Evaluating Congestion Management Schemes in Liberalized Electricity Markets Using an Agent-based Simulator

Thilo Krause
EEH - Power Systems Laboratory
Swiss Federal Institute of Technology Zürich
krause@eeh.ee.ethz.ch

Göran Andersson
EEH - Power Systems Laboratory
Swiss Federal Institute of Technology Zürich
andersson@eeh.ee.ethz.ch

***Abstract*— In this paper we compare different congestion management schemes in liberalized electricity markets using an agent-based simulator. By modelling market participants as adaptive agents in oligopolistic structures, we consider the possibility of strategic behavior and the existence/exercise of market power. Generation companies submit their bids to the market place in order to maximize their payoffs, where we apply reinforcement learning as behavioral agent model. The market is then cleared taking into account specific congestion management methods, such as locational marginal pricing (LMP), market splitting and flow-based market coupling. We demonstrate the functionality of the simulator using a test network, illustrating that different congestion management methods lead to different market dynamics and/or equilibria. Additionally, we assess the effects on the distribution of the surplus for producers and consumers as well as overall social welfare.**

***Index terms*— Electricity market modelling, congestion management, agent-based computational economics, reinforcement learning**

I. Introduction

With the beginning of the liberalization process in the early 1990's, electricity markets headed into a period of extensive changes. Moving away from vertically integrated monopolies, power delivery can nowadays be regarded as consisting of several services, mainly including generation, transmission and distribution. The unbundling of the value creation chain is a common feature of liberalized markets worldwide, although different countries follow different schemes for market organization. While e.g. parts of the United States, Singapore and Chile rely on centralized, pool-based trading concepts, in continental Europe decentralized structures seem to receive higher attention. Nonetheless, crucial to all proposed market designs is the transmission network. "Electricity grids exhibit large economies of scale and must be physically interconnected for maximum trading efficiency, making the grid a natural monopoly within a defined region."[1] Although, transmission access and tariffs are subject to regulation, there is a growing need for market-based pricing concepts in transmission networks.[2] Ideally, these concepts give not only correct economic incentives, but will also facilitate the physical operation of the network. In this regard, congestion management (CM) and pricing methodologies have been subject to intensive research, as these methodologies are crucial for the efficient operation of electricity markets. Looking at the worldwide implementation of CM schemes, different approaches can be identified. A pool-based or centralized market design allows for the use of locational marginal pricing (LMP), zonal pricing concepts such as market splitting or flow-based market coupling try to increase market liquidity by still relying on centralized elements, whereas explicit auctioning of transmission capacity exhibits the lowest degree of centralization, and thus, provides the greatest freedom to traders.[3]. The different international implementation suggests that there is no definite first-best CM system. Every scheme has to be evaluated with regard to the specific network topology, the generation portfolio, the strategic possibilities of market players as well as previous market developments as in different countries there may exist historical factors influencing possible restructuring efforts.

The contribution of this paper is the development and implementation of an agent-based simulator for evaluating different CM methods in liberalized electricity markets. By modelling market participants as adaptive agents in oligopolistic structures, we consider the possibility of strategic behavior and the existence/exercise of market power. The simulator is capable of evaluating locational marginal pricing and zonal pricing (market splitting and flow-based market coupling), where we asses these CM schemes with regard to the distribution of producer and consumer surplus as well as overall social welfare.

The remainder of this paper is structured as follows. Section II introduces the basic principles of multi-agent modelling. Furthermore, we outline the implementation of reinforcement learning as behavioral agent model. Section III summarizes the implemented congestion management schemes and states the related optimization problems. In section IV we describe the decision problem of the generating company as well as determine the function of the Independent System Operator (ISO). In section V we set up a benchmark electricity market and discuss the simulation results obtained under different congestion management schemes. Eventually, section VI concludes the paper.

II. Multi-Agent Modelling and Reinforcement Learning

A. Modelling Concepts for Electricity Markets

To assess and evaluate the various interactions between market players and their influence on the physical as well as the economic level of electricity markets several modelling and analysis tools have been proposed. Generally, methodologies may be characterized as *ex-post* or *ex-ante*. Hobbs et. al. in [4] distinguish the following approaches: a) analysis of existing markets, b) market concentration analysis using current market data, c) equilibria analysis, and d) multi-agent modelling, where either individuals are interacting or artificial agents. While a) and b) are *ex-post* concepts, the latter two allow for *ex-ante* analysis. In this paper we will focus on multi-agent modelling, as this approach allows to analyze the interdependencies of the micro-level (participants) and the macro-level (the overall market structure). We will describe that with an agent-based approach it is possible to assess the influence of possible strategic behavior of generators on the efficiency of specific CM schemes. This bottom-up modelling approach appears suitable to assess the evolution of market characteristics, such as market prices, overall trading volume and social welfare.[5] The main advantages of evaluating congestion management schemes using agent-based modelling (ABM) can be summarized as follows:

- With ABM it is possible to account for the oligopolistic characteristics of electricity markets by abstracting from the assumptions of perfect competition reflecting non-perfect information, limited observability, agents being price-setters rather than price takers.
- ABM allows to study effects related to repetitive behavior and learning of market participants with special emphasis on gaming and market power (see V).
- Agent-based models 'mimic' the structure of real markets. Thus, it is possible to analyze both: the behavior of market participants and the influence of their actions on overall market characteristics.

B. Reinforcement Learning as Behavioral Agent Model

As outlined above, an multi-agent system tries to model the macro and the micro structure of a market. In a second step the system is simulated over a certain time horizon giving the market participants the possibility to interact. With the process of subsequent interaction it may appear obvious that participants should be able to learn, i.e. to acquire knowledge from past actions and decide for upcoming actions in the context of their previous experience. One concept to model the learning process of agents through repeated interaction is reinforcement learning. (see [6] for a survey). In [5] we have intensively described the modelling of market participants using an reinforcement learning algorithm known as Q-learning. Aspects concerning the implementation of the agents have been discussed in the context of matrix games, Nash equilibria and repeated play. Hence, in this paper we restrain from presenting the design principles in full detail. The following paragraph about Q-learning largely follows the description given in [5].

In the context of Q-learning, we assume that the different agents observe the rewards gained from previous actions and use these observations to adjust their strategy in order to maximize their next reward, where Q-learning was initially designed for learning through interaction with a Markov Decision Process.[7]

When an agent i is modelled by a Q-learning algorithm, it keeps in memory a function $Q_i : A_i \rightarrow R$ such that $Q_i(a_i)$ represents the expected reward it believes it will obtain by playing action a_i out of the space of actions A_i. It then plays with a high probability the action it believes is going to lead to the highest reward (R), observes the reward it obtains and uses this observation to update its estimate of Q_i. Suppose that the tth time the game is played, the joint action $(a_1^t, \cdots, a_n^t)$ represents the actions the different agents have taken. After the game is played and the different rewards r_i have been observed, agent i updates its Q_i-function according to the following expression:

$$Q_i(a_i^t) \leftarrow Q_i(a_i^t) + \alpha_i^t(r_i(a_1^t, \cdots, a_n^t) - Q_i(a_i^t)) \tag{1}$$

where $\alpha_i^t \in [0, 1]$ is the degree of correction. If $\alpha_i^t = 1$, the agent supposes that the expected reward it will get by taking action $a_i = a_i^t$ in the next game is equal to the reward it just observed. If $\alpha_i^t = 0$, it means the agent leaves the value of its Q_i-function unchanged.

We will suppose in this paper that the agents select their actions according to the so-called ϵ-Greedy policy. When an agent i uses an ϵ-Greedy policy to choose its action, it selects with probability $1 - \epsilon$ the action which maximizes its believed expected reward ($\arg\max_{a_i \in A_i} Q_i(a_i)$), and chooses with probability ϵ an action at random in A_i. The main reason for an agent to adopt a policy that selects from time to time an action that it believes does not lead to the highest expected reward, is to guarantee that all actions have been tried a sufficient number of times to be able to correctly assess their expected reward. Figure 1 shows a tabular version of the algorithm that simulates reinforcement learning driven agents interacting.

1] Set $t = 0$.
2] Initialize $Q_i(a_i) = 0\ \forall i \in \{1, \cdots, n\}$ and $\forall a_i \in A_i$.
3] $t \leftarrow t + 1$.
4] Select for each agent i an action a_i^t by using an ϵ-Greedy policy.
5] Play the game with the joint actions $(a_1^t, \cdots, a_n^t)$.
6] Observe for each agent i the reward $r_i(a_1^t, \cdots, a_n^t)$ it has obtained.
7] Update for each agent i its Q_i-function according to

$$Q_i(a_i^t) \leftarrow Q_i(a_i^t) + \alpha_i^t(r_i(a_1^t, \cdots, a_n^t) - Q_i(a_i^t))$$

8] If a sufficient number of games has been played, then stop. Otherwise, return to step 3.

Fig. 1. Simulation of reinforcement learning agents

III. Congestion Management Methods

A. Introduction

In the next sections we specify the congestion management schemes implemented in the framework of the market simulator.[1] The following sections describe the implementation of locational marginal pricing, market splitting and flow-based market coupling, where we state the related optimization problems. In order to be able to illustrate the methods, we first describe the essential market characteristics and the topology of our test network. Nonetheless, a crucial objective of the simulator is the adaptability for arbitrary networks.

B. Market Characteristics and Network Topology

Figure 2 illustrates the test network used for the latter case studies. We suppose dealing with a power system in which we have $nbGen$ generators ($G_1, \cdots, G_{nbGen}$), $nbLoad$ loads ($L_1, \cdots, L_{nbLoad}$) and $nbNodes$ nodes ($1, \cdots, nbNodes$). Marginal cost functions of the generators and marginal benefit functions of the loads are assumed to be linear. A detailed description of the network data can be found in the appendix. The dashed lines in figure 2 mark the zones used for the simulation of market splitting. We furthermore assume that only the lines from node 2 to 5 and node 3 to 4 have a relevant capacity limit of $K_1 = 100MW$ respectively $K_2 = 150MW$. For the other lines of the system, we suppose that there exist no power dispatches that may lead to flows greater than their transfer capacity.

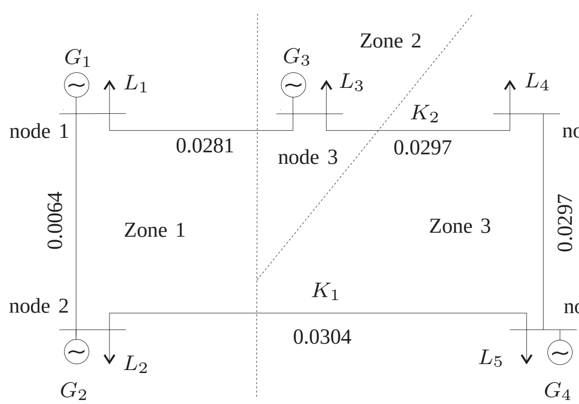

Fig. 2. Power System Description

To simplify the later formulation of the optimization problems (see subsection III-C), we transfer the line reactances into a matrix of power transmission distribution factors (PTDFs).[10]. The PTDF-matrix $P(k,l)$ is presented in the appendix, where we define node 1 as slack node. Element (k,l) of the PTDF-matrix then determines the change of the flow on line l given an additional injection of 1 MW at the slack and the corresponding withdrawal of 1 MW at node k.

[1]Although, the simulator is capable of assessing explicit auctions, we restrain to describe the implementation within the scope of this paper. The market structures associated with explicit auctions differ significantly [3], thus, the modelling approach and results will be presented in a subsequent paper.

C. Locational Marginal Pricing (LMP)

Locational marginal pricing also referred to as nodal pricing or spot pricing was first introduced by Schweppe et. al. in [11]. The general idea of LMP is to 1) model an electricity market with its various economic and technical specifications, such as generators' cost functions, demand elasticity, generation limits, line flow limits etc. and 2) optimize the system, which is synonymous to maximizing social welfare. LMP is often used in conjunction with a pool-based market design. The ISO collects all bids and is then in charge of clearing the market by maximizing social welfare while satisfying network constraints. To realize this objective, the ISO solves the following quadratic programming problem:
Determine

$$(P_{G_1}, \cdots, P_{G_{nbGen}}, P_{L_1}, \cdots, P_{L_{nbLoad}}) \in R^{nbGen+nbLoad}$$

that maximizes

$$\sum_{L_j} \frac{1}{2} m_{L_j} P_{L_j}^2 + n_{L_j} P_{L_j} - \sum_{G_i} \frac{1}{2} s_{G_i}^{bid} P_{G_i}^2 + ic_{G_i}^{bid} P_{G_i} \qquad (2)$$

subject to the constraints

$$\begin{aligned} \sum_k P(k,l)(P_{G_i}^k - P_{L_j}^k) &\leq P_{flow}^{max}(l) && (3)\\ P_{G_i} &\leq P_{G_i}^{max} && (4)\\ \sum_i P_{G_i} - \sum_j P_{L_j} &= 0 && (5) \end{aligned}$$

Here P_{G_i} denotes the power injected by generator G_i; P_{L_j} the power withdrawn by load L_j; $P_{flow}^{max}(l)$ the maximum flow allowed on line l; $P_{G_i}^{max}$ the generation limit of generator G_i and $P(k,l)$ the PTDF-matrix. The slope and the intercept of the marginal benefit function of the loads are determined by m_{L_j} and n_{L_j}. A detailed description of the parameters $s_{G_i}^{bid}$ and $ic_{G_i}^{bid}$, which represent the linear bid function of the generators, is given in subsection IV-A.

By solving the above optimization problem, the ISO can determine the power each generator (load) G_i (L_j) should be dispatched P_{G_i} (P_{L_j}), and through the knowledge of the Lagrangian multipliers, the nodal prices at each node k of the system are given. We denote by n_k the nodal price at the node k. After the market is cleared, each generator G_i is dispatched P_{G_i} and is paid n_k per MW produced.

D. Market Splitting

Market splitting - in accordance with LMP - establishes in case of congestion different electricity prices for different locations in the network. In contrast to LMP where prices might differ for every node, for market splitting a group of nodes is aggregated to one zone. These zones are mostly defined *a priori* as the concept focusses on certain flow-gates, which might be subject to congestion. An example is the Norwegian system, where the system operator splits the national transmission system into two zones (North and South). If the demand for transmission services does not exceed system capabilities, different network zones are not established, and thus, there is only one clearing price for the whole network. Within the scope of the simulator the market splitting formulation of Bjorndal presented in [13] is adopted. Thus, we extend the LMP formulation by a set of two more constraints as shown in equations 6 and 7.

$$s_{G_i}^{bid} P_{G_i} + ic_{G_i}^{bid} = n_{Z_k} \quad k = 1, \cdots, nbNodes \qquad (6)$$
$$m_{L_j} P_{L_j} + n_{L_j} = n_{Z_k} \qquad (7)$$

Equations 6 and 7 'force' the nodal prices in the respective zones to be equal, with Z_k being the allocation of the nodes k to the zones. Within the test network nodes 1 and 2 form zone 1, node 3 represents zone 2 and nodes 4 and 5 are grouped into zone 3.

E. Flow-based Market Coupling (FBMC)

Subsection III-D presented the mathematical formulation of market splitting. In accordance with market splitting, flow-based market coupling is a zonal pricing method establishing one price for a group of nodes (a zone). As FBMC has not been implemented in practice yet, no unique mathematical representation can be found in the literature. Within the scope of the proposed simulator we use the formulation as to be found in [14]. In accordance with the proposal by ETSO [15] and the regulation of the European Directorate-General Energy and Transport, Ehrenmann in [14] identifies the following key features of FBMC:

1. price zones follow country borders
2. intrazonal flows are not represented (assumption of absence of intrazonal congestion)
3. cross-border lines are aggregated into one equivalent interconnector for each neighboring country (zone)

To account for feature 2, we assume that every node within a zone (a country) has the same influence on the congested flowgates, thus, we use the same PTDFs for all nodes in the country (copperplate representation). As there is only one flowgate allowed between each country, the network has to be simplified (feature 3). The possible arbitrariness of this simplification is discussed in [14]. Generally, the zonal PTDFs and the capacity of the equivalent interzonal flowgates have to be determined to maximize the flow on the interconnection[2], without violating the operational constraints in the "real" network. The simplification may not be unique depending on the network topology and may to some extent misrepresent the original network. Figure III-E illustrates the above findings. We assume that node 3 belongs to the same country as nodes 1 and 2. Thus, only two zones are established for FBMC in the network consisting of nodes $1, 2$ and 3 (country 1) and nodes 4 and 5 (country 2). We furthermore set the interconnector capacity to 170 MW, as we have proven that this flow together with a PTDF of '0' for zone 1 and '-1' for zone 2 does not violate the capacity limits of the line in the 'real' network representation.[3] In contrast to market splitting

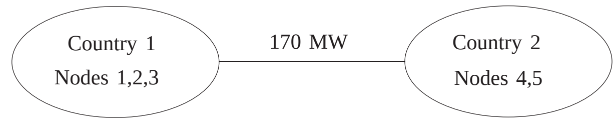

Fig. 3. FBMC Representation of Test Network

there are no zonal constraints for the optimization problem. The mathematical formulation is identical to LMP. Equal zonal prices are determined through the use of one PTDF for all nodes within a zone (country).

IV. Assessment of Market Structure and Decision Problem of Participants

A. Decision Problem of the Power Suppliers

In contrast to perfectly competitive markets where participants are assumed to be price takers and prices are equal to the marginal cost of supply we assume in our model an oligopoly market. Thus, suppliers may bid strategically above their marginal cost as they realize their possible influence on market prices. Subsequently, we consider that generators may deviate their bids from marginal cost (unknown to the outside world) to increase their profits. In [4] two ways of deviating are discussed: a) changing the slope s_{G_i} of the cost function or b) changing the intercept ic_{G_i}. Figure 4 illustrates these strategic choices for the generators. Within

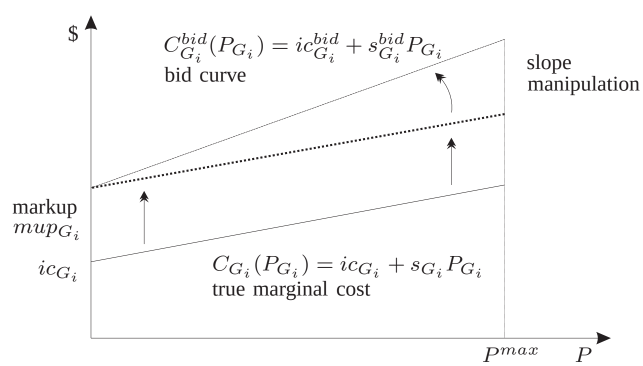

Fig. 4. True Marginal Cost and Strategic Choices

the simulator both strategic choices are implemented. To manipulate the intercept ic_{G_i} generators set a certain markup mup_{G_i}. Additionally, generators may deviate from the original slope of their marginal cost function.

B. Representation of CM schemes and Optimization Problem of the ISO

Section III briefly introduced the CM schemes implemented for market simulation. For LMP the stated optimization problem is a direct representation of the obligations of the ISO

[2] This objective is stated in article 6, paragraph 3 of the Regulation (EC) No. 1228/2003 of the European Parliament and the Council.[16]

[3] In fact, this simplification is arbitrary as there is no 'true' physical equivalent of the test network. The sum of capacities from country 1 to 2 theoretically amounts to 250 MW ($K_1 + K_2$), nonetheless, a capacity of 250 MW on the interconnector would violate the flows in the real network.

in pool-based markets. By optimizing social welfare the ISO determines the optimal generation dispatch. In contrast to LMP, the optimization problems stated for market splitting and FBMC do not represent the exact problems related to the functions carried out by the ISO in the respective market. They rather determine an aggregated, ideal view on the market structure neglecting e.g. transaction costs between different authorities that may exist. In the proposal of FBMC the coexistence of power exchanges and transmission system operators is assumed[15], where both entities are required to interact and iterate during daily operation. The formulation of FBMC in the scope of this paper presents one specific implementation, which aims at predicting a possible market outcome, rather than determining all involved market processes. A similar line of argument applies to market splitting. Nonetheless, the aggregated view on the zonal CM schemes allows for the assessment of the market characteristics described in section IV-D.

C. Simulation Framework

The above stated mathematical framework allows for looking at CM schemes in a compact way. Power suppliers submit bids in the form of linear marginal bid functions to the marketplace, where social welfare is maximized to determine generation and consumption. Bilateral agreements are not modelled. Figure 5 provides a graphical representation of the implemented structure.

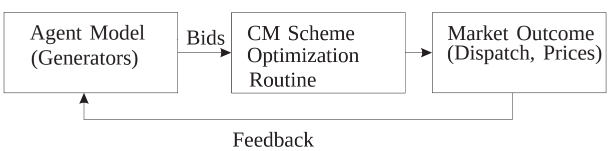

Fig. 5. Flow Chart of Simulator

D. Microeconomic Metrics for Evaluation of CM schemes

Bompard et. al propose in [17] a unified framework for a comparative analysis of CM schemes. In compliance with this framework we will use the following indicators for the evaluation of the CM schemes: total consumption, price level, producer surplus, consumer surplus, merchandize surplus resp. congestion rent and overall social welfare. We furthermore extend the analysis with respect to possible strategic behavior of power suppliers, which may be taken as indicator for market power. The methodology used is further detailed in the subsequent case study.

V. Case Studies

A. General Methodology and Data Specification

In the following, we will use the above described simulating framework to carry out simulations on the test network shown in figure 2. The generation and load data, as well as the PTDFs are detailed in the appendix. As the focus of the simulator is the evaluation of long-term effects of possible market restructuring proposals, we consider demand to be elastic. Loads have the opportunity to react to price changes by e.g. reducing energy consumption or to opt for partial self-supply. The elasticity has been determined in compliance with the values given e.g. in [17] and [14].[4] As specified in section IV-A, power suppliers may behave strategically by deviating their bids from their true marginal cost. This can be achieved by either adding a markup mup_{G_i} to the original intercept ic_{G_i} or deviate from the slope s_{G_i}. To account for these strategic possibilities in the context of Q-learning (section II-B) a set of discrete actions A_i for each generator G_i has to be defined. For the sake of simplicity we restrain to define actions related to the variation of the slope. Simulations have shown that changes of the slope in an adequate range only have a small influence on the rewards of the generators as well as on market dynamics. Thus, we specify the sample set of markups mup_{G_i} for each generator G_i as shown in the appendix in table IV. Each generator may decide between three strategic choices: 1) bid at marginal cost 2) add a markup of 5% and 3) add a markup of 10% to its true marginal cost. This basic action set serves as example to demonstrate the functioning of the simulator. Nonetheless, we have observed effects which may also be relevant in a more realistic framework. As one objective of the simulator is to allow for the comparison of different CM schemes, we will evaluate

- locational marginal pricing (LMP)
- market splitting and
- flow-based market coupling (FBMC)

applying a standardized procedure:

1 Welfare analysis assuming perfect competition
2 Welfare analysis assuming oligopolistic competition
3 Market power analysis

In case of perfect competition no strategic behavior of generators is possible as all market participants are price takers. The market equilibrium can be determined through solving the optimization problems defined in III. For a welfare analysis assuming oligopolistic competition we simulate the market over a certain time horizon using the agent-based framework together with Q-learning. In this context generators are able to learn from subsequent interaction. We stop the simulation when the standard deviation of the Q-functions of each generator does not exceed a certain threshold. This may be interpreted as sign that no significant learning takes place anymore, as generator have obtained a stable expectation of their possible reward for a certain action. Although, there is a high likelihood that the obtained equilibrium corresponds to a Nash equilibrium, we do not explicitly prove this hypothesis. The relationship of Nash equilibria and Q-learning has been discussed in more detail in [5]. In a last step, the obtained Q-functions are used to analyze the magnitude of market power applying the methodology detailed in section V-B.

[4]Results in an LMP based system with inelastic loads have been reported in [5].

B. Welfare Analysis (Perfect Competition)

For a welfare analysis in case of perfect competition we have determined the market equilibria of each CM scheme by solving the optimization problems from section III using the true marginal cost functions of the generators. Table I[5] presents a summary of the results concerning total demand [MWh], producer surplus [$], consumer surplus [$], congestion cost [$], overall welfare [$] as well as minimum $\min n_k$ and maximum nodal prices $\max n_k$ [$/MWh] and the congested line(s). From the results we derived the following observations, where we define LMP as reference case.

- Total demand for LMP and market splitting are identical, whereas for FBMC demand drops by -4%.
- LMP exhibits the highest overall welfare closely followed by market splitting. Welfare for FBMC decreases by app. -2%.
- The allocation of producer and consumer surplus for LMP and market splitting is similar. FBMC exhibits a higher producer surplus and a lower consumer surplus, which is obviously caused by an increase of the overall price level.
- For market splitting and FBMC congestion cost increase by app. 13% compared to LMP.

	LMP	**MaSplit**	change	**FBMC**	change
Total Demand	904	904	0.0%	867	-4.1%
Prod Surplus	2735	2632	-3.8%	3028	10.7%
Consum Surplus	8308	8249	-0.7%	7684	-7.5%
Congestion Cost	1153	1306	13.3%	1293	12.1%
Overall Welfare	12196	12187	-0.1%	12004	-1.6%
$\min n_k$	17.07	17.36	1.7%	18.61	9.0%
$\max n_k$	25.5	24.62	-3.5%	26.22	2.8%
congested line	2-5	2-5	-	1-2	-

TABLE I
WELFARE ANALYSIS (PERFECT COMPETITION)

The results in this case study coincide with the findings of Ehrenmann and Smeers in [14]. LMP exhibits the highest overall welfare, followed by market splitting. Due to the simplifications of the network topology, welfare in a market based on FBMC is likely to decrease.

In the next sections we will extend our analysis by removing the assumptions of perfect competition.

C. Welfare Analysis (Oligopolistic Competition)

For the following welfare analysis we simulate the system using the agent-based framework together with the Q-learning algorithm. Hence, all generators interact and learn from this interaction, where the process of learning is represented by the Q-functions. Figure 6 shows a sample evolution of the Q-function of generator G_4 in an LMP based market. Each curve in this figure represents the development of the expected reward for the different markups. Thus, each curve shows what G_4 believes it will obtain by choosing a certain markup and submitting the resulting bid function. G_4 obviously 'realizes'

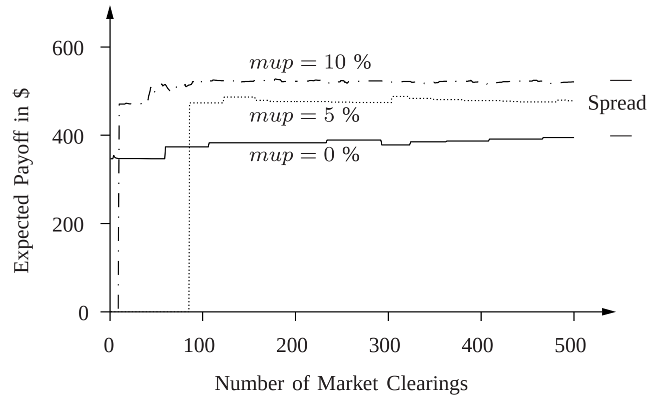

Fig. 6. Development of Q-function G_4 (LMP)

its advantageous position in the network. Due to the limited transfer capacity of the line between nodes 2 and 5 (see figure 2), there is a high likelihood for G_4 to be dispatched. Hence, G_4 receives market power, which it exploits by choosing the highest possible markup. In contrast to G_4, generator G_2 can not benefit from setting a markup above its marginal cost function, i.e. the expected rewards for all actions do no deviate significantly (see figure 7). This observation may serve as

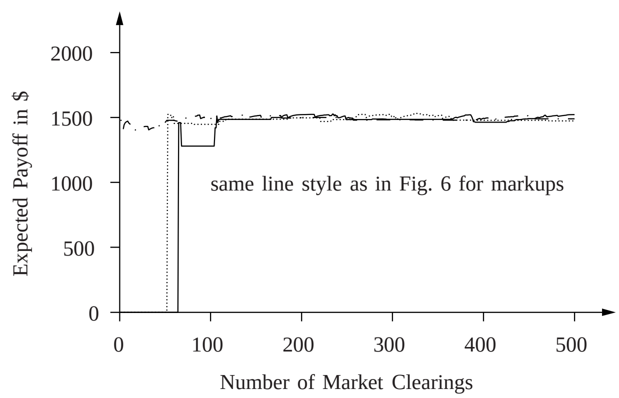

Fig. 7. Development of Q-function G_2 (LMP)

indicator that G_2 is unable to exert market power. In subsection V-D we further discuss the relationship of market power and the characteristics of Q-functions.

A common feature of the Q-functions of G_2 and G_4 is that after about 300 iterations the expected rewards remain almost stable. We use this 'convergence' to define a stop criterion. Repeated simulations have shown that computations can be terminated if the normalized standard deviation of each agents' Q-function falls below a value of 2 percent. In other words: We stop the simulation if all generators have learned a sufficiently precise expectation of the reward they will obtain by playing a certain action. After terminating the simulation we again compute the market equilibria if the generators would indeed choose their greedy, i.e. reward maximizing bids. Table II summarizes the results, where the examination of the results leads to the following observations:

- As in the perfect competitive case, LMP has the highest

[5] Layout adopted from [17].

overall welfare, followed by market splitting and FBMC. Nonetheless, we observe the following decreases of welfare compared to the competitive case: LMP -4%, Market Splitting -7.5% and FBMC -7.1%.

- Comparing the change of welfare for the oligopolistic case itself we find that there are stronger reductions with LMP as reference. For market splitting there is a drop of -3.8%; for FBMC welfare reduces by -4.9%.
- In comparison with the competitive case for all CM schemes producers surplus increases while consumer surplus decreases. This effect seems to be due to generators exercising market power.
- For FBMC the prices increase compared with LMP and market splitting and compared with the competitive case.

	LMP	**MaSplit**	change	**FBMC**	change
Total Demand	864	848	-1.85%	811	-6.13%
Prod Surplus	3372	3554	5.40%	3917	16.16%
Consum Surplus	7590	7263	-4.31%	6748	-11.09%
Congestion Cost	1189	1324	11.35%	1292	8.66%
Overall Welfare	11715	11275	-3.76%	11146	-4.86%
$\min n_k$	17.77	18.37	3.38%	19.73	11.03%
$\max n_k$	26.45	25.87	-2.19%	27.33	3.33%
congested line	2-5	2-5	-	1-2	-

TABLE II

WELFARE ANALYSIS (OLIGOPOLISTIC COMPETITION)

The above welfare analysis has shown that in case of strategic behavior social welfare decreases stronger for market splitting (-3.76%) and FBMC (-4.86%) compared to LMP and perfect competition. Power suppliers are able to raise their surplus while the consumer surplus decreases. In our test network these observations suggest that in both situation - perfect and oligopolistic competition - LMP is the most efficient CM scheme, followed by market splitting and FBMC.

In the following section we will further analyze the distribution of market power.

D. Market Power Analysis

In figures 6 and 7 we have presented sample evolutions of Q-functions for G_4 and G_2 in an LMP market. Whereas G_2 can not benefit from setting a markup, G_4 learns that it can increase its profits as the expected rewards in the Q-function exhibit a certain 'spread'. For bidding at marginal cost G_4 has the lowest expected reward; setting a markup of 10% will lead to the highest reward. In the following we use this difference in expected rewards to determine the magnitude of market power in the respective CM scheme. For each generator G_i and each action a_i we compute the mean value of the expected rewards $(\overline{Q_i(a_i)})$ after the simulation was terminated. We subsequently compute the difference of the mean values in percent, with the marginal bid (no markup) as reference action (a_{MC}) (see equation 8).

$$S_i = \frac{\overline{Q_i(a_i)}}{Q_i(a_{MC})} - 1 \tag{8}$$

Note, that the spread S_i can become negative if the mean value of the expected reward for the marginal action exceeds that of another action. This situation may occur if a generator is better of by behaving competitively.

In our previous examples, the spread for G_4 amounts to app. 28%, while the expected rewards for G_2 are closely distributed within a difference of only 2%. One may argue that for G_2 it is not possible to determine whether setting a markup or not will influence its prospective rewards. A reward variation of 2% may also be caused by overall volatility. Thus, we conclude that G_2 has a) only a limited potential to increase its reward and b) may not be able to sufficiently predict this potential. Hence, G_2 has no market power in an LMP market.

The situation is different for G_4 with a reward spread of 28%. G_4 can be regarded as having a strong potential to increase its reward by strategic behavior and may also be able to observe this potential through daily interaction. Thus, G_4 in the LMP example has market power.

We have carried out the above analysis for all generators in the different CM schemes. To simplify the description of market power we suggest using the following intervals for the spread. If the value is below 5 percent (as in the example for G_2) *no* market power can be perceived or exercised. If the value is between 5 and 20 percent there is a *significant* likelihood for generators to determine their potential for influencing their profits, while for a spread of above 20 percent there is a *high* likelihood for the perception and exercise of market power. Table III presents the results of the market power analysis using the intervals defined above.

Generator	LMP	MaSplit	FBMC
1	high	high	significant
2	no	no	no
3	no	significant	significant
4	high	high	high

TABLE III

MARKET POWER ANALYSIS

The results suggest that the allocation of market power is influenced by the market design. For LMP only G_1 and G_4 have market power, while for market splitting G_3 also receives a significant potential. By simplifying the network topology according to FBMC, and thus, creating larger zonal markets it is not possible to eliminate market power in our test system, although the magnitude changed for G_1 from high to significant. Although, the proposed intervals have no unique foundation the proposed methodology provides the possibility to gain insights in the distribution of market power in different CM schemes.

We are aware of the fact that the proposed approach to determine the magnitude of market power can only be applied if indeed the Q-functions converge. The presence of multiple equilibria in the system may lead to the cycling evolution presented in [5]. In this regard the methodology has to be extended to account for applicability in arbitrary systems.

VI. CONCLUSIONS

This paper presented an agent-based simulator for the evaluation of different congestion management schemes in liberalized markets. Using a Q-learning algorithm, we have stated agent models to account for competition in oligopolistic structures, where power suppliers can act strategically by deviating their bids from their true marginal cost functions. Additionally, we stated the related optimization problems for locational marginal pricing, market splitting and flow-based market coupling to be implemented in the proposed multi-agent framework. Using a simple test network an evaluation concept was applied to assess crucial market characteristics such as the distribution of welfare, price level, total demand etc. The analysis has been carried under the assumptions of perfect and oligopolistic competition, where in a last step a methodology was developed to determine possible market power of generators. The results have shown different allocations of market power for the different congestion management schemes. We therefore conclude, that the distribution of social welfare as well as market power have to be evaluated in conjunction with the specific market architecture.

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Thilo Krause received his Diplom-Wirtschafts-Ingenieur degree in economics and electrical engineering from the Dresden University of Technology in 2002. In 2002 he joined the Power Systems Laboratory of the Swiss Federal Institute of Technology (ETH) in Zürich, Switzerland, where he is working towards a PhD degree in the area of congestion management for liberalized electricity markets.

Göran Andersson (M'86, SM'91. F'97) was born in Malmö, Sweden. He obtained his M.S. and Ph.D. degree from the University of Lund in 1975 and 1980, respectively. In 1980 he joined ASEA:s, now ABB, HVDC division in Ludvika, Sweden, and in 1986 he was appointed full professor in electric power systems at the Royal Institute of Technology (KTH), Stockholm, Sweden. Since 2000 he is full professor in electric power systems at the Swiss Federal Institute of Technology (ETH), Zürich, where he heads the powers systems laboratory. His research interests are in power system analysis and control, in particular power systems dynamics and issues involving HVDC and other power electronics based equipment. He is a member of the Royal Swedish Academy of Engineering Sciences and Royal Swedish Academy of Sciences and a Fellow of IEEE.

APPENDIX

A. Generation and Load Data

The following table summarizes the generation and load data for the test network, with the parameters as described in section IV-A.

Node	Generator					Load	
	G_i	s_{G_i}	ic_{G_i}	$P_{G_i}^{max}$	mup_{G_i}	m_{L_j}	n_{L_j}
1	1	0.02	14	300	{0,5,10}	-0.1	35
2	2	0.02	10	300	{0,5,10}	-0.1	35
3	3	0.02	15	300	{0,5,10}	-0.1	40
4	-	-	-		{0,5,10}	-0.1	45
5	4	0.04	20	300	{0,5,10}	-0.1	40

TABLE IV

GENERATION AND LOAD DATA

B. Power Transfer Distribution Factors

Table V presents the PTDFs for the test network with node 1 being the slack node. The factors have been computed from the line reactances given in figure 2.

	1-2	1-3	2-5	3-4	4-5
1	0	0	0	0	0
2	-0.9432	-0.0568	0.0568	-0.0568	-0.0568
3	-0.2496	-0.7504	-0.2496	0.2496	0.2496
4	-0.5133	-0.4867	-0.5133	-0.4867	0.5133
5	-0.6732	-0.3268	-0.6732	-0.3268	-0.3268

TABLE V

MATRIX OF POWER TRANSFER DISTRIBUTION FACTORS