Impacts of spatial and temporal resolutions on the near-optimal spaces of energy system optimisation models

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***Abstract*—Over the past years, the rising penetration of renewable energy in power systems has led to the need for more detailed energy system models. Specifically, spatial and temporal resolutions have become increasingly important, and multiple studies have investigated their impact on the optimal solutions to energy system optimisation problems. However, these studies have yet to be conducted for near-optimal solutions, which can provide valuable insights to decision-makers. This paper aims to initiate this research by examining the effects of spatial and temporal resolutions on the values of necessary conditions for near-optimality. In particular, we investigate how spatiotemporal resolution changes affect minimal capacity investments in the European electricity grid. Our analysis leads to three key observations. Firstly, we show that minimal capacities for near-optimality exhibit similar trends to optimal capacities when each resolution varies. Secondly, the resolutions that result in higher optimal capacities are also the ones where minimal capacities deviate the least from the optimal capacities. Thirdly, as a result of the second observation, spatial or temporal resolution changes have a greater impact on minimal capacities for near-optimality than on optimal capacities. We conclude by suggesting solutions to expand this research track and gain a deeper understanding of the impact of spatiotemporal resolution on near-optimal spaces.**

***Index Terms*—spatiotemporal resolution, near-optimal space, necessary condition, energy system optimisation model, European power grid**

I. Introduction

Energy system optimisation models (ESOMs) are extensively used to plan the transition to low-carbon power systems at local, national and international levels [1]. These models allow for determining the best system investment and operation for optimising an objective, typically cost.

However, researchers have recently highlighted the importance of going beyond classic cost-optimal analysis by studying near-optimal solutions [2]. These solutions, while less cost-efficient, might be better in terms of other objectives - e.g. energy efficiency, ecological concerns, or social factors - which might be challenging to model. Near-optimal solutions analyses have shown how different the system can become when allowing for slight deviations in cost [3]–[6].

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The results of studies using ESOMs are also affected by the complexity with which energy systems are modelled. This complexity depends on the features that are included in the model. Including more numerous and complex features while providing more detailed studies leads to more complex models, which are, in turn, more time-consuming to model and more challenging to solve. One feature that can easily be modified to tune the complexity of a model is its spatiotemporal resolution. This feature has become increasingly important with the increased penetration of new renewable energy technologies, such as photovoltaic (PV) panels and wind turbines in energy systems. Different studies have thus explored the impact of spatial and temporal resolution on the cost-optimal solution of ESOMs [7]–[11]. However, the impact of this form of complexity on near-optimal solutions has yet to be explored. In this paper, we initiate research in this area by analysing how spatial and temporal resolution affects necessary conditions for epsilon-optimality - a concept introduced by [5]. This analysis is done on a case study whose context is the European electricity grid modelled using the open-source ESOM PyPSA.

II. Literature review

An extensive range of ESOMs exhibiting different features exists [1]. Classical features include the models' temporal, geographical and sectoral scopes, the range of modelled technologies, and the complexity with which they are modelled. Some models implement special features such as price-responsive demands, endogenous technological learning, or macroeconomic interactions. The number and sophistication of these features determine the complexity of each model. Among those features, the model's spatiotemporal resolution is paramount. According to [1], setting it appropriately is the second key step in any ESOM application. When modelling energy systems with high renewable energy penetration, a high - typically hourly - resolution is required to represent the system dynamics properly. For system models representing networks, the spatial resolution depends on the number of modelled nodes. For instance, a spatial resolution of one node per country is often used to model transnational power systems. Still, some representations can be much more precise, e.g., a thousand nodes for the European power system represented by PyPSA-Eur [12].

Some studies have shown how the spatiotemporal resolution affects the quality of the system modelling and the analysis it serves. As highlighted in [7], spatial resolution can impact the system's estimated cost. Depending on the grid model, this cost can be over- or underestimated. Another impact mentioned by [7] is the sub-optimal capacity investment in technologies such as wind and solar when using low spatial resolution. Spatial resolution can also impact the curtailment of renewable sources [8]. The impact of temporal resolution is non-negligible, either. Indeed, as mentioned in [9], aggregating this resolution inappropriately can introduce errors in model outputs and the derived insights. For instance, as stated in [10], a simplified resolution implies an under-evaluation of cost. It can also lead to understating the importance of wind generation and energy storage while overstating the value of solar generation. The work of [11] also supports the underinvestment in wind technology.

Overall, improving spatiotemporal resolution leads to better estimating the system's needs. Another way of improving the quality of insights derived from ESOMs is to look beyond cost-optimal solutions. This approach was first proposed in a case unrelated to energy system modelling [13]. It was recently applied to ESOMs by [2] and has since been used by several researchers [3]–[5], [14], [15]. These authors have proposed different approaches for exploring the near-optimal space, i.e., the space of solutions with an objective value close to the optimal objective value. Some propose computing a series of near-optimal solutions and analysing their properties [3], [14], [15]. Others are searching for near-optimal solutions exhibiting specific properties, e.g., those with a minimum capacity in some renewable technology [4], [5]. Authors of [5] translated this second approach through the computation of ϵ-optimal necessary conditions, i.e., conditions which are true for any solution whose cost is, at most, $1+\epsilon$ times more expensive than the cost optimum. More specifically, the methodology consists of computing an ϵ-optimal space $\mathcal{X}^\epsilon$ defined as:

$$\mathcal{X}^\epsilon = \{x \in \mathcal{X} \mid f(x) \leq (1+\epsilon) f(x^\star)\} \; \forall \epsilon \geq 0 \; , \qquad (1)$$

where $\mathcal{X}$ is the problem feasible space, $f : \mathcal{X} \to \mathbb{R}_+$ an objective function (e.g., the cost), $x^\star$ an optimal solution, and ϵ the suboptimality coefficient that measures the deviation from the cost-optimal value. This space contains all the solutions whose objective value does not deviate by more than ϵ from the optimal objective value. Necessary conditions for ϵ-optimality can then be computed to derive insights from this space. Those are conditions (i.e. functions $\phi : \mathcal{X} \to \{0,1\}$) which are true for every element in $\mathcal{X}^\epsilon$. For instance, using conditions corresponding to constrained sums of investment variables, the authors of [5] showed that for a deviation ϵ of 10%, capacity investment in onshore wind, storage, PV, transmission, and offshore wind could be reduced to 0%, 0%, 15%, 50%, and 60% of their optimal capacities, respectively.

These studies were performed with a fixed spatiotemporal resolution and have thus not explored whether increasing it improves the quality of the insights derived from near-optimal solutions. In this paper, we take the first step in filling this gap by exploring how spatial and temporal resolution impacts necessary capacity investments for near-optimality.

III. Case study

This case study explores the required minimum investments in power transmission, generation, and storage capacities across the European continent to achieve, by 2030, a 99% reduction in greenhouse gas (GHG) emissions compared to 1990 levels while ensuring near-optimality in cost. The goal is to analyse the impact of spatial and temporal resolution on these investments.

To model the European electricity network, the open-source tool PyPSA (Python for Power System Analysis) [16] is used. As described in its online documentation [17], PyPSA allows for "simulating and optimising modern power systems that include features such as conventional generators with unit commitment, variable wind and solar generation, storage units, coupling to other energy sectors, and mixed alternating and direct current networks". It is "designed to scale well with large networks and long time series". This case study uses PyPSA to plan capacity expansion, i.e., determine how much capacity needs to be deployed for each expandable technology at each network node.

PyPSA has been used to model the European network through the PyPSA-Eur project [12]. This model has already been used and validated in a series of studies [5], [18], [19]. In this case study, the default version of the model [20] is used with a few modifications. In addition to onshore and offshore wind, capacities of PV, CCGT (combined cycle gas turbine), OCGT (open cycle gas turbine), transmission, and storage can be extended. The power density of offshore wind is set to 10 MW/km^2 [21] instead of the default 2 MW/km^2. A limit of two times the existing capacity is set on link and line capacities. We consider it a reasonable upper bound on what is possible to build in less than ten years. Finally, nuclear power plants can produce at nominal capacity but have a ramping limit of 10% of nominal capacity per hour, upwards and downwards.

The modelled network contains 6763 lines and 3642 substations [20], and time series for electrical demand and variable renewable generators are available at an hourly resolution. However, the model can be clustered to decrease the number of substations - also referred to as nodes - and, therefore, the number of lines. The temporal resolution can also be reduced by averaging over every n snapshot, where n is a positive integer. This paper studies the following level of clustering: 100, 200, and 400 nodes for spatial resolution and 2, 4 and 6 hours for temporal resolution. The lower limit of a six-hourly resolution was set as decreasing the temporal resolution further led to unreliable storage behaviour.

The cost-optimal network configurations are first computed for all combinations of these resolutions. For each of these optimal configurations, we analyse the sums of new capacities installed for PV panels, wind turbines (i.e., the sum of new capacities of onshore and offshore wind), and transmission (i.e., the sum of new capacities of lines and links) across the European network. Mathematically, we can denote these sums by $\mathbf{d}^T\mathbf{x}_I$ with $\mathbf{x}_I$ a vector of size $|I|$ that collects the different investment variables and $\mathbf{d} \in \{0,1\}^{|I|}$. For instance, the only values equal to 1 in $\mathbf{d}$ could correspond to the investment capacities in wind turbines. The sum would then equal the sum of wind capacities across the network. By changing the values in $\mathbf{d}$, we can obtain investment capacities for different technologies. These sums take different values for each solution to the problem. We denote the value of these sums at the optima by $c^*_{n,h}$ where n and h represent the spatial and temporal resolution of the model, counted respectively in nodes and hours.

Once the optima are computed, the methodology developed in [5] allows determining the minimum new capacity investment needed in PV, wind and transmission to ensure cost ϵ-optimality. To compute the minimum new capacity required in renewable technologies to stay ϵ-optimal, we use conditions of the form $\phi(\mathbf{x}_I) := \mathbf{d}^T\mathbf{x}_I \geq c$ with $c \in \mathbb{R}_+$. If we minimise this sum over $\mathcal{X}^\epsilon$, we obtain a value $c^\epsilon_{n,h}$ equal to the minimal new capacity that needs to be deployed to be ϵ-optimal (see [5] for a proof). These values depend on the model's spatial and temporal resolution and the sub-optimality coefficient. In this case study, we limit our analysis to an ϵ of 10%.

IV. Results

We first analyse the optimal values $c^*_{n,h}$ of new capacities for PV, wind and transmission to see how the system behaves at the optima when changing the resolution. We then analyse how near-optimal solutions are impacted by looking at the minimal new capacities $c^\epsilon_{n,h}$ for these technologies and how these impacts compare to the ones on the optimal capacities.

A. Analysis of optimal solutions

The optimal solutions are computed for time resolutions of 6, 4, and 2 hours and spatial resolutions of 100, 200, and 400 nodes (in order from the least complex system to the most complex). Table I shows the optimal costs for all combinations of resolutions. The values range between 64.4 and 69.8 B€/y, and there is a clear trend: the more complex the network, the higher the cost. Rising investment costs primarily drive the increases. Indeed, increasing the temporal resolution from 6 hours to 2 hours adds between 1 to 2 B€/y in generation capacity investment. This rise is linked to the switch from solar to wind capacity, as shown in Table II. While the added wind capacity is only half that removed for PV, the average wind capital cost is around four times more expensive, explaining the overall rise in investment cost. Improving the temporal resolution decreases the importance of PV because it reveals the mismatch between solar production and demand peaks, making this technology less attractive as it needs to be combined with storage. The increase in storage observed when moving from six to two-hourly resolution confirms this and explains the additional 1.7 to 2.3 B€/y increase in cost. As shown in Table II, transmission investment also increases with the temporal resolution, allowing the absorption of unsmoothed production peaks.

TABLE I: System costs [B€/y] at the optimal solutions for different spatial and temporal resolutions.

	hours [h]		
nodes [n]	6	4	2
100	64.4	67.4	68.4
200	64.7	67.8	68.7
400	65.9	68.8	69.8

PV and wind capacities increase when using a better spatial resolution. This increase can be explained by the better spatial representation of renewable sources linked to the increased number of nodes in the model. Indeed, in the PyPSa-Eur model, wind and PV capacity can be installed at each node and are associated with a node-specific capacity factor time series. When aggregating nodes to reduce the spatial resolution, the capacity factors of different nodes are averaged, leading to losing some of the better capacity factor signals. This increase in renewable generation again implies greater needs in storage capacity which adds between 1.3 to 1.9 B€/y to the total cost. To finish this analysis, let us note that there is no clear tendency when looking at the evolution of transmission capacity with spatial resolution. Indeed, the capacity rises from 100 to 200 nodes before dropping again when reaching 400 nodes. This behaviour is difficult to analyse as topological changes, impacting the total length of the lines and, thus, their capacities in TWkm, occur when modifying the number of nodes in the network. Thus, in the rest of the paper, the analysis of transmission capacity is limited to its evolution with temporal resolution.

B. Analysis of necessary conditions

This section analyses how temporal and spatial resolutions affect the necessary conditions corresponding to the minimal new capacities in PV, wind and transmission and how these impacts compare to the ones on the optimal new capacities. This analysis is divided into three observations derived the results shown in Tables II to IV.

Observation 1: *Optimal and minimal capacities follow the same trends when modifying spatial and temporal resolutions.*

The values $c^\epsilon_{n,h}$ for $\epsilon = 10\%$ are shown in Table II. The effect of spatiotemporal resolution on these values is similar to its impact on optimal values $c^*_{n,h}$. Firstly, increasing the temporal resolution decreases the minimal PV capacities while increasing wind and transmission capacities. Secondly, an increase in spatial resolution increases PV and wind capacities.

TABLE II: New capacities $c^*_{n,h}$ at the optima, minimum new capacities $c^\epsilon_{n,h}$ with $\epsilon = 10\%$, and ratio $c^\epsilon_{n,h}/c^*_{n,h}$.

	$n\backslash h$	PV 6	PV 4	PV 2		Wind 6	Wind 4	Wind 2		Transmision 6	Transmision 4	Transmision 2	
$c^*_{n,h}$	100	488	399	388		297	342	346		76.0	80.3	81.7	
	200	498	410	395	[GW]	312	356	363	[GW]	76.6	81.7	83.6	[TWkm]
	400	513	429	416		324	365	371		70.9	75.5	76.4	
$c^\epsilon_{n,h}$	100	125	85.8	79.8		128	160	163		11.9	14.8	15.2	
	200	130	92.9	85.8	[GW]	146	178	182	[GW]	13.7	16.2	16.7	[TWkm]
	400	144	109	102		157	189	193		11.6	13.9	14.2	
$c^\epsilon_{n,h}/c^*_{n,h}$	100	25.6	21.5	20.5		43.0	46.9	47.0		15.7	18.4	18.7	
	200	26.2	22.6	21.8	[%]	46.8	50.0	50.1	[%]	17.9	19.8	20.0	[%]
	400	28.2	25.5	24.5		48.4	51.7	52.1		16.4	18.4	18.6	

Observation 2: *A resolution leading to a higher optimal capacity than another resolution also leads to a smaller deviation of the minimal capacity from this optimal capacity.*

Table II shows the ratios $c^\epsilon_{n,h}/c^*_{n,h}$ between minimal and optimal new capacities. The first observation is that these ratios vary within narrow ranges. For transmission capacity, the ratios vary between approximately 15% and 20%. This result means that there exist near-optimal solutions costing at most 10% more than the optimal cost and where there is only 15 to 20% of the new transmission capacity installed at the optimum. For PV capacity, these ratios are contained in the range $[20 : 30]\%$; for wind capacity, the range is approximately $[40 : 50]\%$. However, these percentages exhibit structured differences: their variations follow the same trends as optimal capacities. Indeed, the resolutions that lead to higher percentages for each technology have larger optimal capacities. This result can be explained as follows. If the capacity of a technology is larger at the cost optimum for a given resolution, it implies that this technology is more economically valuable at this resolution. When computing the minimum capacity for ϵ-optimality, the model searches for alternative solutions using other technologies for a cost close to the optimum. If the minimised technology is economically advantageous, finding economically attractive alternatives to replace it is challenging, which makes this technology difficult to minimise. Therefore, if a technology is more advantageous at one resolution than another, it has a larger optimal capacity at this resolution and leads to a smaller deviation from this optimum when trying to minimise this technology under a constrained cost deviation. Mathematically, if for resolutions n_a and resolution n_b, we have $c^*_{n_a,h} > c^*_{n_b,h}$ (which, following observation 1, also implies $c^\epsilon_{n_a,h} > c^\epsilon_{n_b,h}$), then observation 2 states that the following inequality is respected:

$$c^\epsilon_{n_a,h}/c^*_{n_a,h} > c^\epsilon_{n_b,h}/c^*_{n_b,h} \quad . \tag{2}$$

This statement is also true if the resolution variation is temporal instead of spatial.

Observation 3: *Modifying the spatial or temporal resolution has more impact on minimal than optimal capacities.*

This statement means that the relative difference between the minimal capacities at two different resolutions is greater than the relative difference between the optimal capacities associated with these same resolutions. Mathematically, let n_1 and n_2 be two different spatial resolutions, with n_1 being the higher of the two (e.g. $n_1 = 400$ and $n_2 = 100$), we have:

$$|c^\epsilon_{n_2,h}/c^\epsilon_{n_1,h} - 1| > |c^*_{n_2,h}/c^*_{n_1,h} - 1| \tag{3}$$

where the first term and second term represent the relative difference between the minimal and optimal capacities, respectively. This result is a consequence of the previous observation and can be proven using (2) where n_a is a resolution with higher optimal and minimal new capacities than n_b. We differentiate between two cases.

Case 1: The higher resolution corresponds to the one with the higher capacity, i.e., $n_1 = n_a$ and $n_2 = n_b$. Ineq. (2) becomes:

$$c^\epsilon_{n_1,h}/c^*_{n_1,h} > c^\epsilon_{n_2,h}/c^*_{n_2,h} \tag{4}$$

$$\Leftrightarrow \quad c^*_{n_2,h}/c^*_{n_1,h} > c^\epsilon_{n_2,h}/c^\epsilon_{n_1,h} \tag{5}$$

$$\Rightarrow \quad |c^*_{n_2,h}/c^*_{n_1,h} - 1| < |c^\epsilon_{n_2,h}/c^\epsilon_{n_1,h} - 1| \tag{6}$$

where (5) $\Rightarrow$ (6) as $c^\epsilon_{n_1,h} > c^\epsilon_{n_2,h}$ and $c^*_{n_1,h} > c^*_{n_2,h}$.

Case 2: The higher resolution corresponds to the one with the lower capacity, i.e., $n_1 = n_b$ and $n_2 = n_a$. Ineq. (2) becomes:

$$c^\epsilon_{n_2,h}/c^*_{n_2,h} > c^\epsilon_{n_1,h}/c^*_{n_1,h} \tag{7}$$

$$\Leftrightarrow \quad c^\epsilon_{n_2,h}/c^\epsilon_{n_1,h} > c^*_{n_2,h}/c^*_{n_1,h} \tag{8}$$

$$\Rightarrow \quad |c^\epsilon_{n_2,h}/c^\epsilon_{n_1,h} - 1| > |c^*_{n_2,h}/c^*_{n_1,h} - 1| \tag{9}$$

where (8) $\Rightarrow$ (9) as $c^\epsilon_{n_1,h} < c^\epsilon_{n_2,h}$ and $c^*_{n_1,h} < c^*_{n_2,h}$.

We obtain the same conclusion, which is also valid if the temporal resolution varies. In our case study, case 1, where the better resolution corresponds to the higher optimal capacity, is valid for wind and transmission capacity for both types of resolutions. It is also valid for PV capacity for spatial resolution, while the variation of PV with temporal resolution corresponds to case 2.

This observation is illustrated by comparing capacities at lower resolutions to those at the case study's best temporal and spatial resolutions, i.e., $h_0 = 2$ and $n_0 = 400$. Table III thus contains the deviations of optimal (or minimal) new capacities at lower temporal resolutions (i.e., $h = 6$ and $h = 4$) from the optimal (or minimal) new capacities at the best temporal resolution $h_0 = 2$, i.e., $|c^*_{n,h}/c^*_{n,h_0} - 1|$ (or $|c^\epsilon_{n,h}/c^\epsilon_{n,h_0} - 1|$). Then, Table IV shows the same type of deviations but from the capacities at the best spatial resolution $n_0 = 400$, i.e., $|c^*_{n,h}/c^*_{n_0,h} - 1|$ and $|c^\epsilon_{n,h}/c^\epsilon_{n_0,h} - 1|$.

TABLE III: Deviations $|c^*_{n,h}/c^*_{n,h_0} - 1|$ of optimal new capacities and deviations $|c^\epsilon_{n,h}/c^\epsilon_{n,h_0} - 1|$, with $\epsilon = 10\%$, of minimal new capacities from best *temporal* resolution $h_0 = 2$. Abbreviation: Transmission (Trans.).

		PV [%]		Wind [%]		Trans. [%]	
	$n \backslash h$	6	4	6	4	6	4
$\lvert c^*_{n,h}/c^*_{n,h_0} - 1\rvert$	100	25.7	2.85	13.9	1.07	6.94	1.79
	200	26.3	3.95	14.0	1.74	8.41	2.22
	400	23.4	3.28	12.8	1.73	7.29	1.22
$\lvert c^\epsilon_{n,h}/c^\epsilon_{n,h_0} - 1\rvert$	100	56.6	7.60	21.3	1.28	21.8	1.98
	200	51.8	8.20	19.6	1.99	17.7	2.99
	400	41.7	7.22	19.0	2.27	18.3	2.11

By analysing the values of these two tables, the third observation is obvious: deviations are more significant for minimal new capacities for ϵ-optimality than for optimal new capacities.

V. Conclusion

In this paper, we initiate the research on the impact of spatial and temporal resolutions on necessary conditions for near-optimality of energy system optimisation models. This new research track starts with the analysis of the expansion planning of the European power grid and necessary conditions for ϵ-optimality corresponding to the minimal new PV, wind and transmission capacities. The impact of spatial and temporal resolution on these values is explored and compared to the impacts on cost-optimal new capacities for these technologies. Three key observations are derived from this analysis. Firstly, the results show that minimal and optimal capacities exhibit the same behaviour when resolutions are modified. In particular, PV, wind and transmission capacities increase with better spatial resolution, while a higher temporal resolution positively impacts only the capacity for wind and transmission. A second observation is that the resolutions for which more capacity is installed at the optimum correspond to the ones where it is the hardest to minimise this capacity when allowing for a constrained cost deviation. Thirdly, we show that temporal and spatial resolution variations impact minimal capacities more than optimal ones.

This study provides a first insight into the impacts of spatial and temporal resolution on near-optimal solutions. This research track could be continued in the following ways. First, analysing the optimal and near-optimal solutions for higher and lower resolutions might increase the reliability of our three observations. Similarly, necessary conditions for different values of ϵ could be evaluated to see if these observations hold for other levels of near-optimality. Secondly, we chose to study the effect of spatiotemporal resolution on near-optimal space using necessary conditions. However, other methods have been developed to analyse near-optimal solutions. A natural extension of this paper is to study the impact of resolution on the insights obtained with these methods. Finally, we tested the resolutions' impacts on a specific case study using one ESOM. Studies using different models must be performed to understand those impacts holistically.

TABLE IV: Deviations $|c^*_{n,h}/c^*_{n_0,h} - 1|$ of optimal new capacities and deviations $|c^\epsilon_{n,h}/c^\epsilon_{n_0,h} - 1|$, with $\epsilon = 10\%$, of minimal new capacities from best *spatial* resolution $n_0 = 400$.

		PV [%]			Wind [%]		
	$n \backslash h$	6	4	2	6	4	2
$\lvert c^*_{n,h}/c^*_{n_0,h} - 1\rvert$	100	4.77	6.97	6.58	8.11	6.31	6.93
	200	2.82	4.46	5.08	3.66	2.39	2.38
$\lvert c^\epsilon_{n,h}/c^\epsilon_{n_0,h} - 1\rvert$	100	13.6	21.5	21.8	18.3	15.1	16.0
	200	9.79	15.0	15.8	6.77	5.82	6.10

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