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Abstract

We observe a rapidly rising share of the passenger car fleet becoming electric as policy makers keep making the purchase and use of electric vehicles (EVs) more favorable in the pursuit of reducing pollution. The electrification of transport will make the transport and energy systems more intertwined: EV-friendly transport policies increase the demand for power, thus challenging the distribution grid's capacity, while electricity policies immediately impact on the generalized costs of driving EVs. This paper develops a stylized economic model for passenger transport in the greater Oslo area where the agents' endogenous choice of car ownership, transport pattern and EV home charging is determined jointly in equilibrium. If enough EV-owning agents charge during power peak hours, costly grid expansions may be needed. We examine how the distribution grid company can respond in order to mitigate these costs with different pricing schemes and how this in turn affects the transport equilibrium. We find that applying peak tariffs for the grid will help strike a better balance between investment costs and EV-owners' disutility of charging during off-peak hours.

Keywords: electric vehicles, climate policy, urban transport policy, transport modeling, electricity distribution costs

JEL classification: H71, Q41, Q48, Q54, Q58, R41, R48

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1 Introduction

The Paris agreement was adopted in 2015 and came into force in 2016 as a response to the imminent threat of climate change. It aims to limit the global temperature increase in this century to well below 1.5°C above pre-industrial levels. The transport sector accounts for approximately one quarter of global energy-related greenhouse gas emissions (International Energy Agency, 2017) and about one third of Norway's greenhouse gas emissions[2]. It is therefore required to deliver major emissions cuts in this sector to meet the objectives of the Paris agreement.

The electrification of transport is viewed as a potent measure to reduce greenhouse gas emissions (International Energy Agency, 2017; WWF, 2012). Several initiatives to promote electric vehicles (EVs) have been launched worldwide, including the Clean Energy Ministerial's EV30@30 campaign for a 30 percent sales share for EVs by 2030. Norway's strategy is to ensure that all new passenger vehicles are zero emission vehicles by 2025. EV-friendly transport policies – including low vehicle taxes, toll road exemptions, and access to bus lanes – have therefore been put in place, which has resulted in the highest penetration of EVs worldwide. By January 2019, there were about 190,000 battery electric vehicles (BEVs) and 90,000 plug-in hybrids (PHEVs) in Norway, a country with only 5.3 million inhabitants. In 2018, BEVs accounted for 31 percent and PHEVs for 17 percent of all new vehicles (Norwegian Electric Vehicle Association, 2019).

According to the Norwegian energy regulator, 1.5 million EVs in Norway in 2030 would only amount to a 3 percent increase in the domestic electricity consumption (Skotland, Eggum, & Spilde, 2016). Hence the main challenge is not expected to be that of aggregate electricity generation. While an EV's energy consumption may be modest, its power consumption could be quite high. The current power demand per electricity consuming unit in a household is normally of the order of from 2.3 to 7.3 kW. Fast chargers currently demand more than 50 kW, and are expected to reach 350 kW in the near future (Skotland et al., 2016).

There are larger reasons to be concerned about power consumption and capacity. Uncoordinated charging (also known as dumb charging) will increase the electricity consumption during the morning and evening peaks (Graabak, Wu, Warland, & Liu, 2016). De Hoog, Alpcan, Brazil, Thomas, and Mareels (2015) point out that if vehicle charging is not controlled, adverse impacts on the distribution network are expected: power demand may exceed distribution transformer ratings; line current may exceed line ratings; phase unbalance may lead to excessive current in the neutral line; and voltages at customers' points of connection may fall outside required levels. A similar point is made in Neaimeh et al. (2015).

Several studies look at the effects low-carbon technologies such as BEVS and PHEVs can have on the electricity market. Hattam and Greetham (2017) look at how EVs affect load profiles on neighborhood level in low voltage networks. Azadfar, Sreeram, and Harries (2015) asses charging behavior from EV users in terms of time of day, duration, frequency and electricity consumption in light of its implication for electricity network management. Barton et al. (2013) look at the challenges for grid balancing when EV charging, heat pumps and the use of combined heat and power (CHP) become more prominent, and stress the importance of demand side management with time-shifting of electricity loads from periods of peak demand to off-peak, and from periods of low renewable energy supply to periods of high supply. Other studies also argue for demand side management (see e.g., Haidar, Muttaqi, & Sutanto, 2014; Masoum, Deilami, Moses, Masoum, & Abu-Siada, 2011) as an alternative to costly upgrades of distribution transformers. On the other hand, Daina, Sivakumar, and Polak (2017a) points out that the impact of demand management schemes like smart charging managed by a charging service provider may be overestimated if they do not take into account the heterogeneity in charging behavior. Some of these studies also argue

[2] Statistics Norway: "Emissions of greenhouse gas emissions, by source. Last year" (in Norwegian)

for pricing schemes that disincentivize charging during off-peak hours (see e.g., Barton et al., 2013; Clement-Nyns, Haesen, & Driesen, 2011; Masoum et al., 2011; O'Connell et al., 2012). The Norwegian Energy Regulator opts for a power-based distribution tariff to meet increasing power demands[3]. In the future, vehicle to grid[4] (V2G) may provide also a means to mitigate capacity problems in electricity distribution (see e.g., Barton et al., 2013; Clement-Nyns et al., 2011; Green II, Wang, & Alam, 2011; Hagem, Greaker, & Proost, 2019; Mwasilu, Justo, Kim, Do, & Jung, 2014), but bidirectional EV charging is in its infancy (Haidar et al., 2014), and seem to come at a relatively high cost due to energy losses, changes in infrastructure, and extra communication between EV and grid (Habib, Kamran, & Rashid, 2015).

When summing up the points made in this introduction, we can make our motivation for this paper clear. We observe a rapidly rising share of the passenger car fleet becoming electric, and we have found that a shift to EVs is key to reach ambitious CO_2-targets at least cost. However, the calculation of these costs did not consider the cost of enhancing the local grid to meet the demand for charging by EV-users. The electrification of transport will make the transport and energy systems more intertwined: EV-friendly transport policies increase the demand for electricity and thus impacting the grid, while electricity policies immediately impact on the generalized costs of driving EVs. As discussed above, there exists some literature that looks at how the electrified transport will affect the need for grid investments and/or demand management in order have sufficient power capacity. Most of these studies assume that transport demand, and therefore EV users' demand for electricity, is exogenous (see also Daina et al., 2017a; Daina, Sivakumar, & Polak, 2017b). This paper contributes to the literature by looking at the mechanisms and outcomes in *both* the transport and energy market, and the feedback in-between them. We use a stylized transport and energy model for the greater Oslo area to study costs and benefits in both the electricity market and transport market jointly. The model allows the agents to choose type of car (or no car), their transport pattern and (if they own an EV) how much to home charge during power peak and off-peak hours. To our knowledge, it is the first time these features have been applied in the same modeling framework. The analysis will give insight into the feedback between the transport market and electricity market and how policies in one market can affect the equilibrium in the other. With this we can assess how polices can be optimized to reach policy goals at least cost.

In summary, we have two research questions: 1) When we factor in the current uniform grid tariff system, what are the welfare impacts of today's EV policies and polices for reaching CO_2-targets at least cost? 2) How can these welfare costs be affected by a better pricing of electricity distribution?

Section 2 briefly discusses policies and market distortions relevant for electromobility and power distribution. Section 3 presents the theoretical model. In section 4 and 5 we present the numerical model, and describe the scenarios we run. In section 6 and 7 we present, analyze and discuss the model results. Section 7 concludes.

[3] The Regulator's is currently working on a new proposal and there is expected to be a hearing in the first quarter of 2019 https://www.nve.no/nytt-fra-nve/nyheter-reguleringsmyndigheten-for-energi/nve-onsker-innspill-til-arbeidet-med-ny-tariffstruktur/ [in Norwegian].

[4] V2G involves using EVs as storage for electricity.

2 Policies for electromobility and power distribution

2.1 The Norwegian power system and electrified transport

The rapid rise in EVs in Norway is to a large degree a result of incentives in Norwegian transport policy (Figenbaum & Kolbenstvedt, 2016; Fridstrøm & Østli, 2018). As pointed out in the introduction, the rise in EVs will entail an increase in power consumption. The focus of this paper is solely on the lower end of the electricity sector value-chain, with the power consumption of households, and capacity in the low-voltage distribution grid.

The energy sector is preparing for the electrification of transport. The Norwegian energy regulator NVE (The Norwegian Water Resources and Energy Directorate) has recently produced two technical reports that assess the strain that electric cars put on electricity transmission. The first report (Skotland et al., 2016) pays attention to how the diffusion of electric vehicles can impact the electricity distribution network. In a scenario where all new vehicles are EVs in 2025, and where the stock of EVs are 1.5 million in 2030 (but where the transport demand per vehicle is as today) the EVs would consume 4 TWh of electricity annually. NVE estimates that 75 percent of the charging of EVs takes place at home, 15 percent at work, and 10 percent is fast charging. NVE finds that 70-80 percent of EV drivers seldom use fast charging. However, NVE expects the demand for fast charging to increase in the future as the next generation of EV owners may not be able to charge at home.

NVE's review indicates that charging of electric vehicles primarily takes place at night, while some also charge their vehicle immediately after work. Figure 1 shows their expected power consumption profile for an average household, with and without home charging of EVs.

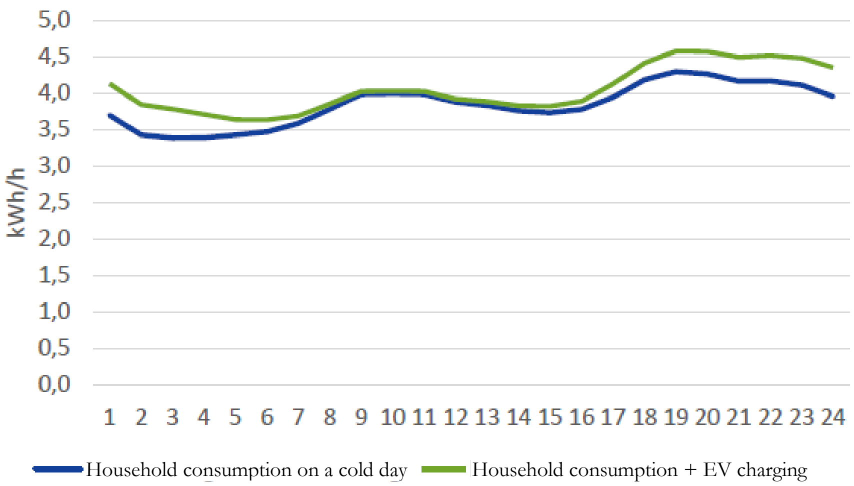

Figure 1: Average household power consumption per hour on a cold day (blue line), and total power consumption for the household when the assumed patter for home charging EV is included (green line). From Figure 4.3 in Skotland et al. (2016).

NVE argues that the introduction of power-based tariffs will provide incentives to postpone charging until after peak-hours. They have recently submitted a proposal for a new electricity tariff based on the demand for power. This is now technologically feasible after January 1st 2019, when smart meters became compulsory for all Norwegian households. This will enable households to closely monitor their temporal consumption profile of electricity, and both distribution grid companies and electricity retailers to bill accordingly.

NVE develops stress-tests for neighborhoods with high EV-density. Assuming periods where 70% of the residents charge their EVs simultaneously, it finds that the power demand can increase by up to 5 kW per household. This results in overload for more than 30 percent of the transformers currently servicing the distribution network. NVE's follow-up report (Skotland & Høivik, 2017) concludes that a full-scale electrification of transport (including also buses and ferries) is primarily a threat to transformers. The upgrade of several of these components is planned today, which reduces the problem of overload in the future. Yet, NVE reports that few of the electricity distribution companies account for the electrification of transport when forecasting the demand for power. As we will discuss below, this could materialize into substantial costs. Skotland and Høivik (2017) assess the costs of upgrading components in the local, regional and transmission grid due to electrification of cars, buses and ferries. They find that they range from NOK 300 000 to NOK 7 000 000 (approx. € 30 000 to € 700 000), where the lower cost components are mainly at the local grid level, whereas the high cost components are at the transmission grid level. The largest share of the needed upgrades is due to electric ferries, and electric cars have the second largest share (mostly on the local grid level).

On the local grid level, the capacity may need to be expanded for the transformer or for the cable between the transformer and the households, or both. In a metropolitan area there will be large variations in neighborhoods' ability to absorb increases in peak power demand with the current infrastructure. And given the need to invest in more capacity, the cost will also vary greatly between neighborhoods. The cost will depend on whether enhancements need to be done for the transformer and/or the cables between the households, the amount of transformer capacity that needs to be installed, whether the new transformer fits in the old box that contained the old transformer, and the costs of digging (i.e. how many meters of cables need to be laid, and the costs per meter, which is generally higher in denser, urban areas).

These costs may or may not accrue to the household that demands higher capacity. Let's say that some households increase their capacity demand so that total capacity demand in the neighborhood exceeds the capacity of the local distribution transformer. The local grid company will invest in a higher capacity distribution transformer, thus undertaking an increase in its capital costs. Local grid companies (or Distribution System Operators – DSOs) are regulated under a revenue cap model, where they set their tariffs based on this revenue cap. The revenue cap is composed of 40% cost recovery and 60% cost norm based on benchmark modeling. This means that at least some of the increase in capital cost will lead to higher tariffs, and these tariffs will have to be paid by all electricity consumers connected to the local grid company, and not just the households demanding more capacity. It can be viewed as a pecuniary external cost (Greenwald & Stiglitz, 1986). That is, the households demanding more capacity do not face the full cost of the capacity expansion, and indirectly impose costs on other consumers.

The case becomes a little different if a household demands higher power capacity than currently installed in the household, and *this* increased capacity demand exceeds the capacity of the local distribution transformer. This household may be required to pay for some or all of the capacity expansion of the transformer through connection charges, in addition to paying for the capacity expansion in his own house. Practices seem to vary between Norwegian DSOs, but the DSO in the Oslo metropolitan areas, Hafslund, will in such a case charge the household that induced the new investment in proportion to the added installed capacity for that household[5]. For example, if a household wants to install 20 kW extra of capacity, and the DSO replaces a 315 kW transformer with a 500 kW transformer, the household has to pay 20/(500-315) = 11% of the cost of the capacity increase. Households that expand in-house capacity in the future will also have to chip in on this transformer upgrade in proportion to their in-house expansion[6]. This would mean that less or none of the investment cost will be dispersed to the other consumers through increased tariffs.

[5] https://www.hafslundnett.no/artikler/bygge-og-grave/anleggsbidrag/6l51MrL1vyaCi0WsisqAQQ

[6] Other households in the neighborhood could have reinforced their household power capacity without having to pay a connection charge, as the total capacity demand would still be within the transformer's capacity. This may look like a set-up for a strategy game between households, where early-moving households can expand their in-house capacity without having to pay extra, but we expect that such games are rare

Instead the scheme provides a price signal to the very households that demand more capacity, thus informing their decision to whether or not the benefits of expanding their in-house capacity outweighs the cost.

The scenario where increased EV ownership leads to higher capacity demand that eventually exceeds the local transformer's capacity, without any household expanding its in-house capacity, is expected to be most prevalent. The reason is that most households will have the possibility of charging an EV at 3.6 kW power without the need for any in-house capacity expansion (conversation with the DSO Ringeriks-Kraft AS). Most would still have to make some adjustments to their in-house electric system as charging an EV is required to be on a separate fuse.

This will lead to situations where, over time, some neighborhoods could drive up grid company investment costs as EV ownership increases, leading to higher tariffs for all customers. Whether higher EV ownership will drive up total neighborhood capacity demand will depend on the number of EV owners, the number that charges at the same time during times of otherwise high capacity demand (power peak hours), and the existing capacity on the local transformer. Such an outcome could be the case if EV owners charge their car right after coming home from work. Although people do not come home at the same time, such behavior would lead to a high degree of simultaneous charging during peak hours.

At the time of writing, no individual household (except those participating in hour-by-hour pricing experiments) have any private incentive to postpone charging until after peak hours. Both electricity prices and grid tariffs are the same throughout the day. And there are many reasons why EV owners would want to charge the EV right away after coming home. First, it is convenient. You plug in, and there is no need to spend mental capacity on timing. Second, you maximize the probability of always having the battery charged for any activity later; planned, spontaneous or emergency.

As discussed above, power tariffs could serve as an instrument to move some of the charging away from peak hours. The tariff difference would have to be large enough to incentivize at least some EV owners to postpone their charging. The needed tariff difference is driven upwards by the fact that Norwegian electricity prices and tariffs on average are lower than in most other European countries, incomes on average are higher (and average incomes of car owners are higher than those of non-car owners), and own-price elasticities for electricity are relatively small (see e.g., Ericson, 2007). User-friendly smart charging systems that automatically seek to minimize charging costs for the EV owner would help moving charging times away from peak hours, even for small price differences[7]. It will also help that future EVs will have such long ranges that normal daily use, even with activities in the evening, combined with night charging, rarely will give any need to worry about inadequately charged batteries. There is also the possibility of introducing behavioral schemes, such as the one in Costa and Kahn (2013), where neighbors are kept informed of their own and other's average electricity usage, thus providing some social pressure to moderate consumption. Grid companies would have the incentive to get EV owners to enroll into such a scheme, so that EV owners can put social pressure on each other not to charge during peak hours, knowing that high levels of EV charging would bring about new investment costs. The efficacy of such a scheme would be an empirical question though.

[7] An example: https://evblog.org/this-ev-charger-saves-up-to-50-on-your-electric-bill/

2.2 Coordination between the players in the Norwegian context

Electrification of transport introduces new challenges and opportunities for both the transport sector and the electricity sector. But these sectors consist of many different players, including policy-makers for road transport, electricity sector regulators, electricity retailers, local grid companies and households. Without any coordination, the costs and benefits could be distributed quite unevenly.

Policy-makers for road transport have been mandated to reduce emissions from transport. As shown in Wangsness, Proost, and Rødseth (2018), in order to reach the emission reduction target at least cost, a large share of transport users would have to switch to EVs. From their point of view, the fact that grid companies need to invest in local grid capacity in certain places to accommodate a larger EV share, is an added difficulty to their emission reduction target. The needed investments and the subsequent increases in tariffs drive up the cost of switching to EVs, meaning that policy packages would have to become more radical in order to reach the targets. This means higher welfare costs in the transport sector.

Electricity retailers benefit from policies for reducing emissions, as higher demand for EVs drives up demand for electricity, making the sector more profitable *ceteris paribus*. Some of that increased profitability will be moderated if the increased electricity demand is curbed by higher tariffs.

Local grid companies' profitability is determined by their costs and their regulated revenue cap. If policies drive up EV ownership and subsequently capacity demand, their capital costs will increase, most likely without a corresponding increase in the revenue cap. Since "EV density" is not an external variable in the current benchmark competition, the cost norm calculation will disfavor grid companies that face increased capacity demand from EV users. A grid company facing such demand increases, will see the policies for reducing emissions as a threat to their profitability. An exception would be a DSO that already is among the most productive and remains among them in spite of the increase in capacity demand from EV owners. Such a company would set the cost norm, and will be able to pass the entire investment cost over to consumers. If then the cost norm is expanded, DSOs who are *not* exposed to higher capacity demand from EV owners will get a larger revenue cap, but no extra costs.

Electricity sector regulators should take the new challenges into account. If capacity demand from EV owners becomes a major cost driver for local grid companies (which remains to be seen), there are at least two measures the regulator needs to take. The first is to incorporate a measure of "EV density" in their benchmarking model for calculating the cost norm for the sector, so that the relatively low costs for grid companies with low EV density are not mistaken for efficiency. The second is to allow for peak power tariffs and incorporate them in the revenue cap. This way, it becomes possible to pass on and signal the additional distribution costs of EV charging to the EV users.

This paper focuses on the greater Oslo area, where policy makers have set ambitious climate goals. This area is broadly made up by the municipality of Oslo and the county of Akershus. Oslo aims to reduce CO_2 emissions by 50% by 2020 (Oslo Municipality, 2016). The corresponding goal in Akershus is a 50% reduction by 2030 (Akershus County Council, 2016). As shown in Wangsness et al. (2018), households will face increased costs one way or another from ambitious emission reduction targets. The fact that grid tariffs could increase when facing these polices only drives up the cost further.

2.3 Distorted prices in transport and power consumption

As shown in Wangsness et al. (2018), there are multiple market failures and policy parameters in an urban transport setting. Most of the policy parameters, be it road prices or public transport fares, seem to be sub-optimally assigned in the case of the Oslo metropolitan area. Acknowledging the transformer capacity issue means bringing another market failure into the mix. As mentioned above, the market failure can be viewed as a pecuniary externality in an incomplete market (Greenwald & Stiglitz, 1986). Since there currently is no explicit price on using more capacity during power peak hours, some consumers may increase their capacity demand without facing the true cost of inducing costly capacity expansions, because tariffs will rise for all consumers and the affected grid companies might face lower profits.

Many papers look at optimal ways for regulators to handle periods with high demand and cost recovery for utilities (and grid companies). Recent contributions include Brown and Sappington (2018) that look at Maximum Demand Charges (MDCs) and Time-of-Use (TOU) pricing for residential consumers. They find that TOU pricing in most cases secures higher aggregate welfare than MDCs. This indicates that if consumers have installed smart-meters, which is the case for most Norwegian households in 2019, TOU pricing would most likely be preferred. It can often be beneficial to apply some element of fixed charges in order to induce efficient consumption and at the same time ensure cost recovery to suppliers (Borenstein, 2016; Brown & Sappington, 2017a, 2017b). This is a common feature in the billing from Norwegian DSOs. It is also worth mentioning that pricing schemes to shift demand away from peak hours (such as TOU pricing, MDCs, Critical Peak Pricing or Extreme Day Pricing) can have additional benefits such as increased reliability (Albadi & El-Saadany, 2008).

Before we introduce the numerical model, we give a simple illustration of how the issues of grid capacity affect the optimal ownership distribution between ICEVs (internal combustion engine vehicles) and BEVs in an urban transport setting. In Figure 1 we consider a fixed number of cars for a metropolitan area that can be either ICEV or BEV. The number of ICEV cars is measured from left to right, the number of BEV cars is the complement on the horizontal axis. We assume that the use of the car (mileage and congestion effects) is identical for owners of each car type, so the average cost of ownership curve is flat for each car type. It is assumed that the average cost of ownership is lower for ICEVs than for BEVs. Hence, without any government intervention, all car owners would choose ICEVs and none would choose BEVs, demonstrated by equilibrium A.

When the number of ICEVs in the urban area increases, the local pollution costs (NO_X, PM) also increase at an increasing rate (see e.g., Thune-Larsen, Veisten, Rødseth, & Klæboe, 2014), which gives us a rising marginal external cost curve. If there were no external effects from EV ownership, then the desired equilibrium would be B. However, when normal use of EVs entails some charging during power peak hours, each EV will add some additional cost to the capacity expansion of the local grid through higher costs of transformers. As costs of transformers are assumed to be linear in capacity for the relevant capacity interval, the marginal cost curve for charging EVs is flat. Taking this into account lowers the optimal BEV-share of the area's car stock to equilibrium C.

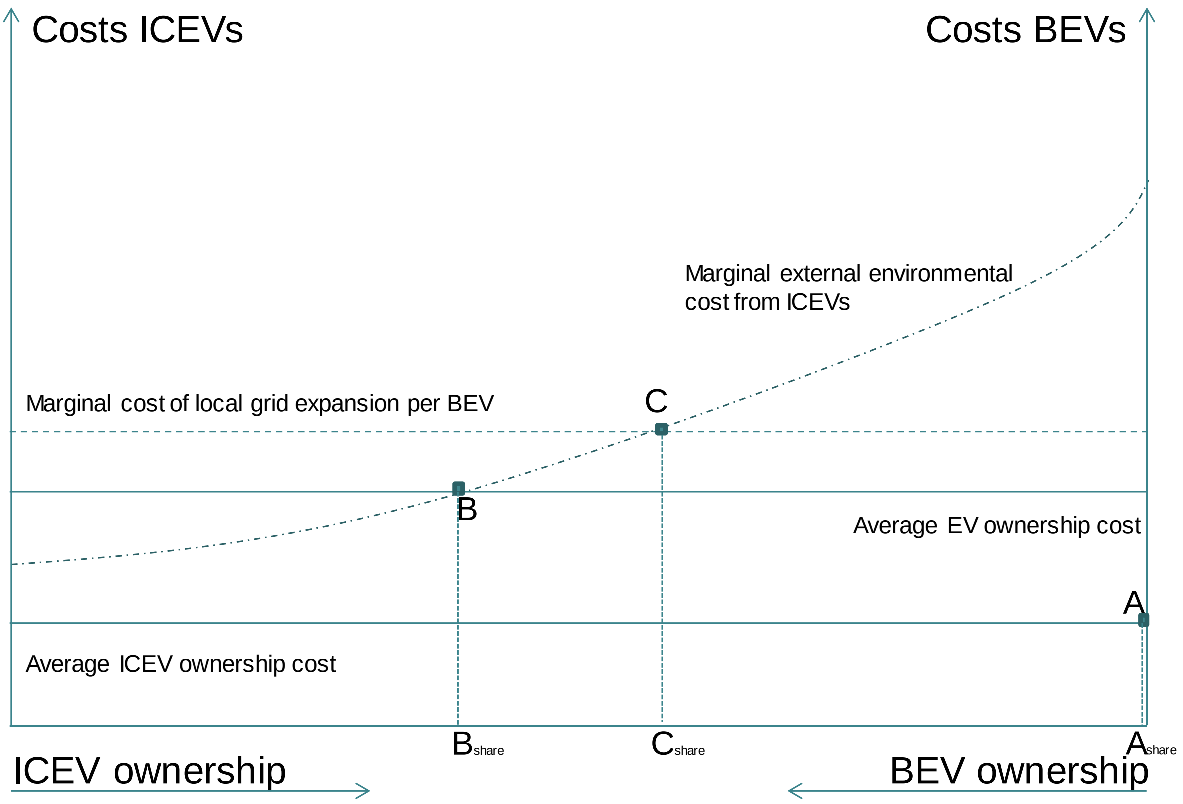

Figure 2: Optimal ownership distribution between ICEVs and EVs

The market failure of inadequately being able to make EV owners face the price of expanding local grid capacity will complicate the problem of maximizing welfare for the citizens in the greater Oslo area, and it will drive up the cost of achieving ambitious emission reduction targets. The modeling exercise will give an indication of how much.

3 The stylized transport and electricity model

The preferences of the modeled agents are represented by a quasi-linear utility function U. Here utility is derived from consumption of other (non-transport) goods and services (normalized to net generalized income m_{net}^{v} for a given vehicle choice *v*), and from consumption of transport. The utility is assumed to be expressed in monetary terms. The transport goods are car kilometers travelled for short daily trips at peak and off-peak (q_c^p and q_c^o, respectively), public transport (PT) kilometers travelled for short daily trips and peak and off-peak (q_b^p and q_b^o, respectively) and the number of long car trips per year, q_{lc}. The utility from transport consumption is represented by a sub-utility function B, which is assumed to be quadratic. U and B, for a given representative individual, are represented by the following:

(1) $$U(m_{net}^{v}, q_c^p, q_c^o, q_b^p, q_b^o, q_c^l) = m_{net}^{v} + B(q_c^p, q_c^o, q_b^p, q_b^o, q_{lc})$$

The social planner's task of maximizing social welfare can first be broken down into two sub-tasks. For whichever car the agent chooses, policies must be adjusted to get the most efficient transport equilibrium. But given efficient transport policies for given car combinations, the social planner also needs the agents to choose the optimal car combination. In the case of a car combination where EVs are chosen, the planner also needs to factor in the social cost of charging the EV.

It is not just the price of electricity that matters, the induced cost of demanding higher local capacity for charging needs to be accounted for. There is a cost of expanding local capacity that needs to be balanced against the agents' preference for charging during peak hours. We model this as a disutility function of charging during off-peak hours.

In the stylized first-best solution, the capacity expansion per EV owner is set to strike the balance between incurred investment costs and the disutility of charging off-peak. This can be interpreted as if the EV owner commits to a charging pattern, and the incurred investment cost in optimum can for the agent be considered a part of the fixed cost of getting an EV.

This incurred fixed cost is a result of cost minimization problem. Assuming a fixed charging speed (3.6 kWh/h) and an exogenous daily charging need of $kWh^o + kWh^p = \Omega$, the problem boils down to how the agent wants to divide her charging hours $h = \Omega/kW$ between peak and off-peak. If she wants to peak charge more than zero during power peak hours, then she has to pay for capacity expansion. We introduce the following simple non-linear programming problem, where F is the fixed investment cost for any transformer, β is the investment cost of additional peak capacity, where charging in the off-peak involves some disutility $disU(h^o)$ as a function of off-peak hours charged, and where the control variable is kWh^p. We operate with annualized investment costs, denoting them F^{ann} and β^{ann}. We solve the problem for a representative day.

(2) $$\min_{kWh^p} p^p kWh^p + p^o(\Omega - kWh^p) + disU(\frac{\Omega - kWh^p}{kW}) + \frac{F^{ann} + \beta^{ann}\, kWh^p/h^p}{365}$$

when $kWh^p \geq 0$

This gives us the following Kuhn-Tucker conditions:

$$p^p - p^o - \frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) + \frac{\beta^{ann}/h^p}{365} + \mu = 0$$

$$\mu \geq 0 \;\; (\mu = 0 \text{ if } kWh^p > 0)$$

where μ is the Lagrange multiplier of the non-negativity constraint. We get three possible solutions, two corner solutions and one interior solution:

1. Interior solution: Optimum is where the marginal disutility of charging time during off-peak hours (weighted by *kW)* equals the price difference between peak and off-peak electricity plus the share of the annuity of the marginal investment cost for expanding peak capacity. With the interior solution, we have that some charging is done during peak hours, 0< $kWh^p < \Omega$, when

$$\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) = p^p - p^o + \frac{\beta^{ann}/h^p}{365}$$

2. No charging is done during peak hours, $kWh^p = 0$, when

$$\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) < p^p - p^o + \frac{\beta^{ann}/h^p}{365}$$

3. All charging is done during peak hours, $kWh^p = \Omega$, $\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) > p^p - p^o + \frac{\beta^{ann}/h^p}{365}$

We denote the cost minimizing choice of the agent kWh^{p*}. Having established this, we can insert it into the social planner's maximization problem.

With our utility function consisting of transport consumption and normalized "other" consumption, costs are subtracted from gross generalized income m_{gross}^{v} in order to get net generalized income. We also subtract gross generalized income by the fixed costs of car ownership $C_{v,\,fixed}^{ann}$, cost of non-transport electricity consumption (where a^{p} and a^{o} represent annual consumption of electricity in peak and off-peak), and annuity of the capacity-independent part of the grid cost F^{ann} paid equally among *n* agents. In the case the agent owns an EV, the subtracted costs also include the annuity of the required investment cost of the chosen charging pattern and any annual disutility of charging off-peak. Since we model annual welfare, the fixed costs are considered as annuities. Finally, the user costs of transport (monetary costs and time costs) for driving car during peak hours, $uc_{ck}^{p}q_{ck}^{p}$, off-peak hours, $uc_{ck}^{o}q_{ck}^{o}$, and on long car trips, $uc_{lck}q_{lck}$, and PT during peak hours, $uc_{bk}^{p}q_{bk}^{p}$, and off-peak hours, $uc_{bk}^{o}q_{bk}^{o}$. The user costs for car includes distance related costs (fossil fuels and/or electricity, repairs, lubricants), toll costs, parking costs and time costs. If the long car trip is done by a BEV, and the trip back and forth is longer than the range of the car, the agent is assumed to need to charge enough to cover the remainder of the round trip. This adds a disutility cost as a function of the charging time. The user cost for PT travel includes access time costs, fare costs, waiting costs and crowding-in-vehicle time costs. We thus have

$$\begin{aligned}(3)\qquad & m_{net}^{v}=m_{gross}-C_{v,\,fixed}^{ann}-p_{el}^{p}a^{p}-p_{el}^{o}a^{o}-\tfrac{F^{ann}}{n}+\tfrac{\beta^{ann}kWh^{p^{*}}}{h^{p}}-\sum_{days}disU\left(\tfrac{\Omega-kWh^{p^{*}}}{kW}\right)\\ & -uc_{c}^{p}q_{c}^{p}-uc_{c}^{o}q_{c}^{o}-uc_{b}^{p}q_{b}^{p}-uc_{b}^{o}q_{b}^{o}-uc_{lc}q_{lc}\end{aligned}$$

Consider k=1,…,n agents that are differentiated by the number of long trips they want to make per year, employment situation and by their mode choice preferences. The social planner's welfare maximization problem for all k agents can then be formulated as follows:

For all k agents, make agents choose vehicle $v=\left[ICEV, BEV\right]$ and number of transport trips with car and/or public transport so that the following social welfare function W^{v} is maximized:

$$\begin{aligned}(4)\qquad & W^{v}=\sum_{k=1}^{n}\left[m_{net,k}^{v}+B_{k}(q_{ck}^{p},q_{ck}^{o},q_{bk}^{p},q_{bk}^{o},q_{lck})\right]\\ & -\left(C_{b}-\tau_{c}^{p}q_{c}^{p}-\tau_{c}^{o}q_{c}^{o}-\tau_{b}^{p}q_{b}^{p}-\tau_{b}^{o}q_{b}^{o}-\tau_{c}^{r}q_{lc}-\tau_{g}g_{c}q_{c}-\sum_{k}\tau_{c}^{ann}k\right)+P_{price}-P_{\text{cost}}-E-F^{ann,v}\end{aligned}$$

The costs of operating the PT system is given by C_{b}, which includes both the fixed and variable operating costs (so it depends on q_{b}^{p} and q_{b}^{o}). It is assumed to be a linear function of frequency. Environmental external costs from the driving of all cars are given by E (so it depends on q_{c}^{p}, q_{c}^{o} and q_{lc}. The government gets revenue from tolls (peak, off-peak and rural), and fares (peak and off peak), and purchase, fossil fuel and electricity taxes. All of these revenue sources are denoted by τ in the equation above. The component P_{price} represents the revenue to the parking company (a transfer), and the component P_{cost} consists of the opportunity cost of occupied parking space. The term $F^{ann,v}$ is the annuity of the costs required to expand local grid capacity. If the car chosen for at least one of the agents is BEV, and the agents in question have $kWh^{p^{*}}>0$, this term will be greater than zero. If not, the term will be zero, and local grid capacity expansion will be unnecessary. We also assumed that marginal electricity production costs are constant in the peak and in the off-peak so setting electricity prices equal to production costs does not leave any profit or loss in the electricity production sector.

For simplicity, we assume lump-sum taxes to finance any public sector deficits. Hence, we ignore labor market distortions, and have a marginal cost of public funds (MCF) equal to 1.

For each combination of v and k, tolls and fares are optimized. Optimal tolls for cars are set equal to the marginal external congestion costs plus the marginal external non-congestion-costs of road use. The optimal fares for PT equal the marginal external crowding cost (which depends on frequency). This is shown in Wangsness et al. (2018). The resulting combinations of policies and vehicle types per agent will give us a range of welfare levels W^v, where the social planner chooses the combination that leads to the highest welfare level.

In this theoretical model we have depicted the optimal solution where the BEV owner faces the marginal investment cost that his charging pattern (which he commits to or is forced not to exceed) imposes on local grid. The fixed component of the investment costs is assumed to be financed through lump-sum taxation or a fixed component on the bill from the local grid company. This can be considered a first-best solution in this dimension. It could be interpreted as a "capacity subscription tariff" to all BEV owners that do not commit to only charge off-peak. This tariff will then optimize incentives not just for purchasing a BEV or not, but also the choice of charging pattern conditional on owning a BEV. The capacities chosen by the BEV owner then give the correct investment signal to the local grid company.

BEV owners are not facing any capacity tariff in the current situation in Norway, but pay regular uniform grid tariffs, as described in section 2. In our model, this corresponds to a situation where $p^p = p^o$, leading to the corner solution where the EV-owner always charges during peak hours, $kWh^p = \Omega$. In the following section, we explore numerically the importance of pricing charging capacity.

4 Numerical modeling

Our numerical model is constructed to capture the most important aspects of vehicle ownership and transport choices for the population of the greater Oslo area. This population is based on the Norwegian travel survey (documented in Hjorthol, Engebretsen, & Uteng, 2014). Of the approximately 60 000 respondents in this survey, about 10 400 (18 years or older) lived in the greater Oslo area, representing about 0.95 million adult inhabitants. Applying frequency weights constructed by travel survey experts at The Institute of Transport Economics, travel survey respondents are extrapolated to a synthetic adult population of the greater Oslo area.

Based on this synthetic population, we construct and calibrate a numerical model in MATLAB using the steps described in in Table 1.

Table 1: Model calibration, step by step

Step	Description
1	Aggregate the National Travel Survey data for the counties Oslo and Akershus (that approximate "the greater Oslo area") into 3 aggregate agents. The selection criteria for the agent groups were whether they were employed or not, and whether they occasionally went on long car trips or not. The groups we get capture important differences in the population in terms of: Baseline travel pattern (PT and car). Employment and incomes (which determine value of time). Car ownership, access to parking at home, etc.
2	Compute generalized transport costs of each agent for each mode and for each car type, for short and long trips.
3	Select own-price and cross-price elasticities for each type of agent for the "travel products" person-km per day by car and by PT, for both peak and off-peak, and long car trips per year (more information in Appendix A).
4	Calibrate each agent's utility function using the data from steps 1, 2 and 3.
5	Check the calibration of the utility functions by simulating the choice of each agent (person-km per day by car and by PT, for both peak and off-peak, and long car trips per year) and cross-check them with observed choices. This step completes the calibration of the agents' utility functions.
6	Construct the speed-flow function for peak car trips based on a linear approximation of peak and off-peak speeds in the greater Oslo area.
7	Construct the cost functions for public transport using a linear function with intercept (fixed costs), and an automatic frequency "rule-of-thumb" optimization rule for peak and off-peak. A similar approach was used by Parry and Small (2009) and Kilani, Proost, and van der Loo (2014).
8	Construct the crowding cost function of public transport (see the Appendix A for more information).
9	Construct linear cost functions for the non-congestion external costs; air pollution, noise & accidents. Values are given in Table 6 in Appendix A based on Thune-Larsen et al. (2014).
10	Construct a welfare function to represent equation (4), that consists of the sum of utility for each agent minus user costs for agents (including taxes, tolls, fares and parking charges) minus transfers to government and parking company minus external costs other than congestion minus the operational costs of PT minus the opportunity cost of parking spaces.

The three aggregate agents go by the names of X, Y and Z. They are categorized by whether they are employed or not (agent Z is not employed), and among the employed whether they go on occasional long trips by car (agent Y does not go on long trips by car). Using this categorization on the synthetic population of the greater Oslo area, we get agents with characteristics displayed in Table 2.

Table 2: Key agent characteristics

Characteristic	**Agent X**	**Agent Y**	**Agent Z**
Estimated number of people	267 955	468 187	210 187
Working/ Not working	Working	Working	Not working
Annual gross income (NOK)	591 183	500 972	320 821
Any long trips by car per month	Yes	No	Yes
Number of short car trips per day	1.9	1.38	1.0
Number of short car trip km per day	20.9	15.6	9.8
Average length of long car trip	191	N/A	175
Number of long car trips per year	19.5	N/A	11.8
Number of PT trips per day	0.4	0.7	0.4
PT km per day	7.6	10.8	6.9
Peak trips car per day	0.9	0.7	0.3
Peak km car per day	10.5	7.7	2.8
Off Peak trips car per day	1.0	0.7	0.7
Off Peak km car per day	10.4	7.8	7.0
Peak PT trips per day	0.29	0.43	0.14
Peak PT km per day	4.5	6.9	2.3
Off Peak PT trips per day	0.15	0.32	0.26
Off Peak PT km per day	3.1	4.0	4.6

Once all the agents' utility functions have been calibrated to fit the observed data, the model is ready for policy analysis. This is done according to the following procedure:

1. The model's objective function is to maximize welfare subject to behavioral and other constraints. For a given scenario we specify which of the policy variables, tolls, fares and/or parking charges, that can vary freely to maximize the objective function. In the equilibrium in optimum, the policy variables have driven agents to choose the transport consumption that maximizes the sum of their utility from transport and other consumption, minus the costs of car ownership and the transport system, including crowding and congestion costs, se eq. (4). The combination of agents and which car type they own is fixed so that we can find the optimal transport market equilibrium for a given combination (in Wangsness et al. (2018) this is done for 20 fixed combinations)
2. Of the combinations that yield the highest welfare, new simulations are done to ensure that the optimal transport equilibria are incentive compatible, i.e. that the agents would choose the car combination that under optimal policies yields the equilibrium with highest welfare. In these simulations, agents will choose the car combination that gives them the highest level of utility. The simulations will find the minimum differences in purchase taxes and VAT between the car types, so that agents choose the optimal car combination.
3. We get the incentive-compatible optimal car ownership and transport market equilibrium

Compared to Wangsness et al. (2018), the model is extended to include agents' choices regarding home charging, in the case where they end up owning a BEV or a PHEV (hereafter EV). The demand for electricity from EV-owners is determined by their travel demand. In equilibrium agents adapt so that private marginal transport benefit equals private marginal transport cost. Among these costs we have the electricity expenses (electricity costs, grid tariffs and taxes).

In the model, the demand for capacity (kW) for charging during peak hours, transforms into a need for the local DSO to replace the old transformer with a new one with higher capacity. The added cost stemming from this increase in demand depends on how much more additional capacity is needed, and how prematurely the old transformer is to be replaced. If it is to be replaced anyway since it has reached the end of its technical life, the latter cost component would be zero. The cost of replacing the transformer prematurely is assumed to be equal to the foregone interest income for the years that are left of the transformer's technical life.

As mentioned in section 2.1, the consequences of more EVs will vary from neighborhood to neighborhood. In our stylized model we only have one representative neighborhood that we expect to represent the average case where more EV charging during peak hours leads to more investments from the DSO. The parameters for the average case can be considered fairly uncertain. We are forced to make at least two key assumptions about uncertain parameters in the numerical model.

1. How large is the disutility parameter for an EV-owning agent to charge her car off-peak, i.e. how responsive will she be to peak tariffs?
2. Given the need for new grid capacity, how many years has the investment been moved ahead, i.e., how much of the fixed investment cost can be attributed to the rise in peak power demand from EV charging?

In order to illustrate the uncertainty and give an idea of the variation in how costly the grid enhancements for accommodating EV home charging can be, we will provide sensitivity analysis for how the results change with changes in these key parameters. The table below shows our baseline assumptions for the model extensions regarding EV-charging:

Parameter	Value	Comment/Source
Cost of new transformer, fixed component (NOK)	190 000	Sidelnikova et al. (2015)
Cost of new transformer, per kW capacity (NOK)	79	Sidelnikova et al. (2015)
Return on capital applied for regulation (%)	6	NVE (2018)
Expected years of technical lifetime for transformer station	30	Sneve, Stene, and Brekke (2005)
No. of years premature the average transformer needs to be replaced due to home charging	0.5	Discussion meetings with DSOs[8]
Marginal disutility parameter α of charging off-peak (NOK per hour), from αh^o (i.e. quadratic disutility function)	0.15	Calibrated from a cross-price elasticity of 0.2, which is applied in the LIBEMOD model[9]
Charging capacity at home (kW)	3.6	Standard for home charging wall box, see e.g., Figenbaum (2018)

Table 3: Parameter values for baseline assumptions regarding EV-charging and grid costs

[8] We have had discussion meetings with representatives from the DSOs Ringeriks Kraft AS and Hafslund Nett. They state that unless households install more in-house capacity, they have not experienced having to replace transformers before schedule even with neighborhoods with high EV-shares. The choice of applying 6 months as our base case is a bit arbitrary, but illustrates the low occurrence of early replacement. We decide to dramatically stress test this number to see what happens if replacements happen 10 years ahead of schedule on average.
[9] The cross-price-elasticity parameters are a result of the model calibration. For more information, see https://www.frisch.uio.no/ressurser/LIBEMOD/

The investment cost is transformed to an annuity over the new transformer's life time. This annuity is what the DSO needs to recover through its tariffs. We will model different pricing schemes for the DSO. As shown in the solutions for eq. (2), the consumer adapts so that marginal disutility of charging off-peak equals the difference in electricity price (including taxes and tariffs). With uniform prices between peak and off-peak, the consumer will cover all charging needs during peak hours. If the DSO applies peak tariffs, the consumers will shift some of her charging to off-peak. We end up with an equilibrium with tariffs and quantities charged at peak and off-peak, and transport costs and amounts travelled.

5 Scenario description

We use the model for analyzing different scenarios with different policies. The policies can be either fixed or be determined endogenously as a way to achieve a policy objective at least cost. The starting point for the scenarios is the reference situation of 2014. This can be considered an equilibrium before EVs were made available on a large scale. In the travel survey, on which the model agents are based, 98% of the cars are conventional. The policies will take us from the reference equilibrium to a new equilibrium in each policy scenario.

The main policy scenarios are the "Business-As-Usual"-scenario and the "CO_2-cap"-scenario. The former scenario is where there is a continuation of the 2014-policies (which were already very friendly towards the purchase and use of EVs), while the latter is where the 50% CO_2 target in the Oslo area is binding. These scenarios were analyzed in Wangsness et al. (2018) without any regard for the impact EV charging may have on the local grid. We will briefly repeat the key insights from those scenarios. In the BAU-scenario Agent X (who works and makes occasional long trips) adapted by switching to a PHEV, Agent Y (who works, but makes no long trips) to a short range EV, while Agent Z (who does not work, and makes occasional long trips) stuck with the small ICEV. In sum, this gave us large emissions reductions (64% reduction), but higher transport volumes (2.1% for a constant population). Compared to the reference situation there is a welfare loss due to higher resource costs for cars and more congestion. In the CO_2-cap-scenario policies are determined so that the target is reached at least cost leading to Agent X switching to a PHEV, Agent Y sticking to a small ICEV, and Agent Z switching to a small EV. The policies are characterized by; 1) higher tolls for all cars, in particular during peak traffic, 2) higher peak fares and lower off-peak fares for PT, 3) higher purchase taxes for ICEVs and 4) no tolls for BEVs driving in rural areas. These policies achieve the CO_2-target, but the equilibrium has a lower welfare level than the reference equilibrium. The welfare cost of reaching the CO_2-target amounts to 6690 NOK per tCO_2.

We revisit these scenarios, but now the impact of EV charging on the local grid is part of the modelling. We run the model for two different pricing schemes the Distribution System Operator (DSO) can apply to respond to increased demand for power for EV charging.

- No ability for DSOs to peak price, i.e. the DSO continues with uniform tariffs
- DSOs apply peak tariffs determined by the *marginal* increase in capacity stemming from charging EVs during peak hours, and covers the rest of the costs by a fixed component

6 Results

We now present the results from the numerical modeling in a way that answers the previously stated research questions. We will also briefly describe the results from the sensitivity analysis, which is documented in Appendix B.

When we factor in the current uniform grid tariff system, what are the welfare impacts of today's EV policies and polices for reaching CO_2-targets at least cost?

This research question focuses on the pecuniary external cost of EV charging with BAU EV policies when there is an incomplete market for using grid capacity, in this case uniform tariffs between peak and off-peak hours. As was shown in Wangsness et al. (2018), the model simulations conclude that Agent X (working, long trips) switches to PHEV and Agent Y (working, no long trips) to small EV in the BAU-scenario without any concern of grid costs. These agents would then start home-charging their vehicles to cover their daily transport needs by car. Their choice of when to charge is reflected by the relative prices between charging during power peak and off-peak hours, and their disutility of charging during off-peak hours. We test the impact of adding this charging behavior under the three different pricing schemes the DSO can respond with, described in the section above.

We find that the main features of the BAU-equilibrium remain the same even though the charging issues have been added. Nevertheless, the added grid costs are tangible costs, and not including them overestimates the welfare in the equilibrium. Without any form of peak pricing, there will be no incentive for the model agents to shift any of their charging to off-peak hours. This spurs investment in transformer capacity that amounts to a welfare cost of 18 mill. NOK (approx. € 2 mill.) per year in the new BAU-equilibrium, compared to an equilibrium where these are not taken into account (as in Wangsness et al., 2018). All agents see a reduction in their general disposable income as tariffs increase. Those who drive EVs and PHEVs get somewhat higher transport costs, and all agents get higher household expenses on their non-car consumption of electricity. The model finds an increase in ca. 18 NOK per agent per year in increased household expenses in non-car electricity due to the increase in uniform tariffs. This is the cost we expect todays EV policies to impose on electricity user is the Oslo area.

We show in Wangsness et al. (2018) that reaching a 50% CO_2 reduction target at least cost implies that Agent X switches to a PHEV and Agent Z switches to a small EV. Before considering any charging issues, we find a welfare cost of 6690 NOK (approx. € 700 or USD 850) per tCO_2 for reaching this CO_2-target.

Adding the issues of charging in the CO_2-target scenario does not change which car combination that is optimal under policies for reaching the target at least cost. Like in the BAU-scenario, the changes in tariffs amount to so small changes in generalized costs that changes in travel patterns hardly change at all. Consequently, the policy variables in the CO_2-target scenario are hardly affected by introducing charging issues.

With uniform tariffs the welfare cost increases by 16 mill NOK per year (approx. € 1.75 mill.), translating into an increase of 27 NOK per tCO_2 (i.e., from 6690 to 6717) in order to reach the ambitious targets. The main results are summarized in the figure below.

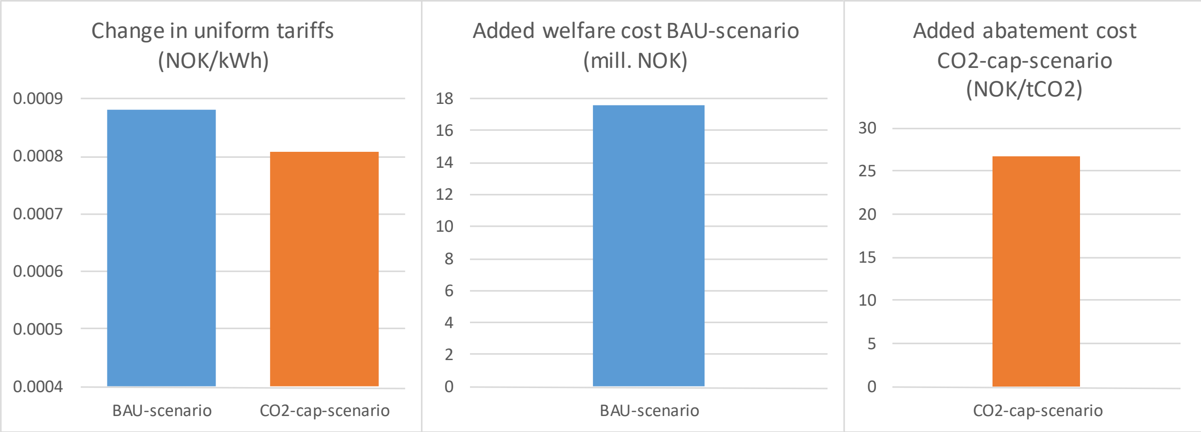

Figure 3: Main results from simulations with uniform tariffs

How can these welfare costs be affected by a better pricing of electricity distribution?

The welfare cost can be reduced by allowing the DSO to apply peak tariffs. This will cause some shifting of EV charging to off-peak hours. While this reduces investment costs, it also increases the disutility cost of postponing some charging to off-peak hours. Consider the scheme where the added peak tariff is only determined by the *marginal* increase in capacity stemming from charging EVs during peak hours, and covering the rest of the costs by a fixed component. In this case the added welfare cost amounts to 12 mill. NOK pear year in the new equilibrium (approx. € 1.3 mill.), which reduced the increase by a third compared to the uniform pricing scheme. Here agents pay ca. 12 NOK more per year in non-car electricity expenses, with a fixed component of about 9 NOK and a 3 NOK increase in expenses due to higher peak tariffs.

We also see welfare improvements from applying a better pricing scheme in the CO_2-target scenario. When applying peak tariffs only to the marginal capacity expansion induced by EVs and covering the rest with a fixed component, the added welfare cost is 17 NOK per tCO_2. This increase is about 37% smaller than under uniform pricing. The main results are summarized in the figure below.

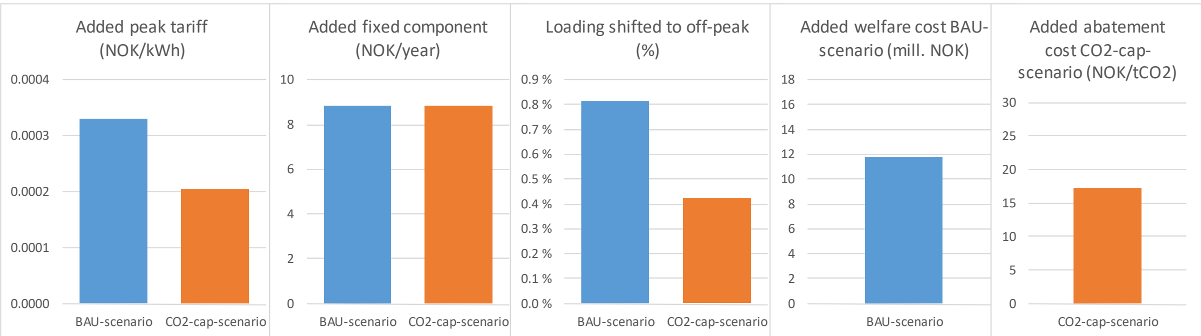

Figure 4: Main results from simulations with optimal peak tariff

Under both pricing regimes, the agents' car choices are unaffected, and the changes in tariffs never cause more than minor changes (less than 0.1%) in generalized transport costs and subsequently in transport use.

Sensitivity analysis

These added welfare costs do not seem so large for an area with a population of 1.2 mill. people. In discussion meetings with DSOs we were told that regular home charging has not spurred many new investments that would not have occurred otherwise, corroborating this story. With regards to home charging, they have not experienced having to move forward investments in higher capacity that is not co-founded by households wanting to increase their own capacity. Our base assumption is that DSOs need to replace the transformer on average 6 months ahead of its expected life span of 30 years (a shortening of less than 2%). We conduct sensitivity analysis where we assume the replacement of transformers on average has to be done 10 years ahead of its expected life span and additional 100 000 NOK (approx. € 11 000) needs to be spent on digging and replacing cables between the transformer and the household. This assumption entails far larger investment costs due to EV charging, and subsequent changes in tariffs and welfare. With the 10-year assumption, the additional welfare cost to the BAU-equilibrium is 304 mill. NOK per year (approx. € 34 mill.) under uniform pricing, compared to an equilibrium where grid costs are not taken into account (as in Wangsness et al., 2018). Further, the added cost is limited to only 193 mill. NOK (approx. € 22 mill.) with peak tariffs for the marginal capacity increase and the rest of the cost covered by a fixed component.

The disutility function is a highly uncertain part of the model, so we test the impact of doubling the marginal disutility parameter. This will only make a difference where peak tariffs are allowed. Higher marginal disutility from off-peak charging leads to less load shifting under the two relevant pricing schemes, thus driving up investment costs in transformer capacity. On the other hand, due to the assumption of a quadratic disutility function from charging in off-peak hours, the low levels of load shifting imply lower absolute disutility costs for EV and PHEV owners. The differences in investment costs and disutility costs seem to balance out, so there is hardly any difference in added welfare costs (less than 1 mill NOK per year) compared to the equilibrium under baseline assumptions.

We also tested the implications of having to replace transformers longer before their life span runs out and of higher marginal disutility of off-peak charging. This is documented in appendix B. In the case where transformers on average need to be replaced 10 years ahead of their technical life and additional costs for cables incur, the added welfare cost of achieving the CO2-target increases manifold. In the case with higher marginal disutility of charging off-peak we get less load shifting, which leads to higher investment costs, but it also lower absolute disutility costs, and these costs roughly balance each other out in the simulations.

7 Discussion and conclusion

We find that as today's EV-policies drive up the EV-share of the car fleet, they also drive up investment costs in the local distribution grid as old transformers need to be replaced prematurely with transformers with higher capacity. Our model finds an equilibrium where the increased cost of transformers leads to between 12 and 18 NOK (approx. € 1.3 - € 2) in added non-car electricity costs per agent, depending on the DSO's pricing scheme.

Are these numbers large or small? We argue that such an increase in expenses is small, and would probably go unnoticed by most households as it represents less than a 0.1% increase in annual electricity costs (including tariffs and taxes) for households with normal consumption between 10 000 and 20 000 kWh per year.

Our sensitivity analysis shows that the cost can get substantially higher if the old transformers have to be replaced sooner than in the baseline. If the transformers need to be replaced 10 years ahead of their technical life and additional costs for cables incur, non-car electricity costs per agent increases to between 205 and 310 NOK per year. While this may be a more noticeable expense for consumers, it is still a small number relative to overall electricity expenses, and well within fluctuations in such expenses due to normal year-to-year price fluctuations.

The shift to EVs and PHEVs is an integral part of reaching the ambitious goals of reducing CO_2-emissions by 50% in the greater Oslo area at least cost. We find that adding the charging issues leads to 17-27 NOK in additional costs per tCO_2e under baseline assumptions. Before adding grid costs the welfare cost of reaching the emissions target amounted to 6690 NOK (about 700 Euro) per tCO_2 (Wangsness et al., 2018), so adding the grid costs means 0.3%-0.4% in extra cost per tCO_2. If the policy makers have committed to the CO_2-target and are willing to pay the cost of reaching it, adding the grid costs is not going to be very discouraging.

Caveats

There are several caveats that are worth mentioning. As discussed in Wangsness et al. (2018) the transport model we use is very stylized with some major simplifications, such as having only five stylized car types and three stylized agent groups. It gives more nuance and insight than single representative cars and agents, but there are still many issues of heterogeneity that go uncaptured. For example, if more heterogeneity is introduced in the users' profiles, the penetration of electric vehicles could be affected more strongly. The added model features in this paper are also quite stylized, with identical neighborhoods with identical investment cost functions for transformers, and with the simplifying assumption of clean-cut differences between peak and off-peak periods.

The model contains many parameters of which many can be considered fairly uncertain, which is also discussed in Wangsness et al. (2018). The model extensions also introduce new uncertain parameters, such as the investment cost function for transformers, the average number of years of premature replacement of transformers when EVs get a large share of the car fleet. The model is static, so it ignores the dynamics of DSOs over years continuously replacing old infrastructure according to schedule, along with the year-by-year growth in the number of EVs. While the model is consistent with experiences over the last few years and expectations for the next few years, the future developments contain a lot of uncertainty. We do sensitivity analysis to address some of this uncertainty.

Given these caveats we advise that the exact numbers should be interpreted with some caution. However, we believe that this analysis helps understanding the mechanisms within and between the transport and electricity market as transport gets electrified. We also think it provides insights into what can be considered major issues and minor issues when designing optimal transport policy moving forward.

Putting the findings in context

This paper gives some new insights into some of the ways the transport market and electricity market may affect each other when a large part of the car fleet is electrified. We find that the increase in demand for electricity and power from EV owners lead to some increase in grid investment costs and tariffs, but not so much that it brings any significant change to the transport market equilibrium. For example, the conclusion that larger differentiation between peak and off-peak tolls and fares are necessary to improve transport market efficiency, remains the same. This was also part of the conclusion from Börjesson, Fung, and Proost (2017) which the model in Wangsness et al. (2018) is an extension of.

Furthermore, the paper finds that allowing for peak pricing in the electricity sector can improve efficiency, a common finding in the extensive literature on peak-load pricing (see e.g. Decker, 2014, pp. 83-85 for an overview). As the transport sector gets increasingly electrified, and EV owners have a preference for charging after coming home from work, i.e., during evening peak hours, peak tariffs can help efficient allocation of grid investments. With user-friendly solutions for smart-charging that automatically adjust charging to minimize charging, the differences in peak and off-peak tariffs would not need to be very large in order to get load shifting from EV charging. In our model, this could be interpreted as a drastic reduction in the disutility of charging off-peak.

Conclusion

We find that imposed cost on the grid from EV home charging amounts to relatively small extra costs on other electricity users, and relatively small additions to the cost necessary to reach ambitious CO_2 targets in the greater Oslo area. Optimized policies for both the transport market and the local grid in order to reach the CO_2-target at least cost, still entails a large shift to BEVs and PHEVs. Even though we find that the added grid costs are relatively small, we also find that they can be reduced by applying peak tariffs instead of uniform tariffs. This is because it provides a better balance between investment costs and the EV owners' disutility of charging during off-peak hours. Agents optimally adjust by shifting the time of charging their car, and the amount of transport consumed is hardly affected at all.

As the literature shows, there are good reasons to consider peak tariffs even in the absence of EV-charging, but EV-charging provides additional reasons. With the possibility of smart charging, load shifting could be done quite effortlessly for EV owners, even with only minor differences in peak and off-peak tariffs.

The overall picture is that the costs of adjusting local grid capacity to meet the demand for charging EVs at home are relatively small. However, it should be possible to empirically test this with cost data from local grid companies and EV ownership data. This is an interesting venue for further research.

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Appendix A: Model details

The cost parameters applied for replacing transformers are taken from the NVE report Sidelnikova et al. (2015). The table below reports the parameter values from that report:

Rated supply voltage (kV)	Cost for new transformer, capacity independent component (NOK)	Cost for new transformer, capacity dependent component (NOK/kW)
5-24	190 000	79
66	1 125 000	91
132	2 125 000	80
300	6 250 000	90
420	8 750 000	58

Table 4: Cost parameters for new transformer. Taken from Table 9-4 in Sidelnikova et al. (2015)

For calibration we need quantities for each agent, generalized prices, and elasticities. The quantities used are kilometers travelled on short trips per day, in peak and off-peak, by car and public transportation (PT), and long trips (100 km+) by car per year. For short trips agents can substitute between PT and car, and peak and off-peak. For long trips, the agents can only choose the number of long trips per year.

A way to visualize this stylized world is a greater Oslo where agents travel by car and PT every day, and a couple of times a month/year, some of them take a longer drive to their cabin, relatives etc.

Generalized prices are described in Section 4.3. The own-price elasticities for short car trips are taken from the newest version of the regional transport model RTM23 (documented in Rekdal and Larsen (2008)). Own-price elasticities for PT and the cross-price elasticities between car transport and PT are taken from the transport model for the greater Oslo area MPMM23 (documented in Flügel and Jordbakke (2017)). The cross-price elasticities for shifting between peak and off-peak, and cross-price elasticities for shifting between both modes and travel time, are the same as those applied in Börjesson, Fung, and Proost (2017). We apply the aggregate elasticity from the National Transport Model (documented in Rekdal et al. (2014)) for long car trips. The elasticity values are given in Table 5Table 5.

Table 5: Elasticity values

Elasticity Parameter	**Value**
Own money price elasticity, peak car trips	-0.152
Own money price elasticity, off-peak car trips	-0.152
Own money price elasticity, peak PT trips	-0.255
Own money price elasticity, off-peak PT trips	-0.284
Cross money price elasticity between peak and off-peak car trips	0.100
Cross money price elasticity between peak car trips and peak PT trips	0.100
Cross money price elasticity between off-peak car trips and off-peak PT trips	0.086
Cross money price elasticity between off-peak car trips and peak PT trips	0.096
Cross money price elasticity between off-peak car trips and off-peak PT trips	0.050
Cross money price elasticity between peak and off-peak PT trips	0.050
Own money price elasticity, long car trips	-0.172

Table 6: Car specific parameters for technology, user costs, and externalities, baseline

	ICEV small	ICEV large	PHEV	EV short	EV long
Purchase price	273 058	503 614	456 036	263 049	720 468
VPT cost	59 977	158 219	44 143		
VAT cost	42 616	69 079	82 379		
Producer price	170 464	276 316	329 514		
Annual tax	2 820	2 820	2 820	455	455
Range (km on full battery)			47.8	190	528
Fuel usage (liters per 100 km)	7.99	9.50	6.15		
Share of city trips in e-mode[10]	0	0	72.7%	100%	100%
kWh-usage per km, summer				0.15	0.17
kWh-usage per km, winter				0.20	0.22
kWh-usage per km, average			0.28	0.17	0.20
Non-fuel costs per km (including taxes, not tolls)	2.05	2.05	2.05	1.98	1.98
Non-congestion external cost per km in city (NOK)	0.70	0.70	0.36	0.36	0.36
Non-congestion external cost per km far from densely populated areas (NOK)	0.16	0.16	0.16	0.15	0.15

With all these values, MATLAB solves a system of 16 equations with 16 unknowns to complete the calibration of the utility function for each agent. This means we obtain the various parameter values of α , β and i (cf. Eq. 2) for the various agents.

The generalized prices for short car trips are the distance-based costs (fuel, repair, lubricants etc.), toll and time costs. Distance-based costs are the same as those applied in the National Public Road Administration's (NPRA) tool for Cost-Benefit Analysis, documented in Cowi (2014). Toll costs are based on reporting from the toll companies to NPRA. The value of time is based on the Norwegian valuation study, documented in Samstad et al. (2010). For long car trips, the generalized prices are distance and time costs for the average long car trip, for a given agent. For BEVs there is an added cost to the trip related to charging the car to fill the gap between the range and the length of the average trip times two (assuming back and forth). The time cost of charging is assumed to be VOT for long leisure trips, weighted by the same disutility weights as applied for waiting time for PT on long trips (0.6).

The generalized prices for PT is given by ticket costs and time costs (on board time, access time and waiting time). Samstad et al. (2010) also provide the basis for VOT for PT trips, waiting time and access time. In the presence of a large share of PT users having either 30-day tickets or 12-month tickets, and different price zones, we apply the method for calculating average ridership payment used in Dovre Group and Institute of Transport Economics (2016).

Additional costs: If agents were to buy EVs, a fixed cost is also added for charging equipment, and for renting parking close to home for the share of agents who do not have easy access to parking at or close to their home. Charging cost equipment is assumed to have an up-front cost 10 000 NOK (Norwegian Environment Agency, 2016). Parking rental is assumed to cost 1 400 NOK per month (median rent for parking space in Oslo in October 2017 on website finn.no).

[10] For PHEVs we assume that they run on electricity 73% of the time on short trips in the city area, and on fossil fuel when going on long trips.

With regards to the rest of the transport system, we have cost functions for PT and speed-flow functions for car transport. The cost function for PT is simply the annual aggregated operating costs for Ruter, the public transport company for Oslo and Akershus, as a linear function of annual frequency. In addition, there is a crowding cost function, where the travel time cost is weighted by a crowding factor. The crowding factor has been calibrated to be a piecewise linear function where the current peak ridership per hour gives a crowding factor of 1.3, same as in Minken (2017), and current average off-peak ridership gives a crowding factor of 1. The crowding factor will not get smaller if ridership falls below this level, so 1 serves as a lower bound for the crowding factor.

The speed-flow functions are based on model simulations from RTM23 on aggregate car travel and travel speed in Oslo and Akershus for a range of scenarios, but with constant road capacity. The result is an aggregate linear speed-flow function. The linearity simplifies the model calculation, but as shown in Arnott, De Palma, and Lindsey (1993), it also serves as a good approximation for a traffic bottleneck model.

Appendix B: Sensitivity analysis

Sensitivty analysis	Pricing scheme	Change peak	Change off-peak	Change fixed component (NOK)	EV-charging during peak	Added abatement cost (NOK/tCO_2)
Double disutility parameter	Uniform tariffs	0.0008	0.0008	0	100 %	27
	Marginal peak tariff and fixed component	0.0002	0.0000	9	99.8 %	17
Replace 10 years prematurely	Uniform tariffs	0.0154	0.0154	0	100 %	512
	Marginal peak tariff and fixed component	0.0002	0.0000	200	99.6 %	320
Double disutility parameter and Replace 10 years prematurely	Uniform tariffs	0.0154	0.0154	0	100 %	512
	Marginal peak tariff and fixed component	0.0002	0.0000	200	99.8 %	320

Table 7: Main results from sensitivity analysis