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Long-term planning of a flexible generation portfolio

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Abstract: We are witnessing an acceleration in the uptake of renewable energy in power systems. Because of the associated variability and uncertainty of renewables, power systems need to have an adequate supply of flexibility to allow for suitable management of short-term operations. So far most of the work in this area has neglected how flexibility needs associated with renewables are fulfilled as part of dispatchable generation capital investments decisions. To address this challenge, we propose an approach to plan the dispatchable generation mix of a power system needed to counteract variability and uncertainty of significant shares of variable renewable generation. The approach exploits the linear time-invariant feature of variable generation using historical phase planes of capacity (in MW) and ramp (in MW/min) to bridge the gap between long-term capacity planning and short-term intra-hour flexibility. This approach is much more computationally tractable than other proposals, while also being able to capture adequately short-term operational features like ramping and net load variability. Numerical tests are performed on a realistic datasets to substantiate the effectiveness of the approach.

Keywords: Bulk power system operations, bulk power system planning, computational tractability, flexibility, ramping, renewable energy generation, variability

Résumé : Nous assistons présentement à une accélération dans le développement des énergies renouvelables raccordées aux réseaux électriques. En raison des fluctuations et de l'incertitude associées à ses sources d'énergie, les planificateurs des réseaux électriques doivent s'assurer qu'ils aient suffisamment de moyens de production flexibles et pouvant être répartis afin de contrer ces fluctuations et l'incertitude associée. Jusqu'à maintenant, très peu d'efforts de recherche ont tenté d'intégrer la dimension flexibilité aux problèmes de décisions d'investissement dans de nouveaux actifs de production répartissables. Dans cet article, nous suggérons donc une approche novatrice à la solution de ces problèmes. Notre approche prend acte du caractère linéaire et temporellement invariant de certains types de production renouvelable en représentant des données historiques de production (en MW) et de rampe (en MW/min) dans le plan de phase. Cette approche permet de compresser la dimension temporelle typiquement problématique dans les problèmes de planification à long-terme où l'on doit y représenter les caractéristiques opérationnelles à court-terme. Du coup, le problème de planification de l'investissement devient très efficace en terme de son temps de calcul en comparaison aux autres approches disponibles. Également, l'approche proposée est en mesure de planifier les investissements de manière adéquate afin de répondre aux défis opérationnels et elle permet d'atteindre des solutions plus économiques que d'autres approches. Des expérimentations numériques à l'aide de jeux de données réalistes fait la démonstration de ces attributs.

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Nomenclature

The main symbols used in this paper are listed here for the convenience of the reader.

Sets and Indices	
i	Indices of discretized capacity intervals $i = 1, \ldots, I$
n	Indices of generation technologies $n = 1, \ldots, N$
t	Indices of operation periods $t = 1, \ldots, T$
Parameters	
C_n^{cap}	Annualized capital cost of generation technology n (\$/MW)
C_n^{inc}	Incremental production cost of generation technology n (\$/MWh)
C_n^{nlo}	No-load cost of generation technology n (\$/h)
C_n^{sup}	Start-up cost of generation technology n
α_n	Cost of ramping for generation technology n (\$/MWh)
β	Value of lost load (\$/MWh)
γ	Value of generation curtailment (\$/MWh)
τ_n	Time constant of generation technology n (h)
G_n	Rated capacity of generation technology n (MW)
D_i	Net load in capacity interval i (MW)
Q_i	Count of net load instances in capacity interval i
$R_i^{\uparrow}$	Upward ramp requirement of net load in capacity interval i (MW/min)
$R_i^{\downarrow}$	Downward ramp requirement of net load in capacity interval i (MW/min)
Decision Variables	
x_n	Capacity of generation technology n (MW)
z_n	Binary variable associated with the choice of generation technology n
$u_{n,t}$	Binary variable associated with the commitment of generation technology n in operation period t
$g_{n,i}$	Operating point of generation technology n in each interval i (MW)
$g_{n,t}$	Power produced by generation technology n in operation period t (MW)
l_i	Load shed in each interval i (MW)
c_i	Generation curtailed in each interval i (MW)
$r_{n,i}^{\uparrow}$	Upward ramp available from generation technology n in capacity interval i (MW/min)
$r_{n,i}^{\downarrow}$	Downward ramp available from generation technology$n$ in capacity interval i (MW/min)

1 Introduction

World electricity consumption is projected to grow significantly through the year 2040, as indicated in the latest *World Energy Outlook* [1]. This necessitates the addition of power system assets to the existing electricity infrastructure. The report also forecasts that renewable energy will be the fastest growing form of electricity generation. Most renewable energy production is dependent on weather conditions, which makes it inherently variable.

In capacity planning of traditional power systems with no or at most shallow penetration of renewable energy, generation adequacy studies leverage the availability of accurate load forecasting tools [2]. Traditional generation expansion planning models, which are solely focused on ensuring adequate generation capacity over a multi-year time horizon, have relied on the use of the load duration curve (LDC) technique [3] for determining optimal investments in new generation capacity, with the objective of maintaining certain reliability standards [4]–[8] at least capital cost. In those models, reliability is evaluated using deterministic criteria such as loss of largest unit ($N-1$ criterion) or probabilistic criteria such as the loss of the load expectation (LOLE) [9], expected energy not served (EENS) [10], or well-being analyses [11].

However, with the decarbonization of the electricity supply high up on the industry's agenda, not only capacity adequacy but also flexibility adequacy is essential when doing capacity planning within power systems with deep penetration of renewable energy generation technologies. Flexibility adequacy is needed, beyond simple capacity adequacy, to provide power system operators with resources to handle the short-term operational impact of variable renewable energy (VRE). In the context of long-term capacity planning, planning for adequate flexibility is akin to planning for adequate rampability of the dispachable generation fleet.

Flexibility is defined as the ability of the power system to deploy its resources to respond to changes in the net load, where the net load is defined as the residual demand not served by VRE [12]. Relevant references on short-term operational impact of VRE are [13]–[15]. In [13], Makarov et al. demonstrate that an increase in installed capacity of wind power generation has a significant impact on the system's load following and regulation requirements. This highlights the importance of ongoing adjustments in system scheduling and real-time dispatch to maintain system reliability. Wind power varies over different time scales ranging from seconds to days. Prevalence of intra-hour fluctuations of wind power have been shown through the study of the power spectral density of the output of wind turbines [14]. These findings emphasize the importance of having the right amount of fast-acting resources in intra-hour time scales to guarantee adequate balance of power. In an attempt to address this issue, a modified unit commitment with the ability to deploy resources over wide ranges of variability power spectrum frequencies is proposed in [15].

Long-term capacity planning in power systems with deep penetration of VRE has so far not received significant attention, with the community having focused more on operational problems through the last 10-15 years. To examine the role of wind in future generation portfolios, capacity credits were considered in [16], wherein the load duration curve technique was employed for long-term generation expansion planning. Several papers including [18] have used stochastic optimization to find the optimal type, size and placement of generation technologies in power systems with significant VRE. Another approach that deals with uncertain demand and generation capacity in transmission network expansion planning using a two-stage robust optimization is described in [20]. Work in [12] underlines the importance of upward and downward flexibility assessment and proposes a process to integrate it with existing planning techniques. A modified unit commitment and construction approach using the concept of representative weeks is proposed in [22] to bridge the gap between operations and planning. To account for flexibility in planning, a matrix is proposed in [23] to evaluate the flexibility potential of generating units. An approach described in [24] uses Monte Carlo simulations to capture operational flexibility in long-term planning. It uses the conventional load-duration curve technique to model key uncertainties in demand, fuel prices, demand elasticity, carbon prices to assess the performance of a number of generation portfolios. Another implementation of the load duration curve methodology in long-term generation expansion planning is described in [25].

Our objective here is to formulate a long-term capacity planning approach which would capture the short-term dynamics associated with variable net load over intra-hour timescales. The most important challenge with such long-term capacity problems is the representation of the short-term operational features. In theory, one would have to represent the entire operational lifetime of the long-term planning horizon (*e.g.*, 20 years) to capture those features with the highest fidelity. This is generally not possible on pure computational grounds; the dimensionality of the planning problem would grow beyond what could be reasonably solved. Such an approach is not ideal also in the sense that its outcomes would be sensitive to the long-term forecasts of the short-term characteristics of the demand and VRE. As a result, typically fidelity of the operational features has to be simplified to limit computational resources and allow for more robustness.

In fact, the 2018 IEA Status of Power System Transformation report [26] states that "Capacity Expansion models (CExMs) tend to take a relatively detailed approach to capital expenditure in the system, but presents an incomplete picture of power system operations, ultimately have some form of flexibility shortfall or redundant flexible capacity." Moreover, this report states that production cost models (PCMs), which simulate least-cost economic dispatch and examine flexibility at timescales from very short-term to very long-term, is lacking in most CExMs. The report thus recommends on coupling PCMs and CExMs to assemble a long-term flexibility strategy.

This paper attempts to fill this research gap by developing a planning tool set to address short-term operational features, like ramping, with a low-dimensionality representation of the intra-hour dynamics of VRE in long-term capacity planning. The use of such representation allows for a computationally efficient and tractable capacity planning approach. The low-dimensionality representation of the VRE dynamics we propose is based on the concept of capacity-ramp historical phase planes, which were introduced in [27] for power system operation problems.

The remainder of the paper is outlined as follows. Section 2 presents existing work in long-term planning which sets the performance baseline of our approach. The concept of capacity-ramp phase planes is introduced in Section 3. Section 4 describes our proposed long-term planning problem formulation. Section 5 presents a case study and results comparing our approach to other state-of-the-art planning approaches. Finally, relevant conclusions are drawn in Section 6.

2 Current approach on long-term generation planning with deep VRE penetration

The logical way to perform long-term capacity expansion in a deep penetration VRE scenario is to optimize jointly capital investments conditioned to a high-fidelity representation of future operations. This type of problem formulation has been proposed previously in [22] as a technique to plan for both capacity and flexibility. In the remainder of the paper, we will refer to this approach as the "Kirschen et al. approach", which will also serve as the baseline for the validation and performance comparisons.

The formulation of the Kirschen et al. approach looks essentially like a unit commitment problem for which capacity gets built at time zero and then gets run for a long-term horizon. As its objective function found in (1) shows, the Kirschen et al. approach co-minimizes investment and running costs. The investment cost of the generation technology C_n^{inv} is defined in (2), and an operating cost proxy $C_{n,t}^{oper}$ is defined in (3). The operating cost is the sum of no load costs, production costs and start up costs. The co-optimization considers three aspects: 1. whether or not a unit is built, 2. if a built unit is committed or not, and 3. the dispatch of built and committed units. The binary variable $z_n = 1$ if unit n is built, and binary variable $u_{n,t} = 1$ if the commitment status of the unit n is on in time period t.

$$
\begin{aligned}
\min_{z_n u_{n,t} g_{n,t}} & \sum_{n=1}^{N} C_n^{inv} \\
& + \sum_{n=1}^{N} \sum_{t=1}^{T} C_{n,t}^{oper} && (1) \\
C_n^{inv} &= z_n G_n C_n^{cap} && (2) \\
C_{n,t}^{oper} &= u_{n,t}[C_n^{nlo} + C_n^{inc} g_{n,t} + (1 - u_{n,t}) C_{n,t}^{sup}] && (3)
\end{aligned}
$$

Obviously, to have a good degree of operational modeling fidelity, the number of operating intervals T must be large enough in terms of years of operation (e.g., 20 years) and to ensure that the approach can capture the shorter-term operational dynamics (e.g., 8760 hours per year).[1]

To address the undue dimensionality of the problem, the authors of [22] sample five representative weeks per year (amounting to 840 hours), and they limit their computations to only one year of operations. Each season is represented by one week, and one additional "extreme" week is considered. The operating cost of each week is weighed by number of weeks in the season. The objective function is subject to the power balance, ramp constraints, minimum and maximum generation limits, and minimum up- and down-time constraints.

3 Capacity-ramp phase planes for power system planning

As argued in the introduction, we propose to address the dimensionality of the long-term planning problem described above. One way in addressing this issue is to find a mean to represent short-term VRE variability time-domain information. Capacity-ramp phase planes based on historical VRE records offer an opportunity for this.

[1] We note that this does not even touch upon matters of uncertainty in the VRE and the demand.

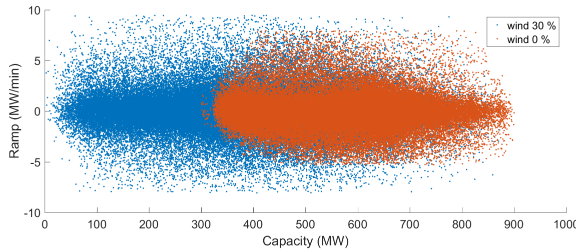

Figure 1: Empirical net load capacity-ramp phase plane.

In the theory of dynamical systems, a phase plane provides a visual description of how states of a system vary jointly. The classical example is the display of the trajectories of the solutions to differential equations in the plane [28]. In [27], the authors plotted historical generation (MW) and ramp (MW/min) of wind power generation data in the capacity-ramp space for various time horizons ranging from five to 60 minutes. It was observed that wind power generation and its ramp are correlated—this is seen through the slanted elliptical shape of the generation-ramp empirical point clouds shown in [27]. It was shown also in [27] that if dispatchable generation was scheduled along with adequate and sufficient flexible resources to be able to respond to a limit trajectory in the capacity-ramp plane, one would obtain adequate and even superior operating performance in comparison to classical dispatch appraches.

The goal here is to assess whether or not such an approach is also adequate for dispachable generation portfolio planning in VRE-rich power systems. We argue that the use of a worst-case capacity-ramp phase plane trajectory as a proxy for the capacity-ramping profile of VRE can remove the need to represent operational time scales in the long-term planning problem. At the same time, a representation of the capacity-ramp capabilities of candidate new power plants need to be constructed.

3.1 Phase planes for net load

To construct the capacity-ramp phase planes for net load, the first step is to compute the net load $D(t)$ from historical time series data of wind $W(t)$ and load $L(t)$ as shown in (4)

$$D(t) = L(t) - W(t) \tag{4}$$

Then, the corresponding ramp $R(t)$ is approximated using a first-order forward difference as shown in (5), where ΔT is the time period between two wind power and demand observations

$$R(t) \approx \frac{D(t+1) - D(t)}{\Delta T} \tag{5}$$

An example of this relationship is presented in Figure 1 for different shares of wind energy.

With this information, the planner has to determine the limit trajectory which to be used as part of the generation planning exercise. For example, the limit trajectory could be set to the largest observed ramp for different capacity levels, which themselves have to lie within $\pm 3\sigma$ of the historical ramp observations, where σ is the standard deviation of the empirical distribution of observed ramps. More or less conservative limit trajectories can be obtained by increasing the range of allowable ramps (going under $\pm 3\sigma$ for less conservative results or over $\pm 3\sigma$ for more demanding planning outcomes). The value of the spread of VRE ramps will impact the planning outcomes in terms of expected energy not served (EENS), expected energy curtailed and operational costs. The use of a larger range of σ can result in overestimation of generation capacity resulting in higher cost of investment and lower probability of load shedding and generation curtailment. On the other hand, a lower range of σ could result in a higher probability of load shedding and generation curtailment during high ramp events, yet with lower investment requirements.

3.2 Phase planes for power flexibility resources

The capacity-ramp dynamics of a dispatchable power system resource can be modeled as a first-order linear time-invariant system, relating the state variables $g(t)$, representing its power output at time t (MW), and $dg(t)/dt$, representing the resource ramp rate at time t (MW/min).

$$\tau \frac{dg(t)}{dt} + g(t) = F(t) \tag{6}$$
$$0 \leq F(t) \leq x \tag{7}$$

The forcing term $F(t)$ represents the resource's dispatch instruction at time t, which is bounded by the resource capacity x in megawatts, and the time constant τ indicates the response time of the unit to dispatch instruction changes. The limit ramping dynamics of the resource are obtained from its maximum and minimum capacity contingent on the current value of the power output as shown in (8) and (9)

$$r^{\uparrow} = \frac{dg(t)^{\uparrow}}{dt} = \frac{x - g(t)}{\tau} \tag{8}$$
$$r^{\downarrow} = \frac{dg(t)^{\downarrow}}{dt} = \frac{-g(t)}{\tau} \tag{9}$$

Using these, limit phase plane for flexible resources are constructed as shown in Figure 2. The approach described here applies primarily to conventional (thermal or hydro) dispatchable generation.

The red and yellow lines represent the maximum upward and maximum downward flexibility limits achievable for a dispachable generating unit. At any given operating point $g(t)$, the available ramping capacity in both directions is dependent on the time constant of the unit and unit capacity limits. For example, natural gas-fired plants tend to have low time constant and are fast acting. Therefore, they are deemed more flexible than other technologies like coal-fired generators, which have longer time constants.

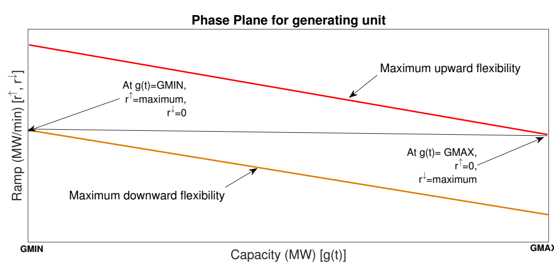

Figure 2: Phase plane for a dispatchable generating unit.

4 Problem formulation using phase planes

4.1 Concept

We now formulate the low-computation cost long-term capacity planning which considers short-term intra-hour operational dynamics through capacity-ramp phase planes explained in Section 3. The underlying idea is to ensure that the aggregate phase plane of capacity and ramp installed dispatchable generating units is able to cover the capacity-ramp phase plane of net load, as shown in Figure 3.

To start, the planner has to discretize the capacity dimension of the net load phase plane into I number of discrete intervals, which may or may not be of the same size. From the limit trajectory obtained with the phase plane of the net load, we obtain an upward, $R_i^{\uparrow}$, and a downward $R_i^{\downarrow}$, ramp requirement (MW/min) corresponding to each interval i of net load D_i (black dots in Figure 3). For each interval i, the planner has to install sufficient capacity to at least satisfy the net load *and* the associated ramp requirements (upward, $R_i^{\uparrow}$, and downward, $R_i^{\downarrow}$).

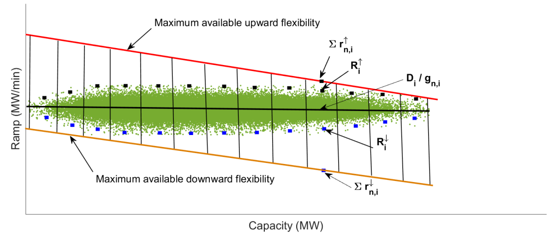

Figure 3: Phase plane matching for net load and planned generation.

4.2 Problem formulation

The planner has at their disposal a catalog of $n = 1, \ldots, N$ possible resources. Each catalog item n has a maximum capacity G_n, a ramping time constant τ_n, as well as capital and incremental operational costs of C_n^{cap} and C_n^{inc}, respectively. The planner selects out of this catalog to satisfy the capacity-ramp phase plane requirements in all capacity intervals $i = 1, \ldots, I$, as explained above. The mathematical optimization problem corresponding to this flexible resource planning approach is formulated as

$$\begin{aligned}\min_{x_n, g_{n,i}, r^{\uparrow}_{n,i}, r^{\downarrow}_{n,i}, l_i, c_i} & \sum_{n=1}^{N} [C_n^{cap} x_n] \\ & + \sum_{n=1}^{N} \sum_{i=1}^{I} Q_i C_n^{inc} g_{n,i} \\ & + \sum_{n=1}^{N} \sum_{i=1}^{I} Q_i \alpha_n (r^{\uparrow}_{n,i} - r^{\downarrow}_{n,i}) \Delta T \\ & + \sum_{i=1}^{I} Q_i (\beta l_i + \gamma c_i) \end{aligned} \tag{10}$$

subject to

$$\sum_{n=1}^{N} g_{n,i} = D_i + l_i - c_i \qquad \forall i \tag{11}$$

$$0 \leq g_{n,i} \leq x_n \qquad \forall i, n \tag{12}$$

$$x_n = z_n G_n \qquad \forall n \tag{13}$$

$$r^{\uparrow}_{n,i} = \frac{x_n - g_{n,i}}{\tau_n} \qquad \forall i, n \tag{14}$$

$$r^{\downarrow}_{n,i} = \frac{-g_{n,i}}{\tau_n} \qquad \forall i, n \tag{15}$$

$$\sum_{n=1}^{N} r^{\uparrow}_{n,i} \geq R^{\uparrow}_i \qquad \forall i \tag{16}$$

$$\sum_{n=1}^{N} r^{\downarrow}_{n,i} \leq R^{\downarrow}_i \qquad \forall i \tag{17}$$

The objective of this optimization problem, as shown in (10), is to minimize the annualized cost of investment in new technologies, their operating cost, the cost of flexibility (ramping) and the cost of load shedding and generation curtailment. The operating, flexibility, load shedding and generation curtailment costs are expressed in annualized basis through the factors Q_i, which represent the number of times the net load capacity falls into interval i based on historical records or forecasts. This allows for a fair comparison of capital and operating costs. Based on [29], the cost of flexibility accounts for the incremental wear and tear incurred during ramping processes.

Table 1: Parameters of potential new generation assets.

n	Type	Min. (MW)	Max. (MW)	Ramp (MW/min)	Incremental cost ($/MWh)	Capital cost (k$)	No-load cost ($)	Start-up cost ($)	Min. up time (h)	Min. down time (h)
1	Fossil_Oil_1	2.4	12	1.8	26.07	214.4	24	68	1	1
2	Fossil_Oil_1	2.4	12.1	1.9	26.08	214.4	24	68	1	1
3	Fossil_Oil_1	2.4	12.2	2	26.09	214.4	24	68	1	1
4	Fossil_Oil_1	2.4	12.3	2.1	26.1	214.4	24	68	1	1
5	Fossil_Oil_1	2.4	12.4	2.2	26.11	214.4	24	68	1	1
6-7	Combustible_Oil_1	4	20	1.5	37.97	272.7	117.3	5	1	1
8-9	Fossil_Coal_1	15.2	76	1.65	14.48	2923.5	76.4	656	3	2
10	Fossil_Oil_2	25	100	1.23	19.09	1786.7	210.1	566	4	2
11-13	Fossil_Coal_2	54.2	155	1.5	11.97	5962.3	120.7	1048	5	3
14-15	Fossil_Oil_3	69	197	1.3	23.91	3519.7	239.2	775	5	4
16	Fossil_Coal_3	140	350	1.8	11.83	13,463.3	132.1	4468	8	5
17	Nuclear_1	100	400	2	8.46	21,170.0	221.2	0	8	5

Constaint (11) presents the basic power balance, that ensures that the capacity requirement of the net load in each interval i is met by the total generation from the generating units that being planned; failing to do so, load shedding and generation curtailment can be used as last resort resources. Equations (16) and (17) ensure fulfillment of flexibility requirements for each interval. Generation limits are defined in (12), and interval-based unit-specific ramping contributions are set in (14) and (15). A binary decision variable is introduced in (13) for each new potential generating unit. If $z_n = 1$ that generating unit is introduced in the generation mix, otherwise it is not when $z_n = 0$.

5 Case Study

In this Section, we compare our flexible generation mix planning approach to that of Kirschen et al. [22] on an adapted version of the IEEE Reliability Test System (RTS-96) [30] and wind and load data for Ireland. The catalog of available conventional generation technologies is shown in Table 1, and offers the planner a total of 17 options. The unit time constants τ_n necessary in the proposed formulation are estimated by dividing the maximum capacity by the unit linear ramp rate. Other operational parameters, including no-load cost, start-up cost and minimum up- and downtime are not used for generation mix optimization; however, these will be used to compare the operational performance of the planning results provided by both approaches.

An important aspect of the proposed approach is that it includes operational timescales within a long-term planning problem formulation. In testing the proposed approach, the net load capacity-ramp phase plane is obtained from a full year of five-minute historical wind and load data gathered from the Irish power system. In the case of Kirschen et al., we use the same data sets, from which we sampled five representative weeks of net load. Moreover, in the case of Kirschen et al., the net load time series have an hourly time step, as used in their paper.

The peak value of the net load is 900 MW when the wind penetration is 0%. The value of lost load β is taken to be equal to $10,000 per MWh, while the value of generation curtailment is $1,000 per MWh, and ramping cost α_n is assumed to be equal to one hundredth of a unit's incremental cost of production. Two scenarios are examined, namely Scenario I with 0% of wind generation capacity and Scenario II with 30% wind generation capacity.

Finally, both approaches are formulated as mixed integer linear programming (MILP) problems and implemented in GAMS, and solved using CPLEX. The solution optimality gap is set to 1 %. The computer used for this purpose is a Windows machine with an Intel Xeon processor and 32 GB of RAM.

Table 2: Generation portfolios for Kirschen et al.'s and proposed approaches.

Selected units n		
Scenario	Kirschen et al.	Proposed approach
I	8, 9, 11, 12, 13, 14, 15, 17 (inst. cap. 1411 MW)	2, 4, 5, 11, 12, 16, 17 (inst. cap. 1097 MW)
II	1, 2, 6, 8, 11, 12, 13, 14, 15, 17 (inst. cap. 1379 MW)	1, 2, 3, 4, 5, 11, 12, 13, 16, 17 (inst. cap. 1276 MW)

Table 3: Investment costs for Kirschen et al.'s and proposed approaches.

Total investment cost (M$)			
Scenario	Kirschen et al.	Proposed approach	Difference (%)
I	94.34	85.75	9.10
II	90.30	97.36	–7.81

5.1 Results of Kirschen et al.'s approach

The generation portfolio planned by applying Kirschen et al.'s approach is shown in Table 2. The resulting total cost of investment is shown in Table 3.

It is pertinent to mention is that Kirschen et al.'s approach is computationally very demanding, and as the size of the generation unit catalog increases it becomes computationally intractable. The 17 generating unit catalog considered here was the largest one that could be solved for using our computing resources. This situation emerges despite the fact that their approach includes hourly, rather than five-minute operational dynamics, and operational planning horizons of 840 representative hours instead of the full yearly 8760 hours. Our approach addresses this issue, and we present its results in the following section.

5.2 Results of the proposed approach

Before applying our approach, the net load capacity-ramp phase plane is computed with a sampling time $\Delta T = 5$ minutes. The data points that lie within $\pm 3\sigma$ of the observed ramping range are considered, as shown in Figure 1. The capacity axis is discretized into $I = 100$ intervals, and Q_i are calculated for all intervals. The investment decision results for both scenarios are shown in Table 2, and the resulting total investment costs are shown in Table 3.

We notice that the proposed approach tends to install less total dispatchable generation capacity (total megawatts) than Kirschen et al.'s. One important feature to observe in the case of Scenario II is that by installing units $n = \{3, 4, 5\}$ the proposed approach gets 36.6 MW of installed capacity with 6.3 MW/min of ramping capacity. On the other hand, the baseline approach installs $n = \{6, 8\}$ for 96 MW and for a ramping capacity of 3.15 MW/min only. Clearly here, the more explicit need for flexibility in our proposal is well-reflected in the unit selections; the units at the margin are smaller and allow for finer-grain balancing and more ramp provision. We see, nonetheless, that the capital investment cost in Scenario II for our approach is larger than Kirschen et al.'s. This is explainable by the fact that unit $n = 16$, which has a very large investment cost, is selected in lieu of unit $n = 15$, which has a lower installation cost. The proposed approach is selecting $n = 16$ here because it is significantly cheaper to run than unit $n = 15$. Since Kirschen et al.'s approach only captures 840 hours out of the full 8760 in a year (9.6%) the significant differences in running costs between $n = 15$ and $n = 16$ are just not captured. This highlights further the appeal of our approach, which is able to represent year-long hour-by-hour operations.

The computational time needed for the solution of our proposed long-term planning approach is only 0.13 s of CPLEX time making it computationally very efficient. Even if the size of the unit catalog is increased, it still remains computationally very effective because the problem size here only grow with N, unlike in Kirschen et al. where the problem grows as N times the number of operational time periods they consider.

Figures 4 and 5 illustrate how our approach allocates generation capacity to match the net load capacity-ramp phase planes for Scenarios I and II. The selected generation portfolio meets the capacity and ramp requirement of the net load from the capacity-ramp phase planes. It can be seen that generating units with low incremental cost are allocated to a larger number of intervals, and more flexible generators are allocated only when the ramp requirement is higher. This is in line with the classical categorization of power plants based on the type of load they serve—baseload, intermediate and peak, but also with sufficient flexibility to capture the relevant aspects driven by increased share of renewable energy.

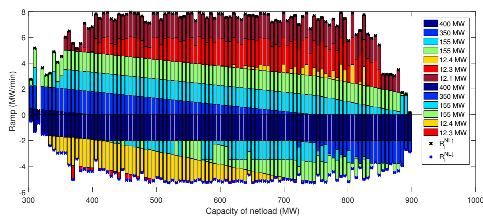

Figure 4: Phase plane matching for Scenario I – wind 0%.

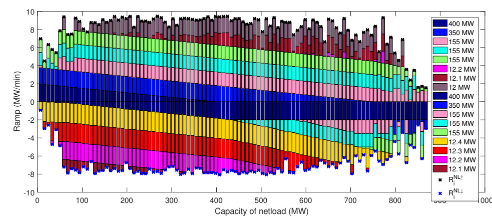

Figure 5: Phase plane matching for Scenario II – wind 30%.

Next, we compare the cost-effectiveness of both planning approaches. First, we compute the net difference in the total investment cost for Scenarios I and II. From the investment point of view, Kirschen et al.'s approach does better than our proposal in Scenario II. However, comparing only the investment costs here does not offer a full picture of the relative performances of the two approaches. The real test is to assess how the different generation portfolios fare over realistic operational scenarios.

5.3 Operations test

In this section, we run the selected portfolios over a full year of operations where units are subject to hourly unit commitment and economic dispatch every five minutes for both wind power penetration scenarios. In all cases, the objective is to minimize the sum of the production costs, start-up costs, no-load costs and the value of lost load and generation curtailment, subject to the constraints of power balance, generation limits, ramp and minimum up-time and down-time as used in [31]. The results shown in Table 4 provide the net present value (NPV) of the operational costs over a lifetime of 25 years and assuming a discount rate of 10% for both approaches.

Table 4: NPV of operational costs for Kirschen et al.'s and proposed approaches.

	NPV of operations cost (M$)		
Scenario	Kirschen et al.	Proposed approach	Difference (%)
I	5276.84	5227.13	0.94
II	3571.58	3512.52	1.65

The results in Table 4 show that the cost of running the generation mix obtained from Kirschen et al. is higher than our proposed approach. Nonetheless, to understand which approach is more cost effective, it is crucial to calculate the difference in the total net present cost, which is the sum of the net present operation cost and investment cost over a lifespan of 25 years. Tables 3 and 4 show that the difference in the total net present cost for Kirschen et al. over our proposal comes up short in both scenarios.

As can be seen from the results in Table 5, the difference in the total cost is positive for both the scenarios, which means that the total cost is lower for our approach as compared to Kirschen et al. approach. In the case of Scenario I, the generation portfolio is flexible enough to meet the variability

Table 5: Difference in total net present costs.

	Total costs (M$)		
Scenario	Kirschen et al.	Proposed approach	Difference (%)
I	5371.18	5312.88	1.08
II	3661.88	3609.88	1.42

needs of the system with zero wind share, which is validated by the lower value of both the investment and the operation cost. In Scenario II, when the share of wind energy reaches 30%, the flexibility needs of the system increases; therefore, our approach invests in more expensive, but flexible, generating units. This increase in investment cost is compensated by lower value of operation cost.

Our proposed approach is more cost effective than Kirschen et al.'s approach, but it is equally important to state that this is because their approach does not foray into intra-hour flexibility dynamics because of computational intractability. This is where our approach substantiates its merit by having minimal computational needs. Their model would outperform our approach if it had sufficient and expensive computational power to capture with high enough fidelity the five minute net load dynamics. On the other hand, our approach is an approximate time-invariant version similar to a load duration curve approach [3]. The important difference being unlike our approach, a LDC approach does not consider flexibility needs of power systems with deep VRE penetrations.

5.4 Expanded generation catalog

To provide further evidence of the computational efficiency of our proposed approach, we provide another illustration running the same case study, but now with a catalog consisting a set of 55 potential conventional generator choices.[2] The investment decision results for are shown in Table 6.

Table 6: Generation portfolio found using the proposed approach—Expanded generating unit catalog.

Scenario	Selected unit capacities (MW)	Installed capacity (MW)
I	12, 12, 12, 12, 155, 400, 400	1003
II	12, 12, 12, 12, 12, 76, 400, 400	936

The generation mix selection problem took 24.8 s of CPLEX time for Scenario I (0% wind) and 9.3 s of CPLEX time for Scenario II (30% wind) to achieve a 0.001% optimality gap using an Intel i7 core machine with 8 GB of RAM. Even with a much expanded set of generating units, our approach takes little time to run. We could not compare this unit selection with Kirschen et al.'s approach for this large generating unit catalog because it was just computationally intractable.

For completeness, the total cost of operation, hourly unit commitment with sub-hourly (five minute) economic dispatch was carried out with the planned generation portfolio for Scenarios I and II. The results are shown in Table 7. Here investment and operating costs are lower than found previously—as shown in Tables 3 and 4—since the planner had a wider array of unit choices.

Table 7: Investment cost and NPV of operational costs—Expanded generating unit catalog.

Scenario	Investment cost (M$)	NPV of operation cost (M$)
I	89.28	4667.14
II	84.15	3283.26

[2]This 55-unit generator options catalog is populated by replicas of the units found in Table 1. Specifically, it contains 10 12 MW units, eight 20 MW units, eight 76 MW units, six 100 MW units, eight 155 MW units, six 197 MW units, five 350 MW units and four 400 MW units.

6 Conclusion

This paper presented a novel time-invariant approach for long-term capacity planning capable of reflecting power system flexibility needs associated with deep penetrations of variable renewable energy sources. This approach is simple and driven by empirical capacity-ramp characteristics of renewable generation. It also provides for a computationally inexpensive solution to design dispatchable generation portfolios in comparison to current state of the art approaches, which rely on high-dimensional finely-grained representations of time-domain operations. In fact, it can take into account intra-hour flexibility requirements; this is something current long-term planning approaches have not been able to address adequately so far.

Future work includes the inclusion of uncertainties in net load phase planes and in the inclusion of further renewable energy investment decisions, which themselves would contribute to modify the ramp-capacity phase planes. Moreover, the consideration of energy storage assets along with different forms of renewable energy need to be explored. To widen its scope, this approach could also be incorporated in transmission expansion planning.

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