ASIA-PACIFIC SOLAR RESEARCH CONFERENCE

Peer Reviewed
2017 Solar Research Conference

Finding High Resilience and Near Optimal Electricity Generation Mixes for the 21st Century

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Abstract

Technology progress, particularly the rapidly decreasing costs of renewable energy, is changing the fundamental structure of electricity industries around the world, including Australia's National Electricity Market (NEM). Determining a suitable generation mix is crucial to managing structural changes in a manner than promotes affordability, reliability and sustainability. To accomplish this, the solution space of possible future energy generation mixes (the contributions of different possible generation technologies including renewables yet also conventional fossil fuel plants) must be studied to shortlist options and determine the costs, benefits and tradeoffs associated with each of these options.

Commonly used tools including linear and mixed integer programming require significant assumptions regarding cost functions, and can struggle to appropriately incorporate the uncertainties associated with these, and other factors such as future policies and changing electricity demand. Other approaches including evolutionary algorithms (EA) can avoid some of these assumptions by 'evolving' lower cost solutions through repeated simulations. This study uses a tool based on an EA known as Covariance Matrix Adaption Strategy (CMAS). Another issue with existing generation mix tools is that they don't generally describe the solution space around the optimal solution. While scenario analysis and sensitivity studies can provide some guidance on key uncertainties, there is an opportunity with evolutionary algorithm based tools to directly map the spread of 'near optimal solutions'.

The study presented here creates a 'hybrid algorithm' whereby on each iteration of the evolutionary algorithm, the best solutions are clustered using the Gaussian Kernal Density Based Clustering method. This algorithm will contribute to the existing body of work on energy modelling techniques in two ways:

- If it is determined that the best solutions are split over multiple clusters, the hybrid algorithm will branch out to explore each of these regions separately. This happens at each iteration meaning that the final result will be a set of optima rather than one optimum. Hence, near optimal solutions can be located in addition to the one global optimum.
- Furthermore, the spread of the points covered by the evolutionary algorithm indicate the shape of the optima they surround. This spread, as indicated by the covariance matrix of these points, can be used to represent the shape of the optima and therefore its flexibility.

After this algorithm was validated against known solution spaces, it was applied to a case study of the Australian National Electricity Market with high renewable penetrations. For a fixed reliability standard and different scenarios of future technology costs and carbon constraints, it was found that additional renewables capacity could actually reduce overall industry costs given its attractive economics and low operating costs.

Imposing a sustainability standard made a small difference in smaller capacities however in large capacities, where more excess capacity existed it was cheaper to use more sustainable sources of energy. This is an important result to note as it can counter misconceptions that pit sustainability against reliability. As the capacity was increased the flexibility of the optima also increased.

1. Introduction

At present, the Australian National Electricity Market (NEM) has one of the world's highest dependencies on coal fired generation. However, recent years have seen far greater deployment of renewable energy driven by factors including Federal and State Government policy and consumers increasingly choosing rooftop photovoltaics (PV). These were facilitated by large falls in the costs of some key renewable technologies including wind and PV. At the same time, a number of old coal-fired generating plants have retired, while gas market developments have impacted on the availability of gas-fired generation (Finkel, 2016). While it is evident that this transition to greater renewables will have improved environmental outcomes, it is essential that this change is managed in a way that economic and social wellbeing is maintained. The state wide South Australian blackout in 2016 raised questions about the impacts of renewables on security and some have argued the only way to avoid such events is to continue to rely on fossil fuel generation.

Australia's Chief Scientist, Alan Finkel, was tasked with reviewing security of the NEM after this blackout. The Review's preliminary report (Finkel, 2016) sets out three objectives to help manage and direct the evolution of the NEM - affordability, reliability, and sustainability of electricity supply. Depending on how these goals are quantified, determining the most suitable future energy generation mix for the NEM can be structured as a least-cost optimisation problem within constraints. Due to the complexity of this optimisation, the existence of many interdependent factors, the high number of variables and the inherent uncertainties in these looking forward, basic formulae and models are not sufficient. The motivation for the study presented in this paper was to develop and execute a rigorous methodology to study such complex and non-trivial solution spaces and derive meaningful conclusions on preferred future NEM generation mixes given the uncertainties and complexities involved. The study had three main objectives:

- **Accuracy:** Many current methods for assessing future generation mixes make assumptions of linearity between variables. As discussed in the literature review, the presence of fixed costs which need to be ammortised over the units produced, along with the feedback created because cost affects demand, means that the assumption of linearity could introduce errors in the model. This study focused on identifying a tool that doesn't require such linearity assumptions.
- **Multiple Optima:** Most current methods of finding an optimum will overlook other potential optima in favour of converging to a single optimum. This study also aims to develop methodologies which can be used to find an optimum as well as other 'near optimal' solutions.
- **Shape of the 'near optimal' solution space:** Most current methods converge to an optimum without giving the user an idea of the shape of the solution space around this optimum. In the case of energy mixes, how wide or narrow an optimum is can indicate how flexible an energy mix is and what sort of trade-offs can be made while maintaining the 'optimality' of the mix. For example, one can envisage that there might be two rather different generation mixes that both deliver a near least cost industry outcome, or that a particular generation mix could be adjusted without major cost impacts. This study also aims to deduce the shape of these optima to enable users to compare different optima based on their flexibility.

Furthermore, these objectives were satisfied within the following bounds:

- Possible future energy mixes were optimised with respect to their overall industry costs as measured by the average $/MWh of an energy mix (including capital costs of the generator, operations and maintenance costs and fuel costs). Reliability and sustainability objectives were modelled as a requirement (e.g. maximum allowable unmet demand and maximum allowable carbon emissions) rather than a quantity to be optimised.
- Future energy mix combinations were limited to solar energy (mainly photovoltaic), onshore wind turbines, black coal, Combined Cycle Gas Turbines (CCGT) and Open Cycle Gas Turbines (OCGT) as these generation technologies appear to the most relevant options for the NEM. Adding other technologies and therefore dimensions is classified as future work.
- The cost model sought to find the least cost mix to meet NEM demand for a given future year, on the basis that all generation was 'green-field', that is, constructed at the same time. Adding in the complexity of pre-existing generation (hence classifying their capital costs as sunk costs) and staged generation investment over a given time horizon is again classified as possible future work.
- The third objective of finding the flexibility of optima and comparing these optima relates to a 'relative' measure of flexibility, not an absolute measure. Since the notion of flexibility itself is a relative construct, this project aims to produce a useful measure of the flexibility of optima and the direction of this flexibility, relative to the flexibility of other optima. This information will be crucial in comparing how useful each optimum is.
- The demand trace was kept constant for this project (i.e. one annual trace used as opposed to increasing the overall demand as the years went by). Increasing demand is a complexity that can be added in future work.
- Incorporating energy storage and the expected improvements in reliability and cost effectiveness is considered as future work.

The structure of the paper is as follows. The next section includes a brief literature review of existing methodologies and concepts. Subsequent sections include a summary of the methodology, how this methodology was validated against known solution spaces before proceeding to the unknown solution space, a discussion and the conclusion.

2. Literature Review

The techniques used in this project were essentially a combination of three key fields; energy modelling, evolutionary algorithms and clustering.

2.1. Energy Modelling

2.1.1. Mathematical Techniques

While many mathematical approaches to optimising energy production costs exist, there are two main ones. Linear programming solves the optimisation problems that exist in the model when "all relationships are expressed as fully linearised terms" (Beeck, 1999). Mixed Integer

Programming is similar to linear programming however it can accommodate for certain variables being limited to discrete quantities (i.e. can handle both linear and staircase functions). Both these approaches rely on a somewhat linear relationship between the cost of energy production and the quantity of energy produced. This relationship is often derived from the metric 'Levilised Cost of Energy' which is the total cost to build and operate a power plant over its life-time divided by the total units of energy produced by the plant over its life-time, subject to certain assumptions. Other tools directly solve the staged mixed integer optimization rather than assuming the capacity factor of different plants. The limitations to these optimization techniques are discussed further on.

2.1.2. *Examples*

Existing energy models include the World Energy Model (WEM), Open Source Energy Modelling System (OSeMOSYS) (Howells, 2011) and the National Electricity Market Optimiser (NEMO) which is discussed in later sections. WEM is a partial equilibrium model. When new plants are required, "the model makes its choice between different technology options on the basis of their regional long-run marginal costs (LRMCs)" (IEA, 2015). At a conceptual level, the LRMC is a very similar metric to LCOE. However, it also takes into account how the region where a plant is built can affect prices. There are many other tools available including the Long-range Energy Alternatives Planning system (LEAP) (Heaps, 1997), as well as commercial tools such as PLEXOS (Energy Exemplar, 2000).

2.1.3. *Limitations*

The models discussed essentially answer the problem that this study aims to solve for, that is, what are the best future generation mixes for an electricity sector under given assumptions. However, they have many limitations that can compromise the accuracy and relevance of their results. Firstly, many of these models rely on the relationships between costs and energy output for various technologies being linear (where the LCOE is the constant of proportionality) or somewhat linear (Mixed Integer Programming for 'staircase' cost curves). Either way these could be unrealistic assumptions. The price of a unit of energy depends on cost of raw materials, operating costs, maintenance costs and the capital costs of building a plant. The amount of capital cost that must be recovered from the sale of each unit of energy depends on how much total energy is produced during the life time of the plant. This in turn depends on energy demand and how competitive this plant is compared to others. This thesis uses an existing tool, NEMO, that uses an evolutionary algorithm through what is essentially a directed trial-and-error process exploring a wide range of possible future energy mixes, but quickly tracking down to better and finally a best solution.

Secondly, most projected generation mixes include a significant contribution made by wind and solar plants. The fact that the ability of these sources to produce energy relies heavily on weather patterns must be taken into consideration and simply using capacity factors may not be enough. This project therefore considers the use of solar and wind traces or probability distributions to achieve greater granularity in the relationship between demand patterns and solar and wind supply patterns.

2.2. *Evolutionary Algorithms*

To avoid making assumptions about the relationship between cost and volume produced (as they could lead to inaccuracies), heuristic optimisation techniques were required. Heuristic optimisation includes Evolutionary Algorithms (EAs), which mimic biological evolution and improve solutions by trialing multiple solutions and then using the best ones to generate the next set of solutions to be trialed. This study used a tool that applies the Covariance Matrix Adaption Strategy (CMAS), a kind of EA. Here, solutions are generated using a gaussian distribution and the best solutions are used to update the mean and covariance matrix of the distribution used to generate the next set of solutions.

2.2.1. *NEMO*

The covariance matrix adaption strategy has already been used in the context of finding the optimal generation mix in the National Electricity Market Optimiser (NEMO). NEMO is an open source model in python created by Ben Elliston at the Centre for Energy and Environmental Markets (CEEM) at UNSW in 2011. It has since been used to conduct many energy market studies including a study into the feasibility of a 100% renewable based energy market (Elliston, 2016). The dimensions of this model include various generation technologies and the regions within which plants may be built. NEMO uses the covariance matrix adaption strategy to find the optimal combination of generation technologies and the regions within which these technologies must exist.

NEMO separates capital costs and ongoing costs, instead of trying to bundle them together and make unnecessary assumptions about how much energy will be sold and therefore how much capital cost needs to be recovered from each unit of energy. While NEMO is effective at determining the location of the optimal energy generation mixes, it still only converges to one solution and further analysis is required to determine if there were other, near optimal solutions. This is where clustering will add value, as described in the next section.

2.3. Clustering

To identify near optimal solutions, other than the one global optimum that the evolutionary algorithm will converge to, cluster analysis can be performed on the solutions trialed to see which regions the better solutions clump around, therefore indicating the presence of another optimum. A range of clustering approaches are available, but this study takes a density based approach. In density based clustering, "clusters are regions of high density separated by regions of low density. Usually density based clustering depends on a density threshold which defines 'low' and 'high' density. Choosing this threshold correctly is the key to a meaningful clustering result" (Kumar, 2006). If the density threshold is too low, separate clusters may be mistaken for one big cluster however if the threshold is too high, clusters may be overlooked. DBSCAN is an example of density based clustering which also highlights its main weakness, the accuracy relies on choosing an appropriate density threshold. Gaussian Kernal Density Based clustering can solve for this as it is not dependent on input parameters (Güngör, Özmen, 2016).

3. Method

The methodology used in this project can be described as a collection of processes, performed on a set of inputs to yield a range of outputs.

3.1. *Inputs*

- **Costs** - The Australian Technology Power Generation Report by the CO2CRC (Bongers, 2015) was the source for the cost inputs. Costs included were; capital cost in dollars per kW of the installed capacity of the plant, fuel costs in dollars per MWhr (relevant for fuel based technologies such as coal fired power stations, however irrelevant for sources such as solar and wind), fixed Operations and Maintenance Costs (O&M) in dollars given as an annual figure per kW of the capacity of the plant and variable Operations and Maintenance Costs in dollars per MWhr.

- **Carbon Emissions** - To ensure that carbon emission limits were met, the tonnes of CO_2 released for every MWhr of electricity produced was also determined from the same report. The total annual carbon emissions would be limited to what was agreed on in the Paris Agreement. If Australia decided to meet these requirements it would have to cut 2005 emissions levels by 28%. In 2005, Australia emitted 17.17 tonnes per capita (World Bank, 2017) with a population of 20.39 million (ABS, 2005) people.

$$Emissions_{CO2} = 17.17 \times 20.39 \times 10^6 = 350 \times 10^6\ tonnes$$

The reduction required would therefore be

$$Reduction = Emissions_{CO2} \times 0.28 = 98 \times 10^6\ tonnes$$

The energy sector accounts for 54% (ABS, 2010) of emissions hence the emissions by the energy sector in 2005 were

$$Emissions_{energy} = Emissions_{CO2} \times 0.54 = 189 \times 10^6\ tonnes$$

Assuming that any emissions reduction would need to come from the energy sector (if other sectors such as transport do reduce their emissions it would be because of electric vehicles thus placing greater demand on the energy sector) the emissions limit would be

$$Emissions_{limit} = Emissions_{energy} - Reduction = (189 - 98) \times 10^6 = 91 \times 10^6 tonnes$$

- **Traces** - The traces relevant for this model are the demand trace, solar trace and wind trace. Each of these were obtained for 2010 from the 'Ozlabs' dataset. There are three probabilistic variables in the analysis – solar supply, wind supply and total demand. To create a probability distribution of what combination occurs how often, traces for each of these were individually spread over 10% intervals with '100%' being the respective maximum. These gave rise to 1000 theoretically possible scenarios, but on analysing historical data it was found that only 269 scenarios had actually occurred. Counting how often each scenario occurred over a year gave the overall probability distribution against which further analysis was conducted.

3.2. *Process*

1. The solution space of energy mixes is a 4D region (since contributions from all five energy sources have to add up to 100%, there are only four degrees of freedom) within a 5D space. A linear transformation is performed on this 4D region to fit it on a 4D space. The first iteration of the Covariance Matrix Adaption Strategy is performed by randomly generating trial points on this new 4D space.

2. The inverse linear transformation is performed on these points to find the energy mix they correspond to.
3. Each energy mix is run through the 269 scenarios established before. For each scenario, how much power each generation technology would supply (given how much solar and wind was available under those weather conditions) to satisfy the overall demand was calculated. These figures, along with unmet power were multiplied by the time spent in that scenario and this energy was summed over all 269 scenarios to yield final energy production figures.
4. Using the previous figures, the carbon emissions and unmet demand in this energy mix is calculated and if these conditions are not met (i.e. if unmet demand > 0.002% or annual carbon emissions exceeded 91 million tonnes as calculated previously) then trial solutions are generated until these conditions are met. After this, the cost per MWhr is determined for each mix.
5. The 'fittest' or 'least cost' mixes are chosen and clustered. If there is only one cluster, the algorithm proceeds to the next iteration. If there are separate clusters, the algorithm will branch out to explore these regions separately
6. Once multiple optima have been established, the evolutionary algorithm is performed once again (without branching) with its starting point centered on the optima located in the previous round of algorithms.
7. The covariance matrix of the points was calculated as it represented the 'spread' of these points. This 'spread' was ultimately used to deduce how wide or narrow the optimum was (if the points were packed closer together this would indicate a thinner optimum).

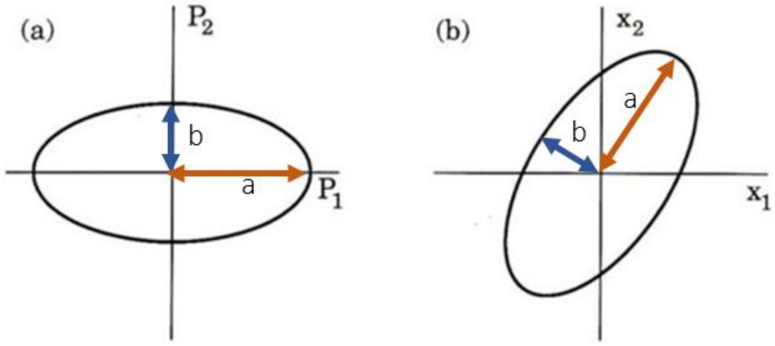
3.3. Outputs

These are the outputs that this methodology will produce.

- **Optimum and Near Optimal Energy Mixes** - Each energy mix will be represented as a percentage contribution by solar, wind, coal, CCGT and OCGT to total electricity generation.
- **Cross-sectional Ellipsoids** – For this project, a way of representing flexibility which was easy to interpret and base decisions on had to be established. The shape of an optimum of a cost curve on a two-dimensional interval can be represented by an elliptical approximation of its cross section. The shape of an optima on a three-dimensional solution space can be represented by an ellipsoid and the shape of an optima on a four-dimensional space (which is the space for this project) can be approximated by a four dimensional ellipsoid. A measure of the flexibility of this optimum is the 4D volume of this ellipsoid given by $\frac{1}{2}\pi^2 abcd$ where a-d are the four radii. The sizes of these radii and the vectors representing the directions in which they exist (i.e. its orientation) can be determined easily using 'Principle Component Analysis' in Matlab of points explored by the evolutionary algorithm. The vector which represents the orientation of the largest radius indicates the direction in which the optimum has greatest flexibility. Since four dimensions would be difficult to display, these concepts are demonstrated in Figure 1. in 2D. The magnitudes of 'a' and 'b' represent the two radii (for a 4D ellipsoid there would be four such radii). The

vectors ‘a’ and ‘b’ can be used to describe how the ellipse is orientated to differentiate between two ellipses of the same size but positioned differently.

Figure 1. Shape of Optima



4. Validation of Techniques

The hybrid algorithm needed to be tested against a known solution so that when it was applied to unknown solution spaces, i.e. electricity generation mixes, one could be confident that the results yielded would be accurate. Different functions in various dimensions, with various optima of various widths were created and the algorithm was tested against them. The following observations were made:

- The hybrid algorithm successfully finds all the optima. At times a very wide optima may be confused as multiple narrower optima. However it is better to have false positives of optima locations which can then be analysed and decided if they are actually one large optima as opposed to an optimum not being detected at all.
- At times, if the algorithm began at a point very close to one of the optima, it would not be able to find the rest. This was solved for by trialing the algorithm with multiple starting points to ensure that all the optima were located.
- Covariance matrices and the ellipsoids of optima calculated from the algorithm were observed to consistently gave a reasonable estimation of the shape of the optima.

Since the techniques were validated successfully, they could be applied to the problem of optimizing energy mixes. The following sections include the results, discussion and conclusion drawn from this application.

5. Results

Energy mixes were explored for a number of different scenarios (different total installed capacities, whether or not the Paris Agreement carbon limit was imposed or not, whether current costs of energy production was used or projected costs) and the following results table show the optimal and near optimal ones. 52GW is the current installed capacity for the NEM (AEMO, 2017). Other installed capacity figures such as 60GW and 77GW were chosen as they produced the most notable results and trends. The cost in $ per MWhr for the energy mix as well as the volume of the cross-sectional ellipsoid is also given. The serial number in the first column will be used to identify various energy mixes in the discussion.

Table 1. Overall Results for All Scenarios

	Total Capacity	Carbon Limit	Cost Levels	Energy Mix as %					$ per MWhr	Volume in e-7
				Solar	*Wind*	*Coal*	*CCGT*	*OCGT*		
1	52GW	Yes	Current	0.1	34.1	22.9	42.9	0.1	44.61	3.55
2	52GW	No	Current	0.2	33.6	43.1	22.9	0.1	42.64	11.97
3	52GW	No	Current	6.0	27.4	42.8	23.8	0.0	42.68	8.49
4	52GW	Yes	Projected	0.2	33.9	22.8	43.0	0.1	42.53	4.55
5	52GW	Yes	Projected	4.4	28.9	22.0	44.4	0.3	42.81	3.63
6	52GW	No	Projected	16.6	15.1	43.5	24.7	0.1	39.95	10.41
7	52GW	No	Projected	5.3	27.7	42.9	23.7	0.3	40.09	12.81
8	52GW	No	Projected	13.0	19.4	38.5	29.1	0.0	39.99	14.8
9	52GW	No	Projected	10.5	22.1	44.7	22.5	0.1	39.97	10.99
10	60GW	Yes	Current	3.5	41.7	30.0	24.7	0.1	40.68	6.02
11	60GW	Yes	Current	0.7	45.1	29.3	24.9	0.0	40.63	7.6
12	60GW	No	Current	0.2	45.5	30.3	23.9	0.1	40.63	21.46
13	60GW	No	Current	6.6	37.7	30.0	25.2	0.5	40.83	11.92
14	60GW	Yes	Projected	14.8	28.6	27.7	28.6	0.4	37.23	6.86
15	60GW	Yes	Projected	11.1	33.1	28.6	27.2	0.1	37.14	7.64
16	60GW	Yes	Projected	6.6	37.6	30.1	25.5	0.2	37.41	6.74
17	60GW	No	Projected	17.9	24.7	31.3	25.9	0.2	37.29	19.68
18	60GW	No	Projected	12.8	30.4	30.0	26.5	0.2	37.29	19.13
19	60GW	No	Projected	14.4	29.1	30.3	25.9	0.3	37.14	17.81
20	77GW	Yes	Current	12.7	47.7	13.2	26.5	0.0	37.56	14.19
21	77GW	No	Current	15.7	44.1	12.4	27.5	0.3	37.63	15.68
22	77GW	No	Current	9.8	50.3	12.2	27.3	0.4	37.70	16.52
23	77GW	No	Current	13.5	46.7	13.5	26.3	0.0	37.59	15.21
24	77GW	Yes	Projected	19.5	40.1	14.3	25.8	0.2	31.67	16.63

The following table shows the vector which represents the orientation of the largest radius in the cross-sectional ellipses for a few notable scenarios. The first column indicates which trial from the previous table they refer to. Note that for trial 6, solar and wind being of roughly equal magnitude but opposite sign indicates that in this solution, the greatest flexibility exists within a one to one swapping of solar and wind contributions.

Table 2. Notable Orientation Results

	Solar	Wind	Coal	CCGT	OCGT
13	-1.9%	4.3%	-1.7%	-0.02%	-1.26%
17	2.6%	-4.0%	1.1%	-0.32%	0.60%
6	3.2%	-3.8%	0.1%	0.5%	0%

The following table shows the 2nd largest radius as a percentage of the largest radius of the cross sectional ellipsoid, as well as the third and fourth. The first column indicates which trial from table they refer to.

Table 3. Notable Shape Results

	2^{nd} as % of 1^{st}	3^{rd} as % of 1^{st}	4^{th} as % of 1st
6	94.77%	58.28%	27.58%
1	34.35%	22.39%	13.13%

6. Discussion

6.1. Total average industry costs

The results indicate that as the total capacity is increased from 52GW to 60GW to 77GW the cost per megawatt hour of electricity decreases. For example, under current costs with 52GW installed capacity and a carbon emissions limit imposed (situation 1) the minimum cost amounts to $44.61 per MWhr. However, in the 60GW scenario under the same costs and carbon emissions limit (Situation 10 and 11), the cost of the minimum amounts to $40.68 and $40.63. Similarly, when the installed capacity is increased to 77GW but with other conditions remaining the same (Situation 20), the minimum cost decreases further to $37.56. Note that the total demand remains the same hence the total energy produced remains the same (since only 0.002% of demand can remain unmet, the variation in energy produced between options is very small). This shows that any extra investment in building generators to in the case of an installed capacity of 60GW compared with an installed capacity of 50GW is offset by the cheaper cost of producing energy. This is because larger amounts of excess capacity mean that renewables can be used to a greater extent without compromising on reliability. Building renewable energy plants and operating them tend to be far cheaper than their fossil fuel equivalents. This is what brings costs down as installed capacity is increased. Adding the impact of rapidly decreasing costs of renewable energy and this trend of decreasing costs with increasing installed capacity is further sharpened.

6.2. Reliability

All optimal solutions determined by this method are sufficiently reliable (i.e. unmet demand as a percentage of total demand is less than 0.002%) as this was set as a constraint for the solutions. The energy mixes in this optimisation problem have been parameterised as percentages of total installed capacity (as opposed to an exact capacity value) therefore the overall shape of the solutions space should remain the same regardless of the total installed capacity. The reliability standard imposed into the model means that this solution space has discontinuities. Therefore, even though the overall shape of the solution space may remain the same, the extent and location of these discontinuities will change as the total installed capacity changes. When the installed capacity is smaller, there is less excess capacity to serve as a buffer for fluctuations in demand, solar and wind energy. As a result, there are more 'patches' in the solution space where the solution is invalid because it is too unreliable. However, when the total installed capacity is increased, this buffer increases making it easier to be reliable and thus these discontinuities and patches of invalid solutions decrease. It is for this reason that the optimal energy mix for 52GW (Say Situation 1 – 0.05% Solar, 34.08% Wind, 22.91% Coal, 42.89% CCGT and 0.07% OCGT) and 77GW (Say, Situation 20 – 12.67% Solar, 47.67% Wind, 13.15% Coal, 26.51% CCGT and 0.01% OCGT) are so different even when current costs are used for both cases. An optimal energy mix that is valid in the 77GW case may not be reliable enough in the 52GW case meaning that in the 52GW case the algorithm has to keep searching for the next local minimum until it finds one that is reliable enough.

6.3. Sustainability

Tests were conducted to compare minimum costs for when a carbon emissions limit was imposed vs when it was not imposed. Under current costs and with 52GW installed capacity, the cost of energy with a carbon limit is $44.6 whereas the cost without this restriction is only $2 less, $42.6. This difference is diminished by the time total installed capacity reaches 60GW with costs in both cases being $40.63. Once the installed capacity is 77GW, it is in fact cheaper to use renewable energy with costs coming out to be $37.56 with current costs and $31.67 with projected costs.

6.4. Flexibility

6.4.1. Impact of Total Installed Capacity on Flexibility

There are two distinct trends between the installed capacity and the flexibility of the minimum cost solution; that of when a carbon limit is imposed vs when a carbon limit is not imposed. When a carbon limit is imposed, the flexibility (as measured by the volume of the ellipsoid cross section) increases as total installed capacity increases (see situations 5, 15 and 24). However when a carbon limit is not imposed, the flexibility still increased from 52GW to 60GW but actually decreased at 77 GW. This increase then decrease is curious and can only be explained by the fact that at 77GW a new, narrower optima was located which would not have been valid at 60GW because it would be unreliable.

6.4.2. Impact of Emissions Limit on Flexibility

Removing the emissions limit means that there are now fewer discontinuities on the solution space (less 'invalid' solutions) and this should theoretically increase flexibility. This is validated in most situations. For example, using current costs, at 60GW total installed capacity, removing the carbon emissions limit increases the flexibility from 7.603e-7 (Situation 11) to 21.463 (Situation 12). However, when the installed capacity reaches 77GW, due to the fact that a carbon limit does not impact the minima found (since renewable energy is cheaper and the excess capacity means it is more reliable) the flexibility remains the same.

6.4.3. Impact of Input Costs on Flexibility

Changing the cost of technology from current costs to projected costs barely influences the flexibility in most cases. However at 52GW installed capacity, with no carbon limit, changing the costs from current to projected does increase the flexibility (situation 3 to situation 7). Without the restriction of sustainability, a drop in cost shifts the 'affordability-reliability' equilibrium resulting in this increase in flexibility.

6.4.4. Orientation

Consider Table 2 in the results section. At 60GW total installed capacity, with no limit set on carbon emissions, changing the input costs from current costs (Situation 13) to projected costs (Situation 17) completely swivels the orientation of the cross section of the optimum (seen by how some of the co-ordinate vectors swap sign). The third situation given in this table, Situation 6, is where the total capacity is 52GW with projected costs and no carbon limit. This is an example of how this orientation vector can be helpful. By looking at this vector and that movement in this direction would be proportional to a 3.22% increase in solar and a -3.80% decrease in wind one can deduce that any flexibility in this option exists from being able to interchange wind and solar.

6.4.5. Shape

Another consideration is how 'round' or narrow an optimum is. Two cross sections can have the same 'volume' and hence the same 'overall flexibility' but for one of them, this volume might be evenly spread amongst the four dimensions creating an almost spherical shape whereas for the other, the length across one dimensions may be far greater than the others creating a very long but slim shape. This shape can be measured by expressing the radius of the ellipse in the second largest dimension as a percentage of the radius in the largest dimension. Thus a '100%' would denote a 'rounder' shape. Table 3 in the results section indicates these percentages for some notable optima.

In the case of Situation 6, the weighting of the second orientation vector is almost as high as the first vector. The weighting of the third vector however is only half as much so and the fourth is even less than that. This indicates a kind of 'fat disk' shape. Situation 1 however, represents a thinner ellipsoid.

6.5. Recommendations

Based on the results and some of the trends discussed, the following lists some recommendations for every installed capacity scenario based on the study approach taken. Note that in all cases, the carbon limit has been imposed due to the goal of 'sustainability'. Furthermore, only the current costs were considered relevant to the 52GW case as that is the NEM's current installed capacity. Similarly in the 77GW case, only projected costs were considered as by the time capacity is built up to that level, costs will have most certainly dropped.

Scenario	Notes	$/MWhr	Volume	Mix
52 GW Installed Capacity	There is only one optimal option for this scenario using the chosen study approach and it has fairly low flexibility	44.61	3.55e-7	1
60 GW Installed Capacity Under Current Costs	There is only one optimal solution for this situation however it is a very flexible solution. In the algorithm, this optimum was located during a run without imposing the carbon limit however it still satisfies this limit	40.63	21.4e-7	12
60 GW Installed Capacity Under Projected Costs	There are three options for this scenario. They are cheaper than what was derived with the current costs however they are a lot less flexible	37.23	6.86e-7	14
		37.14	7.64e-7	15
		37.41	6.74e-7	16
77 GW Installed Capacity Under Projected Costs	There is one best solution at this capacity. This option also has fairly high flexibility	31.67	16.6e-7	24

7. Conclusion

In conclusion, the research and methodology described in this paper successfully produced a shortlist of the best few generation mixes for the Australian NEM and the robustness of these, for a given set of assumptions regarding future generation costs, demand and reliability and emission scenarios.

The method is applied to an existing open-source evolutionary programming based least-cost generation mix tool which doesn't have some of the limitations of conventional linear and mixed integer programming approaches. Furthermore, by modifying evolutionary algorithms, clustering algorithms and covariance matrix theory, not only have the location of the best solutions been identified, but also the location of other near optimal solutions and how flexible each of these solutions are.

Apart from the recommended few energy generation mixes, this project also demonstrated some notable trends. Namely, as the total capacity is increased and the cost of renewables falls rapidly, the total cost (building and operating) of generation over 30 years becomes cheaper per MWhr. Furthermore, keeping emissions below a limit calculated from the Paris Agreement does increase cost modestly but as renewables become cheaper this margin diminishes and more renewables actually keeps costs lower (e.g. 77GW).

While the study presented here is preliminary, it does highlight the opportunity to use clustering to improve the 'value' of least cost modelling exercises for future electricity generation mixes given the uncertainties and challenges involved in this. In particular, this method may provide information to policy makers and other stakeholders about potential pathways open to the NEM as well as the costs and trade-offs that can be made without significantly deteriorating affordability, reliability and sustainability.

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Acknowledgements

I would like to acknowledge the guidance and encouragement provided by my supervisor A/Prof Iain MacGill.