AUCTIONS FOR A BRIGHTER FUTURE

Using an Agent-Based Model to Simulate Auctions of Solar PV in Sweden

Authors

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Abstract

Global warming is one of the most pressing threats to humanity of our time. One of the areas where transitioning towards sustainability is most urgent is in the energy sector. In this thesis, the implementation of an auction-based subsidy scheme for solar photovoltaics (PV) in Sweden is modeled and analyzed. The aim is thus to estimate the total cost of implementing such a system, determine whether allocative efficiency would be achieved and if the cost would exceed the welfare loss from continuing as status quo. The model is based on a previous article where the same subsidy system is simulated for onshore wind power in Germany, in this thesis it is adopted to a Swedish context for solar PV. The results of the simulation are compared to the welfare loss from continuing as usual based on the social cost of carbon dioxide. The auctioning system is discussed in relation to the current main Swedish subsidy scheme used to promote sustainable energy: tradable green certificates (TGC). The simulation exhibits decreasing cost per kWh for promoting solar PV as more auction rounds are carried out. Allocative efficiency is not achieved, however, the cost of implementing the auctions would far subceed the welfare loss from generating the corresponding electricity with the current energy mix. When compared to TGC, the total cost of the auctioning system exceeds the current price for promoting the corresponding expansion through the current system, however, the target expansion is arguably achieved with a considerably greater certainty using the auctioning system.

Keywords: RES Auctions, Solar PV, Sustainability, Climate Change, Renewable Energy, Environmental Economics, Agent-based Modeling, Auction simulation, Sweden

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Björn Danielsson
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1 Introduction

In the latest Assessment Report from the Intergovernmental Panel on Climate Change (IPCC) (2021), it is established that it is "unequivocal that human influence has warmed the atmosphere, ocean and land". The report further states that human-induced climate change already is affecting weather and climate extremes all over the planet. Some of the weather extremes that have become more frequent and more intense include heatwaves, heavy precipitation, and tropical cyclones. The warming of the surface temperature will continue until the middle of this century, even in the most optimistic scenario with the most drastic emission reductions. Both 1.5 and 2 degrees of global warming will be exceeded during this century unless deep reductions in greenhouse gas emissions occur in the coming decades (IPCC, 2021).

According to Sterner and Coria (2002), the most cost-effective way to decrease emissions is via market-based instruments, e.g., carbon tax, cap-and-trade systems or certain auctions. Market-based policies increase the competitiveness of less carbon heavy solutions and technologies, and thus furthers the incentive for transitioning towards a low carbon, or even carbon neutral, economy.

One type of market-based policy instrument intended to reduce emissions from electricity generation by increasing the share of renewable energy is renewable electricity auctions (Lang and Lang, 2015). The basic idea is to offer a certain capacity of electricity and award financial support to the bidder who demands the lowest amount to supply it. In this way, the target expansion of a given renewable technology shall be reached cost-efficiently. Germany is considered a role model in their transition to renewable energy sources due to their history of successful subsidy schemes, and the auction scheme introduced in 2017 is their current subsidy scheme.

Sweden, despite having a low emission-intensity energy mix, has not been as successful as Germany in the adoption and expansion of solar photovoltaics (PV) on a large scale. This can be explained by the fact that solar PV historically has been disadvantaged by the main Swedish subsidy scheme, tradable green certificates (TGC) (Lindahl et al., 2022). The objective of this thesis is thus to evaluate what the outcome of an implementation of the equivalent of the German auctions in Sweden could be. As only projects over a certain capacity can enter the auctions, it was deemed only PV parks, as opposed to residential solar PV, can reasonably enter (Bundesministerium für Wirtschaft und Klimaschutz, 2017). This perspective towards PV parks is interesting in the Swedish context since PV parks make up a very small share of the total Swedish PV capacity compared to the global average share (Lindahl et al., 2022).

To simulate the implementation of an auction-based awarding scheme for financial support of solar PV in Sweden, an agent-based model based on a paper by Anatolitis and Welisch (2017) is used. Anatolitis and Welisch (2017) modeled the outcome of auctions for financial support of onshore wind in Germany. This thesis adopts the model to a Swedish context to find how much implementing this system for PV would cost and whether allocative efficiency would be achieved. 32 auction rounds during the 8 years from 2022 to 2029 was simulated, with the target of increasing Swedish PV capacity by 2.56 GW until 2030; or by 80% compared to 2020 (Our World in Data, 2021a).

As the auctions modeled by Anatolitis and Welisch (2017) now has been held, the modeled outcome is tested against the actual outcome using a t-test in order to evaluate the accuracy of the model and the possible implications for the results of this thesis.

The main advantage and objective of implementing the subsidy scheme is to abate greenhouse gas emission in order to mitigate climate change. To get a perspective on whether this benefit actually outweighs the cost of the auctioning system, the welfare loss from continuing to generate electricity with the current energy mix in the EU is estimated using the social cost of carbon dioxide estimated by Kikstra et al. (2021).

Auction-based subsidy schemes for renewable energy has this far never been used in Sweden and to the authors' knowledge, no simulation of such in a Swedish context has ever been carried out. With the increasing urgency to mitigate climate change by transitioning to renewable energy sources, the importance of effective and cost-efficient subsidy schemes is as great as it has ever been. This thesis explores one possible path forward for Sweden in hopes of contributing to a more sustainable future.

2
Theory

In the following sections relevant literature and theories are presented. First, basic auction theory is presented; the basic auction forms are described, and the premises of an auction explained. Then, how allocative efficiency can be achieved in an auction under certain assumptions is explained. Next, the theory is expanded to include sequential auctions and then multi-unit auctions. After the auction theory section, the learning curve theory is presented and finally the social cost of carbon dioxide concept is explained.

2.1 Auction Theory

An auction can be defined as a market institution in which market participants, given a set of rules, decide prices and resource allocation through bidding. There are four basic auction forms: the English auction, the Dutch auction, the first-price sealed-bid auction and the second-price sealed-bid auction. In the English auction, or ascending-bid auction, the price is raised until one bidder remains. In the Dutch auction, or descending-bid auction, the price is lowered until one bidder accepts the price. In the first-price sealed-bid auction, bidders submit sealed bids and the highest bid wins. The bidders are thus not able to observe the other bidders bids and adjust their own bids accordingly. One example of a first-price sealed-bid auction is the German renewable energy auctions (Anatolitis and Welisch, 2017; McAfee and McMillan, 1987). In the second-price sealed-bid auction, or Vickrey-auction, bidders submit their sealed bids and the winner pays the bid of the second highest bidder (Vickrey, 1961).

Auctions are typically used by monopolists (e.g., the owner of an original artwork) or monopsonists (e.g. a government awarding financial support for expansion of renewable energy). Typically, there is a limited number of bidders which means there is oligopsony (if bidders are buying a good, e.g., an original artwork) or oligopoly (if bidders are selling a good, e.g., if bidders are PV investors) among the bidders. This means there is monopoly (monopsony) on one side of the market (this agent will from now on be called the auction organizer) and oligopsony (oligopoly) on the other side of the market (these agents will from now on be called bidders). According to classical economics, the outcome in such situations is arbitrary; any allocation from the auction organizer attaining all the surplus to the bidder attaining all the surplus is possible. This issue is avoided in auction theory by assuming that the auction organizer has all the bargaining power. It is assumed that the auction organizer can make a commitment to a set of rules and guarantee the bidders that they will not deviate from these after observing the bids. This means the auction organizer acts as the Stackelberg leader, i.e., the behavior of the bidders is dependent on the leader's actions (McAfee and McMillan, 1987).

Acting as the Stackelberg leader is an advantage for the auction organizer because it allows them to set the rules to make the bidders bid in a way that is favorable to them in order to extract maximum surplus. At the same time, the auction organizer's ability to extract surplus is limited by asymmetry of information, i.e., the auction organizer does not know the bidders' true valuation of the offered good/service. This means that the auction organizer is not likely to be able to drive up the price to the maximum valuation among the bidders and thus extract maximum surplus. On the other hand, organizing an auction would be superfluous in case of perfect information; the auction organizer would then simply sell to the bidder with the highest valuation at this price. This is the core of the auction problem: the bidders' valuation cannot be observed (McAfee and McMillan, 1987).

Different goods give rise to different conditions for how bidders value a good and why differences in valuation arise. There are two distinct reasons for why different valuations arise. Firstly, the bidder's inherent valuation of the good, and secondly, their access to information on the true value of the good. These reasons can be illustrated by two extreme cases. In the first case, the bidder's preference is the only reason for difference in valuation; this is the independent-private-values model. This model describes a situation in which the bidder's valuation is strictly dependent on their inherent valuation of the good and thus statistically independent of the other bidders' valuation. The bidders do not know the other bidders' valuation and learning it would not impact their valuation. On the other side of the spectrum, there is the the common-value model in which the good has a single objective but unobserved value. The bidders estimate this value using the information available to them. In this model, learning another bidder's valuation is valuable because it offers information about the true value of the good. In reality, the valuation is likely a mix of these two extreme cases. A bidder's valuation likely depends on both their own inherent valuation and the unobservable; the valuation of other bidders and the true value of the good. This more nuanced description of how valuations arise is capture by the concept of affiliation; the inherent valuation of one bidder might be affiliated with other bidders' valuation and the true value. Put simply, if valuations are affiliated, one bidder perceiving the value of an item to be high means the other bidder's perception of the value likely also is high (McAfee and McMillan, 1987).

2.1.1 How Allocative Efficiency is Achieved in Auctions

To analyze the outcome in the different auction forms, a benchmark auction model is used which is based on four assumptions:

- Bidders are risk neutral,
- the independent-private-value assumption holds: All bidders know their true valuation of the good (but not the other bidders'),
- bidders are symmetric: The valuations of the bidders are drawn from the same probability distribution
- and payment is only dependent on the bid.

Given that the assumptions in the benchmark model holds, it can be shown that all four basic auction forms results in the same revenue to the auction organizer on average; this is the Revenue-Equivalence Theorem (Vickrey, 1961; Holt, 1980; Harris and Raviv, 1981; Myerson B., 1981;

Riley and Samuelson, 1981). It can further be shown that the resulting allocation is Pareto or allocative efficient; the bidder with the highest valuation wins. (McAfee and McMillan, 1987).

In the English, as well as the sealed-bid second-price auction forms, there is a dominant strategy. In the English auction, the dominant strategy is simply to drop out of the auction when the bid amount reaches your true valuation. This means the bidder with the highest valuation will win and they will pay the true valuation of the bidder with the second highest valuation, i.e., the bid amount when the second last bidder dropped out. In the sealed-bid second-price auction, the dominant strategy is to bid your true valuation. This is because the cost for the winner is the second highest bid and thus out of their control. The winner can therefore only influence their probability of winning, which increases the higher they bid. Thus, every bidder maximizes their probability of winning by bidding their true valuation (McAfee and McMillan, 1987).

In a first-price sealed-bid auction there is no dominant strategy, instead the optimal bid is given by a Bayes-Nash equilibrium. In a Bayes-Nash equilibrium, every bidder bids an amount based on their valuation given that all other bidders is using the same strategy, i.e., no bidder can change their strategy to achieve a better outcome. The bidders presume that their valuation is the highest, otherwise participating in the auction would be meaningless. This assumption can be made without cost to the bidder since they will not have to pay if it does not hold. The bidder then has to guess the difference between their valuation and the next highest valuation. The bidder also has to assume that all the other bidders are following the same decision rule as they are. Because every bidder wants to maximize their surplus (their valuation minus the winning bid), this means every bidder will bid their true valuation minus their estimated difference to the second highest valuation. Assuming strategies are symmetric (bidders with the same valuation submit equal bids), it follows that the winning bidder will be the bidder with the highest valuation. This further implies that the outcome of a sealed-bid first-price auction is allocative efficient; the auction organizer receives the highest possible bid (McAfee and McMillan, 1987). The Dutch auction form will yield the same outcome as the first-price sealed-bid auction form because the circumstances the bidders face are exactly the same: the bidders bid without knowing the other bidder's decisions and will pay equivalently to what they bid, if they win (Vickrey, 1961).

In summary, it has been shown that all four auction forms on average yield the same expected revenue to the auction organizer and that the bidder with the highest valuation wins; allocative efficiency is thus achieved in all four (Vickrey, 1961; Holt, 1980; Harris and Raviv, 1981; Myerson B., 1981; Riley and Samuelson, 1981; McAfee and McMillan, 1987).

2.1.2 Relaxing the Assumptions of the Benchmark Model

It follows from the Revenue-Equivalence Theorem that the auction forms cannot be ranked based on efficiency or revenue to the auction organizer. However, this is given that the assumptions of the benchmark model holds and the instruments available to the auction organizer are limited. When the assumptions are relaxed some auctions turns out more beneficiary to the auction organizer and the outcome will be further away from allocative efficiency the more instruments the auction organizer is given (McAfee and McMillan, 1987).

Reserve Price

A reserve price (or a ceiling price if the auction organizer is buying a good/service) can be shown to increase the average selling price. First, a reserve price constitutes a trade-off: if the highest valuation is greater than the auction organizer's valuation but lower than the reserve price, the auction organizer loses out on this potential surplus. However, if the highest valuation is greater than the reserve price which is greater than the second highest valuation, the auction organizer accrues surplus equivalent to the difference between the reserve price and the second highest valuation which it would not have without the reserve price. This tradeoff has a simple solution: The optimal reserve price is the average of the highest possible valuation and the auction organizer's valuation. On the basis of the Revenue equivalence theorem, this result is applicable to all four basic auction forms (McAfee and McMillan, 1987; Harris and Raviv, 1981; Myerson B., 1981; Riley and Samuelson, 1981). To maximize revenue, the auction organizer sets a reserve price and doesn't sell if all bidder's valuation is too low. This means it is possible that the auction organizer does not sell even if a bidder's valuation exceeds the auction organizer's valuation; introduction of a reserve price means the outcome can be inefficient (McAfee and McMillan, 1987).

Perfect Competition

This far it has been assumed that the bidders can be considered oligopsonists (or oligopolists if bidders are selling a good); the number of bidders are limited. If the number of bidders is increased, the valuation of the bidder with the second highest valuation will increase on average; the average revenue of the auction organizer increases (Holt, 1979; Harris and Raviv, 1981). The difference in valuation of the bidder with the highest valuation and the bidder with the second highest valuation will decrease with increased competition which means the bids increase; but as long as the number of bidders is finite there will be a difference which will accrue to the bidder with the highest valuation as economic rent (McAfee and McMillan, 1987). However, as the number of bidders approach infinity, the second highest bid approaches the highest possible valuation; if there is perfect competition among bidders, the entire surplus goes to the auction organizer (Holt, 1979).

Risk-averse Bidders

An auction involves risk: In case a bidder loses, they pay nothing but potentially misses out on the economic rent of winning. The degree of risk aversion thus impacts bidding behavior. In the benchmark model, it is assumed that bidders are risk neutral. With risk-averse bidders, the outcome of the different auction forms differ. But, assuming all other assumptions of the benchmark model holds, the auction organizer will do at least as well with risk-averse bidders as with risk-neutral bidders. In the English and second-price sealed-bid auctions, the dominant strategy remains to bid up to your valuation, so the expected revenue of the auction organizer is the same. However, in the first-price sealed-bid auction (and in the Dutch auction) the expected revenue of the auction organizer increases with increased risk aversion: The more risk-averse the bidder is, the higher they will bid. This is because the probability of winning and earning economic rent increases the higher the bid (McAfee and McMillan, 1987). Thus, the expected revenue of the auction organizer will be larger in the first-price sealed bid auction than in the English- or second-price sealed-bid auctions with risk-averse bidders (Harris and Raviv, 1981; Holt, 1980; Riley and Samuelson, 1981).

Asymmetric Bidders

Suppose that the assumption of symmetric bidders no longer holds: bidders can now be divided into two recognizably different categories; A and B. The total amount of category A bidders is n_A and the total amount of category B bidders is n_B. Assume all other assumptions still holds. The English auction will still achieve allocative efficiency; the price will simply rise until it reaches the valuation of the bidder with the second highest valuation and the bidder with the highest valuation will win. This is not the case in the first-price sealed-bid auction which means the Revenue-Equivalence Theorem no longer holds. Within category A and B respectively, higher valuation bidders will still bid higher. However, this is not necessarily the case across the categories since different category bidders perceives the competition differently: a bidder in category A faces n_A-1 category A bidders and n_B category B bidders while a bidder in category B faces n_A category A bidders and n_B-1 category B bidders. This means the decision rule will no longer be the same across all bidders; a category A bidder's guess of the gap between their own and the second highest valuation will differ from that of a category B bidder. This means the bidder with the highest valuation does not necessarily win; the outcome might be inefficient. However, even though the outcome of the English auction is efficient when bidders are asymmetric, the expected revenue to the auction organizer is not necessarily greater or less than in the first-price sealed-bid auction (McAfee and McMillan, 1987).

Royalties and Incentive Contracts

In the benchmark model it is assumed that payment is dependent solely on the bid. However, in many cases the auction organizer can condition the bidder's payment on additional information about the valuation in order to extract more revenue. One common example is auctions for oil rights on government-owned land. Neither the auction organizer (the government) nor the bidders know how much oil the land actually holds, but this information will be available ex post. By conditioning the payment on the bid plus a royalty per unit of oil, the auction organizer is able to use this information. By increasing the royalty rate the significance of the difference in valuation between bidders is weakened. This means the difference in valuation between the bidder with the highest and the bidder with the second highest valuation is reduced which results in a higher expected revenue to the seller (McAfee and McMillan, 1987, Riley, 1988).

2.1.3 Sequential Auctions

In the previous sections, the assumption was made of an isolated auction occurring only once. However, in reality auctions are often recurring events; one example is the German renewable energy auctions which are typically held four times a year (Anatolitis and Welisch, 2017). As

Jeitschko (1998) demonstrates, this will change the strategy due to learning effects; bidders are now able to use the information from previous auctions to adapt their bids in future auctions and anticipate how information made available in the current as well as future rounds will affect the current auction.

To study the outcome, Jeitschko (1998) has modeled a first-price sealed-bid auction where two identical objects are auctioned in sequence. There are three bidders which can be of two types: low ("low type") or high valuation ("high type"). The valuations are normalized to 1 and 0. The payment to the low type bidders is zero; they simply bid their value. Both bidders have demand for only one unit and it is assumed that the winner in the first auction does not participate in the second. As described in Section 2.1.1, the equilibrium strategy in a first-price sealed-bid auction constitutes a Bayes-Nash equilibrium.

After the first auction the bidders know the type of the winner, but the useful information for the second auction is actually the valuations of the losers in the first auction since only they will participate in the second auction. The bidders get indications about the type of the other losing bidders since they know their bids in the first auction was below the winning bid. The equilibrium strategy in the second auction will thus be a function of the information revealed in the first auction; the bidders decide their optimal bid by adapting their beliefs regarding the other bidder's valuations and strategies based on the outcome of the first auction (Jeitschko, 1998).

In the first auction, bidders of the high type must consider the opportunity cost of winning the first auction, i.e., the expected payment from winning the second auction instead. When considering this opportunity cost, the impact of the information made available after the first auction must be accounted for. This means that in determining their optimal strategy in the first auction, the bidder must consider the expected information revealed ahead of the second from the bid placed in the first (Jeitschko, 1998).

The learning effects create a connection between the two auctions which goes both ways; the equilibrium strategy in the first auction is affected by the opportunity cost of winning this auction, which is affected by the equilibrium strategy in the second auction which in turn is dependent on the outcome of the first auction (Jeitschko, 1998).

The bidders face a trade-off when choosing strategy in the early auction: They can either place a higher bid and increase their chances of winning in the early auction or place a lower bid and increases the probability of losing, which entails them participating in a later auction where more information will be available to them which means their expected payment will increase (Jeitschko, 1998).

According to Jeitschko (1998), the winning bid in the first and second auction should on average be equal. This is explained by three effects; Since the bidder who wins drops out after the first auction and the winning bid is increasing in number of bidders (see Section 2.1.2), this effect lowers the winning bid relative to the first auction. Next, participants in the second auction are generally more likely to be low type bidders. This is because losers in the first auction is more likely low type because they will always lose if a high type participates. This lowers the bids, both because the average valuation is lower but also because high type bidders place lower bids relative to the first auction since they know the other bidders are more likely low types. The final effect works in the opposite way of the previous two; since the second auction constitutes the last possibility of winning, the bidders value winning more highly. There is no opportunity cost of losing this auction as there was in the first one which increases the average winning bid. In equilibrium, the final effect exactly offsets the first two effects (Jeitschko, 1998).

2.1.4 Multi-unit Auctions

The previous auction theory builds on one important condition: only one object (one unit) is being auctioned per auction. Ausubel et al. (2014) shows that when multiple units are auctioned, the same results no longer apply. The difference arises due to differential bid shading; the bidders gain from shading[1] their bids differently across units.

There are two main multi-unit auction formats: pay-as-bid (PAB) auctions and uniform-price auctions. In both auction formats the auction organizer collects bids for different quantities at different prices and then determines the market clearing price. The difference between the two auction formats is the payment; In PAB auctions the winners pay exactly their bid while in uniform-pricing auctions the winners all pay the market-clearing price for all units won (i.e, the highest rejected bid). For single-unit auctions, the uniform-pricing and PAB auctions corresponds to the second-price and first-price auctions respectively; but the efficiency and truth-telling of these auction forms explained in Section 2.1.1 does not carry over to multi-unit auctions (Ausubel et al., 2014).

Ausubel et al. (2014) compares the different auction formats by modeling the outcomes. The auctions are modeled as sealed-bid auctions: bidders simultaneously and independently submit their bids. One important feature of the auction model is that values can be interdependent; the bidder's value of one unit is conditioned on the information revealed by winning or losing previous units. Bidders are symmetric: their valuation is drawn from a joint distribution which is known to all bidders, but each bidder's realized valuation is known only to them.

Ausubel et al. (2014) finds ranking the two formats based on expected revenue and allocative efficiency difficult: scenarios can be constructed where both formats are superior in both expected revenue and efficiency. The main difference between the scenarios is the marginal valuation of the good: constant marginal value or diminishing marginal values.

Constant Marginal Values

Constant marginal values - or flat demands - implies that bidder's valuation of all units are equal, up to a fixed capacity. With flat demands, an auction is ex post allocative efficient if the bidder with the highest valuation wins all units up to their fixed capacity (Ausubel et al., 2014).

In the uniform-price auction, the payment for all winners is given by the highest rejected bid. With the assumption that there is two bidders and two units, this result in that the payment is

[1] Bidding below your true valuation

given by the third-highest bid; the market-clearing price. Like in the second-price sealed-bid auction, the winning bids for the first unit does not set the price but determines the probability of winning. This means, as is explained in Section 2.1.1, that the dominant strategy is to bid your true value for the first unit. For the second unit, increasing you bid increases the probability of winning, but also the expected payment for the first unit since the market-clearing price is increased. Ausubel et al. (2014) shows that with a uniform distribution of values, the effect on the expected pay-off from increasing the bid for the second unit above zero is always negative. Thus, it is strictly optimal for bidders to bid their true value for the first unit and zero for the second; this is a Bayesian-Nash equilibrium and it is ex post inefficient because the two units are always allocated to different bidders, even though one has a higher valuation for both units.

In the pay-as-bid auction, the payment for each unit is equivalent to the winning bid for that unit. With constant marginal values, or flat demands, submitting the same value for both units is an equilibrium since the payment for one unit does not affect the payment for the other unit. For symmetric bidders, this equilibrium will be efficient since both units is allocated to the bidder with the highest valuation. For asymmetric bidders, the equilibrium strategies will be asymmetric which means the outcome will be inefficient, as explained in Section 2.1.2 (Ausubel et al., 2014).

Diminishing Marginal Values

By instead assuming diminishing marginal utility, the behavior of the bidders changes. For the uniform-price auction, bidders will always bid a lower bid on the second unit compared to the first one. This also results in that the Bayesan-Nash equilibrium is ex post inefficient (even if the supply is known) and will yield no revenue to the auctioneer. Even by bidding the true value of the bidders, the equilibrium is not achieved (Ausubel et al., 2014).

For the pay-as-bid auction, the second bid will always be lower than the first one. Furthermore, with a diminishing marginal utility, the bidders will shade their bids for two units differently, which is due to the asymmetry that occur between the units. In addition, the bidders does not bid their true valuation in both the first and second round, with the shading decreases between the rounds (Ausubel et al., 2014).

2.2 The Learning Curve Theory

Knowledge and technology are both important factors when it comes to economic growth. Nevertheless, the exogenous variable “knowledge” is rather difficult to measure. Furthermore, knowledge is something that is acquired and thus varies between individuals, even though the experience and background is the same. One way to obtain this knowledge is by experience, or rather, as Arrow (1962) describes it: “learning by doing”. The concept of learning by doing, and therefore also experience, is assumed to be one of the core factors for technical change and development. The experience is assumed to come from the cumulative gross investments (cumulative production of capital goods) (Arrow, 1962).

Historically, it has been observed that when the cumulative production (or in the case of solar PV; the cumulative installed capacity) the cost decreases. Either via a true cost decrease per unit, or via a increase of efficiency. From this relationship the specific technology's learning curve can be obtained. The concept of a learning curve is established from the assumption of learning by doing, where experience (or knowledge) is obtained by producing more of the technology and is thus measured as the cumulative production. As cumulative capacity increases, and cost decreases, the diffusion of the technology is also said to increase as it is now easier to obtain and adopt, which further enhances the learning. The concept of a learning curve is therefore often used as a motivation for public spending and subsidies, especially when it comes to sustainable energy (Grafström et al., 2021).

Learning curves can further be divided into two different approaches: Single-factor learning curves and a two-factor learning curves. The single-factor learning curve is the one previously described, where the only input into the model is the cumulative production, whereas the two-factor model also includes the effect from e.g. cumulative research and development (R&D) and/or scale economy. The main difference between the two models is that the single factor completely assumes a cost reduction from innovation, while the two-factor model also introduces a knowledge stock variable (Odam and de Vries, 2020; Kouvaritakis et al., 2000).

Although the concept of learning curves has been proven for multiple technologies, the concept of comparing a newer, more developed, technology with an older version might not be fruitful (Grafström et al., 2021). Therefore, the concept of a learning curve only holds if the future assumes a path-dependent development and that the technology do not have any major break-throughs or impasses. One examples of this is the automobile, where the development has been so massive that the early models, e.g., the T-Ford, is completely impossible to compare with the cars of the 21st century (Grafström et al., 2021).

Even though the two-factor model is usually more accurate, it also comes with some difficulties. For example, the data for private R&D is usually impossible to gather and therefore this parameter is usually not included and incorporated when estimating the learning curve. Moreover, when estimating a learning curve, it is not possible to only look at a limited part of the market, since doubling the capacity in one specific country will (most often) not matter for the overall global learning and technology change (Grafström et al., 2021).

The market structure also influences how the learning and price reduction will develop over time. A monopolistic market will not see the same price reduction as perfect competition market, since only one firm has control and thus sets the prices and supply level. Regarding renewable energy, one example of a monopolistic market is wind turbine market. This market is not only hard to enter due to large-scale industrial complexity, but also because of the difficulties of long transportation of the wind turbines. However, solar PV does not have the same issues regarding transportation (Grafström et al., 2021).

According to Grafström et al. (2021), there are also multiple factors that affect the price. For renewable energy the return on scale and geographical distance are one of the two main factors.

Also, since the resources used for production can vary a lot in price, this will certainly also affect the installation cost for the consumer later (Grafström et al., 2021).

2.3 Welfare Loss from Carbon Dioxide Emissions

In order to fairly evaluate one policy against another from a societal perspective, externalities has to be accounted for. When comparing renewable electricity generation against fossil, the negative externalities from carbon dioxide (CO_2) emissions caused by the latter is arguably the most prominent. One estimation of these externalities is the social cost of CO_2 ($SCCO_2$) which measures the total welfare lost globally due to the emission of one extra metric ton of CO_2. Due to the complexity of global warming, estimating all externalities is very complex and many estimates of $SSCO_2$ under a variety of assumptions has been calculated. One of the latest estimations has been carried out by Kikstra et al. (2021) using a cost-benefit integrated assessment model (CB-IAM) which aggregates and represents climate-economy interactions. Kikstra et al. states that these models typically lag behind the current state of science, especially with regards to feedback effects. Kikstra et al. therefore uses the PAGE-ICE CB-IAM, which introduced the feedback effects from changes to the surface albedo as well as permafrost thawing and extends this model to include possible long-term temperature growth feedback on economic trajectories and mean annual temperature anomalies.

Kikstra et al. (2021) provides estimations of $SSCO_2$ for a range of climatic and socioeconomic scenarios. The central value in the paper by Kikstra et al. which will be used in this thesis is based on a combination of the socioeconomic pathway SSP2 and the emission pathway RCP4.5. SSP2 is known as the 'middle of the road' scenario and consist of a world where the socioeconomic development follows the historical pattern; the greenhouse gas (GHG) emissions are intermediate and CO_2 emissions remains on the current level until the middle of the century (Kikstra et al., 2021; IPCC, 2021). The mean $SSCO_2$ calculated by Kikstra et al. in this scenario was \$307 per metric ton CO_2 with an 5%-95% uncertainty range of \$82-\$831.

3
Background

The following sections presents background information that is of interest for this thesis. First, a description of the history and gradual development of the German subsidy scheme for renewable energy is presented. A similar evaluation is then presented for Sweden in addition to a brief description of the Swedish market for centralized PV systems. Next, an overview of how different auctioning systems for renewable energy subsidies has been implemented around the globe is presented. The section is ended with background regarding the agent-based model used in this thesis.

3.1 Solar PV in Germany

By the end of 2020, Germany had the world's fourth largest cumulative capacity of PV with 53.78 GW, outcompeted by China (253.83 GW), the United States (73.81 GW) and Japan (67.00 GW). Up until 2014, Germany was the leading nation in cumulative PV capacity, and it was only in 2018 it was surpassed by the United States and assumed fourth place which it has since held (Our World in Data, 2021a). The solar power generation totaled 48.64 TWh in 2020 which amounts to 8.62% of the country's electricity generation (Our World in Data, 2022b; Our World in Data, 2022a).

The rapid expansion of Germany's PV capacity, and renewable energy in general, is primarily attributed to generous financial support based on feed-in tariffs (FiT) (Frondel et al., 2008; Pegels and Lütkenhorst, 2014). A FiT is intended to accelerate investments in renewable energy systems by offering long term contracts with a guaranteed price per unit of renewable electricity; a tariff. The price is based on the cost of power generation for the specific renewable energy technology and some return on investment. As part of the FiT, it is usually mandatory for the grid operators to purchase all available renewable electricity. Typically, final consumers bear the cost of the FiT through a surcharge on their electricity bill (Jacobs and Sovacool, 2012). A FiT system for renewable energy sources was introduced in Germany as early as 1991. In this system, the tariff was linked to the retail rate of electricity which led to volatility in the FiT system. To remedy this issue, the Renewable Energy Sources Act (Erneuerbare Energien Gesetz, EEG) was introduced in 2000 to ensure stability in the the FiT system. The EEG is considered the main driver of the expansion of renewable electricity capacity in Germany and has been globally know as a role model in promoting renewable energy technology (Frondel et al., 2008; Frondel et al., 2014).

Germany is also considered one of the European countries who have made the most learning investments into renewable energy, i.e., investments into expanding the capacity to increase the collective experience of a renewable technology and thereby decrease costs in accordance with the learning curve theory (see Section 2.2) to ultimately make the technology competitive with fossil sources of energy (IEA, 2000).

3.1.1 The EEG's FiT System

The EEG is still in effect today but has been heavily amended since its introduction (Lang and Lang, 2015). However, between its introduction in 2000, and the major update in 2014, the EEG's FiT system maintained the same basic elements (Voss and Madlener, 2017; Pegels and Lütkenhorst, 2014). In this FiT system, the administratively set fixed price per unit of renewable electricity is guaranteed for a set time period, generally 20 years (FuturePolicy.org, n.a; Oschmann, 2010). The tariffs are technology specific and based on the actual cost of power generation (IEA, 2014). Grid operators are required to preferentially accept power generated from renewable electricity production over fossil fuel or nuclear electricity (Frondel et al., 2014; Oschmann, 2010). Ultimately, the cost of the FiT is born by final consumers through a surcharge on the price per kWh (FuturePolicy.org, n.a; Frondel et al., 2014). In order to increase incentives for cost reduction and adjust for decreasing prices of PV modules, the tariffs for all sources of renewable energy was decreased gradually through amendments of the EEG (Frondel et al., 2014; IEA, 2014; IEA, 2016a; IEA, 2016b).

Despite the international praise and seemingly booming German PV-market, the EEG was heavily debated in Germany in 2014. As Pegels and Lütkenhorst (2014) explains, the massive fall in PV module prices (60% between 2008-2014) surprised policy makers and fueled, together with the FiT scheme, an unexpectedly large expansion of PV installations. This can be considered a success of the EEG, but it comes at a cost. The massive expansion of PV and thereby FiT payments lead to hikes in the electricity price for final consumers. As mentioned in the previous paragraph, the legislature tries to compensate for decreasing PV module prices by lowering the tariff in order to avoid such subsidy expenditure surges. However, as Frondel et al. (2014) points out, there is a fundamental issue with FiT schemes that prevents this: asymmetric cost information. Because it is not in the PV industry's interest to disclose decreases in costs, the legislature is always a step behind in trying to adjust the tariff.

3.1.2 Direct marketing and FiP under EEG

In 2014, the remuneration system for renewable energy sources was fundamentally changed as two new concepts were introduced: Expansion corridors and mandatory direct marketing of renewable electricity (Lang and Lang, 2015).

The expansion corridors were introduced to avoid cost surges such as those that induced the debate in Germany in 2014, while still ensuring steady expansion in line with targets. The expansion corridors work in the following way: Every renewable technology has an annual expansion target (2500 MW for PV) and a corridor, i.e., an upper and lower limit to growth (2400 MW and 2600 MW for PV); if the expansion falls below the lower limit financial support is increased and if it exceeds the upper limit financial support is decreased (Lang and Lang, 2015).

Under the new legislation, direct marketing became mandatory for all new renewable power plants with a capacity over 500 kW commissioned after August 1, 2014 (Voss and Madlener, 2017; Lang and Lang, 2015). The objective of introducing direct marketing was to integrate renewable electricity production further with the electricity market (Lang and Lang, 2015). Mandatory direct marketing means producers of renewable energy are required to sell their generated electricity on the spot market. The producers are then able to claim a market premium, which is computed as the difference between the average monthly market price and a administratively set reference value (Voss and Madlener, 2017; Anatolitis and Welisch, 2017). This type of remuneration system is known as a sliding feed-in premium (FiP) (Anatolitis and Welisch, 2017). Similarly to the FiT system, grid operators are obliged to preferentially accept renewable power, the remuneration is guaranteed for 20 years after commission and final consumers bear the cost (Lang and Lang, 2015). It is important to note that amendments of the EEG do not impact the remuneration to renewable power plants commissioned before the changes come into effect. Instead, these plants will be remunerated through FiT for the time period set in their contract (Lang and Lang, 2015).

The 2014 EEG amendment did not only mandate a switch from FiP to FiT in 2014, but also a switch from FiP to auction-based remuneration in 2017. Introducing auctions as remuneration instruments for renewable energy sources was done as a further step towards market integration. Increased market integration of renewable energy sources is part of the EU guidelines and directives on remuneration to renewable energy producers which requires that the EU's sustainability targets are met in a cost-effective way through market mechanisms (Lang and Lang, 2015; Voss and Madlener, 2017). Auctions is one of the recommended ways of achieving this mentioned in the EU guidelines (Lang and Lang, 2015).

3.1.3 Auctioning of Financial Support under EEG

The first auctions were held in 2015 as part of a pilot project with solar power plants. The pilot project was conducted from 2015 to 2017 with three auctions every year. The main auction form used was pay-as-bid (PAB), but in order to gain more experience, PAB was switched for uniform-pricing for two auctions (Lang and Lang, 2015).

The 2017 amendment of the EEG came into effect on the first of January 2017 and the first official auctions for remuneration to solar power plants were held in February 2017 (Bundesministerium für Wirtschaft und Klimaschutz, n.d.). The number of auctions per year have varied between 3-7 since the introduction of EEG 2017, see Table 3.1 (IEA, 2016c; Bundesnetzagentur, 2021a).

Table 3.1: Summary statistics on PV remuneration auctions 2017-2021, all prices in euro (Bundesnetzagentur, 2021a)

Year	Number of auctions	Auctioned quantity (GW)	Ceiling price (cent/kWh)	Average number of projects	Average winning bid (cent/kWh)
2017	3	0.60	8.84 – 8.91	113	6.22
2018	3	0.57	8.75 – 8.84	71	5.21
2019	5	14.75	7.50 – 8.91	169	6.07
2020	7	12.99	7.50	143	5.60
2021	3	16.37	5.90	254	5.21

The remuneration system works similarly to the FiP system, with the critical exception that the market premium is decided by auction instead of a fixed reference value. At every auction, the German Federal Network Agency (Bundesnetzagentur, BNetzA) offers a certain amount of electric capacity decided in accordance with EU's country specific goals for renewable energy expansion. The bidders then compete for remuneration to provide a share of the offered electric capacity. The auction form is first-price sealed-bid auction: The bidders all submit their demanded remuneration per delivered kWh and the bidder with the lowest prices wins. The awarding of remuneration follows the pay-as-bid (PAB) pricing rule, which means the bidders who win will receive exactly their bid value as remuneration per kWh for 20 years. Every auction has a ceiling price which is the maximum bid value bidders can bid, it can fall or rise but not exceed 8,91 cent/kWh for PV (Anatolitis and Welisch, 2017; Bundesministerium für Wirtschaft und Klimaschutz, 2017).

Bidders submit their form of energy (i.e., wind, solar or biomass), their bid quantity (kW), their bid value (cents per kWh), and further details on their project. Bidders may participate with several different projects in the same auction. For every project, the bidder must deposit a security to the BNetzA. For PV, a security of €5 per kW of capacity must be paid when the bid is submitted and a declaration of permission to erect the solar installation on the site of the project. A second security of €45 per kW must be paid if the project is awarded remuneration (Bundesministerium für Wirtschaft und Klimaschutz, 2017). For PV, the bid quantity must not subceed 750 kW, projects with lower capacity are remunerated through FiT (Anatolitis and Welisch, 2017; Bundesministerium für Wirtschaft und Klimaschutz, 2017). Other than the minimum capacity requirement, the auctions are price-only. In price-only auctions - as opposed to multi-criteria auctions - the winner is picked solely based on the offered price and no other criteria (such as job creation for instance) (Anatolitis and Welisch, 2017). The submitted bids are sorted by the BNetzA by bid value (ct/kWh) in ascending order. In the case of identical bid value, the bids are sorted by bid quantity (kW) in ascending order. All admissible bids up until the auctioned capacity is fulfilled are awarded remuneration. In case a project with a winning bid has not realized more than 5% of the installation before a certain deadline, a penalty of €50 per kW of cancelled bid quantity must be payed (Bundesministerium für Wirtschaft und Klimaschutz, 2017).

In Figure 3.1 the average winning bid of the first auction round of 2017 (auction round 1) until the final auction round of 2021 (auction round 21) is displayed (Bundesnetzagentur, 2021a). Judging from Figure 3.1, there is no clear trend in outcome over the rounds, especially before round 12. However, by looking at the annual average winning bid displayed in Table 3.1 a downward sloping trend can be deciphered.

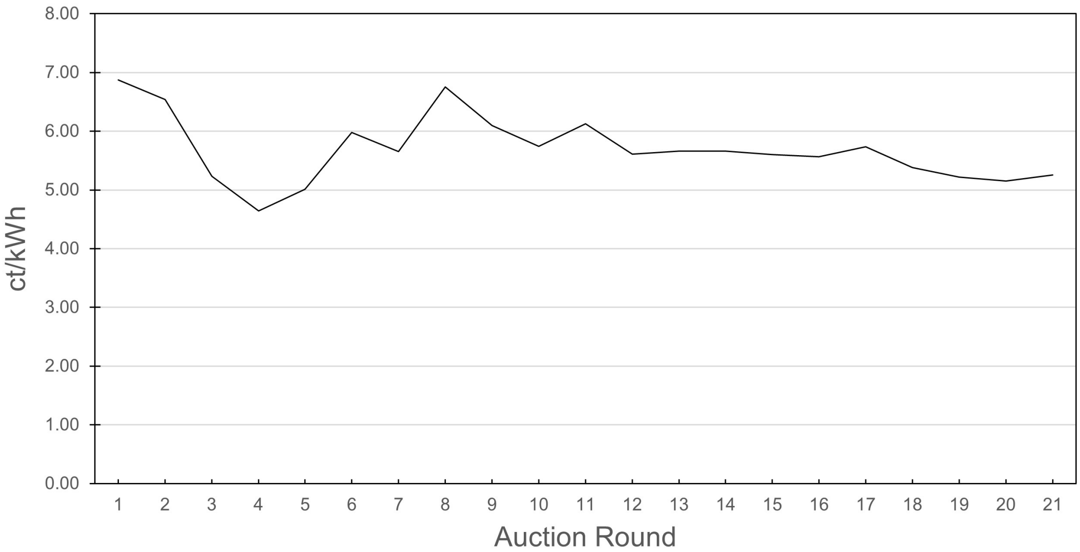

Figure 3.1: Average winning bid in German auctions for remuneration to PV plants (Bundesnetzagentur, 2021a)

3.2 Solar PV in Sweden

Sweden had a cumulative solar PV capacity of 1.42 GW in 2020. This is considerably less than Germany's capacity of 53.78 GW, even when put in relation to population size (6419 kW per every 10 000 inhabitant in Germany and 1406 kW per 10 000 inhabitant in Sweden) (Our World in Data, 2021a; Our World in Data, 2021b, Our World in Data, 2021c). The solar power generation in Sweden totaled 1.05 TWh in 2020 which amounts to 0.64% of electricity production (Our World in Data, 2022b; Our World in Data, 2022a).

Since the early 2000's, several support schemes for PV has been introduced and repeatedly amended in Sweden (Husser and Farrag, 2021). Arguably, the two most important policies was the introduction of renewable electricity certificates (tradable green certificates, TCG) in 2003 and the introduction of a direct capital subsidy program in 2005 (Lindahl et al., 2022; Mundaca and Samahita, 2020).

3.2.1 Market for Centralized PV Systems in Sweden

The Swedish PV market is dominated by decentralized PV systems, most notably residential single-family houses and commercial facilities. The share of centralized PV systems, i.e., PV parks, increased considerably in 2020 but yet only made up 15% of the installed PV capacity in Sweden 2020 (Husser and Farrag, 2021). This can be compared to the global PV market, were 63% of installed PV capacity consisted of centralized PV systems in 2020 (Lindahl et al., 2022). The underdevelopment of PV parks in Sweden is attributed by Lindahl et al. (2022) and Husser and Farrag (2021) to shortcomings of the two major subsidy schemes in Sweden: renewable electricity certificates and direct capital subsidies.

Lindahl et al. (2022) has made a review of all Swedish PV parks commissioned before the end of 2020 with a capacity above 0.5 MW. The review reveals that the first PV park of this scale was commissioned in 2009 with a installed capacity of 2.2 MW. Since then, a total of 24 PV parks has been commissioned with a total installed capacity of 74.1 MW. There are three main business models in the Swedish PV park market: Corporate power purchase agreement (corporate-PPA), cooperative ownership (COOP) and merchants. A corporate-PPA is a long-term contract between the PV park owner and a corporate customer for delivery of electricity. In a cooperative ownership business model, the PV park is typically bought by a economic association which then sells shares to private individuals or companies. In the merchant business model, the owner of the PV park simply sells the electricity on the market themselves, the revenue thus consist of the spot price and potential subsidies (Lindahl et al., 2022).

Lindahl et al. (2022) has studied six completed PV parks in detail of these 24 commissioned PV parks to gain further information on the economic parameters of Swedish centralized PV market. The six parks were all commissioned in 2019 or 2020. Lindahl et al. (2022) calculated the unsubsidized levelized cost of electricity (LCOE) for each of the six parks. LCOE measures the net present cost of electricity over a power plants lifetime and is commonly used for comparing electricity generation costs between technologies. The LCOE can be used to assess the profitability of a PV park; the revenue per kWh from the spot market and the TGCs must cover the LCOE. Based on the six studied PV parks, Lindahl et al. (2022) found that they are bordering on profitability: Two are "on the brink" of profitability, two are "within good margin" and the remaining two needs higher electricity prices than today to be profitable.

3.2.2 Direct Capital Subsidy

A direct capital subsidy works to promote expansion of PV capacity through government remuneration of a certain share of installation costs. A direct capital subsidy of PV was introduced in Sweden for the first time in 2005 and was in effect between 2006 and 2008. This first subsidy scheme for PV was part of an effort to increase energy efficiency in public premises, within which PV investors could apply to get 70% of installation costs covered by the government. The total remuneration per year was limited by the yearly budget allocated to the policy and the remuneration per PV system was limited to a certain cost cap. The total remuneration per year varied between 33 to 38 million SEK and the cost cap per PV system was 5 million SEK (Husser and Farrag, 2021; Lindahl et al., 2022).

This first subsidy scheme was only applicable to installation of PV systems in public premises. However, this was changed in the next generation of direct capital subsidies in Sweden which was introduced in 2009. The new support scheme for PV was a policy designated entirely to support PV expansion and was now available to all actors. It kept the same structure as the 2005 support scheme; investors get remunerated a certain share of investment costs up to a certain cost cap and the total remuneration is limited by the budget (Husser and Farrag, 2021).

The subsidy scheme introduced in 2009 was in effect until 2020 and amended several times. The share of installation cost covered by subsidy and the support limit per PV installation was gradually decreased and the available support differed between actors and over time. In Table 3.2

summary statistics on the direct capital subsidy scheme is displayed and the gradual amendments can be followed (Husser and Farrag, 2021).

Table 3.2: Summary statistics on the direct capital subsidy scheme (Husser and Farrag, 2021)

Year	Covered share of Installation costs	Cost cap per PV system (MSEK)	Total allocated budget (MN SEK)
2006 – 2008	Public premises: 70%	5	138
2009 – 2011	Companies: 55%, others: 60%	2	212
2012	45%	1.5	57.5
2013 – 2014	35%	1.3	210
2015 – 2017	Companies: 30%, others: 20%	1.2	991.6
2018	30%	1.2	1085
2019	20%	1.2	1236
2020	20%	1.2	1035
Total			4965.1

The applications for remuneration constantly exceeded the budget allocated to the policy. This lead to a waiting list to receive subsidy which, at its peak, reached an average waiting time of 2 years. In this way, the subsidy scheme intended to stimulate expansion of PV also constituted an upper limit to the expansion (Husser and Farrag, 2021). The combination of repeated changes in the subsidy scheme and the long waiting list meant potential PV investors did not know with certainty what level of subsidy they would get when applying, which likely haltered the expansion of solar PV in Sweden (Mundaca and Samahita, 2020).

According to both Lindahl et al. (2022) and Husser and Farrag (2021) the introduction of the direct capital subsidy scheme was the main trigger for the establishment of the Swedish PV market but has also lead to skewed expansion where decentralized PV systems have been favored and centralized PV systems underdeveloped. Subsidizing investment cost of renewable energy projects has been found by Polzin et al. (2019) to predominantly promote expansion in the residential segment by reducing upfront costs and as Lindahl et al. (2022) states, this finding is in line with the skewed expansion in Sweden. Husser and Farrag (2021) further explains the underdevelopment of centralized PV systems by the cost cap of the direct capital subsidy scheme; since installation costs are only covered to a certain limit (i.e. the cost cap), the more the installation costs exceed the cost cap, the lower the share of the installation costs are covered. This means the larger centralized PV systems are disadvantaged compared to the smaller, decentralized PV systems, as they will get remunerated for a larger share of their investment costs.

It was announced in 2020 that the capital subsidy would be terminated and applications closed in 2020. The capital subsidy was replaced by a tax reduction for green technology which still is in effect. However, this subsidy is only available to private persons leaving companies and other actors no possibility of remuneration for installation costs (Husser and Farrag, 2021; Energimyndigheten, 2021).

3.2.3 Tradable Green Certificates

Tradable green certificates (TGC) were introduced in Sweden in 2003. The TGCs work in the following way: solar power producers (and other producers of renewable power) receive one certificate per generated MWh from the government; Grid operators are then obliged to buy certificates corresponding to a certain share of the electricity they sell ("quota obligation"). This gives the solar power producers an additional income on top of the price of the electricity on the market. The price for the TGCs is ultimately born by the final consumers through their electricity bill. (Husser and Farrag, 2021)

The initial goal of the TGC scheme was to increase renewable electricity production by 17 TWh between 2003 and 2016. This goal was updated in 2012 when Sweden initiated a collaboration with Norway to create a joint certificate market and increase renewable electricity production by 26.4 TWh between 2012 and 2020. The goal was increased to 28.4 TWh in 2015 and extended in 2017 by another 18 TWh until 2030 (Husser and Farrag, 2021).

The first PV systems taking part in the TGC scheme appeared only in 2005, but since then the share has increased exponentially. However, the total capacity of the participating PV system remains a very small share of the total capacity of the participating electricity providers (Husser and Farrag, 2021).

The weak results in PV expansion from the TGC scheme can be explained by the mechanisms of the subsidy scheme. TGCs are intended to create a market where different renewable technologies compete; the technology producing the most electricity at the lowest price receives the most TGCs. This means the cheapest renewable technologies are promoted and a cost-efficient expansion of electricity production is achieved. This is an advantage of TGC and very much intentional, but it also means relatively mature technologies are favored while immature technologies tend to get locked out (Bergek and Jacobsson, 2010). In Sweden, this meant the TGC scheme was long dominated by biomass, a mature technology, while PV, an arguably rather immature technology in the early 2000s, was locked out (Lindahl et al., 2022).

The price of the TGCs have also varied a lot over time. In the beginning of 2022, the price was only a fraction of what it was in 2018, as can be seen in Figure 3.2.

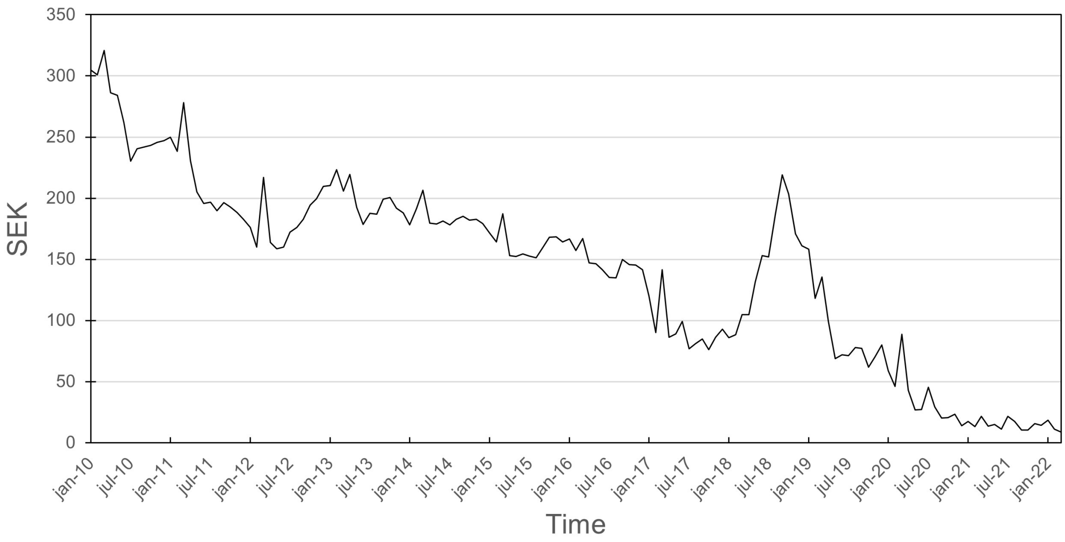

Figure 3.2: Statistical overview of the price for the TGCs (Ekonomifakta, 2022)

3.3 Auctions for Renewable Electricity Globally

Today, auctions for renewable electricity expansion has been implemented in many countries across the world with a wide variety of auction designs as result. To illustrate this, the auctions of three countries with differing auction designs are described briefly in the following subsection.

3.3.1 South Africa

South Africa introduced technology-specific auctions of renewable electricity in 2011. The country initially introduced a FiT scheme in 2009, but after disappointing results the scheme was deemed a noncompetitive procurement and consequently prohibited by procurement regulations. The South African auctions had an initial objective of auctioning out a capacity of 3625 MW over five auction rounds. The share to each renewable technology was fixed and the largest allocations were for wind and PV. The intention of limiting the capacity by technology was to increase competition by reducing supply. As in the German renewable electricity auctions, participants could enter with more than one project (Eberhard and Kåberger, 2016; Bundesministerium für Wirtschaft und Klimaschutz, 2017). To qualify for the South African auctions, the project's capacity could not subceed 1 MW. In contrast to the German auctions, South Africa also implemented a technology specific maximum capacity; for PV it was set to 75 MW. As in Germany, technology specific ceiling prices were set. As opposed to the German auctions, South African implemented multi-criteria auctions where winners were selected based on a 70/30 split between price and economic development considerations. An unusual but important requirement for entry was proof from a bank that the financing for the project was secured. The intention was to outsource due diligence on the projects to the bank in order to minimize the risk of non-realization (Eberhard and Kåberger, 2016).

The South African renewable electricity auctions were considered a success, especially in comparison to the failed attempt at FiT. Four auction rounds were completed between 2012 and 2015 with a total of 6327 MW auctioned. The 2015 auctions saw PV generated electricity prices among the lowest in the world at the time. Eberhard and Kåberger (2016) attributes the falling prices over the auctions mainly to increased competition but also to decreasing prices of equipment (Eberhard and Kåberger, 2016).

3.3.2 Poland

Renewable electricity auctions were introduced in Poland in 2015. The auctions are technology specific and held at least once a year. There are two separate auctions for each technology: One for projects with a capacity under 1 MW and one for projects with a capacity above 1 MW. The auctioned capacity is announced annually. One fundamental difference between the German auctions and the Polish is the payment; while the winners in the German auctions are awarded their submitted bid (under PAB) Polish winners receive the difference between their bid and the market price of electricity (Kulpa et al., 2022; Bundesministerium für Wirtschaft und Klimaschutz, 2017). In this way, the bids have the equivalent function of the reference value in the now terminated German FiP scheme (see Section 3.1.2) (Voss and Madlener, 2017). The winners in the Polish auctions receive support as long as the electricity price subceeds the bid value, but when it instead exceeds it they are instead obliged to pay the government the excess (Kulpa et al., 2022).

The Polish auctions between 2016 and 2021 resulted in a total auctioned capacity of 5329 MW. The PV generated electricity price reached 5 ct/kWh in 2021 which made it the most competitive electricity source in Poland. Since Poland's electricity generation is heavily dependent on fossil energy sources, the increase in emission permit prices in recent years lead to a increase in electricity price which in turn meant the current energy prices far exceed the winning bids of previous auctions. This meant that what was initially intended to be a subsidization scheme today is a source of income for the government (Kulpa et al., 2022).

3.3.3 Spain

Spain held its first generation of three renewable electricity auctions between 2016 and 2017 (del Río, 2018). In 2020, a new auction scheme was implemented and replaced the previous system. One of the main changes in the new auction system was that the auctions now follow a indicative schedule as opposed to the previous auctions which were organized ad hoc. The old generation of auctions provided support for investment costs while the new offer a long-term price for renewable electricity (del Rio and Menzies, 2021).

The new generation of Spanish renewable electricity auctions are price-only pay-as-bid auctions. The auctioned capacity in the first auction (held in 2021) was 3034 MW, of which 1000 MW was dedicated to PV. There is ceiling price, but it is confidential. There is also the possibility of setting a minimum price, which can be implemented in order to prohibit reckless bids and thereby mitigate non-realization. All bidders are required to deposit a security of €60/kW to enter the auction which is given back to the winners. The winners have to pay €60/kW after being awarded which is payed back as the project is realized; in case of non-realization it is kept as a penalty (del Rio and Menzies, 2021).

The support form is two-sided sliding feed in premium; the winning bid corrected by an incentive for market participation as described in Equation 3.1. Using a set adjustment factor (AF), the governing body can control how much of the price received (PR) comes from the winning bid (WB) and the market price (MP) respectively:

$$\mathrm{PR} = \mathrm{WB} \cdot (1 - \mathrm{AF}) + \mathrm{AF} \cdot \mathrm{MP}. \tag{3.1}$$

In this way, the government intends to incentivize electricity generation during the hours with the highest demand and thus the highest market prices (del Rio and Menzies, 2021).

The 2020 auction resulted in a a total awarding of 3034 MW of which two thirds was awarded to PV and the rest to onshore wind. The average winning bid for solar PV was 2.447 ct/kWh (del Rio and Menzies, 2021).

3.4 Agent-based modeling

Agent-based modeling is a concept within artificial intelligence where agents are supposed to act in certain ways to achieve a certain goal. Even though this is something that all computer programs do, agents adapt to change and change their behavior accordingly to the environment and situation. Predominantly, agents are further assumed to act rationally, i.e., act in a way to achieve the best possible (or best expected) outcome (Stuart J. Russell, 2016).

One way to use agent-based modeling is to simulate and predict the outcome of auctions. In the paper by Anatolitis and Welisch (2017), an agent based model is used to simulate and compare the outcomes of two auctioning systems for financial support to onshore wind power in Germany. Anatolitis and Welisch's (2017) article was published ahead of the introduction of auctioning of financial support as main rule under EEG in 2017. As mentioned in Section 3.1.3, pilot auctions for PV support had been held between 2015 and 2017 in which both uniform-pricing and pay-as-bid auctions were used (Lang and Lang, 2015). Anatolitis and Welisch (2017) modeled the outcome under both uniform-pricing and PAB respectively in order to estimate which would yield the most cost-efficient outcome in the future auctions for financial support to onshore wind power.

In the model of Anatolitis and Welisch (2017), every agent is characterized by their randomly assigned project which contains three attributes: The capacity of their planned onshore wind plant (in MW), their cost (LCOE, in cent/kWh) and their discount factor. The assignment of projects starts with each agent being assigned to one of three agent types: Project developers, citizens' energy companies or financial investors. All agents are then randomly assigned a cost from the common cost distribution range, a capacity from the agent-type specific range of capacity and a discount factor which is given by and equal within each agent type. The share of each agent type and differentiation of agent types was chosen to reflect the German market for onshore wind as accurately as possible.

Anatolitis and Welisch (2017) modeled 14 auctions over 3.5 years, i.e., 4 auction rounds per year. The auctions are modeled to follow the rules of the real auctions as closely as possible. This means agents submit sealed bids which are limited by a ceiling price (equivalent to reserve price). The ceiling price is taken directly from the real auctions: In the first three auctions the ceiling price is 7 ct/kWh, after this it was computed as the average of the highest winning bids from the past three rounds increased by 8%. The sorting of bids follows the same process as the real auctions: When the bids have been submitted, the auctioneer sorts the bids in a ascending order (Bundesministerium für Wirtschaft und Klimaschutz, 2017. In case of equal bids, the bids are sorted after capacity in ascending order. Winners are awarded up until the auctioned capacity is fulfilled. The auction capacity is set after the total amount the German government planned to auction out until 2020 (Anatolitis and Welisch, 2017).

After each auction round there is a certain number of winners and losers. The losers participate in the next auction with the same project. If a citizens' energy company wins an auction, they don't participate in the following auction since this agent type has limited resources. This is accordance with the real auctions where this type of agent has a mandatory waiting period after winning. In the model, they are allowed to enter after one to two years. Project developers and financial investors participates in the following auction if they win. When a agent who has previously won enters a new auction, they are assigned a new project with a new cost and capacity. After each auction round, a number of new agents are drawn and participates in the following auction (Anatolitis and Welisch, 2017).

Given their specific attributes, each agent submits their best and final bid (in ct/kWh), along with a corresponding capacity in MW. To simplify, each agent is only allowed to participate with one project in each auction whereas in the real auctions participants are allowed to participate with multiple projects (Bundesministerium für Wirtschaft und Klimaschutz, 2017). How each agent's best bid is decided depends on whether they are competing under uniform-pricing or PAB and is derived by Anatolitis and Welisch (2017) from auction theory.

As mentioned in Section 2.1.4, bidding for a single item in a uniform-pricing sealed-bid auction is equivalent to bidding in a second-price sealed-bid auction which means the dominant strategy is to bid truthfully; i.e your true valuation (see Section 2.1.1). Therefore, the agents in the model of Anatolitis and Welisch (2017) bid their true cost in the uniform-pricing auctions.

Since PAB sealed-bid auctions corresponds to first-price sealed-bid auctions, bidders are faced with a trade-off between probability of winning and profit; the lower the bid, the higher the profit but the lower the probability of winning. If an agent does not win in one auction round, they will be able to participate with the same project in the following auction. This means the expected profit in future auction rounds must be adjusted by the probability of losing previous rounds. Since the bid in one auction round affects the probability of winning that round, it does not only impact the expected profit in the current round but in future auction rounds as well. Thus, the profit of a project entered into the auction is maximized by taking into account a specific period of time and the expected probability of winning over all auction rounds. Here, the discount factor becomes relevant as it determines the time preference. Therefore, the optimal bid, i.e., the bid that the agent submit, is found by maximizing the expected profit *E(π)*, according to Equation 3.2. The equation consists of three parts: the "normal" profit, the probability of winning in the current auction round and the probability of losing in all previous auction rounds. Due to the last part of the equation, the agents that have participated in more auction round will gain an advantage by the fact that they have more information, and therefore have a higher probability to submit a better bid (Anatolitis and Welisch, 2017).

$$
\begin{aligned}
\mathrm{E}(\pi(b)) = &\sum_{i=t}^{T} \delta^{i-t}(b-c_i) \cdot \textit{Pr (Successful bid in round i)} \\
&\cdot \prod_{x=1}^{i-t} \textit{Pr (Unsuccessful bid in round i-x)}
\end{aligned}
\tag{3.2}
$$

Where δ is the discount factor, b is the bid and c is the cost for each agent and project.

After each auction, the participating agents learn the overall average bid and the number of participants. This is another simplification; in the real auctions only the average winning bid is published, not the overall average bid. The agents use the publicized information and adjust future bids in PAB auctions to increase the likelihood of winning.

The discount factor for each agent type was chosen by Anatolitis and Welisch (2017) to simulate a time preference in the agents; a preference for winning sooner rather than later in the PAB auctions. However, the main purpose of the time preference is to differentiate agent types in ability to bear risk; citizens' energy companies as the smallest participant can bear the least risk and thus discounts future revenues the most while the project developers and financial developers can bear higher risk and thus discount less heavily. Put simply, the agents with the highest risk aversion are the least patient to win an auction as they have the strongest time preference. In this way, Anatolitis and Welisch (2017) represents risk aversion through time preference of the agent type.

To account for learning effects in accordance with the learning curve theory (see Section 2.2), Anatolitis and Welisch (2017) has estimated a cost decrease between 0.985% and 1% between every auction round based on studies of the German onshore wind power market.

4
Method

The following sections contains information regarding the methodology of the thesis. First, the process of collecting the material used in this thesis is described. Then, the t-test used to evaluate the model of Anatolitis and Welisch (2017) against reality is explained. Next, a detailed description of the inputs for the simulation used in this thesis is presented. Lastly, the estimation of the welfare loss from continuing as status quo based on the social cost of carbon dioxide concept is explained.

4.1 Collection of Material

To find relevant articles for this thesis, Scopus, a database recommended for the economic field by Gothenburg University Library, was initially used (Gothenburg University Library, n.d.). After a certain amount of material had been collected, the articles were studied in detail. Based on these articles, and continuously throughout the process of writing this thesis, additional articles, data, and other material was collected through snowballing; i.e. by looking at data sources, reference lists, etc. of collected material, new material was found and the process repeated.

4.2 Modeled vs. Actual Outcome of Wind Subsidy Auctions

To evaluate how closely the model of Anatolitis and Welisch (2017) estimated the actual outcome, statistics on the auctions of support to onshore wind power from Bundesnetzagentur (2021b) was used.

First, the average winning bid in each round over the first 14 rounds in the modeled and actual auctions was plotted graphically. To determine whether there was a statistically significant difference between the modeled outcome and the actual outcome, Welch's t-test was performed in **Stata**[1]. Welch's t-test was chosen since the two samples are independent and have unequal variances. In the test, the average winning bid across the 14 rounds modeled by Anatolitis and Welisch (2017) was tested against the actual average winning bid in the first 14 auction rounds with the following hypothesis:

$\mathbf{H_0}$: *The difference in mean is equal to zero,*

$\mathbf{H_1}$: *The difference in mean is not equal to zero.*

[1] StataCorp LLC, 2021

4.3 The Modeling of the Agent-based Auctioning System

To simulate the agent-based auctioning model for solar PV in Sweden **MATLAB**[2] was used. The entire script can be found in Appendix C. To achieve a more accurate answer with a lower risk of extreme values the, the simulation used 50 iterations. The model of Anatolitis and Welisch (2017) is adapted to a Swedish context, this means the same simplifications in relation to the real auctions has been made in the modeling of the simulation in this thesis as in the original. Furthermore, a visual representation of the algorithm used in the simulation can be seen in Figure 4.1

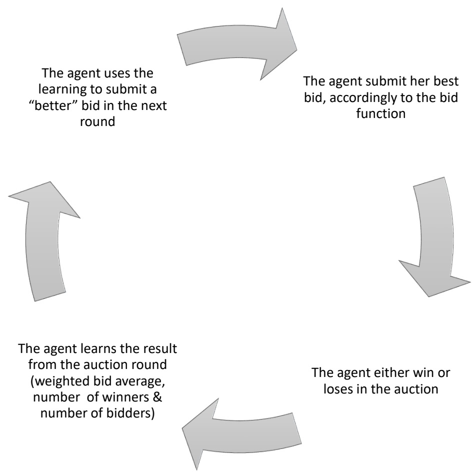

Figure 4.1: Visual representation of the algorithm used in the model

Every iteration consist of 32 auction rounds, which corresponds to one auction per quarter every year from 2022 to 2029. As stated by Statens energimyndighet (2021), it is believed that the total energy from solar in the year 2050 will be between 9 and 11 TWh per year. With a complete linear trend this would result in about 2.56 TWh by the year 2030. According to The Swedish Society for Nature Conservation (Naturskyddsföreningen, 2021), every installed kilowatt of solar PV generates approximately 1000 kWh per year. This would therefore further result in about 320 MW increase of solar capacity per year, and thus 80 MW per auction round.

As previously stated, each agent receives a project with a corresponding capacity and cost. Both of these are stochastic values within a given range. The capacity is assumed to be between 0.75 MW and 40 MW. The minimum capacity is adopted from the actual German PV power auctions (Bundesministerium für Wirtschaft und Klimaschutz, 2017). By studying the capacity range of PV systems in Sweden, the assessment was made that only centralized PV parks would reasonably qualify to enter the auctions in light of the minimum capacity. Therefore, the projects of the agents were characterized as PV parks. In accordance with this decision, the maximum capacity was set based on the biggest Swedish PV park project currently under development (Axfood, 2021).

[2]The MathWorks Inc., 2021

The cost assumes a stochastic value between 2.5-5 ct/kWh. The cost per kWh is the unsubsidized levelized cost of electricity (LCOE). The LCOE used in the model is based on Lindahl et al.'s (2022) study of six Swedish PV park projects commissioned between 2019 and 2020. The LCOE of the six PV parks ranges between 2.737 ct/kWh and 4.939 ct/kWh. For the simulation in this thesis, the cost interval was expanded by ± 0.25 ct/kWh and further rounded-off to account for variation (Lindahl et al., 2022). This thesis does not differentiate between different agent types as in the model of Anatolitis and Welisch (2017) since the available information did not enable characterization of agent types in a meaningful way.

In accordance with the learning curve theory, LCOE can be expected to decrease with increased installed capacity (Sandén, 2005). To account for this, a cost decrease up to 1.78% between auctions is implemented in the model. The value is based on the estimation of VDMA (2022) of a 35% average decrease in PV system prices between 2021 and 2032 for utility-scale systems. By assuming that the cost decreases with the same percentage between each auction round on average, and that there is 4 auctions per year, this corresponds to an average cost reduction of 0.89% ($1-(1-0.35)^{(1/48)} = 0.0089$) between every auction round. The cost reduction for each agent is drawn from a uniform distribution with bounds 0 and 1.78% to account for randomness.

The number of agents was estimated by dividing the average annual installed capacity of PV parks in 2019 and 2020 (i.e. when the six PV parks studied in detail by Lindahl et al. (2022) was comissioned) with the average installed capacity of all PV parks commissioned between 2019 and 2020 with a capacity above 0.5 MW (Lindahl et al., 2022). According to Husser and Farrag (2021), centralized PV parks made up 4% and 15% of annual installed capacity in 2019 and 2020 respectively. This corresponds to 11.2 MW in 2019 and 106.5 MW in 2020 and an annual average of 58.85 MW (Our World in Data, 2021a). The average capacity of PV parks commissioned between 2019 and 2020 was 4.27 MW (Lindahl et al., 2022). On this basis, it is estimated that the original number of bidders is 14. Moreover, since the assumption is that the solar PV market will grow for each year and round, a stochastic number of new agents between 0 and 5 will be added after each round.

Other important variables in the simulation are the discount factor and the ceiling price. The discount factor (δ) is used to motivate the agents to win in an earlier auction round, rather than later. Therefore, since there is only one type of agent the value is less important for this specific model, and is therefore set to the arbitrary value of 0.9; i.e. a discount rate of 10%. Furthermore, the ceiling price is set to the maximum cost (5 ct/kWh) for the first three rounds, and afterward the ceiling price assumes the average highest accepted bid from the three previous rounds. This is a simplification in relation to the model of Anatolitis and Welisch (2017) as they use they use the average highest accepted bid from the three previous rounds plus 8%. A summary of the parameters can be found in Table 4.1.

Table 4.1: Summary of the parameters used in the model

Parameter	
Original number of agents	14
Cost distribution range (ct/kWh)	2.5 - 5
Assumed cost decrease (%)	0 - 1.78
Range of capacity (MW)	0.75 - 40
Discount factor	0.90
Number of new agents	0 - 5
Time Span	t = 1,2,3,4...,32

Equation 4.1 is the expanded version of Equation 3.2 and is what is used to find the optimal bid for each agent (Anatolitis and Welisch, 2017). However, since the model assumes that all agents have submitted a previous bid it does not really work for the first auction round. Therefore, if it is the agent's first time participating in the auction, she will instead submit a (random) bid that is between 1 and 5 % above the specified cost for the project. This also means that the first auction round should be seen more as a "test auction" so the agents have something to learn from.

$$\begin{aligned} \mathrm{E}(\pi(b)) = \sum_{i=t}^{T} \delta^{i-t}(b_i - c_i) \cdot \sum_{j=0}^{n_{t-1,s}-1} \binom{n_{t-1}-1}{j} F(b_i)^j (1-F(b_i))^{n_{t-1}-1-j} \\ \cdot \prod_{x=1}^{i-t} \left(\sum_{k=n_{t-1,s}}^{n_{t-1}-1} \binom{n_{t-1}-1}{k} F(b_{i-x})^i (1-F(b_{i-x}))^{n_{t-1}-1-k} \right) \end{aligned} \tag{4.1}$$

F(·) is the cumulative distribution function (CDF) and captures the agent's belief of how the other agents will bid, given the information from the previous auction round. This gives both the (assumed) probability that the agent will win in the current auction round, but also that the other agents will lose. Moreover, n_{t-1} reference to number of agents in the previous round and $n_{t-1,s}$ to number of winners (successful bidders) in the previously round. Note that -1 is further used since the agent can disregard her own action since it is already known.

To find the optimal bid for each agent, the equation is calculated for 100 different evenly spaced numbers; the lowest being the cost for the project and the highest being the set ceiling price. After all calculations has been made, the agent will select the bid that achieve the maximum expected profit.

After 50 iterations, the total cost was assessed. The total cost was assessed over a time frame of 20 years, since that is how long the winners will receive the subsidy. The assessment is carried out using the median cost for each auction round and iteration. Furthermore, to evaluate how the values of certain parameters affects the results, a sensitivity analysis was also conducted. The analysis uses the changes in the following input variables:

- An increase of 10 % to the cost distribution range, i.e., the range is now 2.75 - 5.5 ct/kWh
- A decrease of 10 % to the cost distribution range, i.e., the range is now 2.25 - 4.5 ct/kWh
- If the market does not expand, i.e., the number of agents is kept constant at 14

4.4 Welfare Loss from Continuing as Status Quo

In order to estimate whether the benefits of the expansion of PV outweighs the total cost of the auctioned subsidizes, the alternative to expanding the PV capacity is assumed to be to continuing to generate electricity using the current energy mix in the European Union (EU). The EU energy mix, rather than the Swedish, was used since the EU has an interconnected electricity market (Svenska Kraftnät, 2021). Consequently, the average greenhouse gas emission intensity of electricity generation of the 27 EU countries was used. This value amounted to 230.7 grams of CO_2-equivalents per kWh in 2020 (European Environment Agency, 2020).

Assuming winners are awarded 20-year contracts and that the auctions start this year (2022) and run until 2029, the winners in the first year (2022) will receive subsidy until 2041 and the winners in the final round (2029) will receive subsidy until 2048. However, this assumes that the full capacity is built in the same year as the auction is won and starts delivering 1000 kWh per installed kW per year in accordance with the approximation of The Swedish Society for Nature Conservation (Naturskyddsföreningen, 2021). This assumption is highly unrealistic since it obviously takes time to build the PV parks, but work for the sake of comparison as it is the total generated electricity that is of interest, not when it is generated. Based on these assumptions, the total electricity generation over the lifetime of the subsidies was estimated to 60.16 TWh. The calculation of the total emission of CO_2-equivalents (TEC) from instead generating this electricity using the current EU energy mix is described by Equation 4.2, where EE represents the average greenhouse gas emission intensity of electricity generation in the EU and TEG the estimated total electricity generation.

$$\mathrm{TEC} = \mathrm{EE} \cdot \mathrm{TEG} \tag{4.2}$$

The total emissions of CO_2-equivalents was then combined with the social cost of carbon dioxide estimated by Kikstra et al. (2021) to \$307 per metric ton of CO_2 to determine the total welfare loss due to this externality. To simplify comparison with the estimated cost of the simulated subsidy scheme, the $SCCO_2$ estimated by Kikstra et al. was adjusted for inflation (6.7% between 2021 and 2022 according to Inflation Calculator (2022)) and converted to euro from U.S. dollars[3] resulting in a value of approximately €307 per metric ton CO_2. The calculation of the total welfare loss (TWL) is described by Equation 4.3, where $SCCO_2$ is the estimate of Kikstra et al., π is the inflation rate, USD/EUR is the exchange rate and TEC represents total emissions.

$$\mathrm{TWF} = \mathrm{SCCO_2} \cdot (1+\pi) \cdot \mathrm{USD/EUR} \cdot \mathrm{TEC} \tag{4.3}$$

A simple sensitivity analysis was carried out to determine the robustness of the result. This was done by calculating by what percentage the mean $SCCO_2$ estimated by Kikstra et al. (2021) would need to increase or decrease to reverse the result, i.e., make the cost outweigh the welfare loss or vice versa.

[3]Assumed exchange rate of USD to EUR (1 year average): 0.9382 (European Central Bank, n.d.-b)

5
Results

In the following sections the results are presented. It starts off with the comparison of the outcome modeled by Anatolitis and Welisch (2017) and the actual outcome. Afterwards, the result from the simulation is presented. Lastly, the estimated welfare loss from producing the corresponding electricity using the current EU energy mix is declared.

5.1 Modeled Outcome Against Actual Outcome in Wind Subsidy Auctions

In figure 5.1, the actual outcome (in ct/kWh) of the first 14 auction rounds are compared to the outcome modeled by Anatolitis and Welisch (2017). The trend of the bids in the actual auctions deviates from the modeled outcome in the first five auction rounds but then converge with the modeled bids in the final 9 rounds (Anatolitis and Welisch, 2017; Bundesnetzagentur, 2021b).

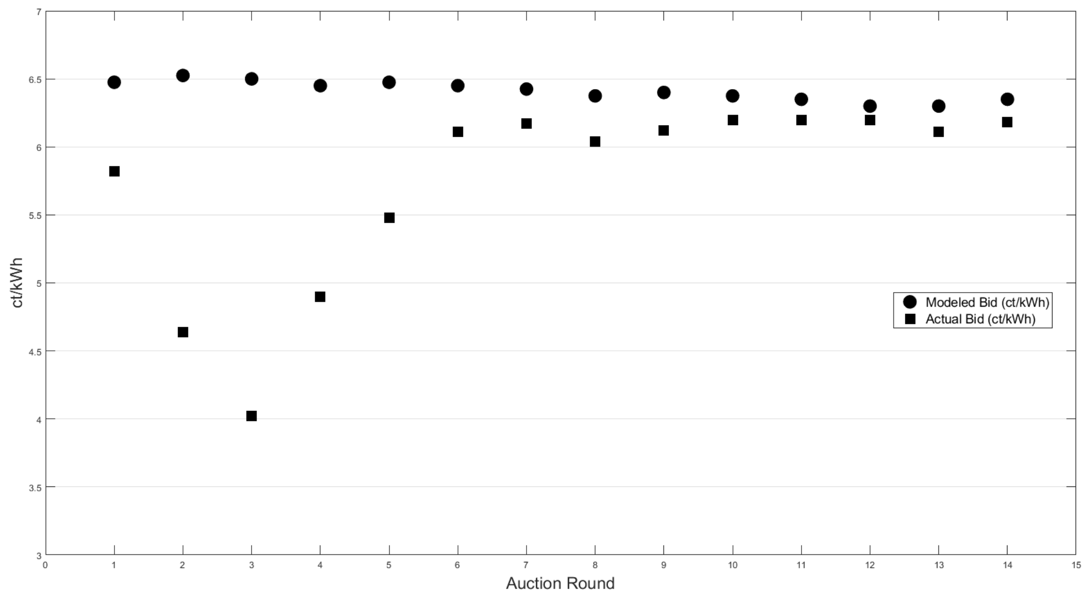

Figure 5.1: Modeled average winning bid vs. actual average winning bid in the first 14 auction rounds for onshore wind power (Anatolitis and Welisch, 2017; Bundesnetzagentur, 2021b).

,

The Stata output from Welch's t-test, with the null hypothesis ($\mathbf{H}_0$) that there is zero difference between the two, is displayed in Table 5.1. The computed p-value is 0.0031; the null hypothesis is rejected at the 95% as well as the 99% confidence level. There is therefore a statistically significant difference in mean between the modeled and the actual outcome. As is clear from Figure 5.1 and the Stata output in Table 5.1, the average modeled bid (6.4 ct/kWh) is notably higher than the average actual bid (5.7 ct/kWh).

Table 5.1: Welch's t-test on actual bid vs. modeled bid (Anatolitis and Welisch, 2017; Bundesnetzagentur, 2021b).

	Observations	Mean	Standard Error	Standard Deviation
Actual Bid	14	5.727	0.188	0.704
Modeled Bid	14	6.411	0.019	0.072
Combined	28	6.069	0.114	0.602
P-value			0.0031	

5.2 The Auctioning Simulation

After simulating the auctioning system for 8 years (32 auctioning rounds), the result presented in Figure 5.2 is obtained. The result is presented in a box plot, where the red horizontal line indicates the median. Furthermore, the blue outline of each box indicates the value within the first (lower, 25th percentile) and third (upper, 75th percentile) quartile. If any value is within ± 1.5 times the interquartile range, the value is within the dashed line (whiskers). All other values (outliers) are presented as red plus signs.

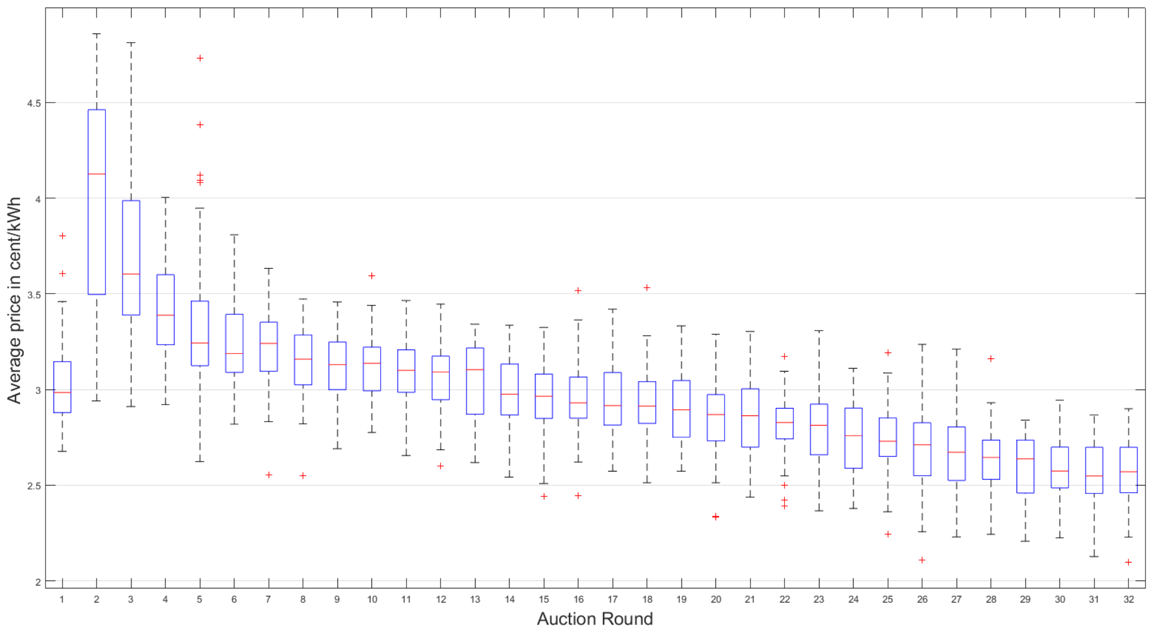

Figure 5.2: Development of prices with the pay-as-bid pricing scheme, with 32 auction rounds and 50 iterations

As stated in the method, the bids from the first round does not follow the same procedure as the rest, which will affect the result for both that auction round and the following one (since the agent will learn incorrect information). However, after a while it is rather clear downward trend of the price. The median price decreases, on average, 0.030 cents per auction round.

The average total cost for each year (4 auction rounds) is presented in Figure 5.3. Since the subsidy from winning an auction is valid for 20 years, the total cost is calculated for the entire lifetime of the subsidy. Moreover, by summarizing over all 27 years it is found that the total cost for the entire auction system would be €381 million.

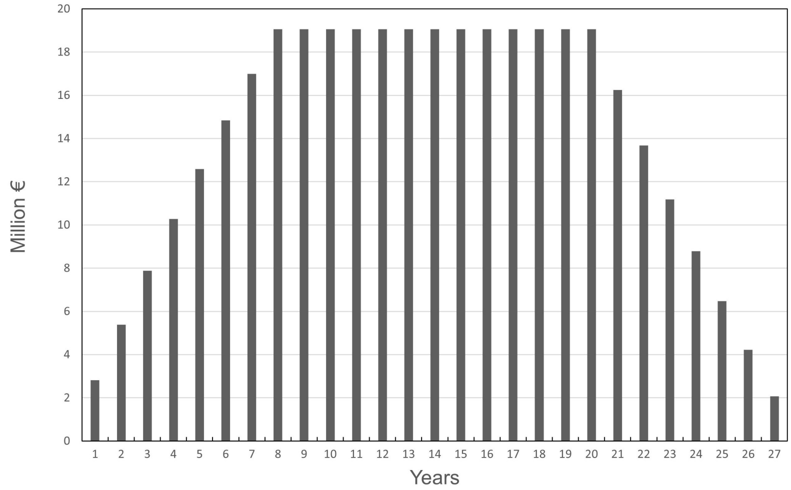

Figure 5.3: Total cost per year for the entire lifetime of the subsidy

5.2.1 Sensitivity Analysis

As can be seen in Figure A.1 and Figure A.2, in Appendix A, the figures show that both an increase and decrease of the cost distribution range will affect the result. The increase brings up the median result for the last auction round from 2.6 to approximately 2.9 ct/kWh, while the decrease brings down result to just above 2.3 cent/kWh. Furthermore, both of the changes affects the results somewhat linearly, as a 10% decrees lowers the total cost to €343 million, and an increase of 10 % increases the total cost to €423 million.

When assuming that the market does not expand, and the number of agents is kept constant to 14, the outcome also changes, as seen in Figure A.3, in Appendix A. In this case the total cost is increased even further, to €470 million. Worth noting, however, is that the price range is far larger as well, which makes the result somewhat inconclusive.

5.3 The Total Welfare Loss from Continuing as Status Quo

Assuming the total capacity of PV is expanded by 320 MW every year from 2022 to 2029, the total capacity of PV subsidized through the auction scheme until 2030 is 2.56 GW. The lifetime of the subsidy is 2022 to 2048 under which a total of 60.16 TWh are generated, assuming every installed kW of PV results in 1000 kWh per year (Naturskyddsföreningen, 2021). By using the average value for emission intensity of electricity generation in the EU (203.7 g CO_2-eq./kWh), it can be estimated that generating this amount of electricity with the current energy mix in the EU would result in the emission of 13.9 million tons of CO_2-equivalents over this time period (European Environment Agency, 2020). Using the social cost of CO_2 estimated by Kikstra et al. (2021) of $307/tonne CO_2 adjusted for inflation and converted to euro to approximately €307, the total welfare loss due to these emissions can be estimated to €4265 million.

The sensitivity analysis revealed that the $SCCO_2$ would need to be decreased by more than 91%, subceeding approximately €27, for the result to be reversed.

6
Discussion

The first sections discusses the strengths and shortcomings of the modeling carried out in this thesis, as well as a discussion of the testing of the model of Anatolitis and Welisch (2017) against reality. Then, the model is discussed in relation to the theory previously presented. Afterwards, implementing the auctioning system in Sweden is discussed in two parts; first in regard to auction theory and then in comparison with TGC. Finally, the total cost of the auction system estimated by the simulation is discussed in relation to the estimated welfare loss from continuing as status quo, based on $SCCO_2$.

6.1 Strengths and Shortcomings of the Model

The model used to simulate the auctioning system will not achieve the same answer for every simulation. This is due to the stochastic variables (e.g., the range of capacity, the cost distribution and number of new agents) used in the simulation, which in return creates some randomness and variations for the result. To secure a more accurate answer the simulation uses numerous iterations, which creates an average and thereby eliminates any extreme values that may otherwise occur. This also means that if not enough iterations are being used, the result might be somewhat questionable. Furthermore, when the agents submit their best bid (according to the function), the bid is not a precise answer, but rather an estimation. To find the bid that yields the highest (expected) return, the model evaluates 100 evenly spaced values, where the individual cost is the lowest and the ceiling price is the highest. This means that the best bid (and thus the result) is more of an estimation, rather than a precise result. However, since the model itself needs numerous iterations to obtain a secure value, this error is relatively small compared to other errors that might could occur due to the randomness within the model.

Other factor that more heavily influences the result of the simulation is the assumed learning curve, the cost distribution, and cost decrease that is assumed to happen until the year 2030. Even though historical examples show a rather clear learning curve for solar PV, this does not mean that the future development will follow the same trend, or that it is even possible to estimate. Lack of certain resources or components, such as semiconductors, could instead mean that the cost will increase over the specific period. The simulation also assumes a fixed capacity to be auctioned out. Changes in regulations might either increase or decrease this, which also would affect the demand for solar PV, and thus alter the results.

Furthermore, as already mentioned, the cost range will have a rather large effect on the outcome of the model. The data used for this interval, although somewhat widened, is based on the six solar parks from Lindahl et al.'s (2022) in-depth review. Due to the small sample, it can reasonably be questioned whether these PV parks actually represent the entire market of large scale solar PV in Sweden fairly. On the other hand, the sample size must be considered in light of Lindahl et al.'s (2022) review which revealed that only 24 PV parks (with a capacity over 0.5 MW) had ever been commissioned in Sweden by the end of 2020.

The result of Welch's t-test showed that there is a significant difference between the outcome modeled by Anatolitis and Welisch (2017) and the actual outcome in the German auctions for financial support to onshore wind power (Bundesnetzagentur, 2021b). Evidently, this result is not in the model's favor. However, it is questionable if it is reasonable to expect that this fairly simple model would generate such precise predictions. The modeled and the actual outcome does converge after about a third of the auction rounds, but while the modeled average winning bid is decreasing (linear trend: -0.016 ct/auction round) over time, the actual average winning bid is slowly increasing (0.01) over the same auction rounds (auction rounds 6-14 in Figure 5.1). However, when including all auction rounds to date (see Appendix B) the actual bids are in fact trending downwards (-0.013) after the first five auction rounds in a similar pace as the modeled bids (Bundesnetzagentur, 2021b). This being said, it is important to interpret the results of the modeling in this thesis with some precaution, especially since the actual average winning bids in the German auctions for financial support to PV plants seemingly exhibits a more unpredictable pattern (see Figure 3.1) than the equivalent auctions for onshore wind power which further complicates precisely predicting the outcome.

Moreover, the model for the simulation assumes a single-unit sequential auctioning system, which is a simplification of the reality. The actual auctioning system is a multi-unit sequential auction system, since that the agents are allowed to participate with multiple different projects at once. This could be considered one of the key factors that differentiate the model used and the reality, which means that the actual outcome would differ from the one presented in this thesis.

Conclusively, as there are also multiple variables that affect the model, that may not necessarily be true for reality, it is rather important to emphasize that the result obtained is solely a simulation and an estimation of one possible way to achieve a larger capacity of solar PV in Sweden.

6.2 Allocative Efficiency and Expected Cost in the Simulated Auctions

The modeled auction form is a sealed-bid PAB auction. This auction form corresponds to the first-price sealed-bid auction conditioned on that a single item (as opposed to a multi-unit auction) is auctioned, as mentioned in section 2.1.4 (Anatolitis and Welisch, 2017). As explained in section 2.1.1, the allocation resulting from a first-price sealed-bid auction will be allocative efficient given that the assumptions of the benchmark model holds (Vickrey, 1961; Holt, 1980; Harris and Raviv, 1981; Myerson B., 1981; Riley and Samuelson, 1981; McAfee and McMillan, 1987). Allocative efficiency means that the bidder with the highest valuation wins the item; or in this case the bidder with the lowest cost is awarded financial support. This is desirable from a societal perspective as it means the expansion is achieved in a cost-efficient way.

To evaluate the efficiency of the modeled auctions the fulfillment of the assumptions of the benchmark model must be evaluated. To begin, it is established that the assumption of symmetric bidders holds; the cost of each agent is drawn from a uniform distribution which means they are symmetric by design.

When bidders lose and learn statistics of previous auction rounds they adapt their bid, but obtaining this information does not reveal any additional information about the value of their project to the bidder as they are perfectly aware of their true valuation; i.e., their cost, LCOE. This means the independent-private-value assumption also holds by design; the bidders know their true valuation and learning another bidder's will not impact their own.

Regarding risk-aversion, the model of Anatolitis and Welisch, (2017) uses the discount factor to simulate differences in risk aversion between agents by making them vary in their patience to win. In our model, however, there is only one type of agent which means the discount factor simply works to simulate a positive time preference; the closer in time one obtains a profit (i.e., wins an auction round), the more utility one derives from it.

The assumption that payment is only dependent on the bid might at first glance seem to fold since the financial support is distributed as a market premium; it is paid per kWh and could seem as an inverse royalty system. However, the authors' would argue that this is not the case. Royalties are used when the true value of the item that is being auctioned is unknown; in the example of the sale of oil rights on government land where the payment is contingent on a bid and royalties to the government per unit of oil, neither the bidders nor the auctioneer knows what the total payment for the oil rights will be. Royalties are used to decrease the gap between the valuation of the bidder with the highest valuation and the bidder with the second highest valuation because this will increase the expected revenue (McAfee and McMillan, 1987; Riley, 1988). In our modeling of financial support to PV however, the bidders know the total amount of kWhs over the PV parks lifetime because it is assumed that they know their LCOE (ct/kWh). Since the bid is submitted in ct/kWh, the total amount of kWhs is not of importance; the bidders are simply trying to maximize the difference between their awarded subsidy and their LCOE while the government tries to minimize this same value.

Based on this discussion it would be argued that the assumptions of the benchmark model holds. This means the simulated auctions would be allocative efficient - or pareto efficienct - given that it is a single-unit auction; the bidders with the lowest LCOE should win. However, the equivalent of reserve price is used, which typically would introduce the possibility of inefficiency since it means the auction organizer could refuse to sell even if a bidder's valuation exceeds their own. This type of inefficiency is not really a concern in the auctions for financial support modeled in this thesis, as the auction organizer's (the government's) valuation is not of importance; the objective is to achieve the planned expansion at the lowest possible cost, there is no explicit cost maximum for the government. The ceiling price works as a cost cap which excludes bidders with too high costs and continually ensures only competitive bidders are able to enter by adapting the ceiling price to the average of the highest accepted bids in the three previous rounds.

By looking at the costs of the winning bidders, it is clear that allocative efficiency actually is not always achieved; the winners are not necessarily the bidders with the lowest cost. This can be explained by the fact that the modeled auctions actually are not simple single-unit auctions, but rather sequential single-unit auctions. In sequential auctions, the bidders shade their bids differently across auction rounds. Hence, bidders shade their bids more or less depending on how many auction rounds they have previously lost, which implicates that it is possible for a low-cost project to shade more and thus lose to a high-cost project.

According to the theory of Jeitschko (1998) (see Section 2.1.3), the average bid across two sequential auctions should be equal since the effects that lower (or in this case, increase) the winning bid in the second auction should exactly offset the effect that increases (or in this case, lowers) the bid in the second auction. However, the first effect does not work in the same way in the modeling of this thesis since the winning bidders do not drop out ahead of the next auction but instead join with a new project. This means the number of bidders is not reduced in the number of auctions, rather it is increased since a number of new agents is typically added after each auction round. As previously explained, increasing the competition increases (or in this case, lowers) the winning bid.

The winning bidders dropping out also causes the second effect in the model of Jeitschko (1998); since the average valuation is lowered, bidders place lower bids . Over the auctions rounds simulated in this thesis the average overall bid decreases at a slower pace than the average winning bid. All bidders take the average overall bid into account when determining their optimal bid, but as the bidders who won in the last round are assigned new projects with reduced costs while losing bidders' costs remain the same, the successful bidders increase their bid shading: they place higher bids. As Anatolitis and Welisch (2017) points out, this has the same effect as the second effect described by Jeitschko (1998).

The final effect described by Jeitschko (1998) is present in the model: as the possibility of winning decreases in lost rounds, the motivation of the agents to win increases which means the bids decrease. Since the modeling carried out for this thesis displays decreasing bids over the auction rounds, the effect of the increased competition and the final effect must reasonably outweigh the second effect. When examining the development of the winning bids, it is important to remember that the outcome in the first auction, and thereby the second auction as well, is unreliable.

Furthermore, as previously mentioned, the German auctioning system is actually a multi-unit system, which this thesis does not account for. As described by Ausubel et al. (2014), by instead using a multiple-unit system, the bidders would instead shade their different bids differently. By assuming that the bidders would have a diminishing marginal utility, the result would reasonably be even further away from allocative efficiency. Moreover, since the shading would increase over time it is unlikely that the cost decrease would be as prominent as simulated in this thesis.

6.3 Implementation in Sweden

In order for any auction to work as intended there has to be enough bidders in order for there to be enough competition. For this thesis, the number of bidders in the initial round was estimated based on the Swedish development of PV parks this far and an additional number of bidders between 0 and 5 was added every round. While the initial number of bidders is rooted in reality, the added number of bidders was chosen by the authors based on the assumption that the Swedish PV park market will grow with time because of the attractive subsidies. If the modeled auction system was to be implemented in Sweden, this assumption is important for its success; the faster the PV market grows, the more bidders and the greater competition which according to the theory of Holt (1979) and Harris and Raviv (1981) explained in Section 2.1.2 will increase the revenue of the auction organizer, i.e., lower the average subsidy awarded per kWh. Judging from the development during the last years, the Swedish PV park market is seemingly growing fast; before 2014, there was only one PV park with a capacity above 0.5 MW in Sweden, between 2014-2016 1.3 PV parks were commission on average per year, between 2017-2019 the corresponding number was 3.7 and in 2020 eight PV parks were commissioned (Lindahl et al., 2022). This is a promising development that speaks in favor of the assumption of a growing market made in the modeling.

Regarding risk aversion, the assumption was made that the agents in the modeling carried out in this thesis are risk neutral. According to Tversky and Kahneman (1980), people tend to be risk averse in situations such as the auctions where a potential gain is at stake, which in combination with the auction theory of Harris and Raviv (1981), Holt (1980) and Riley and Samuelson (1981) explained in Section 2.1.2 would mean the average winning bids in reality would be lower than in the model.

As illustrated in Section 3.3, there is wide variety of ways renewable energy auctions can be designed. An auction consists of many features which has to be decided; how shall the ceiling price be decided? Shall pay-as-bid or uniform-pricing be used as price rule? Shall winners be decided based on price only our other criteria as well? This is just a few examples of decisions that would have to be made ahead of implementing an auction-based subsidy system in Sweden. There is extensive literature on auction design, however this has not been the focus of this thesis as the outset was the German model of auctions for renewable energy with its given auction design. Nonetheless, one aspect related to auction design that should be mentioned at least briefly is how to avoid non-realization of winning projects. The risk of non-realization is considered one of the main weaknesses with renewable energy auctions and arises when bidders are uncertain about the cost of their projects. This can make bidders place and win with bids that turn out too low when the actual costs emerge. There are two main ways of mitigating this issue: financial and physical penalties and prequalifications (Kreiss et al., 2017). Both financial and physical prequalifications are used in the German auctions; a security of €5/kW and a declaration of permission for the site must be submitted to qualify for the auctions. There is also a financial penalty of €50/kW in case the project is not realized within a certain deadline (Bundesministerium für Wirtschaft und Klimaschutz, 2017). The South African government outsourced the process of controlling the projects themselves by simply demanding proof of secured financing from a bank, thus making all projects go through the bank's due diligence process instead (Eberhard and Kåberger, 2016). Spain introduced a minimum price in order to eliminate the most reckless bids (del Rio and Menzies, 2021). Kreiss et al. (2017) has evaluated measures to mitigate the issue of non realization and offer some recommendations. First, Kreiss et al. (2017) recommends auctioning a larger quantity of capacity than the actual expansion target in order to leave a margin for non-realization and thus increase the probability of reaching the target. Second, a high financial prequalification that bidders only regain if the project is realized is recommended as the most distinct measure as it directly makes non-realization costly to bidders and thereby increases realization rate. Finally, physical prequalifications set in relation to the financial prequalifications are recommended, i.e., they should not both be very high (Kreiss et al., 2017). This is only a very brief discussion of non-realization, but as this risk is not accounted for in the simulation it is important to carefully consider ahead of a potential implementation of renewable energy auctions in Sweden. The first recommendation of Kreiss et al. (2017) also constitutes a possible improvement of the simulation; given that the target expansion is 2.56 TWH, it might be more favorable to auction out a capacity corresponding to around 3 TWH instead, in order to increase the probability of reaching the target.

6.4 Auctions Compared to TGC

When assessing if TGC is more cost-efficient than an auctioning system there are multiple factors that must be assessed. One of the obvious factors is the price of the TGC, and as can be seen in Figure 3.2, the price has varied a lot. Therefore, it is not possible to make a fair comparison between the two. However, with the current price level of approximately 20 SEK per certificate, the total cost for delivering the corresponding amount of electricity as the auction system under its lifetime would be around €117[1] million, which is less than the total cost of the auctioning system of €381 million but still in the same magnitude. If the price of the certificate would rise above 65 SEK/MWh however, the total cost of the auctioning system would be lower. Judging by the historical price of TGCs (see Figure 3.2), this level has previously been witnessed.

Judging by this, it seems that compared to the TGC, the auctioning system is not a cost-efficient way of promoting renewable electricity expansion. But first, it should be noted that the TGC and the auction system works to promote sustainable electricity in very different ways and cannot be directly compared. As TGC is not technology specific, its goal is to achieve a cost-efficient expansion of renewable energy by promoting the technology which generates renewable electricity at the lowest price. This is a major strength of the TGC. The auctions are instead technology specific and works to identify and promote the renewable energy projects of a certain technology that can deliver a certain capacity at the lowest price; the aim is cost-efficiency withing each type of renewable technology. This can both be considered a strength and a weakness of the auction system; one the one hand, it means the total price for the expansion in installed capacity of renewable electricity might be more costly than under TGC since less competitive technologies

[1] Assumed exchange rate of SEK to EUR (1 year average): 0.09745 (European Central Bank, n.d.-a)

are also promoted, but on the other hand the risk of locking out immature technologies which potentially could be less expensive in the long term is avoided. Another aspect building on this where the TGC and the auction system differs is the fact that the latter (almost) guarantees that the expansion targets are met (i.e. if non-realization is mitigated effectively) while the first has no such assurance. As long as there are enough bidders and a reasonable ceiling price, the governing body can steer the expansion by the auctioned capacity. For instance, the auctioned capacity in the German PV auctions has thus far always been far exceeded by the entered projects (Bundesnetzagentur, 2021a). At the same time, the fact remains that it might have been possible to achieve the same expansion in a more cost-efficient way had some technologies been promoted more than others. However, it can be argued that the benefit of reaching the target capacity with a greater certainty outweighs the cost difference, especially since the price of the TGC could increase in the following years making it the more expensive option. Hence, by using a TGC system instead the development and expansion of the solar market in Sweden would not be the same as the one assumed in the simulation.

6.5 Avoided Welfare Loss Against Cost of Subsidy

To get a perspective on whether the advantage of expanding the PV capacity actually outweighs the cost, this thesis uses the social cost of carbon dioxide ($SSCO_2$). Given that the alternative to expanding the Swedish PV capacity is to instead generate the corresponding amount of electricity using the current energy mix in the EU, the main advantage of expansion of PV is arguably the avoided emissions of CO_2. The total cost of the subsidy during its lifetime was calculated to approximately €381 million, by using the $SCCO_2$ estimated by Kikstra et al. (2021), the total welfare loss from the CO_2 emissions caused by instead generating the same amount of electricity using the current energy mix amounted to approximately €4265 million.

As the welfare loss is in a different order of magnitude than the cost of the subsidy scheme, it is clear when judging from this simple comparison that the benefits far exceed the cost. Obviously, this is a very simplified comparison; for instance, the CO_2 emissions and other externalities from the production of the PV modules, the construction of the PV parks etc is not accounted for. However, it seems fairly unlikely that this would reverse the outcome.

As mentioned by Kikstra et al. (2021), there is a wide variation in the many estimates of the social cost of carbon dioxide and many challenges still remain to better the estimation. A recent expert elicitation referenced by Kikstra et al. yielded mean $SCCO_2$s between \$171 and \$310 and other estimates deemed central by Kikstra et al. are even higher. With this in mind, and the fact that the $SCCO_2$ estimated by Kikstra et al. has an admittedly large uncertainty range, it is important to remember that $SCCO_2$ is just an estimation and not an exact measure. However, the sensitivity analysis revealed the $SCCO_2$ would need to subceed approximately €27 for the result of this thesis to be reversed which is not only far lower than any of the above mentioned estimates but also outside the 5%-95% uncertainty range of the estimate of Kikstra et al. (2021).

7
Conclusion

This thesis aimed to simulate the outcome of implementing an auction-based system for awarding subsidies to PV parks in Sweden in order to estimate the total cost, whether allocative efficiency would be achieved and determine if the cost would exceed the estimated welfare loss from continuing as status quo. Additionaly, the previous predictions of the model used for the simulation was also evaluated against reality.

According to the simulation, the total cost of expanding the solar PV capacity by 2.56 GW would be €381 million using the auctioning system. This is more than the total cost if instead the corresponding expansion would have been supported through tradable green certificates. However, with TGC it is not possible to guarantee expansion with the same certainty as the auctioning system. Moreover, allocative efficiency was not achieved in the simulated auctions as the bidders with the lowest cost did not necessarily place the lowest bids. This is attributed to the fact that the bidders shade their bids differently across auction rounds which implicates that it is possible for a low-cost project to shade more and thus lose to a high-cost project. By comparing the estimated total cost of the auctiong system with the welfare loss from generating the electricity with the current EU energy mix, the welfare loss from the CO_2 emissions (€4265 million) would far exceed the cost of the auctioning system.

The t-test revealed a significant difference between the modeled and actual outcome in the wind subsidy auctions. However, after the five initial auctions rounds the two seemingly congregate. If all auction rounds to date are included, the modeled trend is impressively similar to the actual one (disregarding the first five auctions). Nonetheless, the results of the modeling in this thesis should be interpreted with precaution, especially since the trend in the actual German auctions for financial support for solar PV plants seemingly exhibits a more unpredictable pattern than its onshore-wind power counterpart.

The sensitivity analysis also shows that the model used in this thesis is rather sensitive towards some of the input variables. A change in the cost distribution range is almost completely linear with the total cost, which makes this input extremely important for the outcome. Since this thesis bases this interval solely on 6 solar PV parks, more research in this area would be beneficial to determine the result. As previously mentioned, as the German auctioning system used to subsidize solar PV actually is a multi-unit sequential auctioning system rather than a single-unit sequential auctioning system, the simulation used might not yield a realistic representation of the reality. It would therefore also be beneficial to expand on the model to include a multi-unit auctioning system.

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A
Sensitivity Analyses

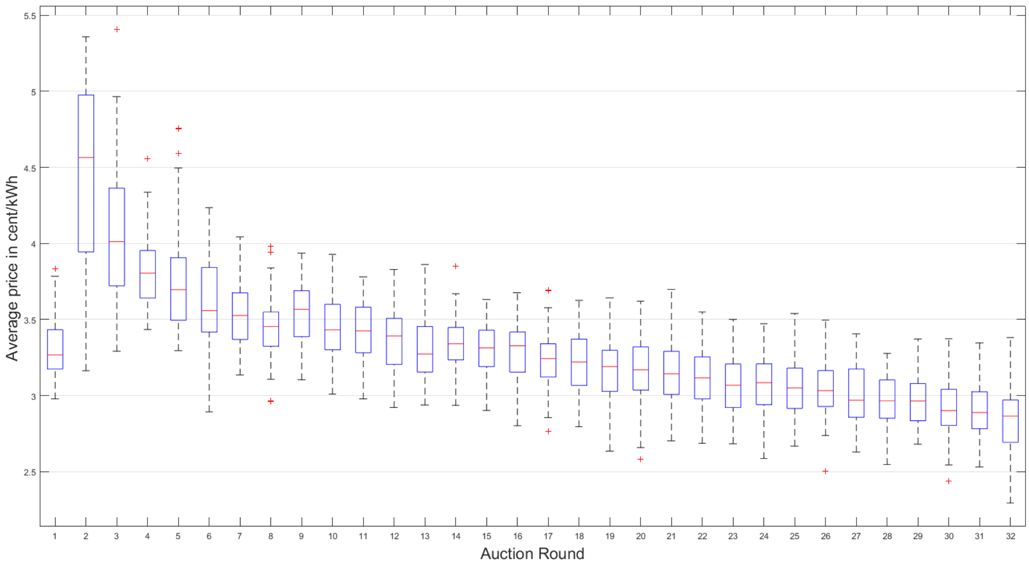

Figure A.1: Development of prices with the pay-as-bid price scheme, with 32 auction rounds and 50 iterations. Cost interval baseline increased with 10 %

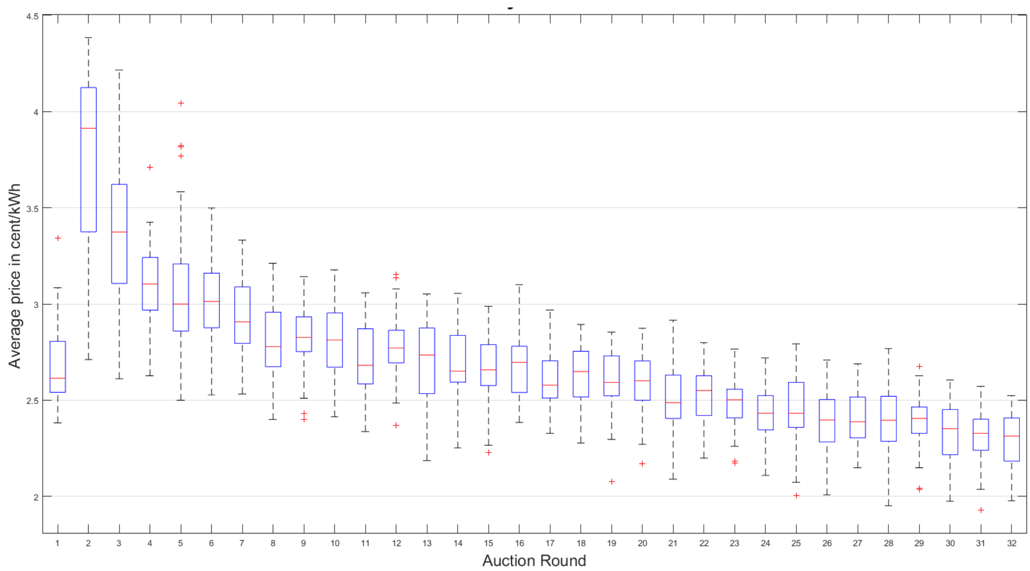

Figure A.2: Development of prices with the pay-as-bid price scheme, with 32 auction rounds and 50 iterations. Cost interval baseline decreased with 10 %

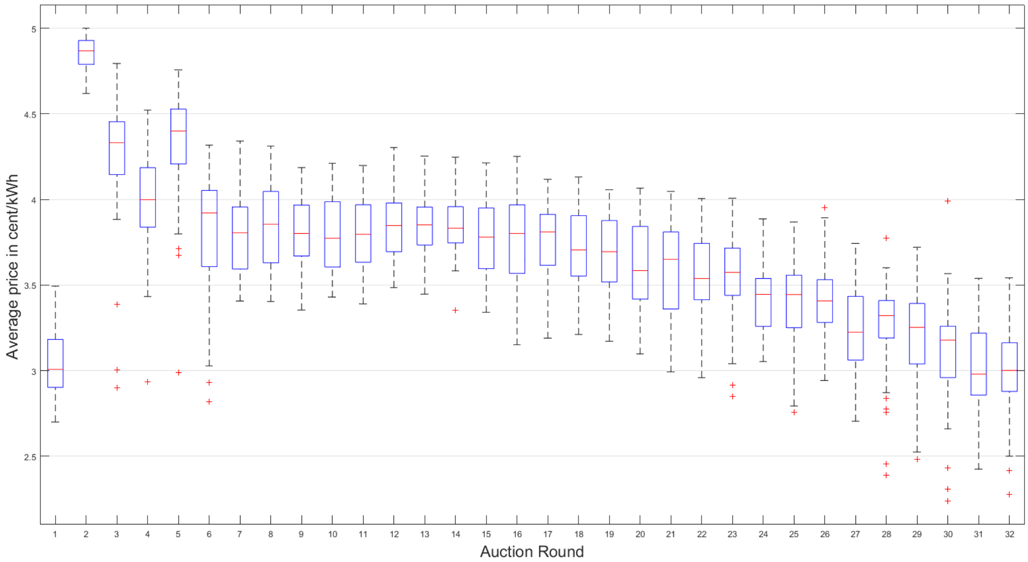

Figure A.3: Development of prices with the pay-as-bid price scheme, with 32 auction rounds and 50 iterations. Number of agents is kept constant at 14 (no expanding market)

B
Modeled vs Actual Winning Bid

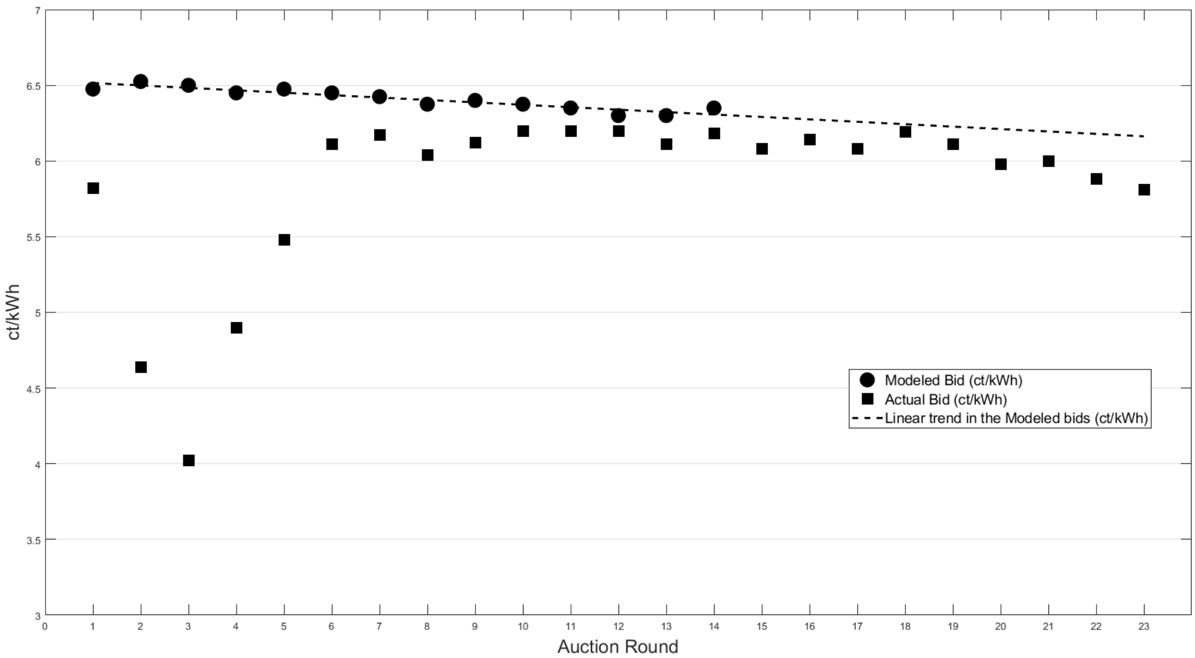

Figure B.1: Modeled average winning bid vs. actual average winning bid for 23 auction rounds (Anatolitis and Welisch, 2017; Bundesnetzagentur, 2021b).

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C
MATLAB Script

```
clc
clear
close all

iteration = 1;

while iteration <= 50  %The entire program will run x times
clearvars  -except Mean_Answer iteration

t = 1;
T = 32; %Number of auction rounds

%Set up for the first round:
nWinners =0;
mu = 0;
sigma = 0;
nCompetitors  = 0; %Does not matter for the first round
Max_nAgents = 14;

for i = 1:Max_nAgents
    Old_Bid(i) = 0;
end

Auctioned_Capacity = 80;   %Capacity that is auctioned out in every
   round

Min_Cost = 2.5; %Minimum Cost (ct/kWh)
Max_Cost = 5;   %Maximum Cost (ct/kWh)

Min_Capacity = 0.75;
Max_Capacity = 40;

%Give every agent a cost and a capacity:
Cost = Min_Cost + (Max_Cost-Min_Cost)*rand(1,Max_nAgents);
Capacity = Min_Capacity + (Max_Capacity-Min_Capacity)*rand(1,Max_nAgents
   );

while t <= T

Max_Bid = Max_Cost;
%After 3 rounds, the possible maximum bid is the average of the last 3
%rounds highest bids
```

```
if t > 3
    Max_Bid = (((max(Answer(:,(t-3))))+(max(Answer(:,(t-2))))+(max(
   Answer(:,(t-1)))))/3);
end

%Number of times every agent have bidded:
    if t == 1
        for i = 1:Max_nAgents
            times(i) = 1;
        end
    else
       for i = 1:Max_nAgents
            times(i) = times(i)+1;
       end
    end

    %Finds the optimal bid:
    for iAgent = 1:Max_nAgents
        Optimal_Bid(iAgent) = Optimal_Bid_function(T,t,Cost(iAgent),
   nCompetitors,nWinners,Max_nAgents,Max_Bid,mu,times(iAgent),Old_Bid(:,
   iAgent),sigma);
    end

    %Create a Auction Vector containing the AgentID, Optimal Bid,
   Capacity
    %and number of times the agent have bidded
    for i =1:Max_nAgents
        Auction_Vector(i,:) = [i Optimal_Bid(i) Capacity(i) times(i)];
    end


%Sort the bids from lowest to highest. If two bids are the same, the
   agent
%with the lowest capacity is favoured

Sorted_Auction = sortrows(Auction_Vector,[2 3]);

Auction_Capacity = 0;

Select_Bid =0; %Clear the variable

%Select the winners in the bidding
    for i = 1:length(Sorted_Auction)
         if (Auction_Capacity)<Auctioned_Capacity

            Select_Bid(i) = Sorted_Auction(i,2);
            ID_Select_Bid(i) = Sorted_Auction(i,1);
            Auction_Capacity = Auction_Capacity + Sorted_Auction(i,3);

         else break
         end
```

```
    end

    for i = 1:Max_nAgents
        Old_Bid(t,i) = Auction_Vector(i,2);
    end

    if t >1
Decreasing_Factor = 0.9822 + (1-0.9822)*rand;   %The price is assumed to
    decrease up to 1.78% per auction round
Min_Cost = Min_Cost*Decreasing_Factor;
Max_Cost = Max_Cost*Decreasing_Factor;
    end

%Give a new project to the agents that won in the previous round
    for i = 1:length(Select_Bid)

         for j = 1:length(Auction_Vector)

             if ID_Select_Bid(i) == Auction_Vector(j,1);

                 Capacity(j) = Min_Capacity + (Max_Capacity-Min_Capacity
   )*rand          ;
                 Cost(j) = Min_Cost + (Max_Cost-Min_Cost)*rand   ;

             end
         end
    end

%SThe bidders that participated in the previous round will learn the
   weighted average bid, number of participants and number of winners
        for i = 1:length(Auction_Vector)
            Sum_Mult(i) = Auction_Vector(i,2).*Auction_Vector(i,3);
        end
        Sum_Mult = sum(Sum_Mult);
        Sum_Capacity = sum(Auction_Vector(:,3));

        mu = Sum_Mult/Sum_Capacity;
        sigma = std(Auction_Vector(:,2))


nCompetitors = Max_nAgents;
nWinners = length(Select_Bid);

%Add 0-5 new agents to the next aution round
Old_Max_nAgents = Max_nAgents;
Max_nAgents = Max_nAgents + randi(5);



%Give a  project to the new agents
    for i = Old_Max_nAgents:Max_nAgents
```

```
        times(i) = 0;
        Cost(i) = Min_Cost + (Max_Cost-Min_Cost)*rand;
        Capacity(i) = Min_Capacity + (Max_Capacity-Min_Capacity)*rand;

    end


    for i = Old_Max_nAgents:Max_nAgents

        Old_Bid(t,i) = 0;
    end

Answer_Bid = Select_Bid;
    for i = 1:length(Answer_Bid)
        Answer(i,t) = Answer_Bid(i);
    end

    for i = iteration
        Mean_Answer(i,t) = mean(Answer_Bid(:))
    end

t = t+1
end

iteration = iteration+1

end

for i = 1:height(Answer)
    for j = 1:T
        if Answer(i,j) == 0
            Answer(i,j) = NaN;
        end
    end
end

figure (1)
boxplot(Mean_Answer)
title('Pay-as-bid', 'FontSize', 24);
xlabel('Auction Round', 'FontSize', 18);
ax = gca;
ax.XGrid = 'off';
ax.YGrid = 'on';
ylabel('Average price in cent/kWh ', 'FontSize', 18);
```