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A Market Based Transmission Planning for HVDC Grid - Case Study of the North Sea

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***Abstract*—There is significant interest in building HVDC transmission to carry out transnational power exchange and deliver cheaper electricity from renewable energy sources which are located far from the load centers. This paper presents an approach to solve a long-term transmission planning problem for meshed VSC-HVDC grids that connect regional markets. This is in general a nonlinear non-convex large-scale optimization problem with high computational burden, partly due to the many combinations of wind and load that become possible. We developed a two-step iterative algorithm that first selects a subset of operating hours using a clustering technique, and then seeks to maximize the social welfare of all regions and minimize the investment capital of transmission infrastructure subject to technical and economic constraints. The outcome of the optimization is an optimal grid design with a topology and transmission capacities that results in congestion revenue paying off investment by the end the project's economic lifetime. Approximations are made to allow an analytical solution to the problem and demonstrate that an HVDC pricing mechanism can be consistent with an AC counterpart existing onshore. The model is used to investigate development of the offshore grid in the North Sea. Simulation results are interpreted in economic terms and show the effectiveness of our proposed two-step approach.**

***Index Terms*—Transmission expansion planning, HVDC transmission, optimization, wind energy.**

I. Introduction

STUDIES of European renewable electricity development have estimated required transmission capacities, in some cases indicating a rate of construction twice the historical rate [1]. By 2050 required transnational capacities in anticipated scenarios increase in some cases by tens of gigawatts, and both follow-up and regional studies [2], [3] indicate the need for reinforcements and new connections. Particular attention has been directed at the North Sea, where the development of offshore wind is already driving the construction of new connections from shore to sea. Visions are developing of an offshore grid facilitating the exploitation of the offshore wind resource and allowing increased trade between North Sea countries [4], [5]. Significant expansion of transmission capacity in reality can encounter technical, regulatory, social, and or legal obstacles. The economic fundamentals of consumption and generation also constrain realistic development. Appropriate choices regarding technology and line routing are necessary for proper cost optimization in actual implementation [2], [6]. Proper accounting of physical flows using impedances, rather than transport models, are key to understanding the connections between actual lines, their cost, and benefits to different regions. Inclusion of the correlation and location of actual injections can be obtained by using several periods, or even all hours of the year, in order to achieve a grid design that is adequate yet not overbuilt [4].

The pace of required development brings challenges of finance; the magnitude of capital expenditures associated with anticipated grid development have been evaluated as a strain on financial viability of the usual financiers of transmission projects, the transmission system operators of Europe [7]. Several national regulators are seeking possibilities to encourage private investment in grid projects [8]. The issue of investment is a crucial factor because that it could slow or threaten the feasibility of transmission development, and yet it is not extensively studied. Issues of repaying investment costs and equitable distribution of costs and benefits have been examined, but only using a simple transport model to balance generator and investor benefits [9], or only considering a fixed grid [10]. Acknowledging that the grid grows in stepwise increases can be a valuable element of realism to inform industry and transmission companies [11]. For expansion planning, a formulation where the line capacities are free to change is key to discovering alternate possibilities that can reward both society and investors.

This paper presents a transmission expansion planning framework whose formulation includes investment recovery through congestion revenue as an implicit strict equality constraint, and allows the consideration of multiple time periods. The framework is intended to be driven by market historical data in the form of hourly regional cost curves. Automatic transformation and clustering is performed to select a subset of hourly samples. The number of samples in the subset, as well as their initial values, are adjusted heuristically in order to match its flow-induced revenues to that of the full sample set. The framework thus balances the need for reasonable computation times against the benefits of a model that allows multiple time periods, maintains an analytical structure, and respects voltage constraints and Kirchhoff's laws. The framework determines the topology, transmission capacities and the power flow of the offshore grid and the resulting distribution of social welfare (defined as benefit of consumption minus cost of generation of each region). By combining both grid and investment recovery constraints and working from market data,

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the framework may deliver useful results that demonstrate how the optimal grid design is not necessarily the least expensive one. As an example, information about the North Sea is processed in a case study at the end of the paper.

II. Methodology

Recent advances in HVDC converter technology and physical limitations of HVAC have triggered interest among system planners to explore widespread application of HVDC for large-scale long distance transmission, including in offshore environments. Many in-depth investigations of transmission planning for AC networks can be found in the literature [12]–[15]. However, HVDC network planning and its integration with the HVAC counterpart requires further development. In our previous work we introduced a Socially Optimal Static Transmission Expansion Planning (STEP) framework for designing a meshed VSC-HVDC offshore grid [16]. We now present an improved weighted formulation of the framework that takes into account the probability of occurrence of various system states. Since forming the optimization problem based on the actual HVDC power flow is too complex, an approximation of the branch flows is used. Finally, an iterative process to make the optimization framework applicable to large-scale real world problems is introduced.

A. Assumptions

In this work, electricity markets are assumed to be perfectly competitive. We use a zonal market model, where the aggregated supply and demand bidding curves of each onshore zone are linear functions of the power generation/consumption of that zone. Only maximum and minimum import and export power constraints per zone are enforced. No inter-temporal constraints on generation are considered. Intra-zonal transmission constraints are neglected. Infrastructure costs are assumed linearly dependent on length and rated capacity of the cables. Finally in the investment model we do not take the impact of discount, inflation and variable interest rates into account.

B. Static Transmission Planning Problem (STEP)

Let us consider a power system with n_b nodes. Each node represents a price zone with a single clearing price double-sided auction market. During its economic lifetime, the zones interconnected by an offshore grid will experience different market conditions. Each operating state t has the nominal duration of one hour. The contribution of zone i to power flows over all interconnectors is entirely captured via the net power injection of that zone into the rest of the system, defined as $P_i^t = P_{G_i}^t - P_{D_i}^t$ and is positive if zone i has generation surplus (i.e. is an exporter), and negative otherwise.

We define incremental social cost (SC_i^t) of each zone i during hour t as cost of generation $C(P_{G_i}^t)$ minus benefit of consumption $B(P_{D_i}^t)$ [17], [18]. The contribution of each zone in the total social welfare is the opposite of the social cost $(SW_i^t = -SC_i^t)$ and is a function of the power injection of that node:

$$SC_i^t = a_i^t \cdot P_i^{t^2} + b_i^t \cdot P_i^t + c_i^t \tag{1}$$

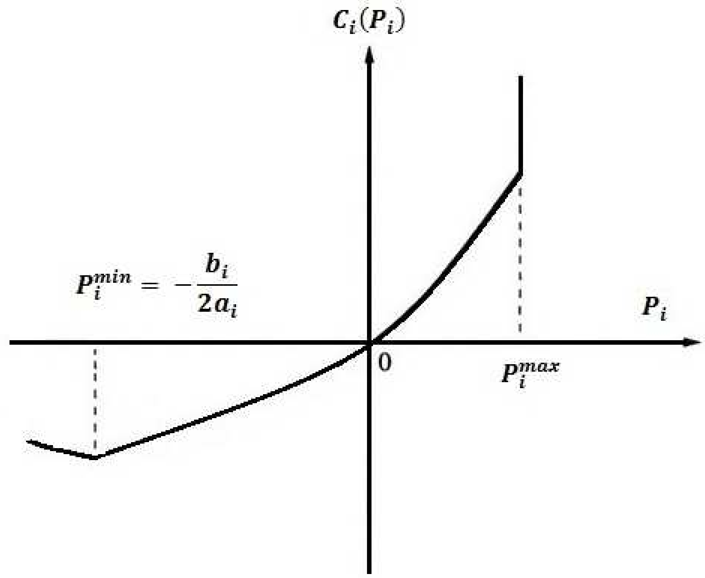

Fig. 1. An incremental typical social cost curve. P_i^{min} and P_i^{max} present minimum and maximum power that region i can inject during operating hour t

where a_i^t, b_i^t and c_i^t are the cost curve coefficients and determined from integrating the area beneath the linearly approximated supply and demand curves for each operating state t. For our research, we are interested in variations of social welfare. As the solution of optimal power flow does not depend on fixed social cost we exclude c_i^t from cost curve formulation. Hence we define the incremental social welfare of zone i at hour t as $C_i^t = a_i^t \cdot P_i^{t^2} + b_i^t \cdot P_i^t$ presented in Fig. 1. The aggregated incremental social welfare of all regions reads as:

$$\Phi = -\sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} C_i^t \cdot \omega^t \cdot n(\mathcal{O}) \tag{2}$$

where n_b is the number of price zones in the power system. $\mathcal{O}$ is the set of operating states analyzed. $n(\mathcal{O})$ is the number of members of $\mathcal{O}$. A vector ω^t indicates the influence of the each operating state in $\mathcal{O}$, with $\omega^t \in (0,1]$. The vector ω^t is a normalized weighting factor : $\sum_{t \in \mathcal{O}} \omega^t = 1$, and allows the option of using a set of representative states as will be demonstrated in Section II-D. If all hours in the economic lifetime were considered, every value of ω^t would equal $\frac{1}{n(\mathcal{O})}$. For zone $i = 1, 2, ..., n_b$, if F_{ij}^t denotes the power flow through one monopole of the interconnector $i-j$ at time t leaving the sending end, the net power injection of zone i into the system equals:

$$P_i^t = \sum_{j=1}^{n_b} F_{ij}^t = P_{G_i}^t - P_{D_i}^t. \tag{3}$$

We assume that the interconnector between node i and j is composed of a number N_{ij} of identical parallel cables, each with conductance g_{ij}. Hence the power flow over one pole of the interconnector $i-j$ during operating hour t reads as:

$$F_{ij}^t = N_{ij} \cdot g_{ij} \cdot [(v_i^t)^2 - v_i^t \cdot v_j^t] \tag{4}$$

where v_i^t and v_j^t are per pole line-to-ground voltage of dc converters at each end of the bipolar interconnector. Due to operating limits, the dc voltage of the converters is bound between 0.9 and 1.1 p.u. As power flow of each dc line is precisely controlled through voltage control of the converters, nodal voltages are considered independent decision variables. In order to include the impact of capacity rating on cable conductance and so on the grid design, the number of parallel lines the interconnector $i{-}j$ is made of N_{ij} is introduced as the second class of decision variable. Next, L_{ij} represents length of the interconnector (in km) and $k_{inv,ij}$ denotes the unit cost (in $Euro/MW \cdot km$) of transmission for interconnection $i-j$ where $i,j = 1, ..., n_b$. Capacity of each interconnector is $N_{ij} \cdot K_{base}$ where K_{base} (MW) is the monopole rated capacity for each of the parallel cables. The total investment cost of building the offshore grid reads as:

$$\Psi = \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \frac{k_{inv,ij} \cdot L_{ij} \cdot N_{ij} \cdot 2 \cdot K_{base}}{2}. \tag{5}$$

The optimization problem is to choose the network topology (N_{ij}) and voltages (v_i^t) such that the resulting zonal injections P_i^t will ensure the electricity supply and demand balance for all zones while minimizing social cost (2) and investments (5) subject to physical and technical constraints (6)-(12) of transmission and generation. It takes on the form:

$$\max_{(v_i^t, N_{ij})} \ \Omega = \Phi - \Psi \tag{6}$$

subject to

$$v_i^{min} \le v_i^t \le v_i^{max}, \qquad \forall i, t \in \mathcal{O} \tag{7}$$

$$P_i^{min} \le P_i^t \le P_i^{max}, \qquad \forall i, t \in \mathcal{O} \tag{8}$$

$$F_{ij}^t = g_{ij} \cdot [(v_i^t)^2 - v_i^t \cdot v_j^t] \le K_{base}, \qquad \forall i, j, t \in \mathcal{O} \tag{9}$$

$$N_{ij} \ge 0, \qquad \forall i, j \tag{10}$$

$$\sum_{i=1}^{n_b} P_i^t - P_L^t = 0, \qquad t \in \mathcal{O} \tag{11}$$

$$P_i^t = \sum_{j=1}^{n_b} F_{ij}^t = P_{G_i}^t - P_{D_i}^t, \qquad \forall i, t \in \mathcal{O} \tag{12}$$

where (7) and (8) are nodal voltage and power injection constraints, respectively and $P_i^{min} \le 0 \le P_i^{max}$. Equation (9) limits the power flow of each interconnector to its maximum capacity. Equation (10) enforces the number of lines to be a positive real number. P_L^t represents total transmission power losses and (11) enforces the real power balance. This is a non-linear non-convex optimization problem. The Lagrangian $(\mathcal{L})$ correspondingly reads as:

$$\begin{aligned}
&\mathcal{L}(v_i^t, N_{ij}) = \Omega(v_i^t, N_{ij}) \\
&+ \sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \mu_{ij}^t \cdot (K_{base} - g_{ij} \cdot [(v_i^t)^2 - v_i^t \cdot v_j^t]) \cdot \omega^t \cdot n(\mathcal{O}) \\
&+ \sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} \alpha_i^t \cdot (P_i^{max} - P_i^t) \cdot \omega^t \cdot n(\mathcal{O}) \\
&+ \sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} \beta_i^t \cdot (P_i^t - P_i^{min}) \cdot \omega^t \cdot n(\mathcal{O}) \\
&+ \sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} \gamma_i^t \cdot (v_i^{max} - v_i^t) \cdot \omega^t \cdot n(\mathcal{O}) \\
&+ \sum_{t \in \mathcal{O}} \sum_{i=1}^{n_b} \epsilon_i^t \cdot (v_i^t - v_i^{min}) \cdot \omega^t \cdot n(\mathcal{O}) \\
&+ \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \xi_{ij} \cdot N_{ij} \\
&+ \sum_{t \in \mathcal{O}} \lambda^t \cdot \left[\sum_{i=1}^{n_b} P_i^t - P_L^t \right] \cdot \omega^t \cdot n(\mathcal{O})
\end{aligned} \tag{13}$$

The Karush-Kuhn-Tucker (K.K.T.) optimality conditions state that any set of v_i^t , N_{ij} that satisfies the constraints (7) - (12) is a local solution to the problem (6) if and only if there exists a set of non-negative Lagrangian multipliers μ_{ij}^t, α_i^t, β_i^t, γ_i^t, ϵ_i^t, λ^t, ξ_{ij} such that multipliers associated with inactive constraints are zero and also derivatives of the Lagrangian with respect to the two decision variables are zero, i.e., $\frac{\partial \mathcal{L}}{\partial v_i^t} = 0$ and $\frac{\partial \mathcal{L}}{\partial N_{ij}} = 0$ $\forall i, j, t$.

C. Analytical solution

1) Full HVDC power flow: The analytical solution to the optimization problem gives the pricing mechanism. This is a relation between hourly zonal prices, power flows of all interconnectors and associated congestion revenues. An ideal pricing mechanism is one in which the power injections P_i^t are only a function of nodal price difference. Solving the optimization problem using actual HVDC power flows as in (9) and limiting the analysis to the case where voltage constraints are not binding gives the pricing mechanism as follows:

$$\begin{aligned}
&\sum_{j=1}^{n_b} g_{ij} \cdot N_{ij} \cdot \left[v_j^t \cdot (\rho_j^t + \alpha_j^t - \beta_j^t) - (2 \cdot v_i^t - v_j^t) \cdot (\rho_i^t + \alpha_i^t - \beta_i^t) \right] \\
&= \sum_{j=1}^{n_b} g_{ij} \cdot \left[\mu_{ij}^t \cdot (2 \cdot v_i^t - v_j^t) - \mu_{ji}^t \cdot v_j^t) \right]
\end{aligned} \tag{14}$$

where μ_{ij}^t and μ_{ji}^t are Lagrangian multipliers associated with interconnector $i-j$ and are strictly positive at line capacity. α_i^t and β_i^t are Lagrangian multipliers associated with maximum/minimum power injections of each node. Schweppe et al. [19], defined short term marginal cost of power injection of node i at hour t: $\rho_i^t = \frac{\partial(C_i^t(P_i^t))}{\partial(P_i^t)}$ as the nodal price. Equation (14) expresses the amount of power to be exchanged between zones as a function of both price and voltage magnitudes. This is not economically desired or interpretable and is not consistent with the existing pricing mechanisms [17]. In the following subsection we address this issue by approximating the HVDC power flow.

2) Linearly approximated power flow: The power flow over an HVDC line at either end can be rewritten as follows:

$$F_{ij}^t = N_{ij} \cdot g_{ij} \cdot \left[(v_i^t)^2 - v_i^t \cdot v_j^t\right] = \\ \left(\frac{N_{ij} \cdot g_{ij}}{2}\right) \cdot \left[(v_i^t)^2 - (v_j^t)^2\right] + \left(\frac{N_{ij} \cdot g_{ij}}{2}\right) \cdot \left(v_i^t - v_j^t\right)^2 \tag{15}$$

The first term on the right side of the equation expresses the power flow at the midpoint of the interconnector and the second term represents half the line losses. Losses typically amount to less than 5% of total power flows of a HVDC cable. Therefore neglecting the second term of (15) introduces no significant error to the power flow calculation and yields the HVDC power flow as:

$$F_{ij}^t \approx \left(\frac{N_{ij} \cdot g_{ij}}{2}\right) \cdot \left(w_i^t - w_j^t\right) \tag{16}$$

where $w_i^t = (v_i^t)^2$. Transmission losses are dependent on voltage magnitude and length of the cable: losses increase as length of the cable increases or operating voltage decreases. Highest transmission losses (and so approximation errors) are expected at the receiving end of the cable, when the system is operated at lowest operating voltage allowed (i.e., $0.9p.u.$ at receiving end). For a $2000MW$ $500kV$ bipolar conventional HVDC link with copper conductor of cross section of $1800mm^2$ and length of $1000km$ (the longest connection distance expected across the North Sea), approximation error at the receiving end amounts to no more than about to 2.25% of the rated power. Considering 1.1% losses for each of the two VSC converters, total approximation error amounts to less than 3.4% at each end. Note that all financial calculations carried out hereafter are based on approximated power flow (16).

3) Pricing mechanism for approximated power flow: We should eliminate equation (11) from the problem formulation as transmission losses are neglected from (16). Using the approximated power flow, one obtains the pricing mechanism for a meshed HVDC grid from the optimality criteria as follows:

$$\frac{\partial \mathcal{L}}{\partial w_i^t} = 0 \Longrightarrow \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} \left(\mu_{ij}^t - \mu_{ji}^t\right) \cdot K_{base} \cdot \omega^t \cdot n(\mathcal{O}) = \\ \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} F_{ij}^t \left[\left(\rho_j^t - \rho_i^t\right) + \left(\alpha_j^t - \alpha_i^t\right) - \left(\beta_j^t - \beta_i^t\right)\right] \cdot \omega^t \cdot n(\mathcal{O}) \tag{17}$$

The pricing mechanism inferred expresses the relation between amount of power to be exchanged, electricity prices in different zones and congestion revenues. By expanding ($\frac{\partial(\mathcal{L}(w_i^t, N_{ij})}{\partial(N_{ij})} = 0$), multiplying both sides by N_{ij}, then taking the sum over all nodes at all times, one encounters the condition that at the optimal grid design,

$$\sum_{t \in \mathcal{O}} R_{np,i}^t = \sum_{t \in \mathcal{O}} R_\mu^t = \sum_{t \in \mathcal{O}} R_\rho^t = \Psi \tag{18}$$

where Ψ is the total investment cost (5), and the other terms comprise total nodal payment $R_{np,i}^t$ at time t:

$$R_{np,i}^t = \sum_{i=1}^{n_b} P_i^t \cdot (\rho_i^t + \alpha_i^t - \beta_i^t) \cdot \omega^t \cdot n(\mathcal{O}) \tag{19}$$

total congestion revenue R_μ^t at time t

$$R_\mu^t = \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} (\mu_{ij}^t - \mu_{ji}^t) \cdot K_{base} \cdot \omega^t \cdot n(\mathcal{O}) \tag{20}$$

and total transmission revenue ${}_\rho^t$ at that time

$$R_\rho^t = \sum_{i=1}^{n_b} \sum_{j=1}^{n_b} F_{ij}^t \left[\left(\rho_j^t - \rho_i^t\right) + \left(\alpha_j^t - \alpha_i^t\right) - \left(\beta_j^t - \beta_i^t\right)\right] \cdot \omega^t \cdot n(\mathcal{O}) \tag{21}$$

The associated grid design and operation pattern comprised by the solution w_i^t and N_{ij} is one that establishes a balance such that the total transmission revenue generated from nodal price differences is precisely the amount paid by transmission costumers at all nodes, and also equals congestion revenues. Therefore, the grid design N_{ij} pays off its initial investment capital Ψ through the operation given by w_i^t.

D. Clustering

At least a year of market behavior (i.e., T = 8760) is required to exhibit relevant operating states. The dimensionality of the search space and the computational intensity of the optimization algorithm make the problem intractable. It is desirable to identify and work with only a subset from the total set of operating states, i.e.,

$$\mathcal{A} = \{\forall t \in [1, T]\} = \mathcal{K} \cap \mathcal{K}^{\mathcal{C}}$$

where $\mathcal{K}$ is a set of operating states whose number of members $n(\mathcal{K})$ is much smaller than the total $n(\mathcal{A})$. Clustering procedures aim to select the least number of representative samples that maintain the majority of information in the original data set intact.

In general, before clustering is carried out one has to determine if the data has any clustering tendency. For high dimension data sets (e.g., 10 features and above) it is extremely difficult to identify patterns of clusters due to curse of dimensionality. One solution to this problem is to apply a good feature transformation technique. Feature transformations are techniques that projects a feature (attribute) vector to a lower dimension space. Principal component analysis (PCA) is a popular statistical technique for unsupervised feature transformation and dimension reduction.

1) Principal Component Analysis(PCA): Consider a data set arranged in a matrix of size $n \times p$ where n is the number of observations and p is the number of relevant features. PCA transforms the original input set into another set of the same size with linearly independent variables called principal components. This conversion is carried out in such way that each successive component carries less information compared to the preceding ones. Thus the first component (column of the PCA matrix) contains the largest amount of information from the original data. One can easily calculate the information share of each component. By selecting the first few components (depending on the application), one accomplishes to reduce the dimension of the data set and make clusters more distinctive. In [20] the connection between K-means clustering and PCA is explored. It is proven that the PCA dimension reduction automatically finds the most discriminative clustered subspace.

The full set $\mathcal{A}$ contains 12 cost curve coefficients of the 6 onshore price zones and wind speed data of the 7 offshore zones. The PCA analysis shows that, out of 19 features related to the different zones, the first two components in the transformed basis contains 79% of the information in the data set.

2) K-medoids Clustering: K-means is a widely used clustering technique in various applications [21]. What makes K-means convenient for power system applications is easy implementation on large-scale data set, and high efficiency as it works directly with the data. A comprehensive review of K-means and other clustering techniques is provided in [22]. For the sake of more transparent results, this work employs K-medoids instead of K-means. In K-medoids clusters are represented by the actual median present in the data set instead of the mean value. Therefore it is more suitable for our application, as it does not produce new samples in the reduced subspace. It is more commonly used when dealing with data sets with outliers [23]. Results of K-medoids clustering depend on the chosen number of clusters and proceeds from an initial selection of a subset $\mathcal{K}^*$ of size $n(\mathcal{K}^*)$.

E. Optimal Power Flow to Validate Clustering

The purpose of this work is to devise a method that finds an optimal design for a HVDC-based meshed grid. In a market-driven transmission expansion approach, price differences resulting in congestion revenues between every two zones are a good indicator of the ability of the clustering method to capture the diversity in the original data set. We propose an iterative verification procedure that validates the results of the clustering and optimization techniques as shown in Fig. 2.

The optimization result of the STEP module (i.e., grid topology and capacities) is not expected to be severely different from the case where the original data set would be used as input, provided that the reduced-clustered data set is a good representative of the original data. To investigate the similarity, we solve the problem of round-the-year OPF for a fixed grid determined from the STEP optimization module. Here transmission topology and capacities are fixed; the OPF problem is solved by controlling the squared reference voltage value of dc converters (w_i^t). The analytical solution to the full problem

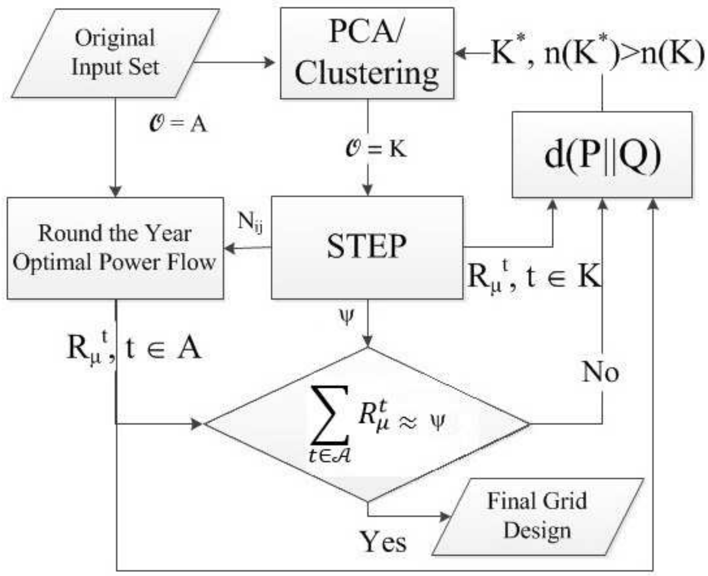

Fig. 2. Schematic diagram of proposed data driven market based transmission planning framework which shows the coordination of an iterative optimization framework and a clustering technique based on congestion revenues R_μ^t

necessitates the equality of nodal payments (19), transmission revenues (21) and congestion revenue (20). However, since the OPF is solved for a fixed grid design (number of parallel lines N_{ij} is pre-determined by the STEP block), the investment costs will not essentially equal transmission revenues. The equality of investment cost with transmission revenue holds true only if data clustering has been conducted appropriately. Only in that case, the stochastic characteristics of the operating states given to the STEP module would be similar to those given to the OPF module and so congestion revenue calculated by STEP (R_μ^t, $t \in \mathcal{K}$ which equals investment cost of building the grid Ψ) would resemble the congestion revenue calculated by OPF (R_μ^t, $t \in \mathcal{A}$). Although OPF is a non-convex problem, it is considerably easier than STEP to solve. The reason is the OPF is solved for each operating state independently, unlike the STEP where the problem is solved for all operating states in one go. Hence the size of the problem (number of independent variables to find) is significantly smaller than for STEP problem: n_b versus $n_b \cdot n(\mathcal{O}) + n_b \cdot \frac{n_b-1}{2}$.

When the congestion revenue from the OPF is not sufficiently close to the total investment Ψ, it becomes necessary to exchange or add one or more operating states from the discarded set $\mathcal{K}^{\mathcal{C}}$, likely resulting in a set $\mathcal{K}^*$ whose size $n(\mathcal{K}^*)$ is larger than $n(\mathcal{K})$, that of the original set. This new selection $\mathcal{K}^*$ is provided to the PCA/Clustering algorithm.

For the purpose of this study, the probability density function of the congestion revenues is selected as the most relevant characteristic of the system. The distribution of congestion revenues for the full set $\mathcal{A}$ of operating hours or observations may be compared against the distribution for the reduced set $\mathcal{K}$. There are several statistical divergence measures which establish a distance of one probability distribution to the other [24]. From distances used in the Jeffrey's divergence, we define the distance between the two PDFs for every congestion value m as:

$$d(P(m)||Q(m)) = ln(\frac{P(m)}{Q(m)}) \cdot (P(m) - Q(m)) \; \forall m \quad (22)$$

where P(m) and Q(m) would here be the probability distributions of congestion revenues R^t_μ over the sets $\mathcal{A}$ and $\mathcal{K}^*$, respectively and the distributions are defined over a discrete set of m congestion values. The empirical distributions are first fitted using a kernel density estimator. Low probability values cause problem at comparison if they are not excluded by a threshold. Thus, the distance measured between congestion revenue probability for an index m is set to zero, if the R^t_μ distribution for $\mathcal{K}^*$ is smaller than the lowest value of the R^t_μ distribution for $\mathcal{A}$.

The distance function (23) provides a metric to measure goodness-of-fit of the two empirical probability distribution functions (ePDF) associated with congestion revenues determined from STEP and OPF. Operating states with larger difference are the missing operating states and need to be added to the input set of the STEP module (the feedback loop in Fig. 2). The iterative procedure continues until $\sum_{t \in \mathcal{A}} R^t_\mu \approx \Psi$.

III. Numerical Results

A. Input Data

In this study, six North Sea coastal states are considered including UK, Norway, Denmark, Germany, The Netherlands and Belgium. Except UK, each state is modeled with one onshore and one offshore price zone. UK is broken in two onshore and two offshore price zones for two reasons. The strong West-East wind pattern exists in the North Sea [5] and large offshore wind capacities UK is planning to install in the next coming years and the huge impact it will have on the rest of the system. Information about all existing and planned wind farms were gathered from an online database provided by the marine consultancy firm 4COffshore [25]. For 2025 this includes a total installed capacity of about 47.8 GW distinguished as 7 offshore zones in Fig. 3. The equivalent multi-turbine power curve of each offshore park is determined as in [26] taking into account the statistical properties of the given offshore location. A generic wind turbine is considered for all offshore locations with cut-in and cut out speeds of 3 m/s and 25 m/s, respectively. All simulations are carried out hourly, based on wind speed data from the year 1994, simulated at 120 m above sea level with spatial resolution of 9 km $\times$ 9 km (Sander + Partner, Switzerland). Cost curve coefficients are determined hourly from empirical aggregated supply/demand curves of onshore electricity markets (i.e., APX-NL, APX-UK [27], NordPoolSpot [28], EPEXSpot [29] and Belpex [30]) from April 1, 2011 to March 30, 2012 (8760 data points) as outlined under II-B. Note social cost curve of offshore wind farms are determined from short term marginal cost of power generation and so it is zero.

B. Assumptions and justifications

Currently trades via power exchanges constitute a small portion of the total power transactions of the onshore zones. The

TABLE I
Annualized Average Cost curve coefficient a of each onshore zone before and after adjustment

Country	DE	NL	NO	DK	BE	UKN	UKS
Before	0.0022	0.0071	0.0020	0.0020	0.0425	0.0066	0.0066
New	0.0015	0.0014	0.0013	0.0013	0.0077	0.0005	0.0005

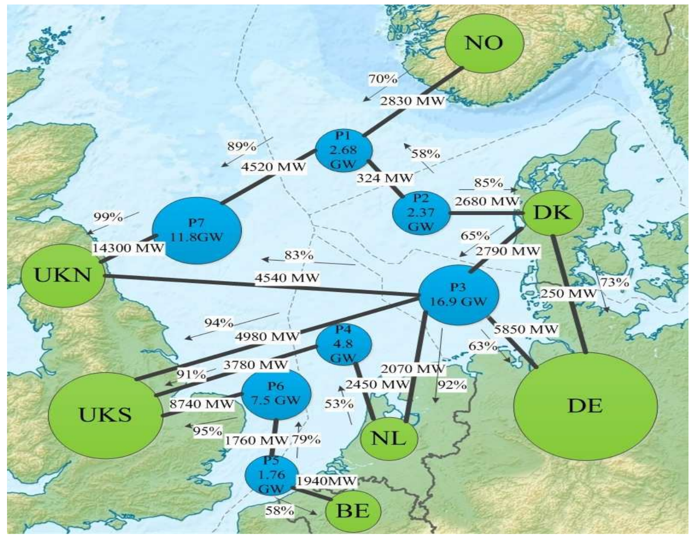

Fig. 3. Modified optimal grid design. Numbers in MW present capacity of interconnectors and offshore wind farms. Numbered arrows show frequency of power flows over each line in the dominant direction

cost curve coefficients derived from today's market data, do not account for all capacity onshore regions have for offshore wind feed-in. Thus determining the optimal grid design using today's data results in under investment. In addition, the short term marginal price of every onshore region becomes negative at $P_i^{min} = \frac{-b_i^t}{2 \cdot a_i^t}$ (in Fig. 1) and causes social welfare loss. To avoid these negative impacts, the a_i^t cost curve coefficient of every onshore zones is adjusted in such a way that P_i^{min} always remains larger than or equal to the available offshore wind capacity of that zone for all the hours. The adjustment is carried out based on two aspects: the share from total power trades that are settled through the power exchange and the capability for wind feed-in of the onshore zone in relation to the installed capacity of its respective offshore wind farm. The a coefficient is depreciated more for small markets (e.g, Belgium) or markets with a small share of power exchange in total power trades (e.g, UK). Table I presents the annualized average a coefficient for every onshore zone before and after adjustment. One may note that a is a measure of market price stability for every zone (refer to (1)). Hence by justifying a coefficient as outlined above, we implicitly assume that onshore markets will be highly liquid with stable prices which is less sensitivity to power trades at the time of operation of the offshore grid. As outlined earlier, the PCA analysis illustrates that the first two components of the reduced space contain 79% of information in the input set. Therefore it is sufficient to cluster the reduced space data set using the first two components of the PCA basis. Solving the OPF for 8760 hours is time consuming process. We reduce the size of the initial data set by separating it into 876 clusters. The clustering is carried out in such a way that impact of every operating hour of the initial data set (with 8760 hours) is preserved. From now on we refer to the 876 subspace as the "original subspace".

C. Grid Design

Table II presents the results of running the OPF for various grid designs determined by STEP for different number of clusters. The optimal design is expected to ensure investment recovery of all interconnectors. Therefore, the ratio of congestion revenue to investment cost of building the grid is considered as a measure of performance that would ideally equal one. It is obvious that investment recovery is outstandingly improved from 5.26 to 0.98 with increase in the number of clusters going through columns in Table II. Another measure of interest is the ability of the reduced set $\mathcal{K}$ to capture the full range of the congestion revenues occurring in the fall set of the operation states $\mathcal{A}$. The full set can be viewed as being split in two: $\mathcal{A} = \mathcal{B} \cap \mathcal{B}^{\mathcal{C}}$, where

$$\mathcal{B} = \{t \in \mathcal{A} : R_{\mu}^{t} < \max_{t \in \mathcal{K}} R_{\mu}^{t}\} \tag{23}$$

is the subset of operating states whose congestion revenue falls in the range of that from the reduced set. It can be seen that the iterate procedure of Fig 2 has driven the size $n(\mathcal{B})$ down to $n(\mathcal{A})$. In practice, it is not plausible to build interconnectors with small capacity. In this formulation $N_{i,j}$ is a continuous. To make the results more realistic, insignificant interconnectors with capacity less than 1 MW are eliminated from the grid. Discarding insignificant capacities may increase the deviation further from the mathematically ideal optimal design. To investigate the impact of above mentioned grid modifications on remuneration of interconnectors, the results of solving the problem of OPF for the modified optimal grid design is compared with the original result in Table III. It can be seen the money flow of the modified grid is slightly different from the original design. Fig. 3 shows the grid design obtained for $K = 16$ where congestion revenues represents 98% of the investment cost thus a reasonable approximation of a local optimum.

D. Discussion

The North Sea states do not benefit equally from the proposed grid. Table IV presents the benefit of each region as annualized Social Welfare (SW) increase in each state. It becomes clear that SW significantly increases in all regions (UK in particular) except for Norway where SW is negative. The loss of benefit takes place as Norway acts as a net electricity exporter. The grid design is observed to be sensitive to today's market prices of onshore zones, which are influenced by the trades over the existing interconnection capacities as expressed by the b coefficient. The last two rows of Table IV present the average market price (MCP) of onshore regions before and after constructing the offshore grid. Note that building the grid induces market price decrease in the net importers and the opposite in net exporters (i.e., Norway). These results are consistent with amendments made to cost curve coefficients a (representing price stability). This amendment implicitly reinforces the impact of stand-alone market price (i.e., the b coefficient) on the grid design.

TABLE II
IMPROVEMENTS IN OPTIMIZATION RESULTS FOR FIVE DIFFERENT NUMBER OF CLUSTERS- ECONOMIC LIFETIME OF 25 YEARS, ZERO INTEREST RATE. ALL NUMBERS ARE CALCULATED ON ANNUAL BASIS

Number of Clusters	8	11	13	15	16
Social welfare $\Phi(B€)$	7.86	8.35	8.18	8.45	8.42
Congestion revenues $\sum_{t \in \mathcal{O}} R_{\mu}^{t}\ (B€)$	2.64	0.72	0.92	0.51	0.59
Transmission revenues $\sum_{t \in \mathcal{O}} R_{\rho}^{t} (B€)$	2.64	0.72	0.92	0.51	0.59
Transmission investment $\Psi(B€)$	0.50	0.60	0.51	0.64	0.61
$\sum_{t \in \mathcal{O}} R_{\mu}^{t} / \Psi$	5.26	1.20	1.81	0.81	0.98
$n(\mathcal{B})/n(\mathcal{A})$	0.71	0.87	0.89	0.99	0.99

TABLE III
ANNUAL INCREMENTAL SOCIAL WELFARE, CONGESTION REVENUE (EQUALS TRANSMISSION REVENUE) AND TRANSMISSION INVESTMENT COST FOR THE ORIGINAL AND MODIFIED OPTIMAL GRID DESIGN AFTER EXCLUDING INSIGNIFICANT INTERCONNECTORS

Design	Social Welfare $\Phi(B€)$	Congestion Revenue $\sum_{t \in \mathcal{O}} R_{\mu}^{t}\ (B€)$	Investment Cost $\Psi\ (B€)$
Original	8.42	0.59	0.61
Modified	8.42	0.60	0.61

TABLE IV
ANNUAL INCREMENTAL SOCIAL WELFARE OF EACH ONSHORE ZONE AND THEIR MARGINAL MARKET PRICE (MCP) BEFORE AND AFTER BUILDING THE GRID

Country		DE	NL	NO	DK	BE	UKN	UKS
Social Welfare $\Phi(B€)$		61.5	49.1	-31.3	13.7	8	389	353
MCP $(€/MWh)$	**before**	49.4	51.1	39.0	46	48.5	56.4	56.4
	after	46.4	48.2	41.5	45.6	47.3	47.1	48.2

For each interconnector, there is an arrow indicating the dominant direction of power flow in Fig. 3. It can be seen that power flows mainly from offshore zones to onshore ones. Norway has the lowest marginal cost of generation before and after the grid is built due to large hydro reservoirs. Therefore for this country power mainly flows from shore to offshore farm P1 to P7 to UK-N. UK-N has the second highest average market price after UK-S. The high market price of the two UK zones makes them net importers of electrical energy (almost 90% of the time power flows from the rest of the system into the UK onshore zones). This phenomenon is happening due to rather stable market price behavior (small a coefficient) assigned to UK onshore zones. Hence regardless of amount of power input, market prices in both UK onshore zones remain rather high. This encourages construction of interconnectors with large capacity. Large a and b of Germany affect the country in two ways. First, it results in construction of interconnector to its own offshore zone with transmission capacity almost half of their installed offshore wind, rest being exported to the two UK zones. Second, it makes their social welfare increase an order of magnitude less than of the two UK zones.

IV. Conclusion

This paper proposed a multiple time period static transmission planning framework applicable to HVDC meshed grids. The analytical solution to the problem gives the pricing mechanism which expresses the relationship between the electricity price of different zones and the congestion charges associated with the interconnectors between them. It is shown, with no significant loss of accuracy, that linearly approximating the HVDC power flow simplifies the mechanism and makes it consistent with its existing AC onshore grid counterpart. The proposed approach computes the expansion plan under which the investment capital will be fully payed off through congestion revenues by the end of the chosen lifetime of the infrastructure. The salient feature of our approach is the use of an iterative algorithm that combines an unsupervised clustering technique with an optimization tool to cope with the large computational burden of this large-scale problem.

Various economic indicators are used to appraise the quality of the transmission expansion plan computed by the algorithm. The output of the model is observed to be highly sensitive to the quadratic and linear coefficients of the social cost curves representing respectively price stability and stand-alone zonal price. Based on the current assumptions and methodology, it can be observed that countries benefit unequally from the offshore grid. Being a winner or a loser depends on various economic, technical and geographical characteristics of the region such as market liquidity, conventional generation fleet profile and wind availability. Norway is a net exporter and the only region who loses benefit. UK benefits the most from the offshore grid, followed by Germany and the Netherlands. The offshore zone of Germany will have the largest number of interconnections and may become a major offshore energy hub in the North Sea grid.

The results of this work can support transmission system planners and private investors as they determine the most economically efficient design they should invest in. The proposed market mechanism provides an economic insight over the operation of a multi-terminal HVDC offshore grid. The future offshore grid will consist of AC and point-to-point DC connections in addition to the multi-terminal HVDC grid considered here. As future work, it is essential to enable the model to choose the capacity of these alternatives. In addition, the impact of intermediate construction delays on development of the grid and money flows ought to be investigated.

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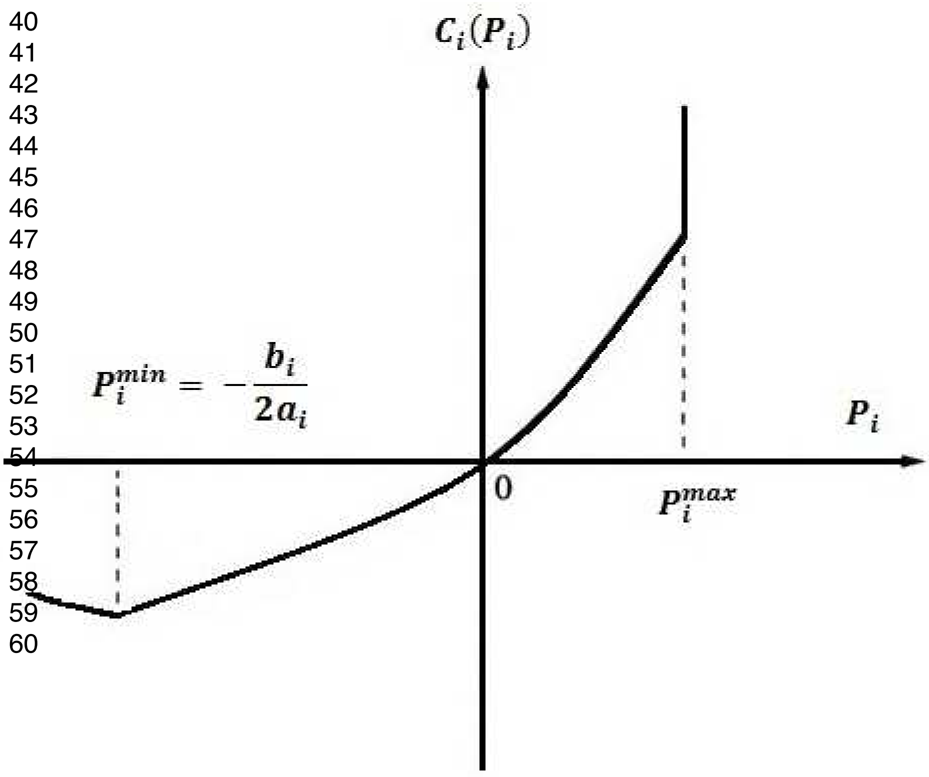
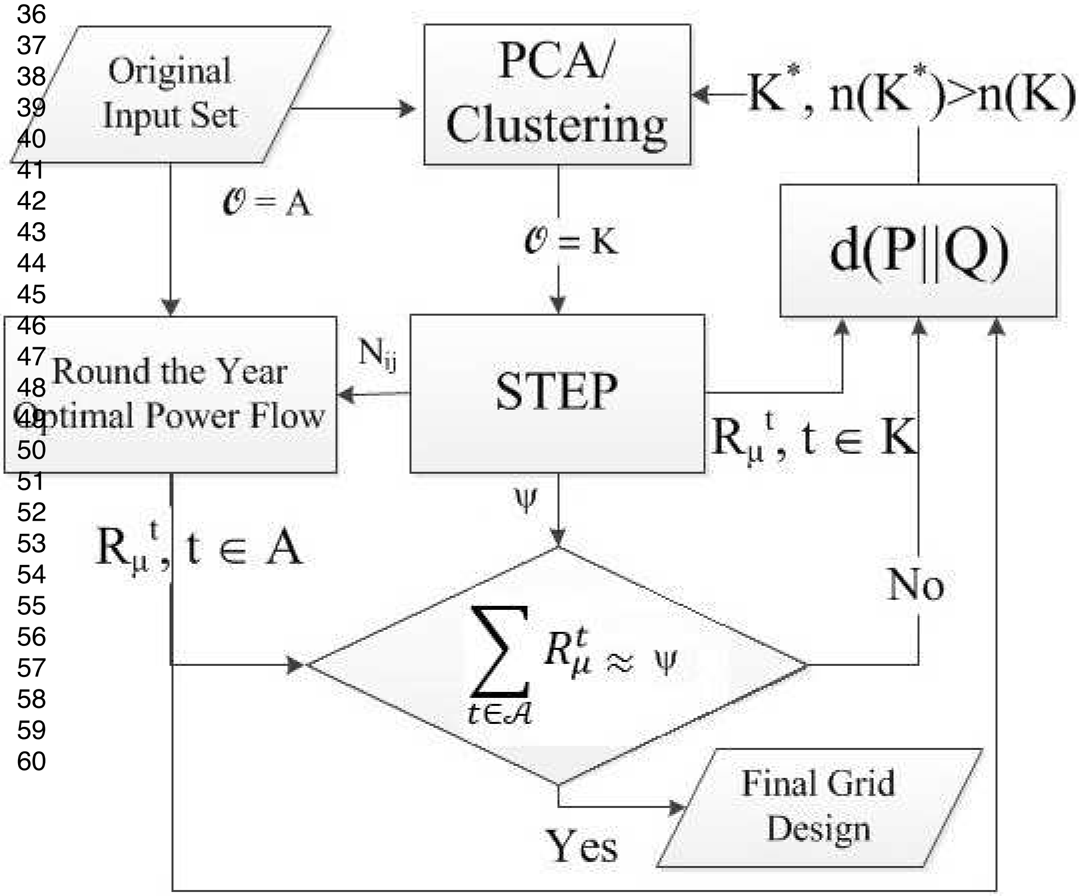
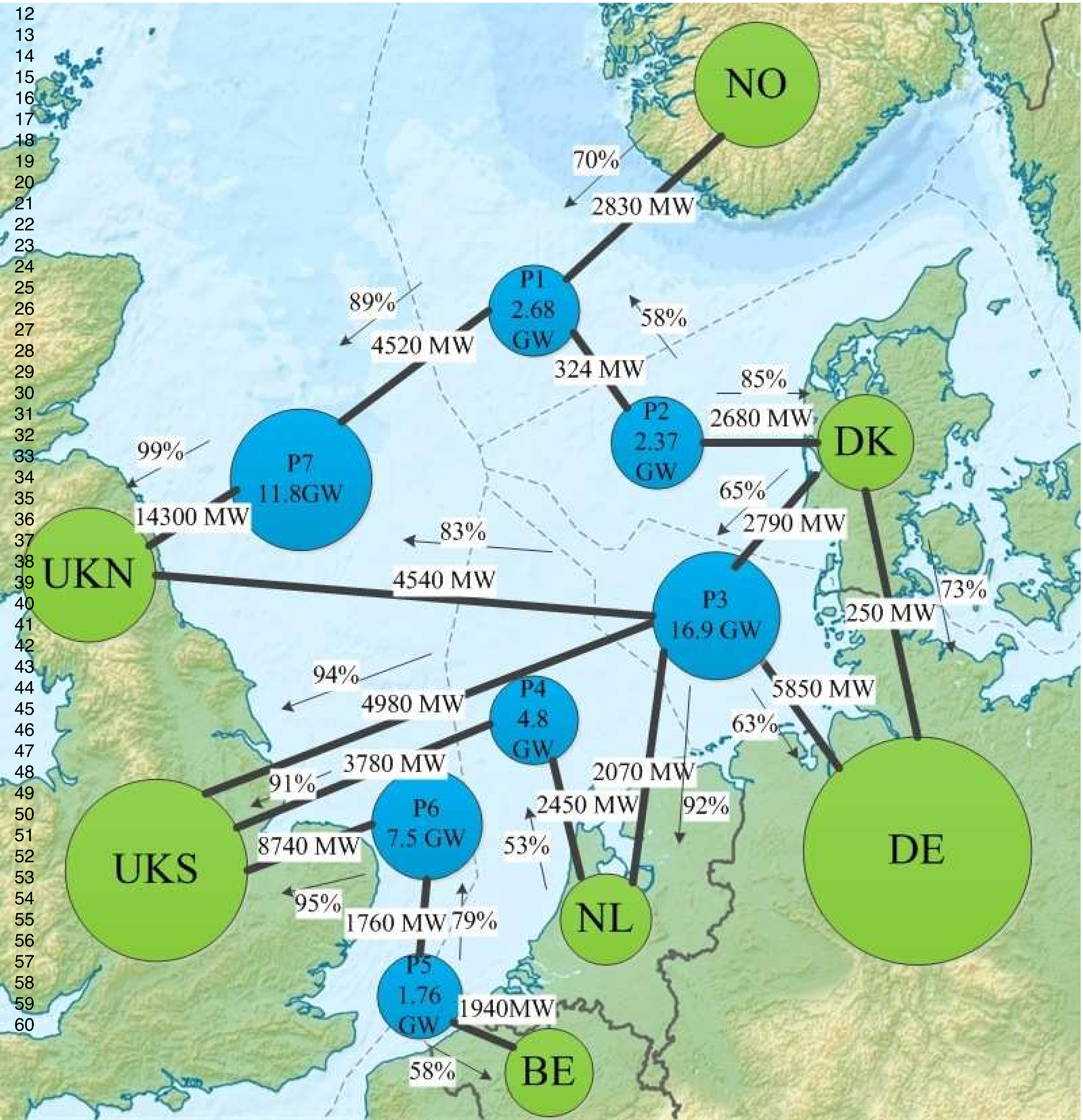


$C_i(P_i)$
$P_i^{min} = -\frac{b_i}{2a_i}$
P_i
0
P_i^{max}


Original
Input Set
PCA/
Clustering
K*, n(K*)>n(K)
𝒪 = A
𝒪 = K
d(P||Q)
Round the Year
Optimal Power Flow
N_ij
STEP
R_μ^t, t ∈ K
ψ
R_μ^t, t ∈ A
No
Σ_{t∈𝒜} R_μ^t ≈ ψ
Final Grid
Design
Yes


NO
70%
2830 MW
P1
2.68
GW
89%
4520 MW
58%
324 MW
85%
P2
2.37
GW
2680 MW
DK
99%
P7
11.8GW
14300 MW
65%
2790 MW
83%
UKN
4540 MW
P3
16.9 GW
73%
250 MW
94%
4980 MW
P4
4.8
GW
5850 MW
63%
3780 MW
91%
2070 MW
2450 MW
92%
P6
7.5 GW
UKS
8740 MW
53%
DE
95%
1760 MW
79%
NL
P5
1.76
GW
1940MW
58%
BE