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Scenario reduction, network aggregation, and DC linearisation: which simplifications matter most in operations and planning optimisation?

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Abstract: Power economic studies are challenging because of growing system sizes, the advance of smart grids, and economic, technical, and policy unknowns. Consequently, system models must be simplified so that they can be solved with many scenarios of renewable output, load, and long-run uncertainties. Scenario reduction, network aggregation, and DC linearisation are three common simplifications. The authors compare their errors and computation times for optimal power flow (OPF) and stochastic unit commitment (SUC), using the IEEE 14-, 30-, and 118-bus test systems, and also briefly discuss impacts on generation and transmission planning. The authors find that the most appropriate simplification depends on the study type, and there are no consistent results concerning which simplification is most distorting. The following example conclusions apply to these cases, but not universally; nonetheless, the findings provide information about what simplifications can matter, which is a helpful starting point for practicing modellers. The authors find that linearisation's disregarding of losses distorts total costs in OPFs, but it causes relatively little error in SUC. Scenario reduction reduces OPF computational times with little distortion but is less effective for SUC. Network aggregation decreases computation effort more than linearisation in OPF, but causes little error unless there are few scenarios.

Nomenclature

Indices

k, i	indices of buses, running from 1 to N
j	index of generators, running from 1 to G
t	index of time intervals, running from 1 to T
s	index of scenarios, running from 1 to S

Variables

k, i	indices of buses, running from 1 to N
b_i/b_j	bid of demand i/generator j
$c_{j0,1}$	cost function constants of generator j
$\mathrm{sd}_j/\mathrm{su}_j$	binary variable, equal to 1 if generator j has a shut-down/start-up, and 0 otherwise
$P_j^{\mathrm{g}}/Q_j^{\mathrm{g}}$	active/reactive power produced by generator j
$P_k^{\mathrm{g}}/Q_k^{\mathrm{g}}$	active/reactive power generation of bus k
$P_k^{\mathrm{d}}/Q_k^{\mathrm{d}}$	active/reactive power demand of bus k
u_j	binary variable, equal to 1 if generator j is on, and 0 otherwise
$V_k(t, s)$	voltage of bus k, hour t, and scenario s
EENS_k	expected energy not served for demand of bus k

Parameters

suc_j	start-up cost of generator j
$P_k^{\max}$, $P_k^{\min}$	active power generation limits at bus k
$Q_k^{\max}/Q_k^{\min}$	reactive power generation limits at bus k
VOLL_k	value of lost load for demand of bus k
$\mathrm{RR}_j^{\mathrm{Up/Down}}$	ramp rate limits for generator j
$T_{\mathrm{off},j}^{\min}/T_{\mathrm{on},j}^{\min}$	minimum off-time/on-time for generator j
$S_{ki}^{\max}$	maximum apparent power from bus k to bus i
$V_k^{\max}/V_k^{\min}$	voltage phasor limits at bus k
y_{ki}	admittance value between buses i and k
$\pi(s)$	probability of scenario s

1 Introduction

Contemporary power systems present increasingly challenging computational problems for at least two reasons. First, the size of systems to be studied has grown, so that power system planners and operators must solve increasingly large optimisation problems [1]. Causes of this growth include increased electricity demand, the proliferation of distributed generation, and tighter interconnections among electricity markets. The second reason is that short-run variability and long-run uncertainty have significantly increased [2]. One cause of this increase is the accelerating penetration of renewables such as solar and wind power and, to a lesser extent, increasingly flexible power demands due to, for instance, demand response programs [3]. These resources increase short-term forecast errors and net load variability in power systems. Meanwhile, longer term uncertainties in technology cost and performance, fuel prices, demand growth, and public policies are also important. Extensive variability and uncertainty mean that the system planners have to simulate and analyse hundreds or even thousands of scenarios. Consequently, power system studies are becoming increasingly complex, and improved methods for power system simulations, including more accurate simplifications, are needed.

This paper considers the problem of simulation and optimal planning of large-scale power systems with large numbers of scenarios, and compares three simplification methods. These methods, which are often used to deal with large systems under multiple scenarios, are (i) reducing the number of scenarios, (ii) obtaining an aggregated equivalent for the network, and (iii) simulating a simpler version of the system by relaxing or linearising some of the constraints [1, 4–12]. Each of these methods has attracted the attention of many researchers. For instance, various algorithms and selection criteria for scenario reduction are proposed and compared in [4–8]. Cheng and Overbye [1] Chang *et al.* [9] studied several procedures for aggregating a large power network in order to obtain a smaller equivalent one. Problem reformulation, such as relaxation or omission of some technical constraints, is an approximation used in other studies [10–12]. The linearised DC load flow is a common example.

Using any of these simplifications introduces some error in model results. For instance, decreased accuracy in stochastic programming resulting from considering smaller sets of scenarios is mentioned in [8]. An assessment of the usefulness and validity of DC linearisation is made in [13]. In [14, 15], the accuracy of some network aggregation methods is evaluated, and recommendations for improvement are offered. However, these diverse simplifications still need to be compared to understand which of them are most effective in reducing computation time without unacceptable error in power system simulations and decisions.

This paper addresses this need by proposing a multi-dimensional power system reduction approach involving scenario, network, and relaxation-based simplifications for economic studies of large-scale power systems with numerous renewable production and long-run scenarios. We compare the impact of each type of simplification upon (i) operating and planning decisions and (ii) estimates of their performance. This work's primary contribution is the comparison of different simplification techniques across a range of critical decision problems and several systems. That is, unlike the previous literature which has been more fragmented (focusing in depth on alternative simplification approaches for one particular modeling dimension rather than comparing across approximations), this paper makes a head-to-head comparison of these three types of simplifications. Although the conclusions of such comparisons will always to some extent be case dependent, they will be useful to illustrate how and to what extent approximations distort results of different types of studies.

The particular simplification methods we apply are as follows. First, we use forward scenario selection [7] as an example of an algorithm for selecting a limited sample from a large potential population of scenarios. Second, for network aggregation, a two-stage aggregation algorithm is used [16]. In the first stage of this algorithm, we partition the power network into a number of areas, based on a so-called similarity matrix, which shows the strength of connection between each pair of the network buses. The partitions obtained are then used to aggregate the original network. Third, we choose the DC linearisation of power flow equations to represent the problem reformulation class of simplifications.

The main focus of our comparison is on static operations and planning studies, including optimal power flow (OPF) and stochastic unit commitment (SUC). However, we also briefly consider generation expansion planning (GEP) and transmission expansion planning (TEP) problems, since power flow studies are often the basis for evaluating investments. The results of the multi-dimensional power system reduction applied to each of these studies are evaluated with respect to the effect of each simplification on the accuracy of the results and the computational time required.

The remainder of the paper is organised as follows. Section 2 reviews the three simplification methods: forward scenario selection, network aggregation, and DC linearisation. Section 3 summarises the OPF and SUC problems. Section 4 compares the effects of the three simplification methods on the mentioned analyses applied to two IEEE test systems apiece (either the 14-, 30-, or 118-bus systems). Section 5 concludes the paper.

2 Multi-dimensional system reduction methods

This section reviews the three techniques that we used to reduce the size of the operations and planning problems.

2.1 Scenario reduction: forward scenario selection

The first simplification technique is to decrease the number of simulated scenarios to consider. One important source of power system uncertainty is variability and unpredictability in generation by renewable resources, such as wind and solar power [2]. In addition, the response of system loads to electricity price variations increases uncertainties in net loads [3]. The number of scenarios that need to be used to capture these uncertainties has been growing as renewables and demand response has become a more important part of the resource mix. The objective of scenario reduction is to select a smaller subset of scenarios that will still satisfactorily represent the covariation of net loads over space and time.

Several approaches can be used to decrease the number of scenarios. Examples are: backward scenario reduction, forward scenario selection, scenario tree construction, and clustering-based scenario reduction [4–8]. We choose forward scenario selection as a practical representative of this class of simplification methods. The reason for selecting this technique is that the forward scenario selection is useful for selecting a small number of scenarios s out of a large initial scenario set. Its idea is to select s scenarios by adding one at a time to the selected set based on a criterion of minimising the average distance to unselected scenarios [7]. Thus, it is a useful technique when s is much smaller than the number of original scenarios. However, we conjecture that since the intent of all scenario reduction techniques is the same (i.e. to minimise the distortion in solutions resulting from choosing a subset), there may be only small differences if other scenario reduction techniques are used. Future research should examine whether the particular scenario selection method can make a significant difference in the ultimate decisions.

2.2 Network aggregation using available transfer capacity

The growing size of power networks is another challenge for economic studies. Reasons for increasing size include load growth, additions of new lines and generators, and tighter interconnections among electricity markets motivated by potential technical and economic efficiencies. Network aggregation is an important means of reducing network size in order to reduce computation times and storage requirements.

There are several types of network aggregation algorithms. However, they all have the same basic principle, which is to find a similarity criterion for the system buses and then to partition the system into some sub-systems based on this similarity criterion. The similarity criterion varies according to the purpose of the analysis in question. For instance, aggregation based on local marginal price (LMP) or power transfer distribution factors may be most suitable for market analyses, while aggregated networks based on voltage or admittance matrices are more applicable to power flow or OPF studies [17]. This paper uses available transfer capability (ATC) values among different buses as the partitioning criterion for network aggregation [16].

The reason for using ATC is that the main goal of this paper is to compare different system simplification methods for technical studies such as OPF and SUC, and/or economic studies such as GEP and TEP. Therefore, the selected partitioning criterion should consider both technical and economic aspects. ATC values show the additional possible power transfer between distinct system buses. Thus, they are physical variables, and can be used for OPF and SUC studies. Meanwhile, if the ATC between two buses is high, it means that more power can transfer between them, and their electricity prices are more likely to converge. Therefore, for purposes of GEP or TEP analyses, such buses logically belong in the same sub-system [18].

It should be noted that the structure of the simplified network depends on the distribution of loads and generation since that distribution affects ATC values between each pair of system buses. To address this issue here, an expected ATC matrix across scenarios is calculated and used for the network reduction. There are at least two ways to calculate the expected ATC matrix. In the first one, the ATC matrix for each scenario in each hour is calculated, and then the probability-weighted average ATC over all scenarios and hours is calculated and used in the network reduction process. However, for very large power systems, this calculation would require an impractically large effort, which conflicts with our goal of making the system analysis faster. The second approach calculates first the mean load and generation, and then makes one ATC calculation based on those values. In future work, it would be interesting to investigate whether a more sophisticated approach, such as making separate ATC calculations and network reductions for each of a small set of representative conditions, might improve the accuracy of the resulting operational or planning studies.

2.3 Problem reformulation: linearised DC load flow

The third important method for increasing the efficiency of power system optimisations is to shrink the problem size by using relaxations or other simplifications of the problem formulation. In this paper, we use the widely used approximation of DC linearisation to represent this class of methods. This approximation, which uses the DC power flow equations instead of the AC equations, simplifies the problem by neglecting transmission resistances, fixing the voltage magnitude of all buses at one per unit (p.u), and replacing the sine functions by their angles [19]. The most important advantage of this approximation is that it linearises the original non-linear power system equations, and allows omission of voltage and reactive power flow variables. This reformulation is much easier to solve than the original AC load flow.

3 Validating problems for the proposed multi-dimensional power system reduction

The impact of the above three simplification techniques upon decisions and estimates of their performance can depend on the operating or planning problem considered. Two power system analyses are used for this purpose. We summarise each below; standard references (e.g. [20]) can be consulted for more complete problem statements.

3.1 Optimal power flow

The OPF problem determines the output of generators such that all loads are supplied and an objective function is optimised. In electricity market analyses, the objective is commonly to minimise production cost or to maximise market efficiency (social welfare or surplus) based on generators' and demands' bids. A concise statement of the OPF problem based on cost minimisation in hour t is as follows. (see (1))

$$\text{s.t.}\, P_k^{\text{g}}(t,s) = P_k^{\text{d}}(t,s) + \text{EENS}_k(t,s) + \text{Re}\left\{ V_k(t,s)\sum_{i=1}^{N} y_{ki}^{*} V_i^{*}(t,s) \right\} \tag{2}$$

$$Q_k^{\text{g}}(t,s) = Q_k^{\text{d}}(t,s) + \text{Im}\left\{ V_k(t,s)\sum_{i=1}^{N} y_{ki}^{*} V_i^{*}(t,s) \right\} \tag{3}$$

$$\left| V_k(t,s) y_{ki}^{*} V_i^{*}(t,s) \right| \le S_{ki}^{\max} \tag{4}$$

$$V_k^{\min} \le \left| V_k(t,s) \right| \le V_k^{\max} \tag{5}$$

$$P_j^{\text{g,min}} \le P_j^{\text{g}}(t,s) \le P_j^{\text{g,max}} \tag{6}$$

$$Q_j^{\text{g,min}} \le Q_j^{\text{g}}(t,s) \le Q_j^{\text{g,max}} \tag{7}$$

$$P_i^{\text{d,min}} \le P_i^{\text{d}}(t,s) \le P_i^{\text{d,max}} \tag{8}$$

$$Q_i^{\text{d,min}} \le Q_i^{\text{d}}(t,s) \le Q_i^{\text{d,max}} \tag{9}$$

The objective (1) minimises the sum of fuel and interruption costs. Constraints (2) and (3) maintain the active and reactive power balances at each bus. Line flow limits, bus voltage limits, generation limits, and consumption limits are guaranteed by (4)–(9), respectively.

3.2 Stochastic unit commitment

The second power system study we consider is SUC. SUC schedules the commitment and dispatch of generators under multiple net load scenarios, and has a time horizon ranging from hours to days. There are multiple formulations of the SUC problem [21]. We use the following in which a single set of commitment decisions are made day-ahead before it is known which scenario will occur. Dispatch decisions in each scenario are made subject to that commitment schedule, and it is assumed that when dispatch decisions are made, the net load for the rest of the day has become known.
(see equation (10) at the bottom of the next page)

$$\text{s.t.}\, P_k^{\text{g}}(t,s) = P_k^{\text{d}}(t,s) + \text{EENS}_k(t,s) + \text{Re}\left\{ V_k(t,s)\sum_{i=1}^{N} y_{ki}^{*} V_i^{*}(t,s) \right\} \tag{11}$$

$$Q_k^{\text{g}}(t,s) = Q_k^{\text{d}}(t,s) + \text{Im}\left\{ V_k(t,s)\sum_{i=1}^{N} y_{ki}^{*} V_i^{*}(t,s) \right\} \tag{12}$$

$$\left| V_k(t,s) y_{ki}^{*} V_i^{*}(t,s) \right| \le S_{ki}^{\max} \tag{13}$$

$$V_k^{\min} \le \left| V_k(t,s) \right| \le V_k^{\max} \tag{14}$$

$$u_j(t)\cdot P_j^{\min} \le P_j^{\text{g}}(t,s) \le u_j(t)\cdot P_j^{\max} \tag{15}$$

$$u_j(t)\cdot Q_j^{\min} \le Q_j^{\text{g}}(t,s) \le u_j(t)\cdot Q_j^{\max} \tag{16}$$

$$\text{su}_j(t) - \text{sd}_j(t) = u_j(t) - u_j(t-1), \quad \forall t \tag{17}$$

$$P_j^{\text{g}}(t,s) - P_j^{\text{g}}(t-1,s) \le \text{RR}_j^{\text{Up}} \tag{18}$$

$$P_j^{\text{g}}(t-1,s) - P_j^{\text{g}}(t,s) \le \text{RR}_j^{\text{Down}} \tag{19}$$

$$\sum_{h=t-T_{\text{on},j}^{\min}+1}^{t} \text{su}_j(h) \le u_j(t), \quad \forall t, j \tag{20}$$

$$\sum_{h=t-T_{\text{off},j}^{\min}+1}^{t} \text{sd}_j(h) \le 1 - u_j(t), \quad \forall t, j \tag{21}$$

The objective function (10) minimises expected operational costs (fuel, interruption, and start up), and is linear. Constraints (11)–(16) are similar to (2)–(7), but are revised for the SUC problem. Equation (17) defines variables related to system start-up and shut-down. Generator ramps are bounded by (18) and (19). Finally, (20) and (21) guarantee that minimum on- and off-times are met for each generator. Shut-down costs are ignored for the sake of simplicity, as are demand bids.

4 Comparisons of simplifications: results

Here, we apply the three proposed simplification techniques to three IEEE test systems for the two types of studies.

In our comparison of the OPF study, two test cases are applied. The first case is the IEEE 118-bus system with 200 scenarios of renewable generation and loads, and the second is IEEE 30-bus system with 22 scenarios of generation and loads. The first system (i.e. the IEEE 118-bus system) is, however, too large for the SUC study, since the SUC formulation is a mixed integer programing problem, unlike the other problems. Thus, for the SUC case, we

$$\min_{V_k, P_j^{\text{g}}, \text{EENS}_k} \sum_{s=1}^{S} \pi(s)\cdot\left\{ \sum_{j=1}^{G}\left[c_{j1}\cdot P_j^{\text{g}}(t,s) + c_{j0} \right] + \sum_{k=1}^{N}\left[\text{EENS}_k(t,s)\cdot \text{VOLL}_k \right] \right\} \tag{1}$$

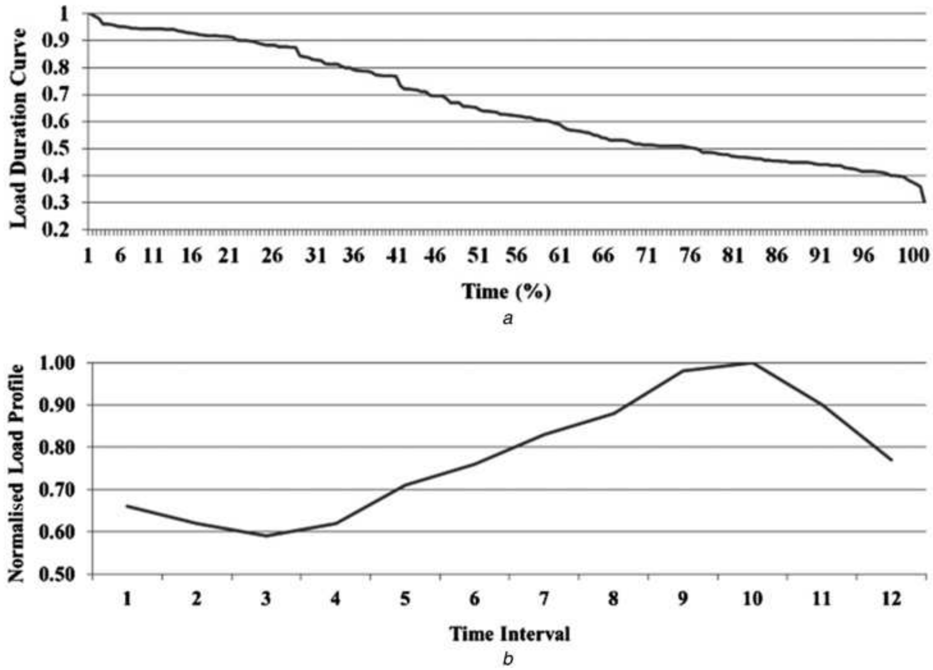

Fig. 1 *Input data used for obtaining the load scenarios*

a Net load duration curve of the net load for IEEE 118 bus system
b Normalised Swedish load profile used to generate load scenarios for IEEE 30-bus and 14-bus systems

use the second, smaller system, i.e. the IEEE 30-bus system with 22 scenarios of 12 two-hour time intervals of generation and loads. In addition, in order to increase the generality of our conclusions from the SUC analysis, we also apply the simplifications of the SUC problem to the IEEE 14-bus system with 12 scenarios of 12 two-hour time intervals of generation and loads.

The reason for using two small systems (IEEE 30-bus and IEEE 14-bus test systems) for the SUC problem is that we need to verify the results of the simplified systems by comparing with the results of the original detailed systems. With the computational capabilities available, it was not possible for us to apply the SUC to the full IEEE 118-bus system. Thus, two smaller systems are used for the SUC problem. If the network being studied in an actual application is too large to use SUC, an important conclusion of this paper's other analyses is that some simplification of the network and reduction of the scenario set are unlikely to distort the results, and SUC can be applied to the simplified system.

Load scenarios for multiple buses are obtained by generating random loads from a multivariate normal distribution, assuming the mean load values given in MATPOWER 4.1 toolbox [22], and using correlations between 0.25 and 1 based on proximity of the buses. Fig. 1*a*, for instance, represents the overall net load duration curve in 200 load scenarios for the IEEE 118-bus system. The normalised Swedish load profile on 1 January 2013 (Fig. 1*b*) [23] is used to generate load scenarios for the SUC of the IEEE 30-bus and 14-bus systems. It can be seen in Fig. 1*b* that the time horizon studied in the SUC problem includes 12 time intervals, i.e. we have assumed that each time interval is equal to 2 hours in a daily scheduling. Wind also is assumed to be independent of load, and correlations among wind sites vary from 0.4 to 1 based on the distance between them.

The SUC is solved with GAMS 23.6 with the CPLEX and BONMIN solvers, while the OPF uses MATLAB R2010. Both are run on a PC with an Intel® Core™ i5 CPU 2.53 GHz processor and 4 GB of installed memory (RAM).

We now explain our experimental design. In order to compare the effects of the simplifying techniques on OPF study for the IEEE 118-bus system, the following steps are executed. First, the IEEE 118-bus system with the original 200 scenarios is solved as the benchmark for evaluating the simplifying techniques. Second, forward scenario selection is applied three times to the original set of 200 scenarios, yielding three sets of scenarios with 20, 5, and 1 scenarios, respectively. Third, four different levels of network aggregation are applied on the IEEE 118-bus system, resulting in four equivalent systems with 66, 46, 26, and 15 buses, respectively. Thus, with 5 network systems and 4 scenario sets (including the original network and set of 200 scenarios), 20 distinct combinations of networks and scenario sets are considered. Fourth, each of the 20 combinations is simulated twice, once with an AC OPF formulation and once with the linearised DC simplification (without losses), resulting in 40 cases. Finally, we compare the results of the cases in order to assess which simplifying technique causes more error in the results of the OPF problem relative to the baseline. The results considered include total costs, losses, and individual generator output. Computation times are also compared for all studies.

In addition, to compare the effects of the simplifying techniques on studies based upon the IEEE 30-bus system, we start by defining a baseline problem by combining the IEEE 30-bus system with an original set of 22 scenarios. Three scenario sets including 12, 6, and 3 scenarios are then defined, as well as two aggregated networks, which have 15 and 6 buses.

We follow a similar procedure to compare the effects of the simplifying techniques on SUC for the IEEE 14-bus system. We first define the SUC baseline problem by combining the IEEE 14-bus system with an original set of 12 scenarios. Two scenario sets including 6 and 3 scenarios are then defined, as well as a single aggregated network, which has 5 buses. The SUC is used to optimise system operations under all 6 possible combinations of scenario sets and aggregated networks.

$$\min_{V_k, P_j^{\mathrm{g}}, \mathrm{EENS}_k, u_j} \quad \sum_{t=1}^{T}\sum_{s=1}^{S}\pi(s)\cdot\left\{\sum_{j=1}^{G}\left[c_{j1}\cdot P_j^{\mathrm{g}}(t,s)+c_{j0}\cdot u_j(t)\right]+\sum_{k=1}^{N}\left[\mathrm{EENS}_k(t,s)\cdot \mathrm{VOLL}_k\right]\right\}+\sum_{t=1}^{T}\sum_{j=1}^{G}\left[\mathrm{su}_j(t)\cdot \mathrm{suc}_j\right] \tag{10}$$

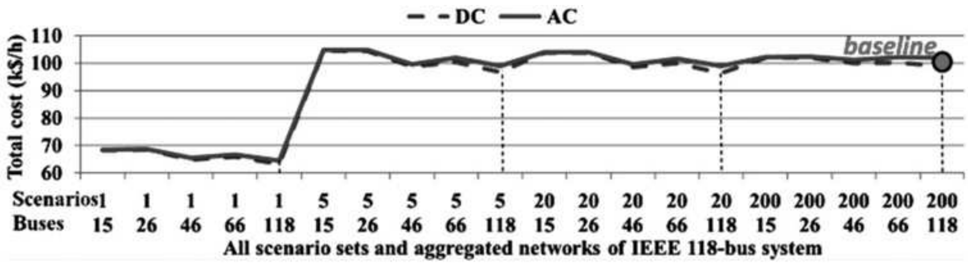

Fig. 2 *OPF results: total operation cost for different scenario sets and aggregated networks obtained by AC/DC OPF for the IEEE 118-bus system (k$/h)*

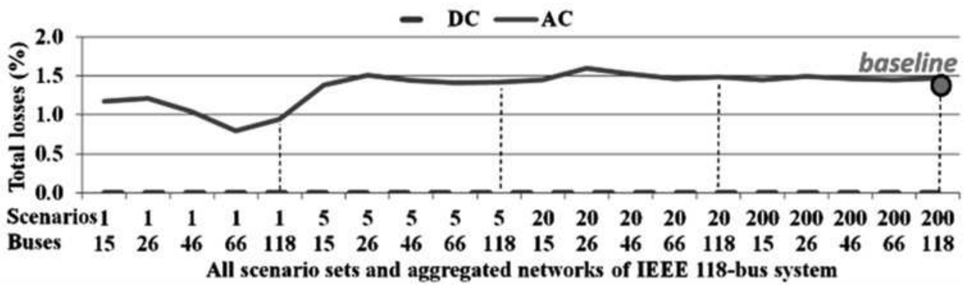

Fig. 3 *OPF results: total system losses for different scenario sets and different aggregated networks obtained by AC/DC OPF for the IEEE 118-bus system (%)*

In theory, the computational time needed to perform the system reduction and scenario reduction should also be considered when comparing simulation times. However, when compared with the optimisation time for the original systems with all scenarios, the computational time used for the reductions is negligible and, therefore, is ignored in our comparisons.

It should be noted that with a few exceptions, which we explain below, all SUC simulations are run with the DC approximation alone. This is because we are unable to solve to optimality the stochastic mixed integer non-linear AC SUC problem in all cases. The DC results are then compared to see whether scenario reduction or network reduction has a greater effect on the SUC results relative to the baseline. The results we compare include computational time, costs, expected energy unserved, and unit commitment schedules.

Due to the space limits, we only present detailed results for one test system (the larger system) for each power system study in the following sub-sections. That is, only the results of IEEE 118-bus system are given for OPF; besides, only the results of IEEE 30-bus system are provided for SUC. However, an extended discussion of the results of all test systems as well as documentation of the scenarios and networks are found in [24]. The results for the smaller systems are qualitatively similar to those described below.

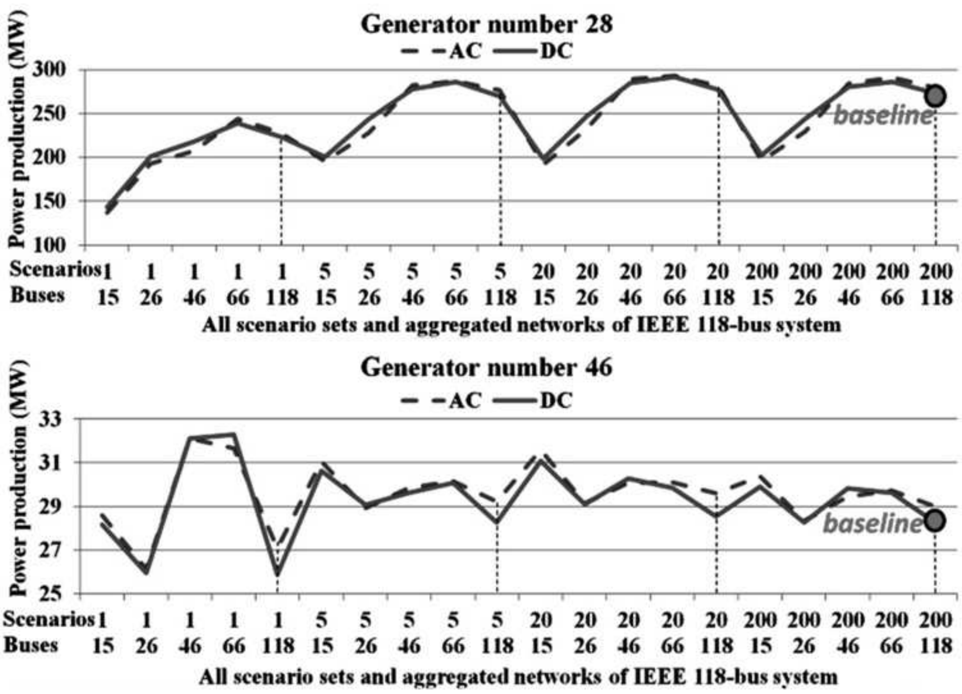

Fig. 4 *OPF results: power produced by two generators of IEEE 118-bus system in different scenario sets and aggregated networks obtained by AC/DC OPF (MW)*

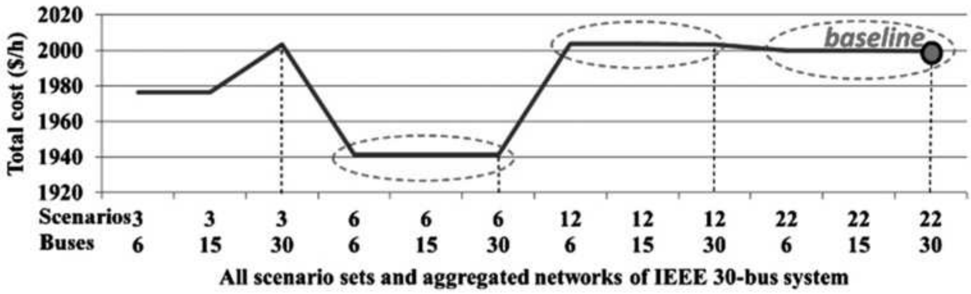

Fig. 5 *SUC results: total operation cost for different scenario sets and different aggregated networks obtained by DC SUC for the IEEE 30-bus system ($/h)*

4.1 Results: OPF problem

First, we compare the results of the simplification techniques applied to the OPF problem. We consider their impact on total system operation costs (Fig. 2), total losses (Fig. 3), and generators output (Fig. 4). The top value on the horizontal axis in each subfigure refers to the number of scenarios and the bottom one is the number of buses in the aggregated network. The right-most point on the diagram is the baseline, which is the original 118-bus system with 200 scenarios for the IEEE 118-bus system.

Fig. 2 shows that considering just one scenario makes the most difference (an average of 34% in cost) for the IEEE 118-bus system but reducing to 5 scenarios makes an order of magnitude less difference than bus aggregation (0.2% difference against 5% difference, respectively). As long as at least 5 scenarios are considered, scenario reduction does not distort expected costs. DC linearisation underestimates costs by 1.4%, on average.

Turning to system losses in IEEE 118-bus system (Fig. 3), these are of course zero in the DC OPF. The figure also shows that aggregating scenarios to a single scenario can significantly distort losses (decreasing them by 15%), but that as long as there are 5 or more scenarios, the impact on losses of aggregating scenarios or networks is relatively minor.

To gain a better understanding of the effects of network aggregation and scenario selection on the OPF results, we compare the output of two generators of the IEEE 118-bus system in Fig. 4. Generator 28's power fluctuates considerably among the different network aggregations. These differences are much greater than the differences among solutions based on 5, 20, and 200 scenarios, although there are pronounced differences compared with the 1 scenario case. Finally, the difference between its generation in the DC and AC OPF cases is negligible. For generator 46, DC and AC results have again minor differences. Meanwhile, neither network aggregation nor scenario reductions cause significant errors as long as the number of scenarios is more than 1.

Regarding execution time, DC linearisation reduces it by less than 10% in both systems, while its reduction due to network aggregation is between 10 and 25%. In contrast, computation time is proportional to the number of scenarios; thus, scenario reduction is more effective in reducing computational effort than other simplifications.

In conclusion, DC linearisation is suitable for OPF analyses if system losses are not of great concern. Regarding the two other simplification methods in our systems, although network aggregation can sometimes reduce system size without causing large distortions, scenario reduction is most effective at reducing computational effort while avoiding large errors in OPFs.

4.2 Results: SUC problem

The IEEE 30-bus system with 22 scenarios is the baseline for our unit commitment analyses. Fig. 5 shows the total operating costs for all the combinations of scenarios and networks, which we obtained using the DC SUC formulation. Moreover, Fig. 6 shows the expected energy not served (EENS) for all the combinations of scenarios and networks.

The figures reveal that aggregating the network makes much less difference than the number of scenarios. (The dashed circles in the figures indicate that for a given number of scenarios, the number of buses does not affect the results.) The commitment decisions themselves are affected more by the number of scenarios, as illustrated in Fig. 7 for Generator 5. For this generator, all aggregated networks have the same commitment as does the baseline, while choice of scenario set makes more of a difference in the commitment.

Fig. 8 depicts the computation time of the DC SUC for all cases of the IEEE 30-bus system. Both scenario reduction and network aggregation reduce execution times, with the number of buses having the greatest impact.

We mentioned above that it is not possible to solve the AC version of the SUC for most cases. However, we did solve the AC SUC using mixed-integer non-linear programming for three of the smallest cases, which allows some comparisons with the DC case. Table 1 shows the DC and AC results for those cases. It can be seen that the DC SUC predicts the results of AC SUC with great accuracy, while also reducing the simulation time significantly. This is opposite to the conclusions of our OPF analyses (where DC linearisation did not considerably reduce the simulation time), demonstrating that the impact of a simplification technique on simulation time depends on the particular power system study being considered.

To summarise the conclusions for the SUC case studies, DC linearisation is an indispensable simplification for SUC, as it is impractical to use the original AC SUC with present computer

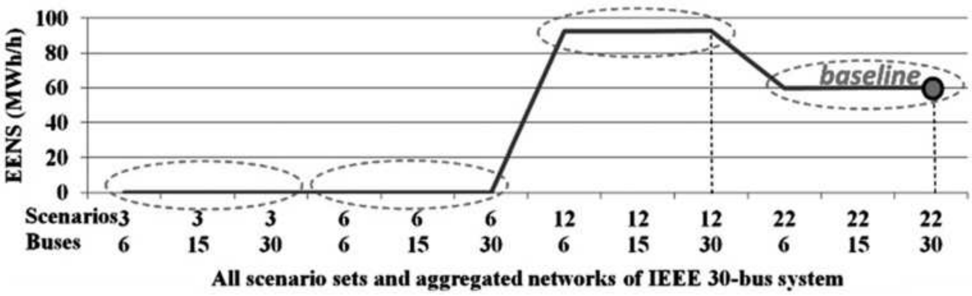

Fig. 6 *SUC results: total EENS for different scenario sets and different aggregated networks obtained by DC SUC for the IEEE 30-bus system (MWh/h)*

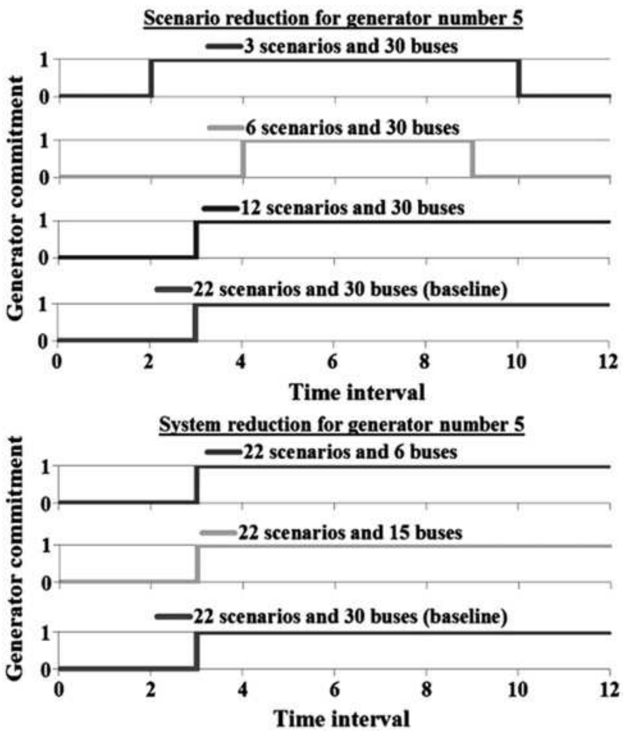

Fig. 7 *SUC results: commitment of generator 5 of IEEE 30-bus system for different network aggregations and scenario sets (the x axis is index for the two-hour time interval)*

capabilities. Scenario reduction can also be used, but at the risk of distorting commitment decisions and costs. Finally, network aggregation reduces SUC execution times while introducing relatively little error.

4.3 Results: OPF for evaluation of generation and transmission investments

We have also compared the three simplification techniques (linearised DC load flow, scenario reduction, and network reduction) in the context of OPF-based economic evaluation of generation and transmission investments. Our general approach was to use the OPF method to calculate system dispatch, LMPs, and operating costs, and then to use those results to compare the profitability (revenue minus operating cost) of new plants at different candidate buses and the system cost impacts of new lines between candidate pairs of buses. Space limitations mean that we must omit detailed explanations of these two problems and discussions of their results, which are available in [24]. We summarised the major conclusions of these two problems as follows.

By comparing the results of OPF-based revenues (from LMPs) and dispatch of new generators at candidate buses, we find that DC linearisation does not considerably change the relative profitability of different candidate buses and, therefore, the best location for new generation. This was the case both for peaking and baseload generation. Further, which bus has the highest prices (and thus profitability for new generators) is also unaffected by scenario reduction and network aggregation as long as a reasonable number of scenarios and network buses are considered.

Turning to transmission investment, our results show that DC linearisation and scenario reduction are acceptable simplifications for economic comparisons of candidate transmission lines as long as we have enough scenarios. However, network aggregation (especially the smallest aggregated networks) can cause considerable underestimation of the benefits, in the form of fuel cost savings, of new lines.

Computational time savings from various simplifications of OPF-based GEP and TEP studies are the same as described in Section 4.1 for OPF because an OPF model is used in all three problems.

4.4 Results: summary and discussion

Table 2 summarises the results of our case studies. The simplification techniques are compared in terms of computation time savings and errors in estimating key economic and technical indices.

The results can be briefly summarised as follows:

First, for our case studies, some scenario reduction yields an acceptable level of accuracy while decreasing computation times in power flow studies, as well as investment analyses that use OPF models for production costing. However, this conclusion is valid only if an adequate number of scenarios (at least 5) are kept.

Second, scenario reduction is more distorting in SUC than in other problems, and results in fewer computational efficiency gains for this problem.

Third, given present computational capabilities, DC linearisation is essential for SUC, although advances in parallel computation and decomposition may make AC-based SUC more practical in the future.

Fourth, some network aggregation can also be useful in OPF and SUC for reducing simulation times without the risk of major errors.

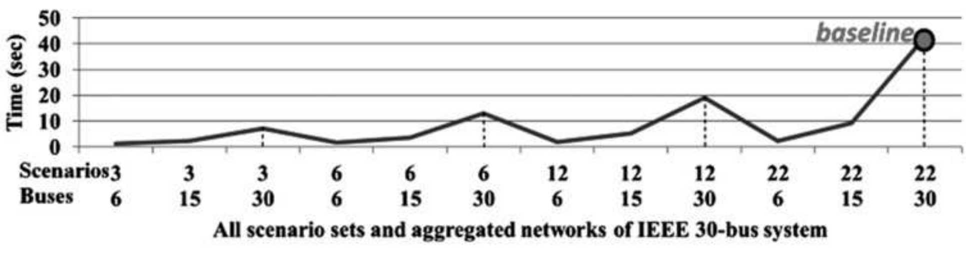

Fig. 8 *SUC results: computation time for various scenario sets and network aggregations obtained by DC SUC for the IEEE 30-bus system (s)*

Table 1 Results for AC SUC and DC SUC for selected aggregated networks and scenario sets

Number of scenarios and system buses	3 scenarios, 6 buses		6 scenarios, 6 buses		3 scenarios, 15 buses	
Simulation results/AC or DC simulation	DC	AC	AC	DC	AC	DC
total operation cost ($/h)	1976.278	2006.309	1941.301	1943.082	1976.278	2009.584
EENS (MWh/h)	0	0	0	0.007	0	0
simulation time	1.37 s	24 min, 55 s	1.67 s	61 min, 17 s	2.35 s	30 min, 41 s

Table 2 Summary comparison of effects of three simplification techniques for four power system studies

Simplification technique	Scenario reduction		Network aggregation		DC linearisation	
Type of study (index)	Time[a]	Error[b]	Time	Error	Time	Error
OPF (Cost, Losses, Generation)	+ + +	− −	+ +	− − −	+	−
SUC (Cost, EENS, Commitment)	+	− − −	+ +	−	+ + +	−
GEP (Prices, Plant Profits)	+ + +	− −	+ +	− −	+	−
TEP (Line Cost Savings)	+ + +	− −	+ +	− − −	+	−

[a]Computational time reduction: + + + is best
[b]Error in estimation of performance indices: − − − is worst

Finally, the profitability of generation and transmission investments can be mis-estimated if large reductions in either scenario sets or networks are used. Although DC linearisation does not considerably reduce computation time in expansion studies that use OPFs for production costing, the errors it causes are also small when an adequate number of scenarios and buses are preserved.

5 Conclusions

We have compared system simplification techniques in the context of OPF, SUC, and generation and transmission investment planning. Three techniques have been considered: scenario reduction (by forward scenario selection), network aggregation (based on an available transfer capacity criterion), and DC linearisation.

Although our results are system specific, we can nonetheless make the following general conclusion: depending on the type of study and on the particular system, any of the simplification methods can either cause large errors, negligible errors, or something in between. Which simplification method is most appropriate will likely depend on the power system study under consideration, and so users of economic models should test for the impact of simplifications on their conclusions.

Any of these three simplifying techniques can involve a trade-off: speeding up calculations can sacrifice accuracy. This paper has shown how consistent metrics of the consequences for decisions and their estimated performance can be used to quantify and understand these trade-offs between methods. However, the best resolution of the trade-off is a function of the situation, depending on the level of accuracy desired and computational complexity that can be handled. For instance, models are sometimes used by an organisation for internal purposes to provide general insights on which decisions are likely to be better (for instance, where generation additions in the network might be more valuable), and are commonly followed up by more detailed, focused studies. In that case, rapid computation may be more important so that many different assumptions and configurations can be tested. In other situations, accuracy may be more important, such as in final design decisions or public documents documenting the economic rationale for certain transmission or generation investments. Thus, the best resolution of the trade-off depends on the users' needs.

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