Influence of the Solar Energy on the PowerTAC Simulation

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Contents

Abstract

Solar energy will be one of the most promising energy sources for the transition to renewable energy in the future. Another promising feature is the introduction of the smart grid where energy consumer can also be energy suppliers. To see how consumers and energy producers react on this change simulations like the Power Trading Agency Competition (PowerTAC) are used. The PowerTAC is a simulated smart grid which tries to imitate the real-world energy market as accurate as possible. The research subject in the simulation is the influence of solar energy on the behavior of the consumers and energy brokers in the simulation. To examine this three research questions where developed to answer how much influence solar energy has, what effect it has on the simulation and what effect it has on the brokers (players). There is a small effect, which leads to a negative demand for energy sources other than solar energy (netdemand). This has no effect on the prices, because the prices only increase in the simulation. The brokers in the simulation make less profits, but this is not caused by the solar energy production because this is stable during the whole simulation . It is recommended to improve the supply of solar energy in the simulation as well as the impact of a pricing mechanism called wholesale buyer. No hard conclusion can be drawn With respect to the influence of solar energy on the profits of the brokers

keywords: Competitive benchmarking, Energy market, Solar energy, smart grid simulation

1 Introduction

On December the 12th 2015, 195 countries signed in Paris an agreement to "let temperature rise well below 2 degrees Celsius"[39]. The main goal of the agreement is "To limit the amount of greenhouse gases emitted by human activity to the same levels that trees, soil and oceans can absorb naturally, beginning at some point between 2050 and 2100" [10]. In other words governments need to reduce there CO_2 emissions in order to have a livable planet for future generations. This is easier said than done because the predictions are that the demand for energy will increase due to economic and demographic growth [38] [2]. On top of that, the expectations are that up to one fifth of the transportation sector will be Electric Vehicles (EV's) by 2030 [3] which will increase the demand for energy even more. So the energy business has the task to reduce their emissions while coping with an even higher demand due to the change to EV's. At last, one of the most used non-polluting energy sources, nuclear energy, is still heavily discussed. Especially with disasters like Fukushima and Chernobyl, the use of nuclear energy is still controversial [17]. It seems that the energy business has one clear solution for the emission problem, fully invest in the use of zero emission renewable energy (RE) sources.Although RE seems favorable because it has zero CO_2 emissions, it also has a downside.

Unlike the stable fossil fuel generated energy, RE needs unpredictable resources like sun or wind. When the resources are unpredictable the production of energy by these sources becomes unpredictable as well [18] leading to variable energy generation (VG). In 2016 the worldwide production of RE was just around 24% from which only 6% is generated by VG's like sun or wind [21]. With these small VG penetrations the impact of unpredictable energy resources on the variance of the production is limited. However multiple studies predict that the use of VG will have a steep increase in the coming decade. Especially for the increase of use in solar energy (SE), scientist have high expectations ranging from low 360 % increase [38] till a high 800 % increase [2] increase until 2040 [18] [21] [41]. Also predictions of solar and wind energy on the proportion of the the worldwide energy supply are predicted to be around 15% in a low scenario [38] to 100% in a very optimistic scenario [36] in 2040. The contribution of VG's will be significant in the future and therefore also variance in the energy production.

This change in energy production, along with the variance that comes with it, creates some future challenges for the grid operators and energy companies [34]. For example, an increase in variance is a challenge for grid operators because off potential grid damage or blackouts[20]. Energy companies on the other side, have to deal with the fact that the energy demand becomes less predictable due to the variance, which could lead to over-or-underproduction. To cope with this problem researchers as well as energy companies make use of simulations to predict what the impact of VG's will be. An advantage of the use of simulations is that new implementations and regulations can easily be "tested"[35]. Where in the real world the implementation of new regulations takes multiple years, a simulation can be changed and tested in just a couple of days .

One common open source simulation is the Power Trading Agency Competition (PowerTAC). This simulation has a yearly competition where players act as energy brokers and compete against each other. The brokers can win by creating a portfolio with the best balance between supply and demand. The supply and demand are of energy are generated by so called 'wholesalers' and 'energy consumers', which are programmed by the developers of the PowerTAC simulation. By using the log-files the developers and researchers can analyze the behavior of the brokers and improve the simulation. Because the simulation is used for testing multiple scenarios in the energy market, the main goal for the developers is to mirror the simulation to the real-world as accurate as possible [34]. Factors that contribute to this accuracy are the use of real-world variables like weather forecasts and market regulations. Also the introduction of RE sources and EV storage in the simulation contribute to a more realistic simulation [32].

But the use of real-world variables is not a guarantee for real-world broker behavior. Recent studies [6] [5] [32] have shown that adjustments where needed to influence the behavior of the brokers and create a more realistic simulation. With the knowledge that RE sources will have a significant impact in the future[2], the question arises if this impact also flows through the simulation. Although the introduction of RE is covered in these studies the impact over multiple years has not been studied yet. This study tries to give an insight in what influence RE, and especially SE has on the behavior of the brokers in the simulation. This will be answered by thee research questions, which apply to the pricing and energy use of the brokers. By pointing out where the simulation does not correspond with real world data, this study mainly contributes recommendations for the developers as well as for the users of the PowerTAC simulation

The paper consist a literature study in which is explained what currently the researched effects are and what literature concludes about this subject. Furthermore some solutions for the effects are discussed and some explanation is given about the PowerTAC simulation. After that the research questions the proposed hypotheses are discussed. The methodology is shortly explained. After that the results are displayed and at last the conclusions and recommendations are drawn and in the conclusions paragraph.

2 Literature

2.1 Consumer Competitiveness

As told in the introduction the world needs to change from fossil fueled energy sources to RE sources. A solution to cope with this problem is the implementation of a smart grid (SG) [22]. Previously electricity grids consisted of an energy plant which distributed only to the local city or neighborhood where the plant was located. A SG is a countrywide connected electrical system that does not only provide energy from the energy plant to the consumer, but a consumer can also supply to the energy network [22] (see Figure1).

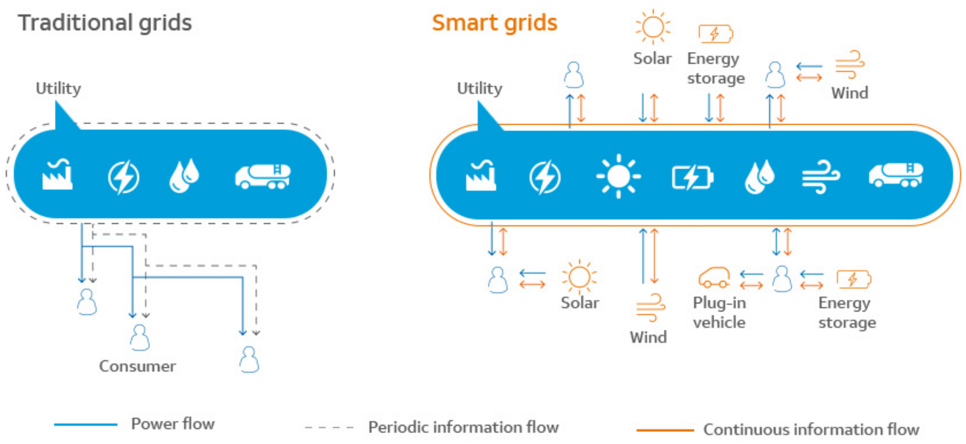

Figure 1: Structural view of traditional grid and smart grid **(source:[45])**

The creation of this two-way market seems positive for consumers, but also brings complexity for grid operators who have to balance the energy supply and demand. What makes it more complex is that every person connected to the grid becomes a new actor who can use, generate or store energy from the grid. Energy consumers connected to the SG can "sell" their generated energy to other consumers or to power suppliers [16]. In the previous decades the price of RE per Kilowatt hours (KWh) was more expensive than the price of fossil fueled generated energy [42]. If you as a consumer wanted to sell back your own generated energy back to the grid, the price was higher than the price offered from wholesale suppliers. So selling your own generated energy was very hard in that time. This price difference created a barrier for energy consumers to chose for the more expensive RE or chose to generate their own energy [42].

Due to innovations in RE and SE a so called 'price parity' was achieved in 2017. This means that the price of renewable energy per KWh in the top 30 Western counties was as expensive as the price of coal or nuclear generated energy [42]. having this 'price parity' energy consumers connected to the SG can now offer competitive prices to wholesalers or other energy consumers. Selling back to the grid can now become a profitable investment for consumers. A study of SG Customer Collaborative (SGCC) indicated that supply of energy though the SG could lead to an positive Return on Investment (ROI) in the range of 1.5 in a normal scenario up to a RIO of 2.6 in the best scenario [14]. This economical incentive makes it attractive for energy consumers to generate their own energy.

2.2 General Suppliers and Societal Benefits

The development of the SG also has effects on grid operators and energy suppliers. First, the two-way market of the SG generates not only energy but also a lot of information from both consumers and suppliers. This stream of information can be helpful to increase the prediction models of the energy suppliers[24]. With better prediction models energy suppliers can decrease over-or-underproduction which leads to a more efficient energy grid [25]. Apart from the more efficient use of energy, this efficiency can also have a positive effect from a cost efficient view. Improved predicting models mean that energy suppliers can better anticipate on demand peaks, leading to decreased operating and maintenance cost [24]. On the other hand, the SG creates a more competitive energy market which can be negative for energy suppliers. Not only will the consumption from energy consumers decrease because of self-generated energy, they will also offer competitive prices to sell their surplus to the grid. More competition means that suppliers need to lower their offered prices which could lead to a decrease in income [24].

The fact that a SG has multiple actors is also positive for the flexibility of the grid. The two-way market makes it easier for energy suppliers and grid operators to get or store their needed energy by multiple actors [25]. This increased flexibility leads to better grid reliability. In general grid reliability means that there is a reduction in disturbances and lower frequency in the grid. A lower frequency decreases the chance of damaging the grid [24]. Another advantage of a multi actor market is that the network is more secure [24]. In the traditional grid an energy plant is connected to a certain region. If there is an accident or a cyberattack on the energy plant, the whole region will have no power. This happened for example during the California energy crisis in 2000 [9] or the Northeast Blackout in 2003 . In a SG with multiple actors such an attack or disturbance can be compensated by other energy plants or even energy consumers. Assuming that consumers don't have gas turbines or nuclear plants in their backyard, all the energy generated and contributed to the grid by consumers is clean renewable energy. So the connection to a smart grid cuts both ways for consumers, by decreasing CO_2 emissions while making a profit of selling your surplus to the grid.

2.3 Consumers Demand

All the effects above where of a more macro perspective on the SG. When looking at a closer view other effects become clear. As example we look at the SG of California, which is operated by the California Independent System Operator (CAISO). Since 2010 CAISO started as one of the first states in the US with the implementation of the SG [11]. The current setup of CAISO's grid relies for 71% on stable energy sources like natural gas, hydro, nuclear and oil generated energy. The other 29% relies on different RE sources like wind, solar and geothermal, where on average 48% is generated by SE. It is important to notice that this 48% is on average because SE can only be produced during the day. This difference in production is displayed in figure 2 where the total RE energy production during every hour of the day is displayed. When looking at figure 2 the impact of the SE on the total RE production becomes clear. During night hours the solar contributes nothing to the RE production where during day hours SE can contribute up to 70% of the total RE production [13]. As told in the previous paragraph due to the use of the SG, consumers are expected to produce more SE because it is profitable for them. Also the introduction stated a high increase in production of solar energy is expected. Both factors have impact on the SE production and impact will be much higher in the coming decades.

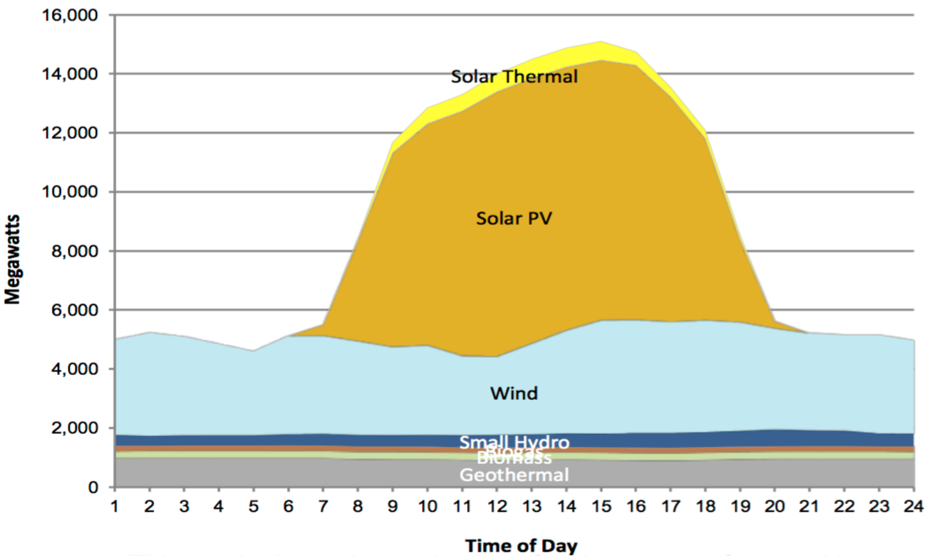

Figure 2: hourly production of all CAISO's RE's on October 19th 2017 **(source:[13])**

2.4 The Duck Curve

The fluctuations of the RE supply impact the total supply of CAISO. Although the contribution of solar energy to the total supply is less than the contribution to RE's, there is still an impact. The contribution of SE to the total supply is on average 14%, with peaks up to 29% on a very sunny day [13]. Because energy can not be stored on large scale the total supply is assimilated on the total energy demand in the grid during the day [44]. So in case there are no unforeseen circumstances like a blackout or a storm, it is assumed the the energy supply is the same as the energy demand.

The impact of the SE on the total supply is displayed in figure 3. Figure 3 shows the daily production on random warm summer day when the SE production has the most impact. The total energy supply E_{Supply} is displayed in figure 3 with the blue line. The blue line indicates that there is an increase in supply from around 4 A.M until 8 P.M. The generation of SE E_{solar} is implicated with the grey line. In the case of California The SE production ranges from 7 A.M until 7 P.M, but for other regions this depends on multiple variables like latitude and season of the year [46]. When a large part of the energy production during the day is produced by solar energy the netto demand(ND) E_{net} decreases. Because the curve of the net demand line looks like a duck's back (Figure 3: orange line)[46], this phenomena is called the 'duck curve' (DC). ND is the total energy production minus the SE production and can be explained by the following formula [46]:

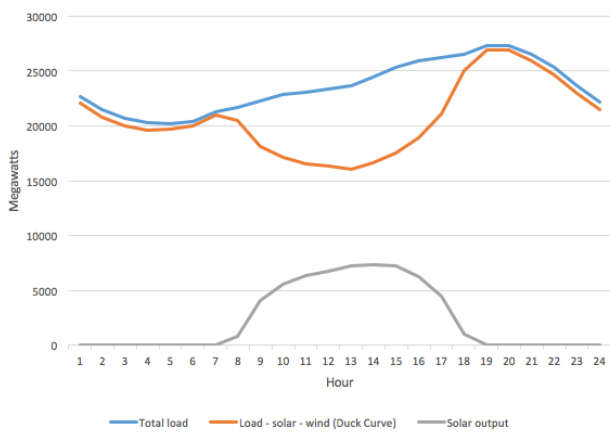

Figure 3: Total energy production during summer day 2015 in California **(source:[31])**

$$E_{net} = E_{demand} - E_{RE}$$

Vlahoplus et all. [46] researched the DC commissioned by the Consultancy firm ScottMadden. They used the data of California's grid operator CAISO [46], which is representative for the previous used examples. First Vlahoplus et all. came to the conclusion that most predictions from CAISO where too positive and the real magnitude of the DC was bigger than expected. Vlahoplus et all. also noted that the effect of this curve created two problems namely; *oversupply risk* and *short steep ramps*. The *oversupply risk* is created during the day when the SE's produce energy. When the SE produce a significant portion of the total energy supply, the energy generated during the day is more than the demand on the grid leading to oversupply (see Figure 4). This oversupply is increasing faster than CAISO's prediction tools expect.

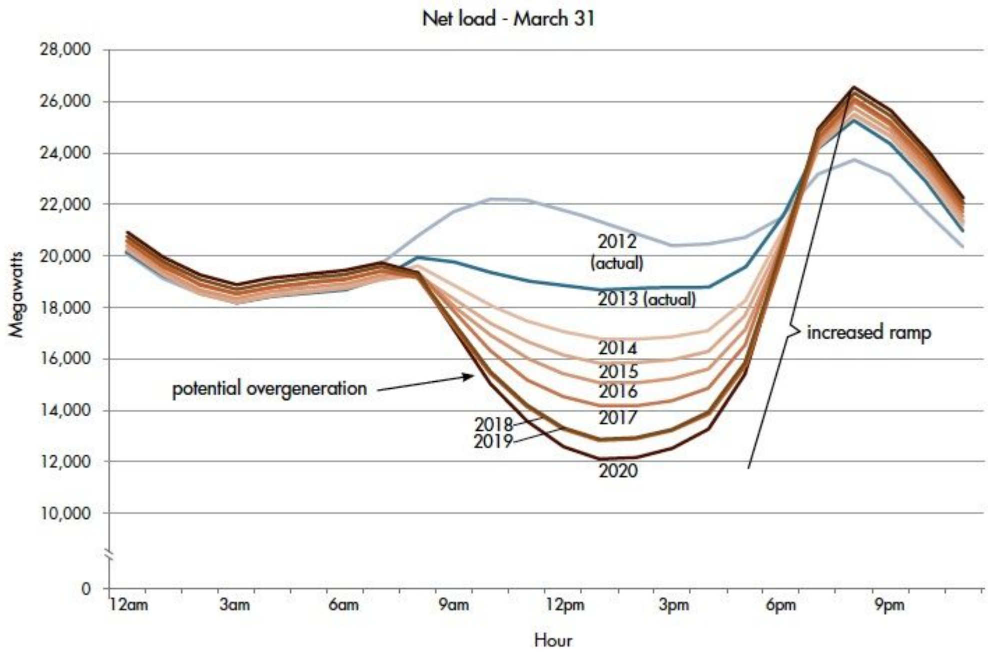

Figure 4: CAISO ND predictions from 2012 until 2020 during March 31 **(source:[46])**

The second problem, *the short steep ramps*, occurs in the time period between 6 p.m and 9 p.m. Within this time period the supply of SE decreases because the sun goes down. Also in this period there is a peak in the total energy demand during the day. A combination of these two elements leads to a steep increase of energy demand during a three hour period and cause problems in the operating grid. Vlahoplus et all. also found that the effects of the DC are depended on some variables. First, it depend on what percentage of a significant portion of the total supply need to be SE [20]. Second, seasonal effects, size and latitude are also important for magnitude of the effect [46].

At last, Vlahoplus et all. recognized that the presence of a what they call "utility-scale solar power" also has effect on the net load of a grid operator. with "utility-scale solar power' Vlahoplus et all. mean the power generated from private solar panels which will not be distributed by the grid system in the paper also refereed to as "system load". If a large part of the region produces it's own energy with PV's the demand for energy from the grid decreases. It seems a positive effect because it reduces the pressure, but unfortunately it can not decrease the peak demands where the grid face the most pressure.

Both the risk of oversupply and the steep increase ramp have effects on the energy grid [7]. Anna Fero for example mentioned that grid operators transfer the energy with certain frequencies[20]. If a grid is transporting more energy than usual, the transporting frequency increases [7]. When the frequency increases too much because of overproduction there is a potential chance of damaging the grid[7]. If the grid is transporting a smaller amount of energy than usual the frequency decreases with possible blackouts as result. So not only energy suppliers but also gridoperators desire a less fluctuant energy market.

2.5 Balancing the Supply and Demand

The fluctuations in the energy grids have always been a common phenomena. As told in the paragraph "Duck Curve", it is not possible to store large amounts of energy, so supply and demand must be balanced [44]. To manage the peaks and drops the ISO's need to balance the supply and demand. In most cases the ISO's use the energy market as balancing tool to balance supply and demand [12]. The energy market is a regulated brokers market where brokers buy and sell energy from producers and sell it to the consumers. The consumers are in this context, energy companies or retailers. "Retailers" deliver directly the asked amount of energy for a fixed price to the customers. The brokers make profits by accurately predicting the demand and try to buy the correct amount of energy that is needed to feed this demand. In a the ancient centralized energy market the offered energy is produced by large energy suppliers called "wholesalers". In a SG market also small suppliers can offer their energy to the market.

Generally there are two sorts of markets where brokers can trade energy: the *day-ahead market* and the *real-time balancing market*. The day-ahead market is a trading market where brokers can buy their predicted amount of energy. In this market it is possible to buy or sell your energy from 7 days up to 24 hours before of the time-of use[19]. The wholesalers offer a certain amount of energy to the market for a certain price. The brokers have multiple models from the ISO's that predict what the demand would be. Then the brokers buy the energy from multiple wholesalers until they reached the predicted amount. The bids in the Day-ahead market have an one hour increment[19].

When ISO's made a mistake and developed some over-or-underproduction, the surplus is sold or bought on the real-time balancing market. This is called "up-regulation" when the brokers need to buy energy and "down-regulation" when the brokers . In this market the brokers can buy energy up to 75 minutes before the time-of-use of the energy in 5 minute increments instead of hourly increments [33]. An example of a brokers' forecast is displayed in figure 5. Because the real-time balancing market is the last chance for ISO's to balance the supply and demand, the brokers are more eager to buy energy, leading to a more volatile market [44]. This more eager and volatile market is also an opportunity for the broker to make their highest profits.

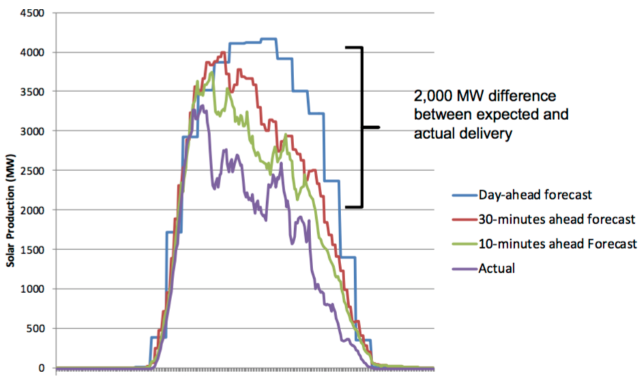

Figure 5: Example of CAISO's forecasts in the Day-ahead market and Real-time market on July 18 2015 **(Source:[30])**

For example when "broker A" expects that the demand will be high the next day, "Broker A" buys a lot more energy then "Broker B" and "Broker C" on the day-ahead market. When his expectation comes out (high demand), "Broker B" and "Broker C" have not enough energy to supply, so they have to buy it from "Broker A ". Because the other brokers need the electricity and need it in a short term "Broker A" can ask a much higher price, and therefore makes more profit. On the other hand when "Broker A" misjudged the demand and the demand was lower than expected, there is oversupply (see Figure 5). When there is oversupply, "Broker B" and "Broker C" don't need energy and therefore "Broker A" payed too much in the day-ahead market which results in losses.

2.6 Other Balancing Methods

As told above the energy market is an important balancing method for ISO's but not the only one. Sometimes the energy market is not sufficient enough in balancing the supply and demand, like for example in the California energy crisis. The State Of California made huge losses in it's energy supply during the 90's because of too expensive energy contracts and nuclear facilities. This led to an average energy price that was 40% higher than the national average. After protests the State of California decided to deregulate the wholesale market and set a fixed price for retailers. The ISO had to purchase the energy from the wholesalers for a variable price and sell it to the retailers for a fixed price. This gave the wholesalers the power to influence the prices with their energy production. On purpose the wholesalers produced less energy so the demand was higher and the ISO had to pay prices up to 800% of the normal price for their energy. This led to a bankrupt ISO and a lot of blackouts during that period [9].

Apparently the energy market in California didn't enough create enough competition for wholesalers because it set a fixed price for retailers. To avoid a crisis like this, governments and ISO's created regulations to stabilize the market[9]. Although these measures helped to stabilize the market, imbalances in the energy market still occur. This is caused by the inelastic energy demand and supply and its effect on the prices. The demand of the retailers depends on multiple factors like weather, efficiency and economic growth [44]. Also the wholesalers' supply is depended on factors like fuel price, weather and gridcosts[44]. With all these factors influencing the supply and demand it is hard to create an accurate forecast, like it can be seen in figure 5. As explained in the example above a wrong forecast has much influence on the profit of the brokers in the volatile real-time balancing market. This is why ISO's are searching for tools and mechanisms to create more flexibility in demand and supply.

To increase flexibility on the demand side, ISO's try to influence the demand by using pricing mechanisms. Figure 4 shows that there is a big difference in demand between the peak and low hours of the day. This difference can be reduced by making it more attractive to use energy during the low demand hours of the day. Usually the retailers offered contracts with fixed energy prices to their customers regardless what the energy demand was. In case of fixed contracts the retailers lost money when the demand was high, because the energy was expensive on the market. Not only made this the retailers completely depended on the very volatile real-time market, it made the market also very inefficient [27]. Figure 6 explains this better, where P are the prices, Q_{pk} is the energy consumed during peak hours and Q_{offpk} the energy consumed during off-peak hours. A fixed rate created a dead weight, which is loss to society [29], during the peak and off-peak moments. By offering more variable contracts to customers, retailers can mitigate their decency on the high volatile energy market. This changes not only the behavior of the customers, but also creates a more stable demand for the retailers. The only requirement is that the retailer need to create awareness by communicating the real-time prices to the customers [40].

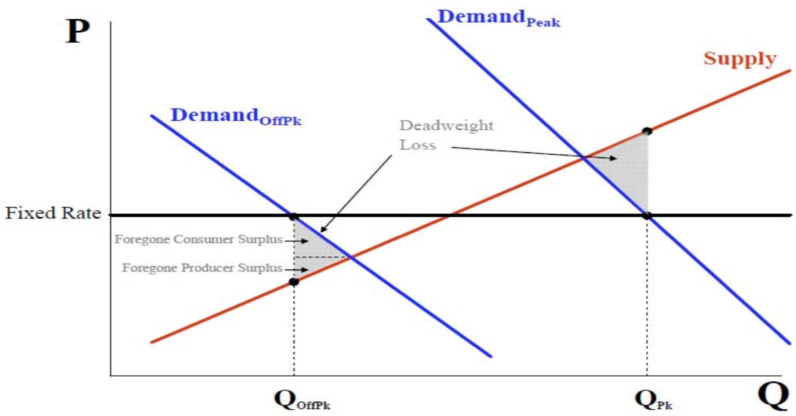

Figure 6: Energy market with fixed tariffs **(source:[27])**

The introduction of the SG also contributes to a more inelastic demand side. As stated in the paragraph "General supplier and societal benefits", the flexibility is increased because of better information and a different market setup [25]. Before the SG the energy supply was a one way directed market where the brokers bought energy from the wholesalers as cheap as possible and tried to sell attractive contracts to retailers. The introduction of the SG changed this market from a centralized to a decentralized market.

Flexibility is also needed on the supply side of the energy market. What could potentially help to stabilize the energy supply is the use of batteries. Batteries would allow ISO's to store the energy during oversupply and contribute this stored energy to the retailers during peak-hours. It is still too expensive to store large amount of energy, but with new innovations and investments this could help in the future. Due to the SG not only ISO's can store energy but also small scale suppliers. For example it is possible to store energy on small scale with EV's. With an expected increase of EV's [32] this could be a potential market balancer, but for now it is not profitable enough.

In a market where a lot of contribution comes from RE sources the problem of inelastic supply is even bigger. For example, Denmark aims to have 50% of his generated energy be produced by RE's in 2020 which they seems to reach [43]. The more the grid is depended on RE's the more uncertain supply you have because RE's are solely depended on the uncontrollable weather. for example, in case of a strong wind it could happen that the wind energy is suppling 100% of the energy demand. This could cause problems because energy grids are not very flexible due to technical and economical reasons [12]. For example hydrogen and nuclear plants need a minimum generation for safety reasons[12]. Also coal and gas turbines are not flexible in their energy production, because of fuel dependency and startup time. These wholesalers can decrease their production but must at all the times produce a minimal amount of energy. Therefore these wholesalers are called "must-run producers" [8]. The problem is that during a hard wind day, the produced wind energy is much cheaper than the energy from the must-run producers. The solution of the Danes is to sell their surplus to their neighboring German and Scandinavian imbalance market [26]. The imbalance market is an connected network of multiple regional energy markets where over or underproduction can be sold to other regions [37]. At the moment this is implemented in just a few regions but intentions are made expend this market in more regions. Another option for ISO's is to command wholesalers to reduce energy production during overproduction, generally referred to as curtailment. The disadvantage is that this option leads to very inefficient use of energy [8]. Another problem is that the must-run producers can't be curtailed. because this is the least favorable option ISO's see energy curtailment as a final balancing solution.

2.7 PowerTAC

The California energy crisis made it clear that the introduced market was not tested well. To test an energy market researchers and regulators often use simulations [5]. What makes it hard to create a simulation for the energy market is that there are human actions and decisions involved. To solve this problem Ketter et all. [35] developed a setup for simulations called Competitive Benchmarking. Simulations with Competitive Benchmarking try to simulate human decisions by adding thee elements to the simulation; platform, process and alignment. The platform is needed to connect players and researchers and have them compete in one environment. With process is meant that the results and behavior of the competing players must be stored so it can be analyzed and tested with respect to the research questions. With alignment is meant that the simulation need periodically adjustments and improvements, in order to reflect the real world. Ketter et all. used this setup to develop multiple simulations including a simulation of the energy market called Power Trading Agency (powerTAC).

The PowerTAC simulation, simulates a liberal energy market of a certain region in the world with a smart grid network [34]. The competition contains at least 9 players from university teams. Each "player" is taking place in the seat of an virtual energy broker. These brokers play in a competition which is played only a couple of days per year. The main goal of the competition is to win the competition by earning the most profit in the market. The trading rules of this virtual energy market are based on real-world energy markets of the Scandinavian NORDPOL or the North-American FERC dependent on the simulated region. This also includes a day-ahead market and a real-time balancing market like explained above. The structure of the simulation is explained in figure 7. Figure powertac shows that the players not only compete in the wholesale market but also behave like retailers by offering contracts to customers. These contracts offered by the brokers can be of any kind (fixed, time-of-use, offpeak-on-peak), for any price and for any supply. An algorithm decides if the customers accept the offer of the broker or choses the offer of the competing broker.like I said the PowerTAC simulates a SG market, so customers not only demand but can also generate and store energy. The algorithm is based on historic behavior of the customers in the retail market. For example, there is a probability based randomness that the customers do not evaluate all the contracts. On the other hand do customers hardly change from energy contract. To create a more attractive retail market the customers change more often from supplier. The supply is calibrated on the supply of the region where the competition takes place. Since 2015 RE sources where added to the wholesale supply. To decide how much they produce the real-time weather statistics like temperature, wind speed and cloudiness of the region are included in the algorithm. The wholesale supply is determined by the sum of both. The simulation also included real world pricing mechanisms like dynamic pricing, curtailment and capacity charges. With respect to alignment in the Competitive Benchmarking paradigm, the simulation needs periodic improvements. To improve the PowerTAC simulation this research tests some real-world principles described above in the literature. The theories that will be tested in this researched are described below in the section "Research Questions and Hypotheses"

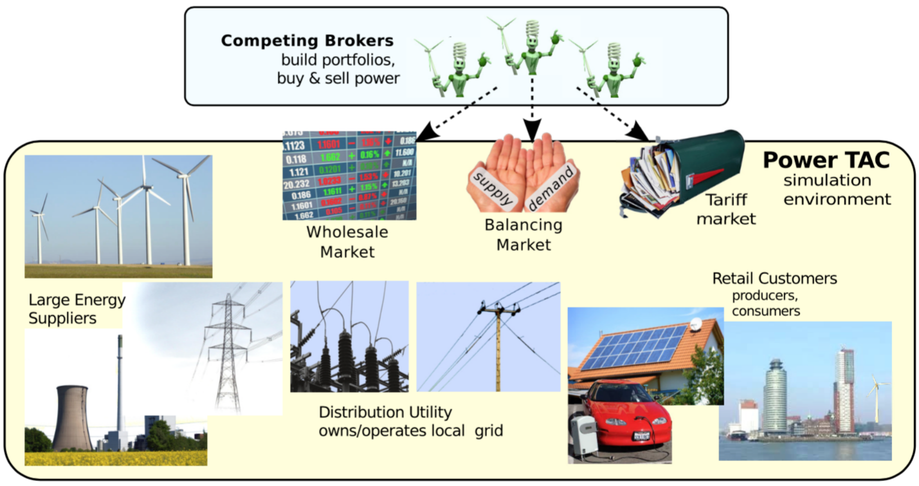

Figure 7: Schematic structure of the PowerTAC energy market **(source:[34])**

3 Research Questions and Hypotheses

3.1 Research question 1

As told in the literature, PowerTAC tries to simulate real world energy problems as accurate as possible [34]. To simulate the real world as accurate as possible, the developers evaluate each year's competition. They observe the behavior of the brokers and the implemented price regulations and try to develop new price regulations if necessary. These improvements have led to a more realistic simulation over the years, but there are always effects that aren't researched yet. Especially with rapidly changing environment changing from fossil fuel to green energy, some interesting topics arise with respect to the simulation. For example in the Introduction and in the Literature, is stated the energy demand as well as the SE production has increased over the years and is expected to increase even more in the future[1][38][41] [36]. This increase in SE lead to a lower ND during the day and increased ramp during peak hours like in figure 4 [46]. But do this phenomena also occurs in the simulation? to test this the following hypotheses needed to be proved:

Hypothesis 1: The total energy demand <u>*increases*</u> *over the years in the PowerTAC simulation*
Hypothesis 2: The SE production <u>*increases*</u> *over the years in the powerTAC simulation*
Hypothesis 3: The increase in SE production leads to a lower ND over the years in the PowerTAc simulation

Some subjects on this topic where slightly covered in a research of Ansarin et al[6]. After the introduction of SE in the simulation, Ansarin et all. noticed a steep increase in imbalance which was more than the real world data. This led to a decrease in ND during the day when the SE production was at his top. This indicates that the DC is present in the simulation. Another research with respect to the DC was done by Vlahoplus et all. The main conclusion from the research of Vlahoplus et all. was "the DC is real and growing faster than expected". The research of Ansarin et all. only had data of the 2014 and 2015 competition, so calculating an increase over multiple years was not possible in his research. With new data ranging from 2014 to 2017, possible DC patterns could be analyzed and the hypotheses can be answered. Vlahoplus et all [46]. tested this by calculating the lowest ND of each day in the year and rank the days in a descending order. Because the PowerTAC has different games played on random days, this conclusion can't be tested in this way. What can be tested is the average ND for each competition and how much this increases or decreases. So in a way we can test the if the conclusion of Vlahoplus et all. also applies for the simulation. If the magnitude is negative it is in line with the conclusion of Vlahoplus et all. Therefore the first research question is:

Research question 1: What is the magnitude of the deceasing ND in the powerTAC simulation?

3.2 Research question 2

By answering the first research question, it can be determined if the decreasing DC is present in the simulation. If it is present the average ND declines each year because of the SE production. By determining this pattern a logical successive question would be, how does this pattern influence the simulation and the brokers? Therefore the second research question is:

Research question 2: What effect does the decreasing DC have on the simulation?

To find out what could potentially happen, it makes sense to look at real-world examples where the effects of a decreasing DC are already present. In the literature there was an example of Denmark which aims to produce 50% of its energy by RE's in the year 2020 [43]. This region is far ahead when it comes to the use of RE's, so is a good predictor of the effects in the future. During a windy day it could happen that there are hours where the RE sources produce enough energy for the whole country. The RE contribution of the powerTAC differs per region but is definitively, not as high as Denmark [34]. This doesn't mean that it can happen that the weather condition are right and the demand is low so 100% of the produced energy comes from RE's. If this is true the simulation should make adjustments like Denmark because of the must-run producers. An easy way to test this in the simulation is to focus on the ND since the ND is the total supply (E_{demand}) minus RE (E_{RE}) [13]. If 100% of the energy generation is provided by RE, the ND is 0 or negative. Because each hour corresponds with one timeslot the following hypothesis was created:

Hypothesis 4: An <u>increase</u> in RE production leads to a <u>increased</u> number of time slots with a negative ND?

In the case of Denmark, a part of the produced energy is distributed to the imbalance market during the oversupply, so the must-run producers can keep producing [26]. The powerTAC is a closed simulation without any imbalance market to sell to, so this is no option to reduce the oversupply. A real world example of a region with a lot of RE production but <u>without</u> an imbalance market is Texas. The consequence of not be connected to the imbalance market is that the oversupply stays in the market which has influence on the prices [23]. Generated energy from RE's have no producing costs so is in general cheaper than the energy from the must-run producers. Because it is cheaper, broker prefer to buy this energy instead of the more expensive must-run producers. During oversupply the RE producers need to deliver their energy because it can't be stored so they offer it for any price they want, even if they have to pay for it. When the circumstances are right this lead to negative prices on the real-time market, meaning that customers get paid to use energy. The question is if this could also happen in the simulation? Therefore the next hypothesis is created.

Hypothesis 5: Negative ND leads to negative bidprices

3.3 Research Question 3

The example of the energy market in Texas implicates that although there are multiple balancing methods used, extreme values can still exist. With a growing world wide energy market[1] [41] and RE production [38] these extreme values will appear more often. The question arise how does the energy market react on this. Do they profit from these extreme values or does the market get to saturated because of the SG? To see how the simulations react on this the following research questions was established:

Research question 3: Do brokers profit from the decreasing ND?

As stated in the literature the the decreasing ND is caused by the contribution of RE's[31]. This causes oversupply during the off-peak hours of the day. In line with general economic laws, oversupply leads to lower prices [27]. This is also in line with what happens in the real-world [15].<u>hypothesis 5</u> already tests this phenomenon, but only for the extreme values. The question arises if the overall prices are also dropping in the simulation?. This can be tested in *hypothesis 6*. Another phenomenon what happens in the real-world is that the contribution of RE's make the energy grid less predictable and reliable because RE's are dependent on the weather. A more volatile energy grid should also have effect on the prices. this will be tested in *hypothesis 7*. The brokers make profits by purchasing energy as cheap as possible and try to sell it for the highest price via contracts to the customers. The so called "market spread" is generous for brokers when the markets are more volatile because then there is more difference between ask and demand price[28]. In the last hypothesis (*hypothesis 8*) is tested if this also responds with the PowerTAC simulation.

The following hypotheses where established to answer research question 3:
Hypothesis 6: Increased SE production leads to <u>lower</u> average prices in the energy market
Hypothesis 7:Increased SE production leads to <u>increased</u> price volatility
Hypothesis 8:Increased price volatility lead to higher profits for brokers

4 Methodology

As told in the literature I will use the PowerTAC simulation for the research. The PowerTAC is a simulation based on real world parameters and with real people involved. Although this increases the performance of the simulation it is still a simulation with simulated outcomes. Therefore this research can be seen as an experiment.

The simulation has been running now for 6 years meaning that data date back until 2012. In each year there is a competition with at least 9 competing real-life brokers, which are in most cases University teams from all over the world. Each year has four rounds. The first round is a trail round, the second is a quarter final, the third is a half final round and the last is the final round with at most 8 competitors. The most valuable round for research is the final round because in this round the effect of competitive benchmarking are highest because the best brokers compete here. Also all the non-working algorithms are eliminated in the qualification round so the chance of outliers is lower in this round. In the final round the 8 competitors compete with each other in around 200 games(this changes per year). Each game has around 60 days of trading, (this is chosen randomly), with a minimum of at least 55 days. with 24 timeslots in a day this leads to a dataset of at least 1320 rows per game or 264.000 rows per year. All the data is stored in data logfiles which is available online at powertac.org. The available data contains the following years: 2014 (72 games), 2015(230 games), 2016 (198 games) and 2017 (284 games). The data used in this research is downloaded from this site and converted to a readable format. This is done with the logtool-examples available on github.com, which creates the needed data in a .csv file. These files are easy to read in my analyzing program called Rstudio. All the analyses, plots and graphs in the results are made in this program.

For the research, competition data of multiple years is needed to compare and answer the research questions. As told before the simulation is evaluated every year after the competition has ended. The developers analyze the behavior of the brokers and develop new regulations or pricing methods. These new regulations will be implemented in next years' competition. These changing rules makes it harder to compare each years' competition.

One other factor that changes, is the region in which the competition is played. Because the simulation tries to be as real as possible, each years' round takes place in another region somewhere around the world. This changes some external factors like weather and sun hours per competition. Each game has around 60 days of simulated data so seasonal effects and sun hours can have effect on the data. Therefore this research uses as much data as possible per competition year. Each year has around 200 games, counting for around 11.000 days of data. The expectation is that this amount of simulated data will stabilize the external and seasonal effects on the results.

The change in the pricing and game regulations after each competition, can't be stabilized this way. All the changes that the developers make are all explained in so called "game specification" for that year. By searching through the game specification of each year it is possible to know what the changes are and if the data of the year before can be compared. If there is change in regulation it is explained in the results what this change is and how it affect the data. The used data is depended on these change of rules, but it is preferred to use as much data as possible to have the best results. In the best case the data from 2014 until 2017 is used. The results of all the analyses are explained below in the paragraph "Results".

5 Results

5.1 What is the magnitude of the decreasing DC in the PowerTAC simulation?

Hypothesis 1: The total energy demand increases over the years in the PowerTAC simulation

To answer the first hypothesis, the average energy demand should be calculated. To calculate the energy demand, the logtool "ProductionConsumptionWeather" is used. To give a better insight in the demand, not only the average demand of the whole year is calculated, but also the average demand per hour. Figure 8 and Table 1 show the results.

Table 1:

Year	Average Demand	Standard deviation
2017	61.852	6.771
2016	62.141	9.334
2015	61.936	11.279
2014	62.883	12.398

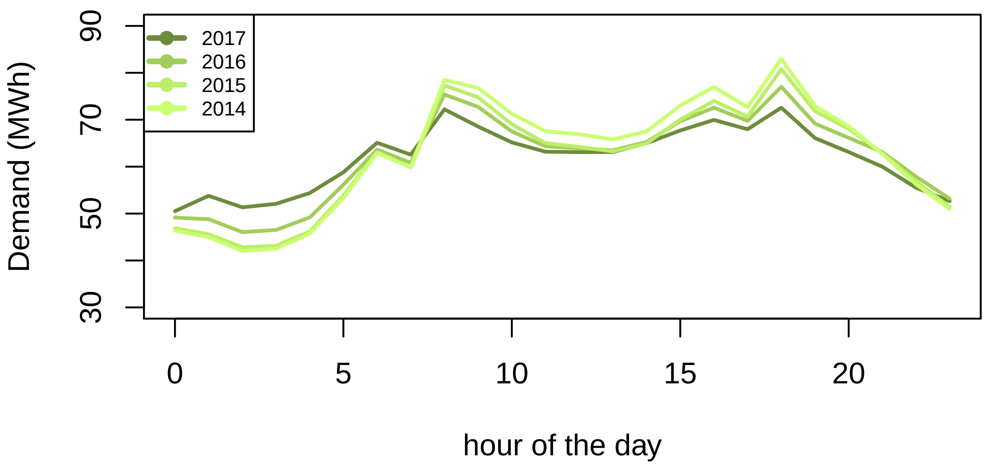

Figure 8: Average daily demand per year

When looking at table 1 it can be concluded that there is no significant increase in the energy demand over the years. The average energy demand is always around 62 MWh and the biggest difference between each year is just 1.53%. What can be noted when looking at the standard deviation is that this is decreasing over the years. This is also visualized in Figure 8 where the 2017 competition seems to have the least difference between peak and off-peak hours. When looking at the peaks it can be noticed that the peaks of 2017 are lower than the peaks in 2014 and 2015. After the 2015 competition Ansarin et all. [6] researched the peak demands and noted that the fixed peak charges where only increasing the peaks. in the 2016 competition Ansarin et all. introduced a capacity charge that was dependent on the height of the peak instead of a fixed price. It seems that the introduction helped to stabilize the balance in the competition, so the introduced pricing mechanism works. Another noticeable result is that the demand increased during the night hours (1 A.M till) . There is no real explanation for in the literature, so this might be a subject for further research.

So it can be concluded that *hypothesis 1* is false, because there is no increase in the total energy demand. What can be proven is that the introduction of the dynamic peak pricing of the research of Asarin et all. did have its effects on the simulation by decreasing the peaks demands.

Hypothesis 2: The SE production increases over the years in the powerTAC simulation

To answer this hypothesis the average SE per year should be calculated. To do this the logtool "SolarProduction" was used. For better explanation, the production per hour is plotted in the figure 9. There was no production in 2014

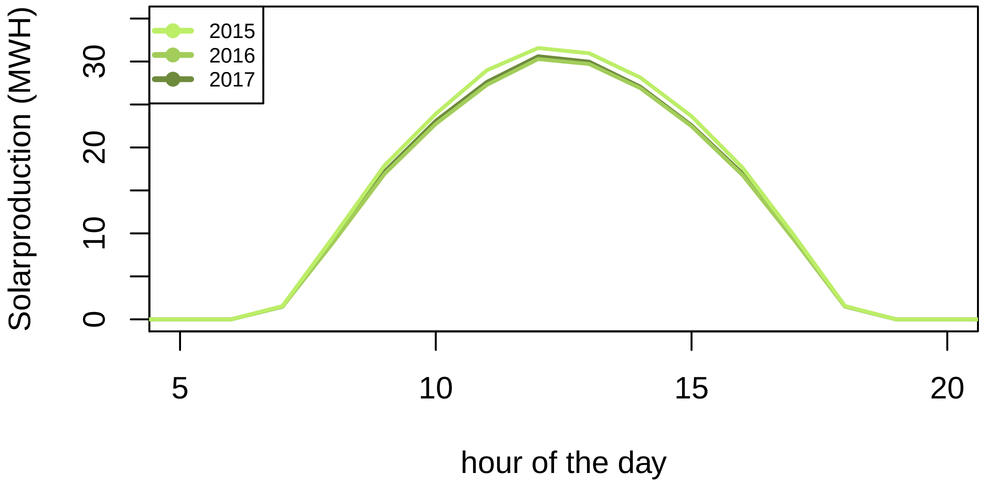

Figure 9: Solarproduction over the years

This figure shows that there is almost no increase in the SE production. In fact there is even a small decrease when you compare the 2015 production with the 2017 production. With no increase in the SE production a decreasing DC seems not to reflect with the real-world. What could cause the stable SE production is the fact that each years' competition takes place in a different region. So it could happen that the 2015 competition took place in a very warm region and the 2017 competition took place in a could region. In that case the SE production capacity increased over the years but was limited by the hours of sun. To test this a table with the weather pattern was created.

Table 2: Weather patterns per competition

Year	Average SE production	Average Temperature	Average Cloudiness
2017	9.023	20.42	0.278
2016	8.931	21.13	0.284
2015	9.385	21.83	0.275

What can be concluded from Table 2 is that the average temperature in 2017 is slightly lower than in the 2015 competition. But this is not enough to to explain the stable SE production. *hypothesis 2* is false, and therefore does the simulation not corresponds with the reality. The worldwide increase in SE was in around 33% in the year 2016 [18]. This increase is very high and would disrupt the market in the simulation, but a little increase in the SE production might be more realistic.

Hypothesis 3: The increase in SE production leads to a lower ND over the years in the PowerTAC simulation

To answer *hypothesis 3*, *hypothesis 2* needed to be true. Unfortunately this is not the case. Nonetheless can be tested if there is a decreasing ND in the simulation. The ND data came from the logtool "Totaldemand" where the hourly ND is calculated and plotted in figure 10. To show what the influence of the SE introduction is the 2014 comptetition is also included in the figure.

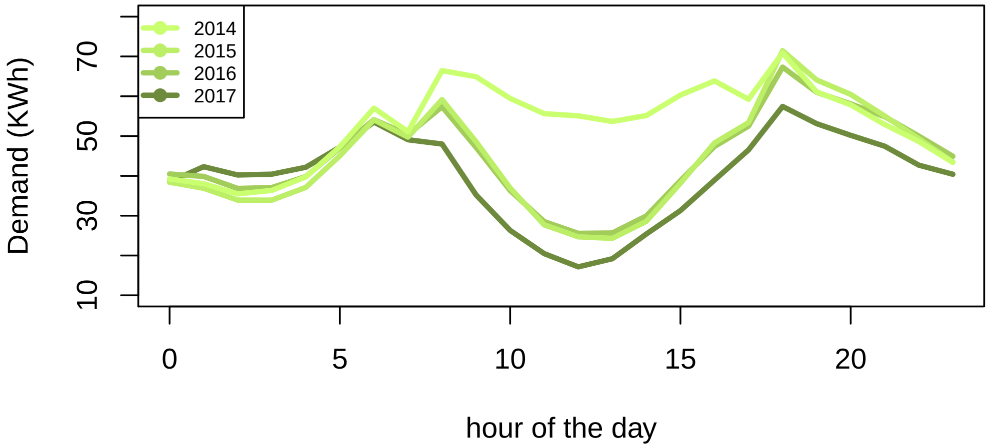

Figure 10: Average daily demand per year

Although there is no increase in SE , figure 10 shows that the ND is decreasing over time. When looking at *hypothesis 1* this could not be explained by a decreasing energy demand, nor could this be explained by the increase of SE. Another variable energy source, the wind energy, could not be the cause either because the contribution of Wind energy is way to small to influence the ND. It can be concluded that *hypotheses 3* is partly true. The average ND is decreasing, but if this is caused by the SE production can not be verified.

(maybe caused by the wind table)

Research question 1: What is the magnitude of the deceasing ND in the powerTAC simulation?

To find out what the magnitude of this effect is, the differences between each year are analyzed. Because there are large fluctuations in the hourly demand, there is also a focus on the difference between the highest and lowest demand during the day. The results are displayed below in table 3

Table 3:

Peak	Hour	2015	2016	change 15-16	2017	change 16-17
Moningpeak	8	59.2	57.4	-3%	48	-16.3 %
Noon dip	12	24.7	25.6	3.5%	17.1	-32.9 %
Eveningpeak	18	71.4	67.3	-5.8%	57.4	-14.7 %
Total Average change	$1-24$	44.3	44.6	1.8	39.7	-11.5%

Table 1 shows the differences of ND at the peaks and the off-peak hours as well as the average ND in each year. What can be concluded is that the difference between 2015 and 2016 are almost none existent and the differences between 2016 and 2017 are more present. With an average difference of 11.5% in ND with peak up to 32.9%, a decrease in ND is present in that year. Because there are just three years of data, it is hard to see if there is a real trend going on. An option to test if there is a downward trend is to extend the trend with the forecasts for the next years by using exponential smoothing. With exponential smoothing the predicted ND's of the 2018 and 2019 game can be calculated.

Exponential smoothing analyze the data of the previous years to find seasonality and trends. With the previous data it tries to create a model to predict future datapoints. There are two sorts of methods to create an exponential smoothing model, additive and multiplicative. The multiplicative method is used when the prediction uses increases of decreases in seasonal effects [4] the additive method doesn't. Because in this analysis the subject is to look for seasonality, the model was created with the multiplicative method.

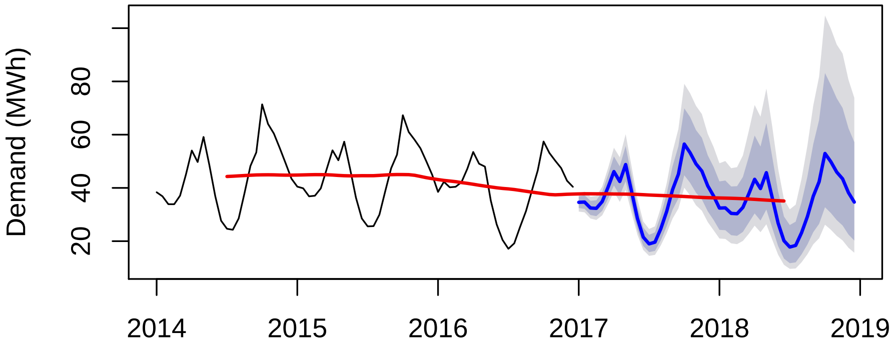

Figure 11: ND's over the years including predictions and trendline

Figure 11 shows what exponential smoothing looks like. The hourly ND's of the previous three years are analyzed and a model was created. This model predicts the future datapoints within an 90% (light gray area) and a 80% (dark gray area) chance of occurrence. The figure becomes wider because the predictions in the far future are less accurate then in the near future. This is why is chosen to predict only 2 years ahead. the blue line is the best fitted prediction, and the red line states the trend in the whole timeperiod.

To give a better indication, the predictions where merged in a table like Table 3 and the differences between the fitted line (blue line) and the occured data where calculated. The difference between the 2018 prediction and the 2017 competition was a 4.3 % lower ND on average where the difference between 2018 and 2019 was 6.3 percent. Also the trend direction of the trend can be calculated, with exponential smoothing. The trend shows that there is a small decrease of ND over the 5 year period with a magnitude of 2.3% a year. So the conclusion from *research question 1* is that the magnitude of the decreasing ND is 2.3% per year.

5.2 What effect does the decreasing DC have on the simulation?

Hypothesis 4: An <u>increase</u> in RE production leads to a <u>increased</u> number of time slots with a negative ND?

Although the magnitude is small, the presence of the decreasing DC is still there and should be something to take into account with respect to the simulation. The question arises what effects are on the simulation. As told in the section "Research Questions and Hypotheses" there are hours in the real-world that the ND becomes negative [23]. Since there are around 264.000 timeslots in each competition, the scenario that the ND becomes negative is fairly possible. To analyze this, a code was developed to count how many times in a game the ND was below zero. All the data is plotted in a boxplot and is showed in figure 12.

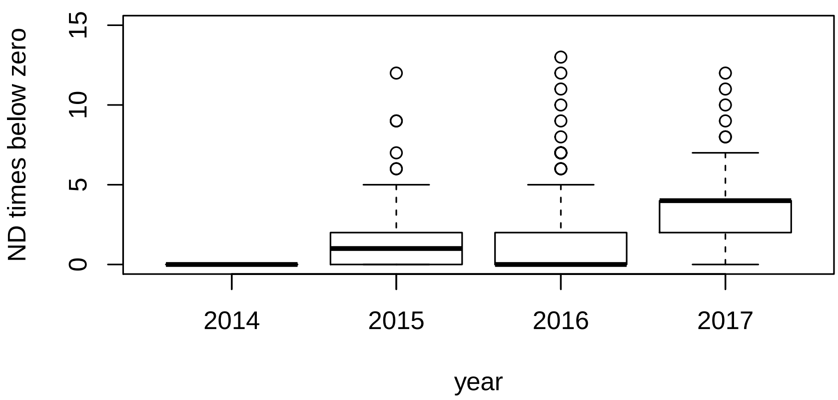

Figure 12: boxplot with times ND < 0 per year

Although exponential smoothing can not be applied here to calculate the trend there is still a trend visible when looking at figure12. The boxplots show that the times that the ND is negative is increasing over the years. Because there is no increase in RE production, it can not be concluded that this trend is caused by the increase in RE production. Therefore *hypothesis 4* is partly true. There is an increased number of timeslots with a negative ND, but this is not caused by the increase in RE production.

Hypothesis 5: Negative ND leads to negative bidprices

To answer *Hypothesis 5* the "MktPriceStats" and the "TotalDemand" logtools where used. A dataset was created where all the timeslots that had a negative ND where stored. This dataset was matched with the variable "timeslot" and "game" to the prices from "MktPriceStats". Because "MktPriceStats" is a dataset with all the offered prices, the lowest offered prices where chosen because they have the highest possibility to be cleared. The new created dataset with prices and ND's is plotted in figure 13.

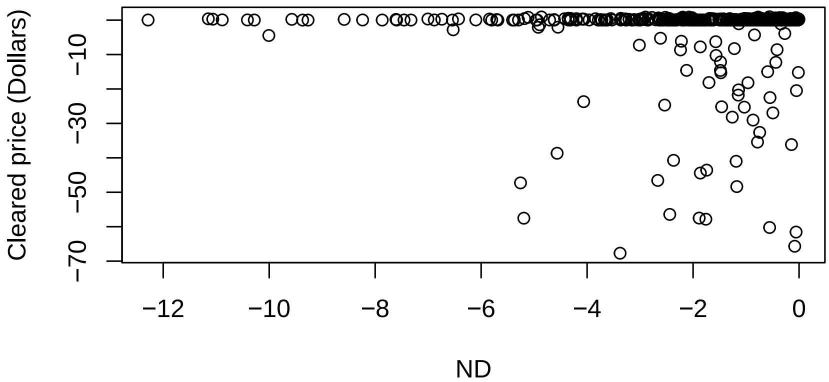

Figure 13: cleared prices when ND is < 0

Figure 13 shows that a lot of prices are offered slightly above 0, no matter how negative the ND is. Of all the 486 negative ND occurrences only 60 had negative prices, which is around 12.3 % of the whole population. This indicates that brokers are not prepared to pay the customers to use energy, like this happens in the real world. What is also noticeable is that when negative prices are offered, they tend to be very negative, with outliers up to -67.70 Dollars. There is no logical explanation for these very negative prices in the literature. There is also not a significant correlation between the price and the ND (cor=-0.095 pvalue=0.8761).

It can be concluded that *hypothesis 5* is false because the prices are more often positive than negative when the ND is negative. It can also be concluded that broker are eager to make profit on there purchased energy no matter how much oversupply there is. When referring back to *Research question 2* it can be concluded that the effect of a decreasing DC is that there are more timeslots with a negative ND. The decreasing ND does not seems to have influence on the prices.

5.3 Do brokers profit from the DC?

Hypothesis 6: Increased SE production leads to <u>lower</u> average prices in the energy market

Hypothesis 6 was created by the general economic definition that oversupply would lead to lower prices. *Hypothesis 2* showed that there is no increase in SE production, so it is hard to draw a conclusion for this hypothesis. Another effect that could influence the prices is the demand, which was tested in *hypothesis 1*. The conclusion from *hypothesis 1* was that the energy demand was also stable over the years. If both demand and supply are stable the expectation would be that the prices are stable to. Therefore the hypothesis can be changed to *Hypothesis 6 : The stable demand and supply should lead to stable prices in the PowerTAC competition* . The data of the "MktPriceStats" logtool was used and led to the results shown in figure 14.

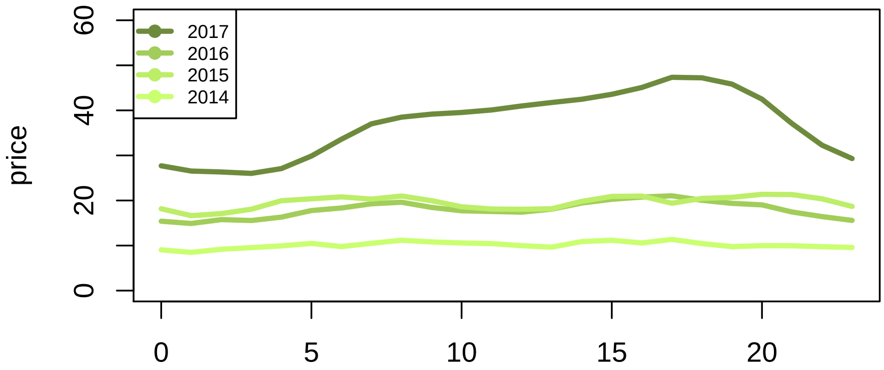

Figure 14: average energy prices per hour

The stable demand and supply should have led to stable prices, but figure 14 shows that there is an increase in the prices. What must be noticed is that the lines in the graph are the average bid prices of the brokers. The increased prices could be explained by the fact that there are more active brokers so there are more bids on timeslots. When looking at the 2014 data there are more timeslots "open", meaning that there are no bids for the wholesalers. This is noted as a zero which would lead to a lower average. So it can be concluded that *hypothesis 6* is false, instead of a decrease or stable price, there is an increase in the average bidprice.

Hypothesis 7:Increased SE production leads to <u>increased</u> price volatility

For this hypothesis, the same problem occurs as the previous hypothesis, namely there is no increase in SE production. However the conclusion from *hypothesis 6* was that there is an increase in prices, which could be caused by the increased activity of the brokers. Both could influence the dependent variable price volatility. To test this the bidprices in the "MktPriceStats" logtool where used. the volatility is calculated as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \overline{x})}{N-1}}$$

Where σ is the volatility, N is the number of bids, x_i the cleared bid and $\overline{x}$ the average bid.

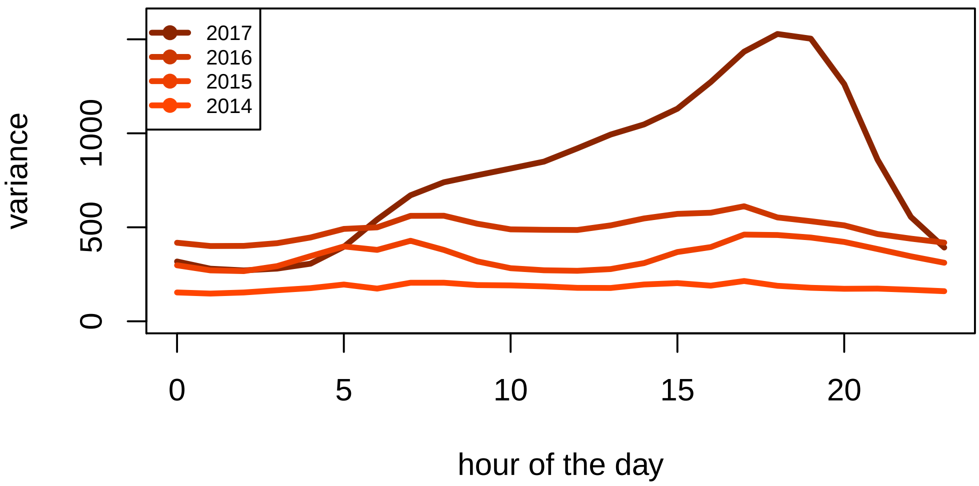

Figure 15: Volatility per hour of the day

What can be concluded from figure 15 is that the volatility is increasing over the years. Especially during the peaks hours in the 2017 competition the volatility is much higher than in the previous years. This can be explained by an adjustment made by the developers. In the 2017 competition the supply was enlarged with a factor 11 and the so called "Grid Buyer" (GB) was introduced [34]. To stabilize the enlarged market GB buys rougly 10x the demand of the PowerTAC broker, so the supply for the brokers stays the same. The demand of the GB is calibrated on the real-world demand of the North Operations Region of the Midwest ISO, which covers the Northern US and part of the Canadian grid. Concluding this, *Hypothesis 7* is partly true. There is increase in price volatility, but again not caused by the dependent variable SE production, but caused by an adjustment in the simulation.

Hypothesis 8:Increased price volatility lead to higher profits for brokers

Before answering *Hypothesis 8*, it must be noted that it is very hard to draw a correlation between the dependent and independent variable, because the brokers' strategy changes each year. A difference in profit can be caused by price volatility but also a dozen other variables. Also the fact that each years' competition has a different composition of players . The best way to see if there is an in difference in profits over the years, is to compare the profits of players who competed in all the four competitions (2014 until 2017). There are 4 players who meet this requirement namely: AgentUDE, COLDpower, Maxon and CrocodileAgent. The profits are from a dataset created with the "BrokersAccounting" tool, where the cash position of the brokers is referred to as profit. Figure 16 shows the profits.

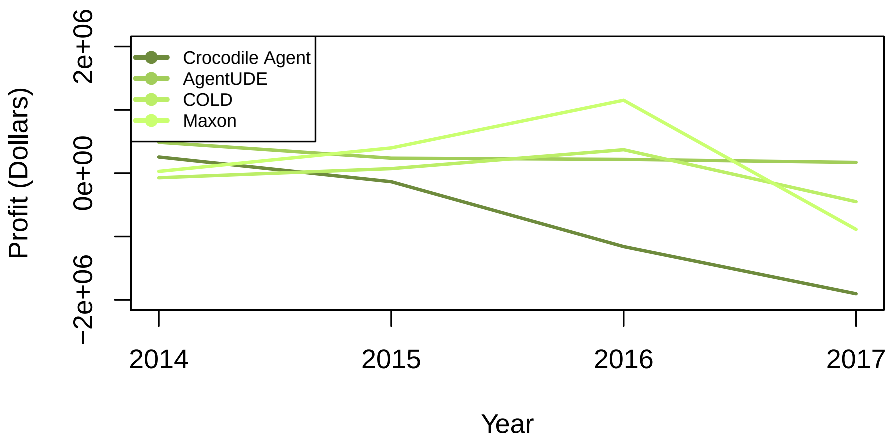

Figure 16: average profits of each broker in each competition year

Although there is a small peak in the profits in the 2016 competition the overall trend seems decreasing. In the 2017 competition the the best broker had an average profit of just 170,030 dollars where in the 2016 competition brokers sometimes made more on average more than a million per game. All the other players had negative average profits. As told above, there can be multiple factors that influence the profits of the brokers, so a causal relation can't be proven. To come back to *research question 3: "Do brokers profit from the DC?"* a negative answer should be given. The brokers in the competition pay more for energy and receive less profit.

6 Conclusions and Recommendations

To find out where the simulation does not correspond with the real world, three research questions and 8 hypotheses where prepared. *Research question 1* had three hypotheses to test the real world principles. The first hypothesis was showed that there was no increase in the energy demand. Nevertheless it could be concluded that pricing mechanism of Ansarin et all. worked. The second hypothesis (and most important because other hypotheses made their assumptions on this) was false. There was no increase in SE production, and this was not caused by the temperature. Although the SE production was not increasing over the years there was a decreasing ND effect. What causes this decreasing ND effect was not clear but it's magnitude was an average 2.3% decrease each year. Since the real-world increase in SE was around 33% in the year 2016 [18], and the increase in the simulation was slight negative, It is recommended to revise this supply variable. A 33% increase is very high and would probably disorder the market, but at least an increase would make the simulation more realistic.

Research question 2 looked at the consequences of the decreasing ND curve. *Hypothesis 4* checked whether there where moments where the RE production supplied the whole market. The conclusion was that this is happening and will probably happen more often in future simulations. The consequence in the real-world was that the prices became negative meaning that wholesalers pay brokers to use their energy. This was not the case in the simulation but. Most prices approached the zero but where offered slightly above the zero. It seems that the brokers want to make a profit no matter how much oversupply there is. The tackle the problem of negative ND's, it is recommended to use a pricing mechanism, because the brokers seems to be very affected by this. The Wholesale buyer seems to be best mechanism for this. The wholesale buyer as described in the 2017 manual can be seen as "An industrial site that uses electric power when the price is low enough to process heat or electrolysis."[34]. Giving the Wholesale buyer a more significant role in the simulation might decrease the ND problem.

Research question 3 contained three hypotheses which where focused on the effects of a decreasing ND for brokers. Where *hypothesis 6* expected a decline in average bid-price because of the oversupply created by SE production, the opposite happened. The average bid-prices in the year 2017 where almost twice as high as the 2016 and 2015 competition. Also the price-volatility in simulation increased during the years. This is probably caused by the introduction of GB in the simulation. The possible explanation for the price increase could be the more active brokers, but this was not proven in this paper. Both *hypothesis 7* and *hypothesis 6* showed the effects to the dependent variable but couldn't prove the causation because of the number of influences on both variables. What causes the increased price and price-variance might be a subject for future research. At last the profits of the brokers where analyzed. Although only half of the competition was analyzed a downward trend was visible. Referring back to the research question "Do brokers profit from the decreasing DC", the answer does not seem positive for the brokers. They makes less profits nor can they buy cheaper energy. Whether this is caused by the decreasing ND, is not proven but seems unlikely. Other factors like GB and the strategy of other brokers are more likely be have influence on the prices. The GB was introduced to prevent brokers in cornering the market, but it seems to have a big influence on the results of the brokers. Therefore the recommendation is to evaluate if the introduction of the GB does not have to much influence on the profits of the brokers. On the other hand, this seems a good challenge for the brokers and could also lead to better predictions.

With respect to *research question 3* it is hard to draw hard conclusions and causalities because there are many factors influencing the competition. I tried to minimize the bias, by describing as much characteristics as possible, but to draw hard significant conclusions is still not possible. It could be possible if an experiment is set up where all the other variables where stable. Unfortunately due to time reasons this wasn't possible for me but this could be possible in a future research.

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