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Consequences of Uncertainty from Intraday Operations to a Capacity Expansion Model of the European Power System

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***Abstract*—The European Energy Transition envisions a high deployment of variable renewable energy sources (VRES) by 2050. Some estimates expect that 60-to-70% of power generation will be entirely covered by VRES technologies (i.e., solar and wind). This creates challenges for balancing VRES with conventional, flexible generation (e.g., gas and storage). Consequently, VRES are transforming how electricity markets will operate and how balancing needs between day-ahead (DA) and intraday (ID) electricity markets are coordinated. The importance of the ID market increases due to the uncertain short-term nature of VRES. However, there is limited research on how forecasting errors in between market stages affect investment decisions in capacity expansion problems. In this paper, we investigate how an increased amount of uncertainty from forecasting errors between a DA and an ID market affects investment decisions in the power system. We have developed a multi-horizon stochastic capacity expansion model containing both DA and ID markets under uncertainty. The model emulates the European power system developments under given emission targets of EU policies towards 2050. In the comparison of the standard single market approach to the market sequencing, the results indicate: 1.) Forecasting errors significantly impact investment decisions, resulting in 10% lower VRES investments and 40% higher flexible capacity investments, 2.) Cross-border transmission is a crucial contributor to flexibility and volume increases by 10-20% when accounting for forecasting errors, 3.) investment needs for storage capacity decrease significantly compared to an over-valuation in the standard method of capacity expansion models.**

***Index Terms*—power generation planning, energy system model, capacity expansion, forecasting uncertainty**

I. Introduction

As the share of variable renewable energy sources (VRES) in an energy mix grows, the uncertainty with electricity production increases [1]. Weather conditions are susceptible to forecasting errors, and thus, the forecasts for the production of wind and solar might differ from actual production conditions.

The day-ahead (DA) market matches supply and demand based on the best available information one day before delivery. The intraday (ID) market can handle deviations from the forecasts by facilitating trade of positions until one hour before real-time. Multiple factors can contribute to the volume traded in the ID market, such as weather forecasting errors, demand change and generator outages. Any deviations remaining at the scheduled delivery time are typically handled by a transmission system operator (TSO) in the balancing or capacity market.

In the last five years, the installed capacity of solar and onshore and offshore wind has increased by 41%, resulting in significantly increased uncertainty and more volume traded in the ID markets [2]. With this in mind, the volume in the ID market likely continues to increase with the expected expansion of VRES.

In line with the development of the energy mix in recent years and the projected increase in VRES capacity, the scope of this paper is to address the following research questions:

1) How do forecasting errors from VRES production affect investment decisions in the power system?
2) How are power system operations affected by including forecasting errors from market sequencing?

II. Literature review

To balance supply and demand with high shares of VRES, flexible electricity producers or consumers are required [3]. Several papers highlight the importance of flexibility in a power system with large shares of VRES and the role that storage, transmission, flexible electricity producers such as hydropower and gas, and demand-side flexibility will have on the reliability and security of supply of such a power system [4]–[6]. While the need for additional flexibility is well explained, the technology used to meet the flexibility demand is still largely discussed.

An NREL study [7] and De Jonghe et al. [8] indicated that energy storage would be a key component to provide flexibility in a power system with large shares of VRES. Denholm and Hand [9] also highlight the need for energy storage in the future and estimate storage capacity to be one day in demand to avoid high curtailment. Child et al. [10] analysed the flexibility requirements and advantages for a high penetration on VRES. Their results indicated that, while energy storage and flexible generators would be key contributors to flexibility, transmission provided the most value-for-money flexibility.

Developing mathematical optimisation models is a common approach to analysing investments and operational decisions in a power system. Power system optimisation models are typically divided into capacity expansion and operational models. Capacity expansion models typically focus on investments and energy mix, while operational models focus on market aspects.

Large multi-market modelling usually uses linear operational models. Zipf and Möst [11] analysed the direct and indirect costs of variable VRES in the German power system by utilising a two-stage operational optimisation model with DA and ID scheduling. Their results indicated that an increased amount of variable VRES in a power system leads to both increased direct and indirect costs due to the forecasting errors related to VRES. On the contrary, different studies on multi-stage operational optimisation models without an investment stage show that an increased share of variable VRES leads to a lower total cost than the current energy mix [12], [13].

Kulakov and Ziel [14] investigated how forecasting errors caused by VRES influenced electricity prices in the market stages. They found a non-linear correlation between ID and DA prices. Abrel and Kuntz [15] explored the impact of uncertainty from VRES on unit commitment power dispatch. They found that increased uncertainty triggers more unit commitment from inflexible energy sources. With the increased uncertainty, a more diverse energy portfolio was emphasised to balance the VRES forecasting errors between the market stages. Barth et al. [16] also investigated the impact of wind uncertainty on a power system by creating a five-stage stochastic market model. The objective was to establish the reserves' role in such a power system and the cost associated with the reserves. The results indicated that the importance of reserves increased in such a system, and regulated hydropower was the main contributor to the reserve market. Morales et al. [17] developed a model analysing the issues with conventional market design due to VRES's stochastic nature. They identified a lack of a cost-recovery guarantee for flexible producers. They proposed a solution where the DA market is cleared while factoring in the anticipated balancing cost resulting from forecasting errors. Borggrefe and Neuhoff [18] highlighted the need for a market design that facilitates potentially improved conditions in the ID market compared to the DA market.

In addition to multi-market modelling, capacity expansion models are also of great interest to issues addressed in this paper. Seljom and Tomasgaard [19] developed a model to analyse investment decisions in the Danish power system. A deterministic and a stochastic approach were utilised, with significant differences in the results. The stochastic approach was more realistic and resulted in significantly lower investments in VRES. This is supported by Nagl et al. [20] and Backe et al. [21], who concluded that VRES are typically significantly overvalued and flexible providers undervalued.

Ehremann and Smeers [22] developed a capacity expansion model addressing the issues with investment risks in a power system. They approached the issue by including stochastic properties in the discount rate to incorporate the risk of investing in VRES compared to dispatchable energy sources. The results indicated that by adding financial risk, the system costs increased. Sun et al. [23] analysed the US power system with a capacity expansion model focusing on transmission flow between different regions.

They found that transmission might be an underestimated technology in capacity expansion models. In 2012, Giraldo et al. [24] investigated the impact of adding emission constraints to a capacity expansion model. Both an emission tax and an emission cap were included. They showed that adding such constraints increased the total costs somewhat but that the investments and, thus, the solution applied to a real-world scenario. Villavicencio [25] developed a capacity expansion model aiming to encapsulate some of the operational issues of VRES. It was concluded that proper modelling of the system- and operational requirements increase with a large penetration of VRES.

In addition to models focusing on capacity expansion and market modelling, there is some research on models combining capacity expansion and market sequencing. Pineda and Morales [26] developed a model with both an investment stage and market sequencing. Their results indicated that forecast errors caused a significant decrease in investment in VRES capacity in a power system when considering forecasting errors between market stages. However, Pineda and Morales [26] used a small model covering the Danish power system, documenting no change in transmission or energy storage.

Much research has been conducted on the capacity expansion model, but a better understanding of how short-term forecasting errors affect long-term investment decisions is insufficient. Therefore, we analyse the consequences of forecasting uncertainty between the DA and ID markets on investment decisions. We introduce market sequencing and extend an existing investment planning and DA operation model with short-term deviations from DA clearing based on historic ID trading activities. By comparing our model under appropriate cases, we can assess how short-term forecasting errors influence the investment decisions in long-term planning.

III. METHODOLOGY

In the following, we present a novel extension of a two-stage capacity expansion model to simulate forecast errors. The first stage represents investments, and we assume the second stage represents the DA market clearing. We then extend by a third ID marketstage, where the uncertainty of the DA forecast is revealed. This method is then compared with the two-stage stochastic program.

A. The EMPIRE model

The model in this paper is based on the open source model EMPIRE [27]. EMPIRE is a capacity expansion model with one investment stage and one operational stage. EMPIRE has been used in several different publications [28]–[31] and in European and national research projects [27]. The model represents the EU-27 plus Switzerland, Norway, the UK, Bosnia and Herzegovina, Serbia, and North Macedonia.

The investment stage in EMPIRE represents investments in technologies such as generators, cross-border transmission capacity, and energy storage. The operational stage represents different stochastic scenarios where investments are used to satisfy hourly demand without exceeding an emission cap, similar to the approach used in [15]. Export and import of electricity are possible between neighbouring countries and zones in the operational stage. We use a discrete formulation for the multi-stage stochastic programming model, where all scenarios are given with equal probability.

Electricity demand, technology costs, technology options, and operational characteristics are inputs to EMPIRE. The outputs includes technological investments and operational decisions within all stochastic scenarios. EMPIRE is a linear capacity expansion model spanning eight investment periods representing five years each. Each stochastic scenario within each investment period comprises four regular seasons with 168 representative hours for winter, spring, summer and autumn. Additionally, we add two peak seasons with 24 hours with extreme conditions. Each stochastic scenario and season contains perfect information of load, VRES and hydropower availability, Uncertainty in the third stage is represented by one scenario from historic realisations.

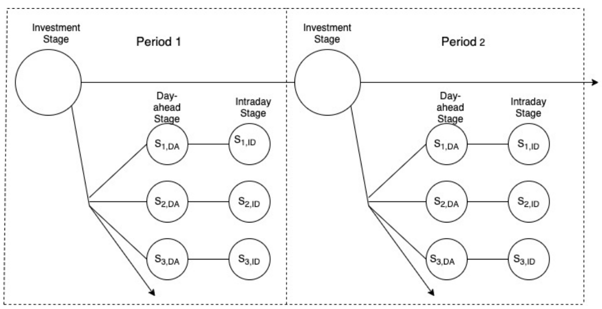

Fig. 1. Illustration of scenario-tree in the model.

B. Intraday Volume

We assume each second-stage scenario is based on forecasts one day before real-time. However, it is possible that the forecast is not precise and realisations deviate. This has to be accounted for in the third stage. So far, capacity expansion models assume perfect information and optimal dimension capacities that are non-optimal for actual realisations. The third-stage scenario represents a relative change in the ID market compared to the previously cleared DA market, where actual load and generation are revealed with perfect information. As only some generators can change their output on short notice and partake in the third stage, all generators are categorised into flexible and inflexible units.

C. Model formulation

In this subsection, we show the essential parts of the model. The whole formulation is in the Appendix A.

Our model follows characteristics of EMPIRE and contains capacity expansion costs for generation, transmission and storage. Additionally, scaled operating costs for the representative periods and costs for loss of load are added. Handling of the DA and ID market stages is done in the constraints, and only costs for the last stage of the ID markets are considered in the objective function. Since multiple years are investigated, investments and operations are discounted by an annuity factor.

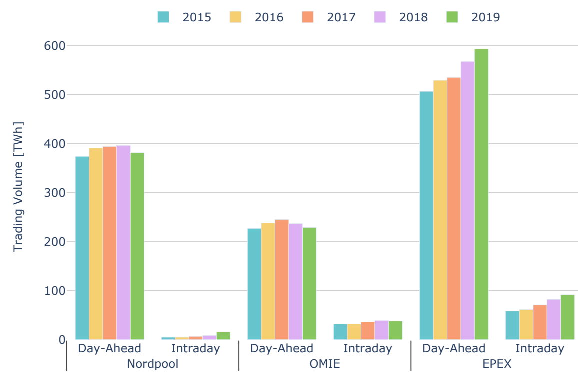

Fig. 2. Intraday and Day-Ahead volumes for selected European electricity markets, retrieved from [32]–[34].

$$
\begin{aligned}
\min z = & \sum_{i \in \mathcal{I}} (1+r)^{-5(i-1)} \times \\
& \Big[\sum_{n \in \mathcal{N}} \sum_{g \in \mathcal{G}_n} c^{\text{gen}}_{g,i} x^{\text{gen}}_{n,g,i} + \sum_{l \in \mathcal{L}} c^{\text{tran}}_{l,i} x^{\text{tran}}_{l,i} \\
& + \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{B}_n} \left(c^{\text{storPW}}_{b,i} x^{\text{storPW}}_{n,b,i} + c^{\text{storEN}}_{b,i} x^{\text{storEN}}_{n,b,i} \right) \\
& + \vartheta \sum_{\omega \in \Omega} \pi_\omega \sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in \mathcal{N}} \Big(\sum_{g \in \mathcal{G}_n} q^{\text{gen}}_{g,i} (y^{\text{gen,inflex}}_{n,g,h,i,\omega} \\
& + y^{\text{gen,flexID}}_{n,g,h,i,\omega} + y^{\text{gen,InterID}}_{n,g,h,i,\omega}) + q^{\text{ll}}_{n,i} y^{\text{ll,ID}}_{n,h,i,\omega} \Big) \Big]
\end{aligned} \quad (1)
$$

The System balance has to hold in both DA and ID electricity markets. The anticipated load with the expected generator availability and storage and transmission operation are balanced in the DA. In the ID, an additional clearing takes place with adjustments in generation according to the changed forecast. The inflexible generation has the same variable in both stages.

$$
\begin{aligned}
& \sum_{g \in \mathcal{G}_n} (y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,Flex,m}}_{n,g,h,i,\omega} + y^{\text{gen,inter,m}}_{n,g,h,i,\omega}) \\
& + \sum_{b \in \mathcal{B}_n} \eta^{\text{dischrg}}_b y^{\text{dischrg,m}}_{n,b,h,i,\omega} + \sum_{a \in \mathcal{A}^{in}_n} \eta^{\text{tran}}_a y^{\text{tran,m}}_{a,h,i,\omega} \\
& - \xi^{\text{load,m}}_{n,h,i,\omega} - \sum_{b \in \mathcal{B}_n} y^{\text{chrg,m}}_{n,b,h,i,\omega} - \sum_{a \in \mathcal{A}^{out}_n} y^{\text{tran,m}}_{a,h,i,\omega} \\
& = 0 \\
& \forall\, m \in \mathcal{M},\ n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega.
\end{aligned} \quad (2)
$$

At the core of our analysis are the variations in the ID market. Constraints (6) ensure operation of the ID within the ramping constraints of generators. (7) state the maximum allowed difference between the day-ahead and ID market in terms of generation output and transmission for every hour in every period, for all scenarios, and in all nodes. The parameter, v_g, is identical to the ramping parameter.

$$(1 - v_g) * y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} \leq y^{\text{gen,FlexID}}_{n,b,h,i,\omega} \leq (1 + v_g) * y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} g \in \mathcal{G}^{\text{Flex}}$$
$$\forall\, n \in \mathcal{N},\ h \in \mathcal{H},\ i \in \mathcal{I},\ \omega \in \Omega. \quad (3)$$

D. Assumptions and Simplifications

For this work, we assume that all mentioned electricity markets are perfectly competitive and there is no strategic behaviour between players. Also, we assume an interest exists to update forecasts and balance out arising forecast derivations in the ID market. In order to interpolate future behaviour from historical data, we assume that no structural changes in regulation and remuneration schemes occur. On the technical side, we assume a linearisation of integer generation constraints for fully flexible storage systems.

E. Data

ID deviation quantities come from historical time series from ENTSO-E between 2015 and 2020. After the DA market clears at 6 pm, TSOs must upload a forecast for the generator and load for each market zone for the following day. Differences between the cleared market and real-time are caused by the uncertainty associated with forecasting and have to be traded on the ID market. Unfortunately, the provided data from ENTSO-E is incomplete and misses segments we interpolated in some periods.

Four second-stage scenarios per investment period are generated for all seasons using random sampling from historical time series from ENTSO-E between 2015 and 2020 based on the method presented in [19]. Further, we generate only one third-stage scenario to keep our problem computationally tractable. With one third-stage scenario, we do not consider uncertainty between the second and the third stage. However, we get an indication of how forecasting errors impact investment decisions, even though the forecasting errors are known with perfect foresight within each second-stage scenario.

IV. Case Study

We implemented two different cases of the European electricity market under the same setup as in previous publications of EMPIRE [28], [29], with investment periods from 2025 until 2060. The demand profiles increase over time and are based on a EU reference scenario [35].

Case 0: Benchmark Case: The Benchmark Case uses EMPIRE without any market sequencing. The model is identical to the one developed by Skar et al. in [36], thus containing an investment and an operational stage. Forecasting errors in the operation are omitted. The size of the optimisation problem spans over 37 million constraints and 24 million variables.

Case 1: Additional ID derivations: Case 1 represents the European power system with market sequencing. It builds upon Case 0 and adds forecasting errors with perfect foresight within each stochastic scenario. In the ID stage, the operations are readjusted so that supply matches actual demand. Case 1 consists of 158 million constraints and 94 million variables.

V. Results and Discussion

Costs for investment and dispatch between the two cases differ significantly, with an increase in costs caused by the market sequencing compared to the benchmark. This is expected describes how costs follow the gradient of uncertainty throughout the setup. The solution with higher uncertainty consequently costs more than the one with less uncertainty. Since forecasting errors induce uncertainty costs follow and are thus higher compared to perfect information. Our results are consistent with increased costs under uncertainty found in the literature [37]. Besides, the literature suggests that intermittent generation influences the balancing requirements in an ID market [38]. Borggrefe and Neuhoff [18] highlight the need for a market design that facilitates a possible integration of intermittent generation between market stages.

A. Composition of generation types

Looking into the investments reveals structural changes in the composition of the generation types in anticipation of uncertainty. Figure 4 shows that the investments into non-flexible generation stay relatively constant over all periods. However, flexible generation increases at the cost of intermittent generation following the gradient of uncertainty. Intermittent generation capacity is down -6% for case 1 compared to the benchmark case. However, the total invested capacity in intermittent generation stays below the benchmark case.

Investments into flexible generation increase by 41% when introducing market sequencing, caused by additional bio- and gas generators. The sum of the invested capacity for all types is decreasing (with -4% in case 1 compared to the benchmark), caused by the lower load factors of intermittent wind and solar generators.

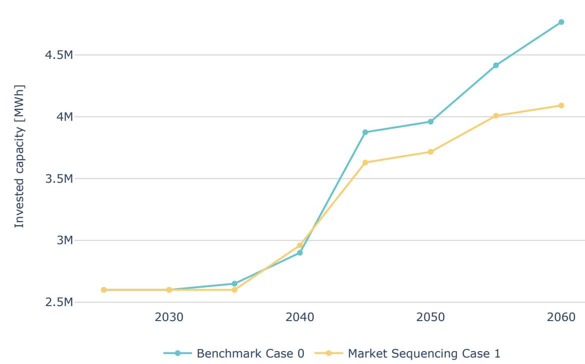

Fig. 3. Installed storage capacity over time

The substitution of intermittent with flexible generation significantly affected the investment into storage. The benchmark case shows 42% higher investments into power from storage, with an 16% increase in storage capacity compared to the case with market sequencing. As seen in Figure 3, the deviation in power and capacity occurs mainly after 2040. Ignoring forecasting errors by the absence of market sequencing consequently leads to an overvaluation of storage. The literature on investments in energy storage indicates that the future will likely see significant increases in capacity [7], [9], [39], which we can support from our findings. However, energy storage's role is less significant when including forecasting errors and market sequencing. This can partly be explained by the changed ratio between flexible and intermittent generation, as in the previous paragraph. Another reason can be the modelling choice of not having a curtailment penalty. Including this could boost storage usage to cover the excess supply in times of high renewable infeed. Concerning operational decision, case 1 utilizes storage significantly less than case 0, which aligns with the investments.

Investments in transmission are very similar across the cases. The installed transmission capacity increases over time. This seems reasonable and caused by the increased intermittent capacity in the later periods, which causes more stress on the transmission system [4], [10]. However, operations of the transmission system differ significantly between the cases. Case 1 sees an 10-20% increase in transmission volume compared to case 0. The high volumes indicate that the transmission system substantially contributes to the system's flexibility when including forecasting errors and mitigates the reduction of storage power. Our findings are supported by similar findings in the literature [6], [10], [23], [40].

We show the development of installed capacities grouped by type in Figure 5 at the example of case 1. No significant differences between the benchmark and deterministic cases time are apparent.

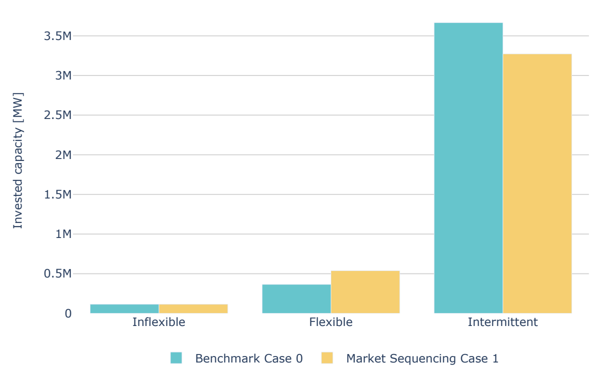

Fig. 4. Invested capacity for each generator type over all periods for the three cases

VI. Conclusion

In conclusion, we find a lower VRES capacity in the sequenced case with uncertainty of ID operation than in the non-sequential market, which highlights the importance of close to real-time forecasting uncertainty for investment planning. Operations of cross-border transmission are crucial for flexibility and increase when accounting for forecasting errors. A reduction of needed storage capacity is possible when accounting for forecasting errors and can be attributed to changes in the composition of the generation types. Therefore the inclusion of forecasting errors between the electricity markets are significant for correct capacity allocation in a capacity expansion problem.

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APPENDIX

A. Full Model Description

Objective function:

$$\begin{aligned}\min z = &\sum_{i\in\mathcal{I}}(1+r)^{-5(i-1)}\times\\ &\Big[\sum_{n\in\mathcal{N}}\sum_{g\in\mathcal{G}_n} c^{\text{gen}}_{g,i}x^{\text{gen}}_{n,g,i} + \sum_{l\in\mathcal{L}} c^{\text{tran}}_{l,i}x^{\text{tran}}_{l,i}\\ &+\sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}_n}\left(c^{\text{storPW}}_{b,i}x^{\text{storPW}}_{n,b,i} + c^{\text{storEN}}_{b,i}x^{\text{storEN}}_{n,b,i}\right)\\ &+\vartheta\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\Big(\sum_{g\in\mathcal{G}_n} q^{\text{gen}}_{g,i}(y^{\text{gen,inflex}}_{n,g,h,i,\omega}\\ &+y^{\text{gen,flexID}}_{n,g,h,i,\omega} + y^{\text{gen,InterID}}_{n,g,h,i,\omega}) + q^{\text{ll}}_{n,i}y^{\text{ll,ID}}_{n,h,i,\omega}\Big)\Big] \end{aligned} \tag{4}$$

The system balance for both electricity markets of DA and ID:

$$\begin{aligned}&\sum_{g\in\mathcal{G}_n}(y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,Flex,m}}_{n,g,h,i,\omega} + y^{\text{gen,inter,m}}_{n,g,h,i,\omega})\\ &+\sum_{b\in\mathcal{B}_n}\eta^{\text{dischrg}}_b y^{\text{dischrg,m}}_{n,b,h,i,\omega} + \sum_{a\in\mathcal{A}^{in}_n}\eta^{\text{tran}}_a y^{\text{tran,m}}_{a,h,i,\omega}\\ &-\xi^{\text{load,m}}_{n,h,i,\omega} - \sum_{b\in\mathcal{B}_n} y^{\text{chrg,m}}_{n,b,h,i,\omega} - \sum_{a\in\mathcal{A}^{out}_n} y^{\text{tran,m}}_{a,h,i,\omega}\\ &=0\\ &\forall\, m\in\mathcal{M},\ n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{5}$$

Ramping constraints for the maximum allowed difference between the DA and ID market in terms of generation output and transmission for every hour in every period, for all scenarios, and in all nodes. The parameter, v_g is identical to the ramping parameter:

$$\begin{aligned}(1-v_g)*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} \le y^{\text{gen,FlexID}}_{n,b,h,i,\omega} \le (1+v_g)*y^{\text{gen,FlexDA}}_{n,g,h,i,\omega} g\in\mathcal{G}^{\text{Flex}}\\ \forall\, n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{6}$$

Constraints for transmission lines increase between DA and ID markets:

$$\begin{aligned}&y^{\text{tran,DA}}_{a,h,i,\omega} \le y^{\text{tran,ID}}_{a,h,i,\omega}\\ &\forall a\in\mathcal{A},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{7}$$

Production from all types of generators are limited by the available installed capacity in all market:

$$\begin{aligned}&y^{\text{gen,t,m}}_{n,g,h,i,\omega} \le \xi^{\text{gen,m}}_{n,g,h,i,\omega} v^{\text{gen}}_{n,g,i}\\ &\forall m\in\mathcal{M},\ t\in\mathcal{T},\ g\in\mathcal{G}_t,\ n\in\mathcal{N}, h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{8}$$

For thermal generators, ramping limits apply:

$$\begin{aligned}&y^{\text{gen,inflex}}_{n,g,h,i,\omega} - y^{\text{gen,inflex}}_{n,g,h-1,i,\omega} \le \gamma^{\text{gen}}_g v^{\text{gen}}_{n,g,i}\\ &\forall\, g\in\mathcal{G}^{\text{Ramp}}\cap\mathcal{G}_n,\ n\in\mathcal{N},\ s\in\mathcal{S},\ h\in\mathcal{H}^-_s,\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{9}$$

Storage starts and ends at installed capacity and can cycle in between representative periods and years:

$$\begin{aligned}&\kappa_b v^{\text{storEN}}_{n,b,i} + \eta^{\text{chrg}}_b y^{\text{chrg,DA}}_{n,b,h^1_s,i,\omega} - y^{\text{discrg,DA}}_{n,b,h^1_s,i,\omega} = w^{\text{stor,DA}}_{n,b,h^1_s,i,\omega}\\ &b\in\mathcal{B}_n,\ n\in\mathcal{N},\ s\in\mathcal{S}, i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{10}$$

$$\begin{aligned}&\kappa_b v^{\text{storEN}}_{n,b,i} = w^{\text{stor,DA}}_{n,b,|\mathcal{H}_s|,i,\omega}\\ &\forall\, b\in\mathcal{B}_n,\ n\in\mathcal{N}, s\in\mathcal{S}, i\in\mathcal{I},\ \omega\in\Omega\end{aligned} \tag{11}$$

The balance of storage is ensured between operational time steps:

$$\begin{aligned}&w^{\text{stor,DA}}_{b,n,h-1,i,\omega} + \eta^{\text{chrg}}_b y^{\text{chrg,DA}}_{b,n,h,i,\omega} - y^{\text{discrg,DA}}_{b,n,h,i,\omega} = \eta^{\text{bleed}}_b w^{\text{stor,DA}}_{b,n,h,i,\omega}\\ &b\in\mathcal{B}_n,\ n\in\mathcal{N},\ s\in\mathcal{S},\ h\in\mathcal{H}^-_s,\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{12}$$

Storage level is limited by the capacity in each time step and market:

$$\begin{aligned}&w^{\text{stor,m}}_{n,b,h,i,\omega} \le v^{\text{storEN}}_{n,b,i}\\ &\forall\, m\in\mathcal{M}, b\in\mathcal{B}_n,\ n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{13}$$

Constraints (14)-(15) limit the charge- and discharge power to the respective limits:

$$\begin{aligned}&y^{\text{chrg,m}}_{n,b,h,i,\omega} \le v^{\text{storPW}}_{n,b,i}\,,\\ &\forall\, m\in\mathcal{M},\ b\in\mathcal{B}_n, n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega\end{aligned} \tag{14}$$

$$\begin{aligned}&y^{\text{dischrg,m}}_{n,b,h,i,\omega} \le \rho_b v^{\text{storPW}}_{n,b,i}\\ &\forall\, m\in\mathcal{M},\ b\in\mathcal{B}_n, n\in\mathcal{N},\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega\end{aligned} \tag{15}$$

For hydroelectric generators, the energy generation is restricted by seasonal historical realisations:

$$\begin{aligned}&\sum_{h\in\mathcal{H}_s} y^{\text{gen,Flex,m}}_{g,n,h,i,\omega} \le \xi^{\text{RegHydLim}}_{n,i,s,\omega}\\ &\forall\, m\in\mathcal{M},\ n\in\mathcal{N},\ g\in\mathcal{G}^{\text{Flex}}\cap\mathcal{G}_n,\ s\in\mathcal{S},\ i\in\mathcal{I},\ \omega\in\Omega\end{aligned} \tag{16}$$

$$\begin{aligned}&\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{g\in\mathcal{G}^{\text{Hyd}}\cap\mathcal{G}_n} y^{\text{gen,Flex,m}}_{n,g,h,i,\omega} \le \xi^{\text{HydLim}}_n\\ &\forall\, m\in\mathcal{M},\ n\in\mathcal{N},\ i\in\mathcal{I}.\end{aligned} \tag{17}$$

Transmission is limited by net transfer capacity:

$$\begin{aligned}&y^{\text{tran,m}}_{a,h,i,\omega} \le v^{\text{tran}}_{l,i}\\ &\forall\, m\in\mathcal{M},\ l\in\mathcal{L}, a\in\mathcal{A}_l,\ h\in\mathcal{H},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{18}$$

All annual emissions are limited by an emission cap:

$$\begin{aligned}&\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\sum_{g\in\mathcal{G}_n} q^{\text{CO2}}_{g,i}\\ &\cdot(y^{\text{gen,inflex}}_{n,g,h,i,\omega} + y^{\text{gen,Flex,m}}_{n,g,h,i,\omega} + y^{\text{gen,inter,m}}_{n,g,h,i,\omega}) \le Q^{\text{CO2}}_i\\ &\forall\, m\in\mathcal{M},\ i\in\mathcal{I},\ \omega\in\Omega.\end{aligned} \tag{19}$$

Constraints (20)-(23) ensures that both existing capacities, as well as invested capacity, is counted for total capacity. There are restrictions on investments and available capacity by technology in each node:

$$v^{\text{gen}}_{n,g,i} = \bar{x}^{\text{gen}}_{n,g,i} + \sum_{j=i'}^{i} x^{\text{gen}}_{n,g,j}$$
$$g \in \mathcal{G}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},\ i' = \max\{1, i - i^{\text{gen}}_g\} \tag{20}$$
$$v^{\text{tran}}_{l,i} = \bar{x}^{\text{tran}}_{l,i} + \sum_{j=i'}^{i} x^{\text{tran}}_{l,j}$$
$$l \in \mathcal{L},\ i \in \mathcal{I}, -i' = \max\{1, i - i^{\text{tran}}_l\} \tag{21}$$
$$v^{\text{storPW}}_{n,b,i} = \bar{x}^{\text{storPW}}_{n,b,i} + \sum_{j=i'}^{i} x^{\text{storPW}}_{n,b,j},$$
$$b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I},\ i' = \max\{1, i - i^{\text{stor}}_b\} \tag{22}$$
$$v^{\text{storEN}}_{n,b,i} = \bar{x}^{\text{storEN}}_{n,b,i} + \sum_{j=i'}^{i} x^{\text{storEN}}_{n,b,j}$$
$$b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, i' = \max\{1, i - i^{\text{stor}}_b\} \tag{23}$$

Constraints (24)-(31) limit the maximum allowed capacity of a technology in each node:

$$\sum_{g \in \mathcal{G}_t} x^{\text{gen}}_{n,g,i} \leq \bar{X}^{\text{gen}}_{t,n,i}, \quad t \in \mathcal{T},\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{24}$$
$$x^{\text{tran}}_{l,i} \leq \bar{X}^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ i \in \mathcal{I}, \tag{25}$$
$$x^{\text{storPW}}_{n,b,i} \leq \bar{X}^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{26}$$
$$x^{\text{storEN}}_{n,b,i} \leq \bar{X}^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{27}$$
$$\sum_{g \in \mathcal{G}_t} v^{\text{gen}}_{n,g,i} \leq \bar{V}^{\text{gen}}_{t,n,i}, \quad t \in \mathcal{T},\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{28}$$
$$v^{\text{tran}}_{l,i} \leq \bar{V}^{\text{tran}}_{l,i}, \quad l \in \mathcal{L},\ i \in \mathcal{I}, \tag{29}$$
$$v^{\text{storPW}}_{n,b,i} \leq \bar{V}^{\text{storPW}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}, \tag{30}$$
$$v^{\text{storEN}}_{n,b,i} \leq \bar{V}^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{31}$$

Some storage technologies $b \in \mathcal{B}^{\dagger} \subseteq \mathcal{B}$ have dependencies between power and energy capacity:

$$v^{\text{storPW}}_{n,b,i} = \beta_b v^{\text{storEN}}_{n,b,i}, \quad b \in \mathcal{B}^{\dagger} \cap \mathcal{B}_n,\ n \in \mathcal{N},\ i \in \mathcal{I}. \tag{32}$$

B. Results

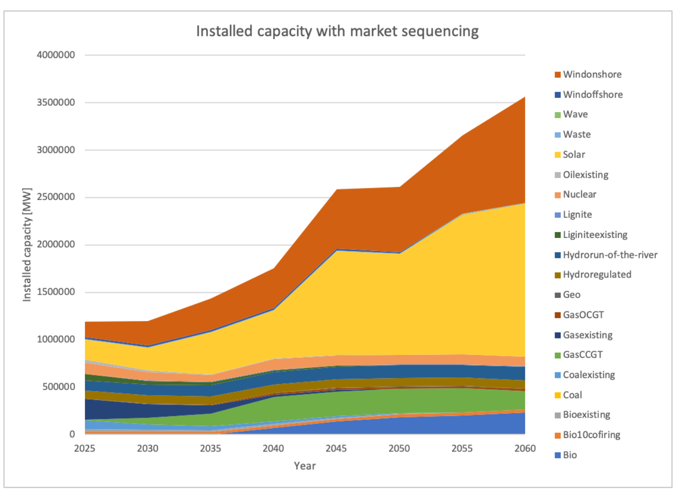

Fig. 5. Installed capacity over time for case 1 by type