + \ell^{(a)}_{\mathrm{M},t} = 0 \tag{7}$$

To ensure this constraint, we assume that the power provided by the market/grid is not restricted to any boundaries.

C. Electricity Market

Every prosumer^{+}within our game is connected to one shared market $\mathcal{M}$. In this paper, three different types of market structures are used for our model implementation: (I) *Time-of-Use (TOU)*, (II) *Demand-Offer (DO)*, and (III) *Hybrid*. The first market $\mathcal{M}_{\mathrm{TOU}}$ returns the price of buying and selling electricity based on the time of day divided into low-tariff (nighttime) and high-tariff (daytime) givin in (9). In contrast, the second market type $\mathcal{M}_{\mathrm{DO}}$ calculates the price dynamically on the basis of the residual loads (see 8) of every participant in (10). The third market $\mathcal{M}_{\mathrm{Hybrid}}$ is a combination of the other two and calculates the price dynamically within the high-tariff rate.

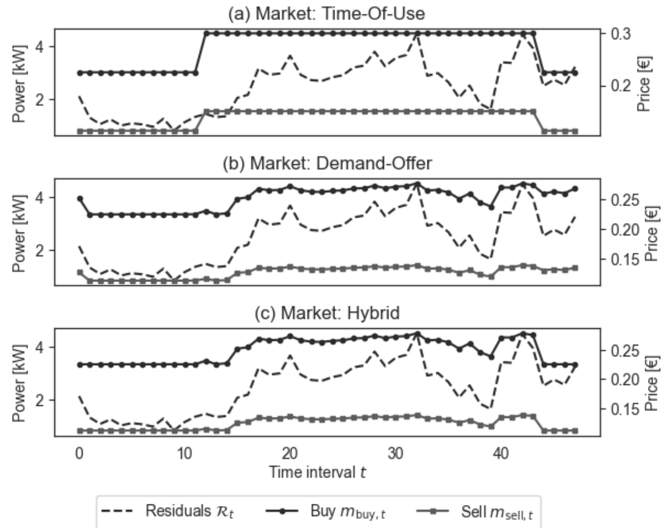

Figure 3. Available different market structures: (a) Time-Of-Use, (b) Demand-Offer, and (c) Hybrid

$$\mathcal{R}_t = \sum_{a}^{\mathcal{A}} \ell^{(a)}_{\mathrm{R},t} \tag{8}$$

$$m_{\mathrm{buy},t} = \begin{cases} \mathrm{M}_{\max}, & \text{if } t \in \mathrm{M}_{\mathrm{HT}} \\ k \times \mathrm{M}_{\max}, & \text{otherwise} \end{cases} \tag{9}$$

$$m_{\mathrm{buy},t} = \mathrm{M}_{\max} - \frac{j}{\mathcal{R}_t}, \quad \text{for } \mathcal{R}_t \neq 0 \tag{10}$$

$$m_{\mathrm{buy},t} = \begin{cases} k \times \mathrm{M}_{\max}, & \text{if } t \in \mathrm{M}_{\mathrm{LT}} \\ \mathrm{M}_{\max} - \frac{j}{\mathcal{R}_t}, & \text{otherwise} \end{cases} \tag{11}$$

The price for selling electricity to the market is tied to the one for buying $m_{\mathrm{sell,t}} = m_{\mathrm{buy},t} \times l$ with $l \in]0,1[$, this ensures that rational prosumers prefer self-consumption over selling produced electricity. An example of the daily price calculations for the different markets based on the same residual load is shown in Figure 3.

D. Strategy

In our game, every agent can select a strategy $\sigma \in \mathcal{S}$. We define a strategy σ as a sequence of actions for an agent in every time interval $t \in T$. An action α is a tuple of storage and market operation. Basically, these actions are power values for $\ell^{(a)}_{\mathrm{S},t}$ and $\ell^{(a)}_{\mathrm{M},t}$ after strategy execution. Depending on the agent type and their corresponding properties and actions (see

TABLE I
AGENT CLASSIFICATION AND THEIR ACTIONS

Agent	Property			Action	
	Consumption	Production	Storage	Market	Storage
a_{C}	√	×	×	√	×
$a_{\mathrm{C+}}$	√	×	√	√	√
a_{P}	×	√	×	√	×
$a_{\mathrm{P+}}$	×	√	√	√	√
a_{S}	×	×	√	√	√
a_{CP}	√	√	×	√	×
$a_{\mathrm{CP+}}$	√	√	√	√	√

Table I), unable actions are set to zero. In the following, two concrete strategy definitions are given: (a) SPILLOVER and (b) PRICEDEPENDING(τ)

a) Spillover: This strategy prioritize the storage utilization over selling overproduced electricity. In every time step t, the difference between production and consumption is calculated. This strategy is described in detail in Algorithm 1.

Algorithm 1 Strategy definition for SPILLOVER

Input: Agent a, time step t
Output: Market power $\ell^{(a)}_{\mathrm{M},t}$, Storage power $\ell^{(a)}_{\mathrm{S},t}$

procedure SPILLOVER(Agent a, t)
  $r \leftarrow \ell^{(a)}_{\mathrm{R},t}$
  $s \leftarrow \mathrm{SOC}^{(a)}_{\mathrm{t}}$
  $\ell^{(a)}_{\mathrm{M},t}, \ell^{(a)}_{\mathrm{S},t} \leftarrow 0$
  if $r < 0$ **then**
    $\ell^{(a)}_{\mathrm{S},t} \leftarrow$ CHARGE(s, r) ▷ From Equations (4-6)
    $\ell^{(a)}_{\mathrm{M},t} \leftarrow r - \ell^{(a)}_{\mathrm{S},t}$
  else
    $\ell^{(a)}_{\mathrm{S},t} \leftarrow$ DISCHARGE(s, r) ▷ From Equations (4-6)
    $\ell^{(a)}_{\mathrm{M},t} \leftarrow r - \ell^{(a)}_{\mathrm{S},t}$
  end if
  return $\ell^{(a)}_{\mathrm{S},t}, \ell^{(a)}_{\mathrm{M},t}$
end procedure

It can be seen that the strategy returns values for market and storage power. If an agent doesn't utilize these properties (see Figure I), the strategy return zero for that value.

b) PriceDepending: In contrast to *Spillover*, this strategy focuses the price given by the market. An agent always buys from the market if the price is less than a percentage of the maximum market price $\mathrm{M}_{\max}$ defined by an individual threshold $\tau \in [0, 100]$. Only if this is not the case, an agent charges its storage system at overproduction $\ell^{(a)}_{\mathrm{R},t} < 0$ and discharges it to cover consumption.

To evaluate the different strategies, we define the following utility function

$$\pi^{(a)}_{\sigma} = \sum_t^T (\ell^{(a)}_{\mathrm{M},t} \times c_t)$$
$$c_t = \begin{cases} m_{\mathrm{buy},t}, & \text{if } \ell^{(a)}_{\mathrm{M},t} \leq 0 \\ m_{\mathrm{sell},t}, & \text{otherwise.} \end{cases} \tag{12}$$

Algorithm 2 Strategy definition for PRICEDEPENDING

Input: Agent a, time step t, threshold τ
Output: Market power $\ell^{(a)}_{\mathrm{M},t}$, Storage power $\ell^{(a)}_{\mathrm{S},t}$

procedure PRICEDEPENDING(a, t, τ)
  $r \leftarrow \ell^{(a)}_{\mathrm{R},t}$
  $s \leftarrow \mathrm{SOC}^{(a)}_{\mathrm{t}}$
  $\ell^{(a)}_{\mathrm{M},t}, \ell^{(a)}_{\mathrm{S},t} \leftarrow 0$
  if $m_{\mathrm{buy},t} < \mathrm{M}_{\max} \times \frac{\tau}{100}$ **then**
    $\ell^{(a)}_{\mathrm{M},t} \leftarrow r$
  else
    if $r < 0$ **then**
      $\ell^{(a)}_{\mathrm{S},t} \leftarrow$ CHARGE(s, r) ▷ From Equations (4-6)
      $\ell^{(a)}_{\mathrm{M},t} \leftarrow r - \ell^{(a)}_{\mathrm{S},t}$
    else
      $\ell^{(a)}_{\mathrm{S},t} \leftarrow$ DISCHARGE(s, r) ▷ Equations (4-6)
      $\ell^{(a)}_{\mathrm{M},t} \leftarrow r - \ell^{(a)}_{\mathrm{S},t}$
    end if
  end if
  return $\ell^{(a)}_{\mathrm{S},t}, \ell^{(a)}_{\mathrm{M},t}$
end procedure

An agents' payoff $\pi^{(a)}$ for a specific strategy σ is the sum of money paid or earn in every time step t in (12). Since electricity purchase from the market results in negative costs (see (7)) and vise-versa, the payoff is denoted as the inverse costs. Therefore, a rational agent tries to maximize their resulting payoff. Taken all the previous definitions together, we run in the following a concrete game with specified settings and evaluate the corresponding results.

IV. EVALUATION

After the formal description of the used game model, we evaluate our defined strategies with real-world data described in Section IV-A. Therefore, we present an algorithm for calculating the optimal state for our game–the Nash equilibrium (Section IV-B). After defining a concrete game setup, we present the agents' payoffs under the three previous defined types of electricity markets in Section IV-C.

A. Data Set

For our game implementation, we are using a real-world data set recorded by AUSGRID in the New South Wales (NSW) region in Australia [22]. As part of the *Solar Bonus Scheme* program introduced by the Australian government, electricity consumption and photovoltaic production data from a total of 300 randomly selected residential households were recorded. Altogether, the half hour resolution of the meter data over a time period of three years from 1st July 2010 till 30 June 2013 results in more than 50.000 data points.

B. Nash Equilibrium

To determine the optimal strategy for every agent, we first calculate the Nash equilibrium for the proposed game. In game theoretic approaches the Nash equilibrium is the solution

TABLE II
GAME EVALUATION WITH AGENT SPECIFICATIONS AND RESULTS

Agent	Equipment	Strategy Selection	Market			Price of not knowing the future		
			Demand-Offer	Time-of-Use	Hybrid	Demand-Offer	Time-of-Use	Hybrid
$a^{(0)}$	$\mathrm{C} = 290.87\,\mathrm{kW}$	Optimal	-29.45	$-30,49$	$-28,28$	–	–	–
	$\mathrm{P} = -73.17\,\mathrm{kW}$	Yesterday	-29.55	$-30,49$	-28.36	0.10	**0**	0.08
	$\mathrm{P_{max}} = 1.7\,\mathrm{kW}p$	Steady	-29.54	-30.49	-28.34	**0.09**	**0**	**0.06**
	$\mathrm{SOC_{max}} = 2\,\mathrm{kW\,h}$	No Battery	-29.82	-30.86	-28.63	0.37	0.37	0.35
$a^{(1)}$	$\mathrm{C} = 151.05\,\mathrm{kW}$	Optimal	-11.19	-11.76	-10.88	–	–	–
	$\mathrm{P} = -63.83\,\mathrm{kW}$	Yesterday	-11.43	-11.92	-11.11	0.24	**0.16**	0.23
	$\mathrm{P_{max}} = 1.36\,\mathrm{kW}p$	Steady	-11.20	-11.97	-10.90	**0.01**	0.21	**0.02**
	$\mathrm{SOC_{max}} = 2\,\mathrm{kW\,h}$	No Battery	-12.73	-13.17	-12.25	1.59	1.41	1.37
$a^{(2)}$	$\mathrm{C} = 170.74\,\mathrm{kW}$	Optimal	-14.32	-14.44	-13.57	–	–	–
	$\mathrm{P} = -68.73\,\mathrm{kW}$	Yesterday	-14.46	-14.44	-13.70	0.14	**0**	0.23
	$\mathrm{P_{max}} = 1.48\,\mathrm{kW}p$	Steady	-14.37	-14.44	-13.61	**0.05**	**0**	**0.04**
	$\mathrm{SOC_{max}} = 2\,\mathrm{kW\,h}$	No Battery	-15.56	-15.68	-14.80	1.24	1.24	1.23

where no agent increases their payoff in varying only his strategy unilateral [14]. To reach the equilibrium state in our game, we propose an iterative approach in Algorithm 3 where systematically strategies are ruled out. The set of resulting

Algorithm 3 Iterative Nash calculation

```
Input: Agents 𝒜, Strategies 𝒮, Iterations i
procedure NASH(𝒜, 𝒮, i)
    Initialize Agents A with random Strategy from S
    count ← 0
    while count < i do
        for all a ∈ A do
            P empty list of length |S|
            for all σ ∈ S do
                π(σ) ← CALCULATEPAYOFF(a, σ)
                P ← P + π(σ)            ▷ Append π and σ to list
            end for
            σ_max ← max(P)              ▷ Strategy with max. payoff
            a(σ) ← σ_max                ▷ Set σ_max as agent's strategy
        end for
        count ← count +1
    end while
end procedure
```

strategies for every agent $\sigma^{(a)}$ defines the optimal state within our game. Based on this state, the difference in every agents' payoff for choosing another strategy is calculated and named as the price of not knowing the future.

C. Game Results

For our proposed game $\mathcal{G}$, we choose three different agents $\mathcal{A} = \{a^{(0)}, a^{(1)}, a^{(2)}\}$ from the data set. The set of available strategies is composed of the previously described *Spillover* and *PriceDepending* as well as no battery utilization at all $\mathcal{S} = \{\sigma_{\text{Spillover}}, \sigma_{\text{PriceDepending}(\tau)}, \sigma_{\text{NoBattery}}\}$ with $\tau \in [0, 100]$. Markets are initialized with $k = 0.75, l = 0.5$ and $\mathrm{M_{max}} = 0.30$€. We play the game for a whole week from Monday till Friday. For every day in the week and every market type $\mathcal{M}_{\text{DO}}, \mathcal{M}_{\text{TOU}}, \mathcal{M}_{\text{Hybrid}}$, the optimal strategy based on the previous calculated Nash equilibrium (see Algorithm (3)) is taken as a benchmark. For every agent $a \in \mathcal{A}$, we replay the game with the following three different strategy selection methods (1) *Yesterday*: the agent selects yesterday's optimal strategy; (2) *Steady*: the agent initially selects SPILLOVER and never changes it; (3) *No Battery*: the agent never uses its storage unit at all. Afterwards, we present the difference between the agents' optimal payoffs and the almost optimal payoffs–the so-called *price of not knowing the future*. The specifications of every agents' storage and production capacities as well as the total sum of production and consumption over the whole week are given in Table II. The last three columns correspond to the *price of not knowing the future*, where the lower values are better–indicated in bold font. A final discussion of the results in Table II and an extensive summery follows next.

V. CONCLUSIONS

With the rise of prosumers and the ongoing integration of RESs, the existing power grid is evolving from a centrally managed critical infrastructure to more and more distributed SGs. Prosumers capable of producing electricity are now able to buy from and sell to the market based on their individual rational goals. To study these interactions between actors in a SG and market operators, a agent-based representation of the prosumers with different properties (see Section III-B and Table I) is presented. These properties and their resulting actions are used to define strategies for varying storage unit utilization in Section III-D. Furthermore, different types of electricity markets in terms of price calculation are defined in Section III-C. A dynamic market ($\mathcal{M}_{\text{DO}}$), where every agent influences the price depending on their actual demand. A time based price mechanism, where the tariff is divided into day-tariff and night-tariff ($\mathcal{M}_{\text{TOU}}$) as well as a combination of both types ($\mathcal{M}_{\text{Hybrid}}$). All of this, can be modeled and evaluated in a game between rational prosumer agents and an electricity market.

After the formal definitions, a game composed of three agents, an electricity market $\mathcal{M}$, and a concrete strategy set $\mathcal{S} = \{\sigma_{\text{Spillover}}, \sigma_{\text{PriceDepending}(\tau)}, \sigma_{\text{NoBattery}}\}$ is played.

Therefore, every market type is studied for a stable configuration, the Nash equilibrium, with an iterative Algorithm (3). Divergent from the resulting agents' payoffs, three other strategy selection methods are compared and the divergence is presented–the so-called *price of not knowing the future*. It can be seen from presented results in Table II that no major difference between strategies in the TOU market is noticed with one exception for agent $a^{(1)}$–except at no battery utilization at all. This can be explained by the fact that neither of the proposed strategies exploit this circumstances. For the remaining market types, a *steady* usage of the SPILLOVER strategy is a pretty good choice for an almost optimal strategy–or in reducing the *price of not knowing the future*.

The promising results of our presented game theoretic approach encourage us for further developments and improvments. Possible extensions are implementations of broader strategy spaces or simulating more agents or whole real-world grid structures. Another interesting aspect are long-term analyses in terms of grid stability as well as reliability.

ACKNOWLEDGMENT

The research presented in this paper is supported by the Federal Ministry for Economic Affairs and Energy BMWi (FKZ 03ET1585A) and Bayern Innovativ. The authors would like to thank D. Hehenberger-Risse, J. Straub, N. Körber, and S. Wang for the enlightening discussions.

REFERENCES

[1] A. Wallis, R. Egert, M. Mühlhäuser, and S. Hauke, "A framework for strategy selection of atomic entities in the holonic smart grid," in *10th International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies (ENERGY 2020)*. IARIA, October, pp. 11–16.

[2] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, and F. Blaabjerg, "Review of energy storage system technologies in microgrid applications: Issues and challenges," *IEEE Access*, vol. 6, pp. 35 143–35 164, 2018.

[3] J. Barton and D. Infield, "Energy storage and its use with intermittent renewable energy," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 441–448, Jun. 2004.

[4] R. Dufo-López and J. L. Bernal-Agustín, "Multi-objective design of PV–wind–diesel–hydrogen–battery systems," *Renewable Energy*, vol. 33, no. 12, pp. 2559–2572, Dec. 2008.

[5] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of energy storage for microgrids," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 142–151, Mar. 2012.

[6] H. Morais, P. Kádár, P. Faria, Z. A. Vale, and H. Khodr, "Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming," *Renewable Energy*, vol. 35, no. 1, pp. 151–156, Jan. 2010.

[7] M. Ross, R. Hidalgo, C. Abbey, and G. Joos, "Energy storage system scheduling for an isolated microgrid," *Renewable Power Generation, IET*, vol. 5, pp. 117 – 123, 04 2011.

[8] P. S. Kumar, R. P. S. Chandrasena, V. Ramu, G. N. Srinivas, and K. V. S. M. Babu, "Energy management system for small scale hybrid wind solar battery based microgrid," *IEEE Access*, vol. 8, pp. 8336–8345, 2020.

[9] M. Korpaas, A. T. Holen, and R. Hildrum, "Operation and sizing of energy storage for wind power plants in a market system," *International Journal of Electrical Power & Energy Systems*, vol. 25, no. 8, pp. 599–606, Oct. 2003.

[10] H. Moradi, M. Esfahanian, A. Abtahi, and A. Zilouchian, "Optimization and energy management of a standalone hybrid microgrid in the presence of battery storage system," *Energy*, vol. 147, pp. 226–238, Mar. 2018.

[11] B. Zhao, X. Zhang, J. Chen, C. Wang, and L. Guo, "Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 4, pp. 934–943, Oct. 2013.

[12] E. Reihani, S. Sepasi, L. R. Roose, and M. Matsuura, "Energy management at the distribution grid using a battery energy storage system (BESS)," *International Journal of Electrical Power & Energy Systems*, vol. 77, pp. 337–344, May 2016.

[13] G. Barchi, M. Pierro, and D. Moser, "Predictive energy control strategy for peak shaving and shifting using BESS and PV generation applied to the retail sector," *Electronics*, vol. 8, no. 5, p. 526, May 2019.

[14] Z. M. Fadlullah, Y. Nozaki, A. Takeuchi, and N. Kato, "A survey of game theoretic approaches in smart grid," in *2011 International Conference on Wireless Communications and Signal Processing (WCSP)*. IEEE, Nov. 2011, pp. 1–4.

[15] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

[16] P. Vytelingum, T. D. Voice, S. D. Ramchurn, A. Rogers, and N. R. Jennings, "Agent-based micro-storage management for the smart grid," in *The Ninth International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010) - Won the Best Paper Award (14/05/10)*, 2010, pp. 39–46, winner of the Best Paper Award Event Dates: May 10-14, 2010.

[17] A. Loni and F.-A. Parand, "A survey of game theory approach in smart grid with emphasis on cooperative games," in *2017 IEEE International Conference on Smart Grid and Smart Cities (ICSGSC)*. IEEE, Jul. 2017, pp. 237–242.

[18] P. Chakraborty, E. Baeyens, K. Poolla, P. P. Khargonekar, and P. Varaiya, "Sharing storage in a smart grid: A coalitional game approach," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4379–4390, Jul. 2019.

[19] A. Chis and V. Koivunen, "Coalitional game-based cost optimization of energy portfolio in smart grid communities," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1960–1970, Mar. 2019.

[20] N. Yaagoubi and H. T. Mouftah, "Energy trading in the smart grid: A distributed game-theoretic approach," *Canadian Journal of Electrical and Computer Engineering*, vol. 40, no. 2, pp. 57–65, 2017.

[21] M. Pilz and L. Al-Fagih, "Recent advances in local energy trading in the smart grid based on game-theoretic approaches," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1363–1371, Mar. 2019.

[22] E. L. Ratnam, S. R. Weller, C. M. Kellett, and A. T. Murray, "Residential load and rooftop PV generation: an australian distribution network dataset," *International Journal of Sustainable Energy*, vol. 36, no. 8, pp. 787–806, Oct. 2015.