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MEGS: Modelling energy and grid services to explore decarbonisation of power systems at lowest total system cost

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ABSTRACT

Finding the generation mix with the lowest total system cost for deep levels of decarbonisation is critical for electricity consumers and taxpayers, who together need to cover the costs of the entire electricity system. MEGS is an electricity system scenario tool designed to explore options to approach the optimal mix for a particular decarbonisation target. A future system must also maintain system security and "keep the lights on". To ensure this, MEGS also models grid services, such as firm capacity, inertia and frequency response, ensuring that there are sufficient volumes of these balancing mechanisms available to the grid operator. MEGS has been validated against outturn generation data for the Australian National Electricity Market and has been used to explore the lowest cost frontier at high levels of decarbonisation.

1. Introduction

The drive to reduce CO_2 emissions in line with the Paris Agreement [1, 2] is leading to the transformation of electricity systems around the world. The growth of renewables, such as wind and solar PV, are a key part of this transformation, and they are forecasted to form a major part of many electricity systems in the future [3–5]. As variable renewables are no longer just a small perturbation on a conventional system [4–7], great care needs to be taken to ensure that the grid services traditionally delivered by thermal plant will still be available [8–15]. The potential scarcity of these grid stabilising services on a highly renewable system [13–18] is shifting the focus away from just balancing energy to the more complex task of ensuring the system remains operable and that the "lights stay on".

Models of the electricity system are important tools that planners and policy makers use to develop and test the implications of policy options and understand possible future scenarios. Therefore, it is important that models of the electricity system are adequately equipped to ensure that the requirement for the most critical grid services are as central to their algorithm as is balancing of energy – which has historically been the most important requirement. Furthermore, stakeholders, planners and policy makers need to critically assess the cost to the consumer of any future system and strive to minimise this cost whilst also achieving ever more stringent environmental targets. For too long, simplistic technology-based cost metrics like Levelised Cost of Energy (LCOE) and its derivatives [15,19–21] have been used to attempt to find the lowest cost solutions to decarbonisation. However, such energy-only metrics which do not consider the whole system say nothing about the value of a technology being added to the system, especially ones that deliver grid services alongside, or rather than, energy [20,22–25]. This can result in key decision makers using misleading information which may lead to the dismissal of valuable technologies critical to a future system, because they are judged solely on their ability to deliver energy, rather than lower total system cost within a complex electricity system.

This increasing complexity has been explored by others [26,27] in these wide ranging reviews of the Generation and Transmission Expansion Planning (GTEP) problem. Relevant here is the overview of modelling grid services on timescales from sub-second to seasonal and how storage contributes to the renewable variability problem [28]. Some modelling has specifically dealt with the need for sufficient inertia [29], others have compared the accuracy of AC power modelling with the simplicity and tractability of DC models for GTEP with significant penetration of variable renewables [30]. No attempt will be made here to repeat these substantive reviews, but the focus will be on one such model and its simplifying assumptions.

This paper presents Modelling Energy and Grid Services (MEGS), a model which addresses critical grid services such as reserve, inertia and firm capacity alongside the need to balance energy at each timestep. This allows it to find the portfolio of assets that deliver the lowest total

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system cost, which may include some technologies that have an LCOE which is not the lowest or is undefined. The requirements for this new model are presented, and its assumptions and solution procedures are discussed in detail. The model results have been validated against market data for the Australian National Energy Market (NEM) and its runtime performance as a function of required resolution is presented. An example of how MEGS may be used to evaluate generation options in a highly decarbonised world is used to demonstrate its capabilities.

1.1. Model requirements

The fundamental objective of MEGS is to model both thermal generation based electricity systems, typical of many grids until recently [4, 31], and fully decarbonised electricity systems of the future, which are likely to be made up of a wide range of generation and storage technologies [4,6,32,33]. The MEGS model outputs are designed to be those most useful to system planners and policy makers in order to assist them identify technology portfolios that will lead to reduced emissions, whilst maintaining the essential system security, all at minimum cost to the consumer. The first power grid the MEGS model was applied to was the Australian NEM, where each of the five states have very distinct generation resources and are only weakly interconnected [13]. To achieve that the following requirements had to be met:

Generation Technologies: MEGS had to be capable of modelling those technical characteristics of thermal and variable renewable technologies to which the key outputs are most sensitive. For example, MEGS specifically needed to be able to resolve the dynamics of generation on an hourly basis to capture ramp up and down of solar, a weekly basis to model the effect of weather patterns on wind, and a seasonal basis to account for significant differences in renewable resource availability.

Storage Technologies: As energy storage is going to be an important aspect of a decarbonised grid [4–6,31], MEGS had to be able to track their state of charge, to ensure energy storage limits were not exceeded. This translated into a requirement that MEGS solve timesteps in a chronological sequence rather than using a representative time-slice approach [34,35].

System Security: MEGS needed to be able to demonstrate that the most important non-energy grid services could be supplied to all modelled regions. There are many of these services [18] but the most important were judged to be (i) having enough firm capacity (or equivalent) to maintain a sufficient margin over demand, (ii) having sufficient supply of upwards frequency response and fast acting reserve at each time step, (iii) having a minimum level of inertia at each timestep. These three effectively dealt with grid security over the relevant time scales, at the year, minute and sub-second timescales. It was assumed that intermediate timescales, and the other grid services such as downwards response, fault current provision and black start capability, could be suitably covered by satisfying the three services modelled, or procured at little additional cost if required.

Regional: The matching of generation and imports to demand and exports had to be achieved for each model region for each time step. In addition to balancing energy regionally, the system security constraints identified also had to be met in each region, with the proviso that interregional transmission lines could transfer some energy or be used to meet the reserve requirements.

Computation Speed: It was considered useful to be able to run hundreds and occasionally thousands of scenarios in a reasonable time (overnight) on an average computer. To achieve this the problem formulation would have to be efficient and there should be a simple way to trade off resolution with run-time.

2. MEGS implementation

2.1. Assumptions

It was recognised in the model development process that to have the required resolution in time, and yet solve in minutes on an average computer, it would require a trade-off with resolution elsewhere. The most important assumptions are as follows:

Simplifying Assumption 1: Generation technologies may only operate in one of four modes, with a fifth mode for storage. The production of energy and provision of grid services of these modes is illustrated in Table 1 where:

- Capacity (*CAP* in MW), is the nameplate capacity
- Minimum Stable Generation (*MSG* in MW), is defined as the lowest possible output if the unit is on
- Spinning Reserve Level (*SRL* in MW), is defined as the highest possible output if the unit is providing all possible upwards reserve
- Inertia Constant (P*INC* in MW.s), is the inertia added to the system when the plant is synchronously connected

Fig. 1 illustrates this graphically by showing generation and reserve outputs for the allowed operating regime between MSG and full capacity of a typical thermal generator.

Simplifying Assumption 2: Any proportion of a generation or a storage fleet can operate in one of the allowed modes. This trade-off is at the unit commitment level, the problem formulation is made linear by allowing power generation to be a continuous variable rather than it being quantised at unit level, and thus dispenses with any integer variables in the formulation. This allows the use of a linear programming (LP) solver rather than a mixed integer programming (MIP) solver, resulting in a significant time saving. Resultant errors can be small as shown in the example of Box 1, based on the coal fleet of New South Wales [36] and expected heat rate curve [37].

Box 1: A simplified example is taken from the fleet of coal plant in New South Wales There are 16 units of average size of about 600 MW supplying most of the load. If the required output was 6300 MW (with no reserve or inertia requirements) a MIP solver would commit 11 units, 10 at full load and one would be running part load. An LP formulation would run 10.5 units at full load. The error is the difference between half the emissions of a unit a full load and the emissions of a unit at half load (less than 0.6 full load emissions), as a proportion of the emissions of 11 units, which will be less than 1%. This is well within the accuracy of publicly available generator technical parameters such as heat rate.

Simplifying Assumption 3: Reduced availability uses the "squeezed MW" approximation. In reality, the loss of generator availability arises because plants are completely taken off-line for a

Table 1
Possible operational modes for generation and storage in MEGS showing equations for Power, Reserve and Inertia plant contributes to the system (Nomenclature in Appendix A).

Mode	Power (MW)	Reserve (MW)	Inertia (MW.s)
o: Off	$PPWR_{p,m} = 0$	$PPWR_{p,m} = PCAP_p - PSRL_p$ (fast start plant only) $PRES_{p,m} = 0$	$PINR_{p,m} = 0$
m: Running at MSG	$PPWR_{p,m} = PMSG_p$	$PPWR_{p,m} = PCAP_p - PSRL_p$	$PINR_{p,m} = PINC_p$
s: Running at SRL	$PPWR_{p,m} = PSRL_p$	$PPWR_{p,m} = PCAP_p - PSRL_p$	$PINR_{p,m} = PINC_p$
c: Running at CAP	$PPWR_{p,m} = PCAP_p$	$PRES_{p,m} = 0$	$PINR_{p,m} = PINC_p$
f: Storage filling at CAP	$PPWR_{p,m} = - PCAP_p$	$PPWR_{p,m} = PCAP_p - PSRL_p$	$PINR_{p,m} = PINC_p$

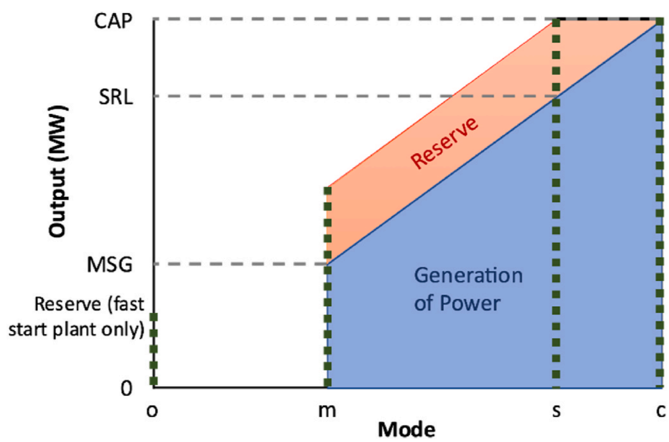

Fig. 1. Schematic of a thermal generator's output of power and reserve for each mode of operation.

period (such as during an outage), or because there is a restriction on output for a period (such as a mechanical derating or reduced renewable resource). However, in MEGS, all availability loss is modelled as a reduction in plant capacity. Loss of availability from mechanical issues are averaged over time, reductions due to renewable resource availability and thermal plant weather sensitivity are specified for each time step as a time series of capacity factors.

Simplifying Assumption 4: Non-energy grid services can be adequately represented by satisfying the need for one upwards fast reserve product and inertia. Simple electricity grid models do not take account of grid services, but as non-energy grid services become more important in highly renewables scenarios [12,13,18], more detailed models have incorporated some grid services or linked a unit commitment and dispatch model with a long term energy system model [38–40]. Likewise MEGS has been designed from the outset to take the most important of these grid services into account. Firstly, it ensures there is sufficient frequency control and fast reserve services available by modelling the requirement for one upwards reserve product. This is used to represent all frequency response and fast reserve services such as spinning reserve, fast start natural gas units and storage with headroom. Secondly it uses inertia to represent both the need for a minimum level of inertia in each region (as typically set by the grid operator) and system strength/fault current requirements. Inertia is treated as a local (regional) constraint as it is not usually transferred via an interconnector, and system strength is inherently local in nature [13].

Simplifying Assumption 5: Within each day, storage is optimised alongside generation on a perfect foresight basis. Intra-day timesteps are optimised together, rather than in a time sequential manner. This results in all the time series data affected by weather, such as the availability of renewables, demand and reserve requirements, being known by the optimiser for all time steps within the day. Hydro must use its predicted inflow within the day and short term storage must start and end the day at the same storage level. The same is true for long term storage, except the closing level must differ from the start of the day by the budgeted discharge or charge amount.

2.2. Characterisation of generation and storage

Generation within the model is characterised as aggregated fleets of units of similar parameters. This categorisation is within the user's control, typically however, all plant with the same fuel and technology type within a region might be represented as one plant fleet. Ideally a fleet should contain more than a few units, so that the assumption that it be treated as a continuum is valid. Likewise, energy storage is bundled into fleets with similar characteristics. However, as most energy storage technologies are very flexible, with low MSG and low start-up costs, there is a reduced requirement to have as many units in each aggregated fleet, as the neglected integer costs and constraints are less important. This is also true of very flexible generation technologies such as hydro or peaking plant.

2.3. Treatment of Energy Storage

Energy storage is defined within the model in terms of its storage horizon which is the period over which an operator might expect to optimise its arbitrage opportunities [31,41]. This horizon is set as a multiple of the storage duration by the user. For example, a storage facility with 12 h of storage will take at least 24 h for a full cycle and likely much longer when taking into account idle time, intermediate or low load factor operations. Typically, the storage horizon is set between 5 and 10 times the duration.

Short term storage facilities (defined as having a storage horizon of less than a day) are optimised within the day, as per the Simplifying Assumption 5.

For storage with a long horizon, MEGS makes use of previously calculated seasonal average demand based on 10 years of data for each region. These half hourly timeseries were created by taking the mean of the 10 half-hourly demands for the same day of the year. The regional capacity factors of renewables were similarly calculated beforehand by averaging 10 years of data. A "seasonal average" net demand curve for the region in which the storage is located is then be constructed by MEGS by using the known renewable capacities and subtracting output from the averaged demand.

MEGS also constructs a "perfect foresight" net demand curve for the region by subtracting renewable generation (based on its availability time series) from the time series for demand for the scenario-year. These two new timeseries are then combined to create a "limited foresight" net demand curve for the region in the which the storage is located (or for the whole system if storage generation could exceed demand). For day 1, the limited foresight curve is entirely based on the perfect foresight curve, and for days beyond the weather horizon (typically 7 days), the forecast is entirely based on the seasonal average curve. Between these two extremes, the forecast is a mixture of the two, for example with a 7 day weather horizon day 2 is constructed from 1/7 perfect foresight +6/7 seasonal average. This is shown graphically at the top of Fig. 2.

The limited foresight curve is used to estimate the generation and filling of each fleet of storage facilities assuming the storage is used for peak shaving and is refilled during the trough periods, taking account of its round trip efficiency and storage volume. These are then used to fix the energy budget for each storage facility on the first day, and these values are fed into the storage constraints of the main optimisation. This is illustrated at the bottom of Fig. 2 where the red generation area in day 1 (net of the purple filling area) sets the energy budget for the day being modelled. This whole process is repeated before the main optimisation algorithm for each day, thus ensuring the energy budget for the storage facility is consistent with an operator's best view of the demand for the stored energy resource and opportunities to refill over the whole storage horizon.

2.4. Regions and links

Each region is represented within MEGS as a node, to which specific generation and storage capacities are attached. Each region must be supplied by a minimum level of inertia from sources within that region. These minimum inertia levels may be published by the system operator (eg in the Australian National Electricity Market [42,43]) or calculated from limits on the Rate of Change of Frequency and maximum credible infeed loss (e.g. in the Great Britain system [44]).

Regions also have an individual timeseries of power demands and reserve requirements, based on historic data for the scenario-year being modelled, which must be met at each timestep. These may be met from within the region or via transmission from a connected region (if that

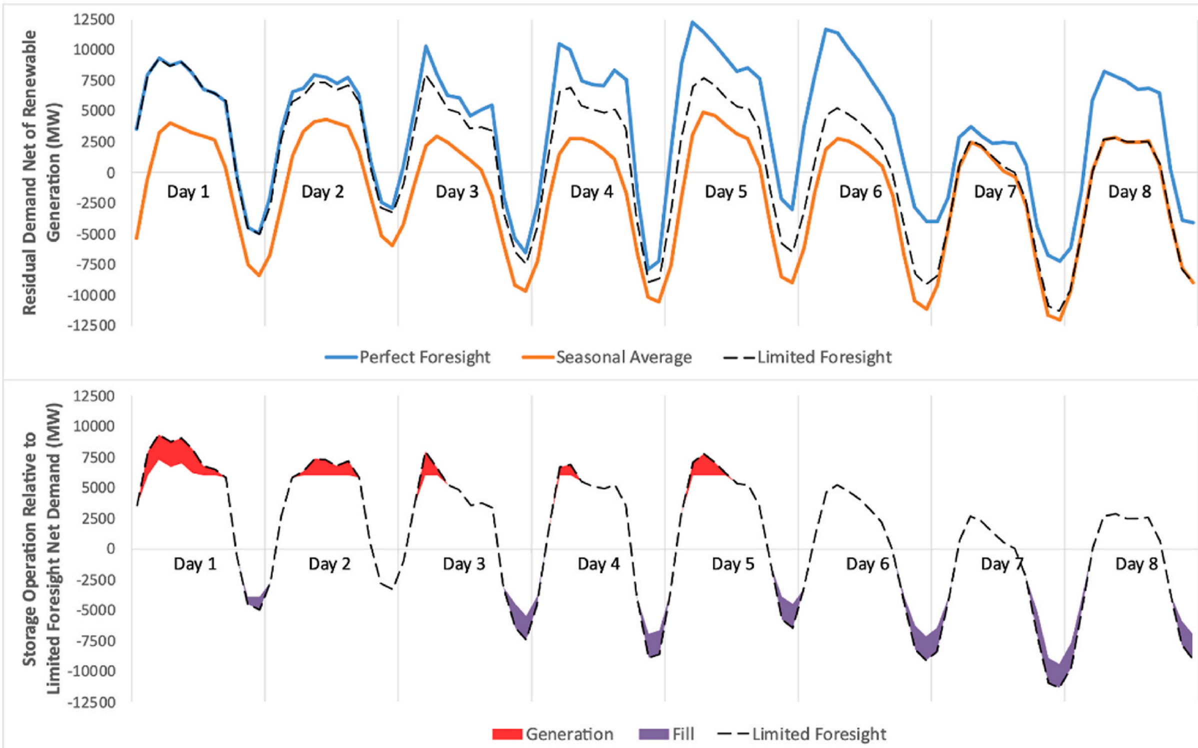

Fig. 2. Composition of the modelled limited foresight net demand curve (top) and simulated storage operation (bottom)over an eight day period.

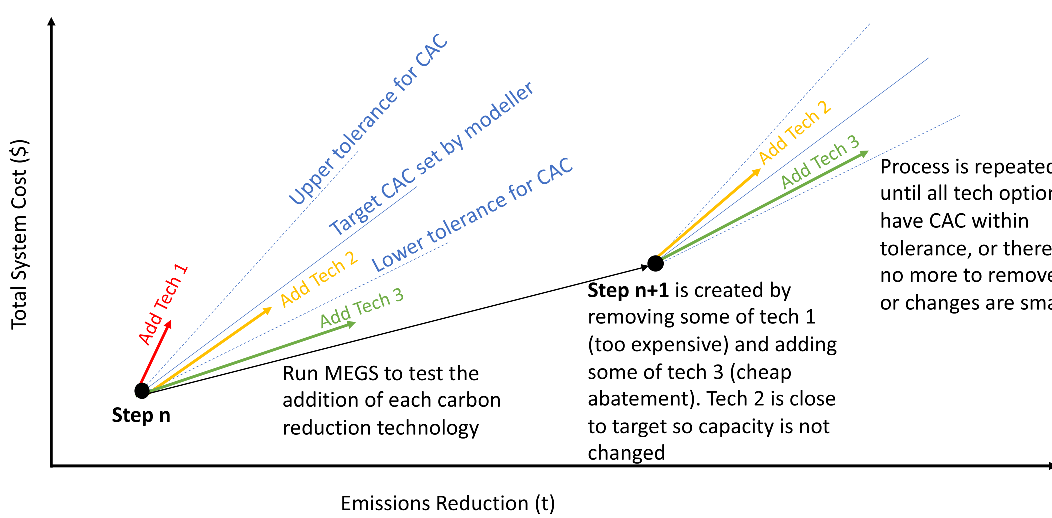

Fig. 3. Schematic of MEGS optimising the generation portfolio for a given Carbon Abatement Cost.

region has spare capacity). Note that some generation technologies (such as variable renewable generators which are subject to weather uncertainty) might increase the requirement for reserve when they are running.

Regions can be connected via unidirectional transmission lines referred to here as links. Two antiparallel links are used to represent a normal bi-directional interconnector. These links can transport power and reserve, but the sum of the two is limited to the overall link capacity. Links can have costs associated with the transfer of power and reserve, which can be used as a proxy for losses which are not modelled directly.

Box 2: Objective Function

Nomenclature in Appendix A

System Short Run Cost: This is minimised on a daily basis, subject to the constraints which follow.

Equation 1 Daily system short run cost construct

$$srcday_d = \sum_{t\in T_d}\left(\sum_{p\in P} PCAP_p\left(TSD\sum_{m\in M} PVOC_{p,m}\, proplant_{p,m,t} + \frac{1}{2}PSUC_p\left(propstart_{p,t} + propshutd_{p,t}\right)\right) + TSD\sum_{l\in L} LCAP_l\, LVOC_l\, prolpow_{l,t}\right)\forall d$$

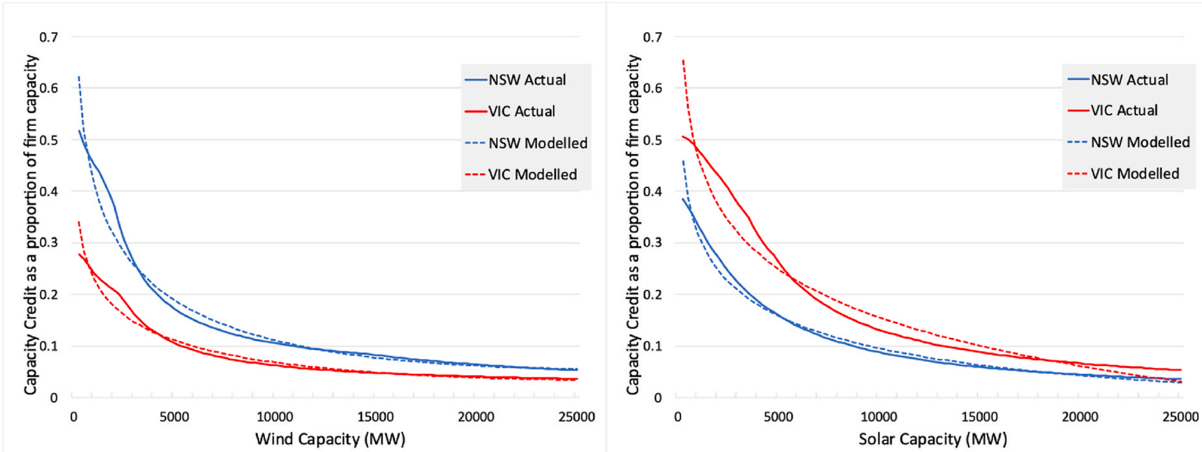

Fig. 4. Capacity credit of wind and solar in New South Wales and Victoria as a function of capacity of that technology.

2.5. Core algorithm

The objective function and core constraint equations are given in boxes 2–3. MEGS solves each day of the year in a time sequential manner using a rolling-horizon approach. MEGS has been written flexibly so that in theory the user can specify other time periods, such as grouping days together or specifying a period of six months. However, days and years are the most natural time periods to model, and in practice have formed the framework for most of the modelling, so these terms are used throughout this paper. The following process is then repeated for each day.

1. The next day is defined as the next *TSPD* timesteps
2. For each storage facility, the storage budget allocation algorithm is run as described in the Treatment of Energy Storage section
3. The objective function and constraints are composed using data for this day
4. The linear programming solver is called and returns the proportion of plant running in each mode, and the proportion of link capacity devoted to carrying energy and reserve for all timesteps in this day
5. All results are saved and step 1 repeated for the next day
6. After all days have been run then key outputs such as total system cost and emissions are calculated

Box 3: Constraints
Nomenclature in Appendix A
Energy Constraint: Energy must balance within each region for each timestep.
Equation 2 Demand Equality Constraint

$$DEM_{r,t} = \sum_{p\in P_r}\sum_{m\in M} PAVL_{p,t}PPWR_{p,m}proplant_{p,m,t} + \sum_{l\in L_r} LIMP_{l,r}LCAP_l prolpow_{l,t}\ \forall r,t$$

Reserve Constraint: There must be sufficient reserve within each region for each timestep.
Equation 3 Reserve Sufficiency Constraint

$$RES_{r,t} \le \sum_{p\in P_r}\sum_{m\in M} PAVL_{p,t}PRES_{p,m}proplant_{p,m,t} + \sum_{l\in L_r} LIMP_{l,r}LCAP_l prolres_{l,t}\ \forall r,t$$

Inertia Constraint: There must be sufficient inertia within each region for each timestep.
Equation 4 Inertia Sufficiency Constraint

$$IRQ_r \le \sum_{p\in P_r}\sum_{m\in M} PINR_{p,m}proplant_{p,m,t}\ \forall r,t$$

Other constraints: There are other constraints not given here but can be found in Appendix A

2.6. Implementation

MEGS is controlled from an Excel spreadsheet and associated macros which set up a new directory for each run. The scenario and asset data is held in this spreadsheet and exported via a set of comma delimited (CSV) files. Libraries of historical generation and simulated output from Renewables Ninja [45] and NEM Review [46] are also available in CSV format. The core of MEGS is written in MATLAB which reads in relevant data and makes use of the linear programming solver in its optimisation toolbox. Results are written back to CSV files which can be automatically imported by the same spreadsheet that holds the data, for further analysis and chart plotting.

2.7. Scenario tools

MEGS has been designed to have a number of scenario tools available to allow either the core algorithm to be run for different scenarios, or for each run to influence subsequent runs in a goal seeking algorithm:

1. **Exploration Mode.** A series of runs can be composed by increasing the capacity of specified plant in steps. After running a base year, MEGS will increment the first fleet of plant by specified steps and reduce the capacity of other generation fleets to the point where the same security standard is being met. This allows the exploration of incremental increases in a new technology, whilst replacing an existing technology.
2. **Stochastic Mode.** MEGS can be set to explore changes to input parameters in a stochastic manner within limits set be the user. For example the user might specify a uniform distribution for the amount of new build for set generation fleets, a range of historic years that can be used for weather or some log-normal distributions for fuel prices. MEGS will then randomly pick some input parameters according to the given distributions and run a series of scenarios. Typical uses might be to plot total system cost (TSC) against decarbonisation for each scenario and determine the lowest cost frontier, examine a range of different weather years to determine its impact on emissions, or explore the impact of fuel price uncertainty on TSC.
3. **Optimisation Mode.** MEGS can be set to explore the effect of adding an incremental amount to each fleet of technologies specified by the user, and run each new scenario. However, in subsequent steps, MEGS will then choose those increments that achieved an emissions reduction at a Carbon Abatement Cost (CAC) [47–50] that was less than a user-specified value. Fleet capacities will be updated with those increments to create a new starting point and the process repeated. If a new run shows the CAC has exceeded the user value then it will cause MEGS to reverse out of the change. As decarbonisation proceeds CACs are generally found to rise and the process reaches its conclusion once all CACs are within a tolerance of the target (Fig. 3).

2.8. Maintaining System Security

"Keeping the lights on" not only means ensuring there is enough reserve and inertia, but also that there is enough firm capacity to meet net demand at all times. Whilst MEGS is operating with one of the scenario tools that automatically adjusts generation capacity it is important that the capacity additions and removals do not end up with a scenario that fails to meet demand, or is expensively over-supplied, either outcome is unrealistic and cannot be compared with other scenarios.

To allow MEGS to autonomously explore increases in capacity of some generation fleets the user must specify at least one fleet of firm capacity that can be gradually decommissioned in response to the capacity additions, so that the probability of load shedding remains constant.

However, some technologies cannot be assigned a static capacity credit value which is independent of the system. This is particularly true for variable renewables. In a system with little wind the first additions of this technology are likely to have a significant impact on meeting the peak demand. However, in a wind dominated system the residual peak demand (net of the renewable generation) is likely to be a during a period of low wind, so adding more wind power will have little effect on meeting this peak. To model these effects MEGS needed a dynamic concept of capacity credit.

Capacity credit of new build is defined here as the capacity of reliable fossil plant that can be retired, whilst leaving the loss of load probability unchanged when the new build is added. An example of calculating capacity credit is provided in Box 4, based on the security standard of the NEM [51].

Box 4: Example of calculating the Capacity Credit curve for wind in the Australian NEM

Capacity Credit is calculated "off-line" before MEGS is run and the capacity credit profile is incorporated as an input to MEGS as data on fitted curve. It is calculated by taking 10 years of half hourly data on demand and starting with an initial estimate for the total available capacity of thermal plant. The sum of the excess of demand over available capacity is then calculated. This simplistically represents the unserved energy for that level of capacity. The total capacity is iterated until unserved energy, as a proportion of total demand, is equal to 0.002%, the security standard for the NEM. This process is repeated with demand reduced by the generation from an additional 1 GW wind farm, and the difference in capacities is the capacity credit of that first GW of wind. This latter process is repeated for increasing amounts of wind and an exponential curve fit through the results as shown in Fig. 4 which illustrates the process for New South Wales and Victoria. This clearly shows the law of diminishing returns; there is a very significant reduction in the ability of renewables to meet peak demand (net of renewables) as penetration increases.

2.9. Resolution and performance

The scenario tools require many individual scenarios to be produced, so it was important that MEGS achieve a manageable solution time. Ideally the aim was to achieve a 5-min run time for a medium resolution scenario. MEGS was run on a Macbook Air™ with a 1.6 GHz dual core Intel i5 processor with 8 GB RAM. The test case was the Australian NEM with 87 plant and 5 regions. It was run three times with a different plant mix each time and this process was repeated for five different temporal resolutions. The average run times for a one year simulation at each resolution are shown in Fig. 5.

If a large ensemble of runs is required, then a time step length of 5 or more hours allows for a run time of around 1 min or less. When a detailed modelled output with fine time resolution is required, then step length may be reduced to 2 h, this would result in a run time of up to 11 min. It can be seen that for a medium resolution of 3.5 h granularity the run time is significantly faster than the target of 5 min (refer to Fig. 5).

Note that a step length can be chosen that does not divide 24 h exactly. This enables calculation days to be based on data taken from more 'sets of times' in the day, rather than having the bias of always missing, or always including, the cardinal points in the day. For example, if a time step of 3.5 h is chosen with 7 time steps per day, then Day 1 is based on data from 00:00, 03:30, 07:00 etc, whereas Day 2 is based on 00:30, 04:00, 07:30 etc and day 3 is a set of times that are half an hour later again.

2.10. MEGS model outputs

MEGS is configured to produce the following annual results for each scenario run:

- Total System Cost
- Components of TSC, vis annualised capex, fixed costs and running costs
- Annual total system CO_2 emissions and broken down by region

When MEGS is configured for exploratory, stochastic and asset optimisations, it also produces:

- Carbon abatement costs compared to a defined base case
- Parameters that may have changed between scenarios such as plant capacities, fuel prices and weather year.

For the most detailed runs undertaken at high resolution MEGS can produce time series data of any internal timestep variable. The most

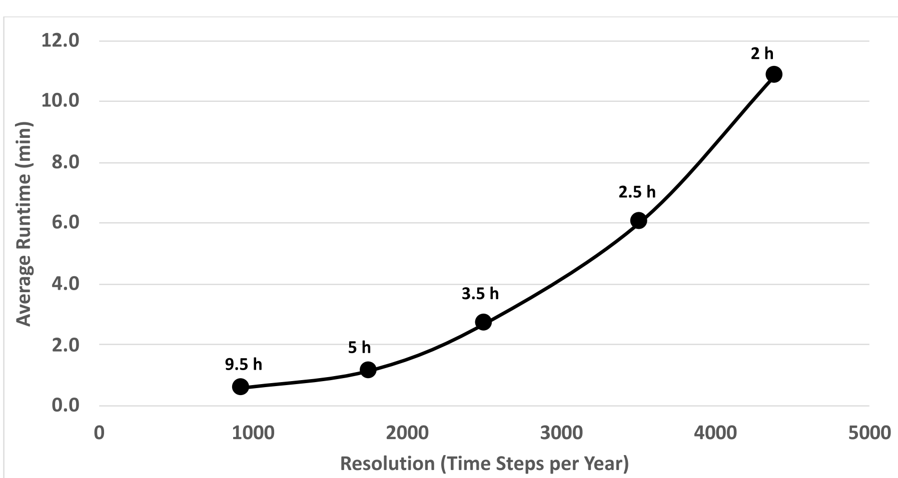

Fig. 5. Run time for MEGS as a function of resolution.

useful of these outputs are offered to the user as a choice and include plant generation, plant reserve, plant curtailment, storage filling, plant start-ups, link flows and system short run marginal cost (derived from the shadow price of the demand constraint).

3. Validation

Validation of electricity system models against actual data increases confidence in the outputs and leads to an increase in trust amongst both the public and policymakers. Energy models, however, are frequently criticized for being insufficiently validated, with the performance of models rarely checked against historical outcomes [52,53]. MEGS has been validated against actual data for the Australian NEM.

3.1. Australian National Electricity Market

The Australian NEM comprises five weakly interconnected states, each with different resources and mix of generation technologies [13]. The MEGS model was first validated by comparing the generation for each of the NEM regions for a particular year [54]. The modelling results where then compared to the actual dispatch pattern for each technology type, for each region and the whole NEM. Fig. 6 compares the annual energy production as determined by MEGS with actual data as reported by NEM Review [46]. It can be seen that on the whole agreement is very good. The differences are relatively small, however MEGS results show less gas generation than reality and models New South Wales (NSW) as generating more of its own power (and thus importing less from Queensland (QLD) and Victoria (VIC). This is likely to be due to differences in natural gas fuel contract prices (which are not available in public data) or the effect of local, intra-state constraints forcing small gas plant to be used to support the grid out of merit.

To investigate whether MEGS was modelling the correct behaviour of the various generation plant, its modelling output was examined on a more granular level. Fig. 7 shows the first week in May 2010, chosen because renewable output varies significantly with very low wind resource on Sunday but strong winds two days later. The examination shows that very similar running patterns between the model results and the actual output. Victorian based brown coal operates as almost base load with occasional dips as expected. NSW and Queensland black coal power plants operate either at baseload or load following in MEGS, with a high overall load factor exactly as they are seen to do in the chart of actual generation. Natural gas plant is modelled with slightly too little output as has been discussed previously. The modelled and actual hydro power plants operate very flexibly around the variations caused mostly by the intermittency of renewables. While there are some small differences, some of these are also caused by the lower resolution (there are just 7 time steps each day) used in the MEGS modelling.

3.2. MEGS in action

This section illustrates a typical application for the MEGS modelling approach, based on the need to decarbonise the Australian NEM by 2050 [1]. The aim is to determine which portfolios of generation plant will give the lowest TSC to consumers for a range of different decarbonisation targets in 2050. This is best tackled by Stochastic MEGS, running in low resolution to explore a broad range of solutions [55]. Data has been be sourced from the following:

1. Most data are based on Australian Energy Market Operator (AEMO) Integrated System Plan 2019 (ISP) Fast Change scenario (ISP-FC) [13].
2. Some costs not found in the ISP are taken from AEMO Costs and Technical Parameter Review: Report Final Rev4, by GHD [56].
3. Commonwealth Scientific and Industrial Research Organisation (CSIRO) GenCost 2018 cost forecast [57] is used to project capex learning rates.
4. Some costs of specific projects are taken from other sources such as the award of contract to Salini Impregilo for Snowy 2.0 hydro project [58] and other confidential industry project data for future CCS development costs

Fig. 8 shows the result of running more than 3000 scenarios with varying amounts of low carbon capacity such as nuclear, fossil carbon capture and storage (CCS), bioenergy CCS (BECCS), wind, solar PV, and energy storage (both pumped hydro and batteries). For each scenario a random capacity of each technology was added to the system (within pre-determined limits); energy security was maintained at current levels by adding unabated open cycle natural gas power technologies, or closing some existing coal plant as described in “Maintaining System Security”. A full year’s simulation was run for each scenario at a low resolution (920 time steps) and TSC per unit of demand plotted against decarbonisation achieved from a 2005 baseline (blue points). Within the pre-determined technology limits, it can be seen that there is effectively no limit to how expensive the system can be with some technology mixes being greater than $230/MWh, but there is a clear frontier representing the lowest TSC configuration. This frontier slopes upwards with a slight increase in gradient for deeper decarbonisation representing an increasing marginal cost of abatement.

In addition to being able to determine the slope of the lowest total system cost frontier, the Stochastic MEGS results may be used to examine the impact of technology constraints. For example, also highlighted on Fig. 8 as red points, are the subset of points with no CCS (neither fossil nor BECCS) within the modelled scenario. For levels of decarbonisation below 80% the lowest cost frontier remains unchanged, so scenarios along this portion of the frontier may or may not include CCS. Between 60 and 80% decarbonisation, having CCS within the

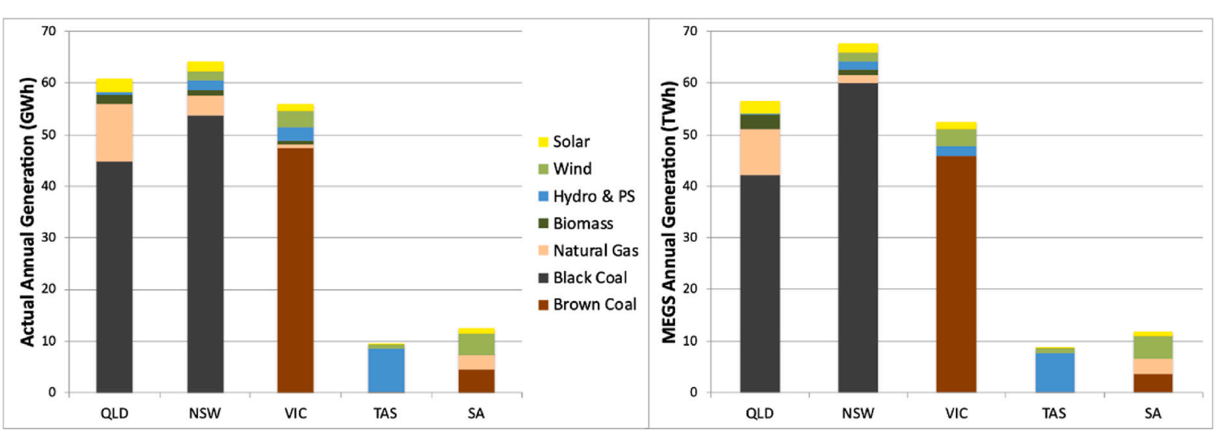

Fig. 6. Generation in 2015 from NEM Review database (left) and as predicted by MEGS (right).

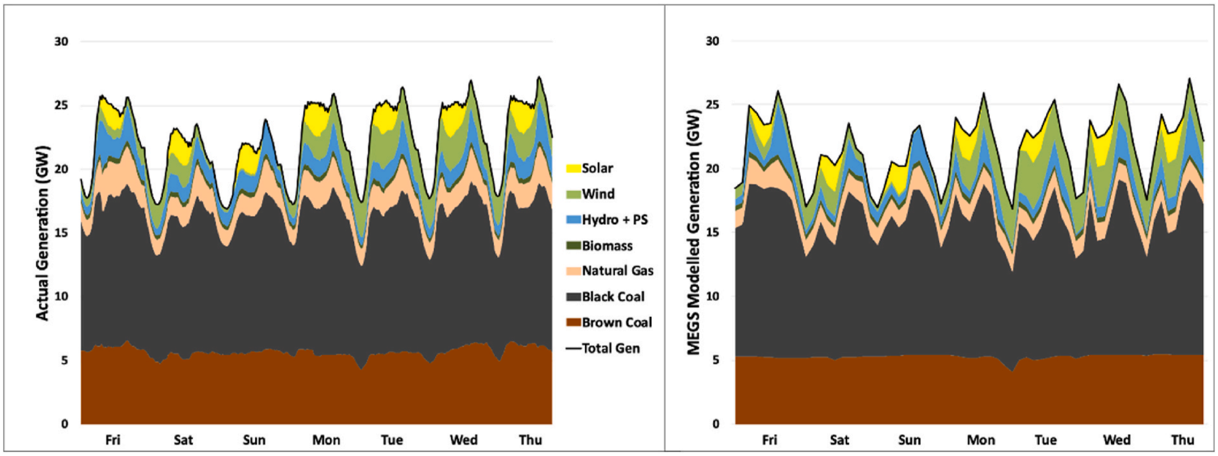

Fig. 7. Comparison of actual generation (left) and MEGS results (right) for a complex weather week.

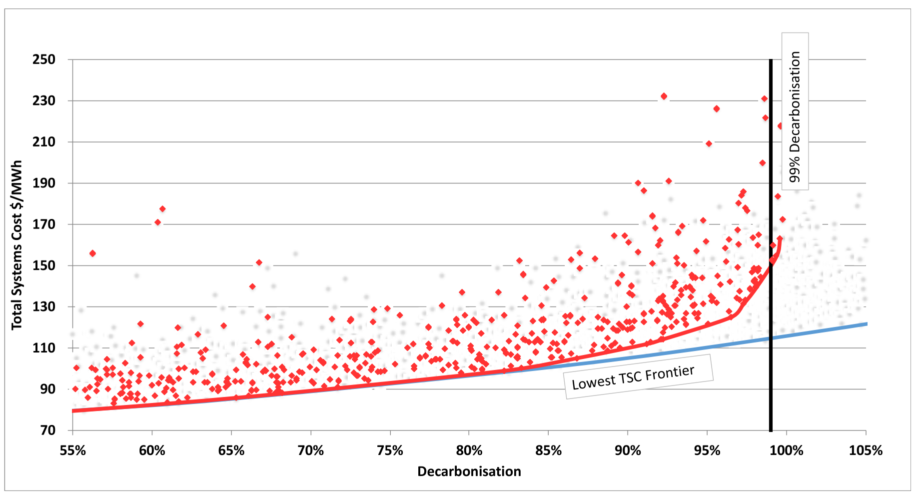

Fig. 8. Scatter plot of 3000 scenarios generated by MEGS for 2050, highlighting in red those scenarios without CCS.

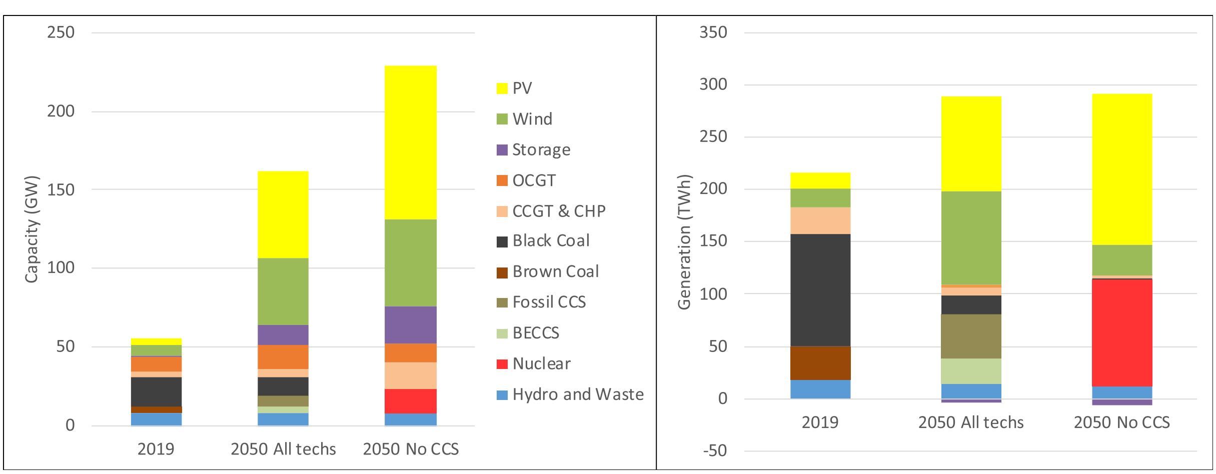

Fig. 9. Capacity and generation for the lowest cost scenarios at 99% decarbonisation using all technologies and with no CCS compared to current system.

portfolio of generation plant neither increases, nor reduces costs of the total system. However, for deep decarbonisation above 80%, the unconstrained and constrained curves visibly separate and only scenarios with CCS achieve the lowest TSC. This is illustrated further by examining the scenarios closest to the respective lowest cost frontiers at the 99% decarbonisation level. At this level of decarbonisation, the two frontiers are $37/MWh apart, representing an increase in system cost due to the unavailability of CCS of $10 B/year.

The modelled portfolios of the lowest cost scenarios with and without CCS at 99% decarbonisation are shown in Fig. 9. Both of these portfolios show that there is a need for a huge growth in capacity from the system of 2019 (currently at 56 GW) [13], with both showing nearly 100 GW of renewables is required. It is interesting (even surprising perhaps) to observe that both unabated coal and gas remain part of the net zero solution, with their emissions offset by BECCS.

If CCS is unavailable for whatever reason, it can be observed that nearly 70 GW of extra capacity is required. Most of the extra capacity is delivered as variable renewable (particularly solar PV) and storage capacity. The firm capacity, when CCS is constrained, is delivered by nuclear instead of the mix of fossil CCS and BECCS. It should be noted however, the generation chart shows that for the "No CCS" scenario there is much less generation from the larger wind generation fleet; this is due to the wind often being curtailed, having to fit around increased solar PV output and inflexible nuclear.

4. Discussion

This paper introduces MEGS, Modelling Energy and Grid Services, by laying out its core assumptions and formulation. Its performance, validation and some sample results are explored.

MEGS has added to the portfolio of tools that decarbonisation strategists, system planners and policy makers can use. No model can truly represent the complexity of the power system, but MEGS has made strides by ensuring that some of the more important engineering requirements on the shortest timescales, such as the need for inertia and frequency response, are maintained at the same time as meeting long term requirements of having enough dependable generation to cover peak demand. By combining that with some assumptions that allow a linear formulation, fast run times can be achieved which allows many simulations to be run.

This in turn has revealed some interesting results that are not necessarily intuitive, such as allowing some unabated coal in the decarbonised 2050 scenario. Using fully depreciated assets for peaking duty is a low cost way to deliver the requisite firm capacity. The modelling has also shown that without CCS being available there is a reliance on nuclear and a significant over build of renewables with consequential curtailment to achieve 99% decarbonisation.

This underscores the value of MEGS, it brings the focus back to reducing emissions at minimum cost to the consumer, whilst maintaining a secure electricity system. Ultimately it is consumers' bills (or taxpayers' subsidies) that matter most to policy makers, not metrics like levelised cost which are designed to ensure investors make sufficient return on energy sales.

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Credit author statement

Andy Boston: Conceptualisation, Methodology, Software, Investigation, Formal analysis, Data curation, Writing – original draft. Geoff Bongers: Conceptualisation, Data curation, Investigation, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Nomenclature and Constraint Equations

Nomenclature

The nomenclature used throughout is given in Table A1, Table A2, and Table A3 below

Table A1
Indices Used in MEGS

Index	Set	Description
d		$d \in D = \{$ all days $\}$
l		$l \in L = \{$ all links $\}$
m		$m \in M = \{$ all modes of operation $\}$
p		$p \in P = \{$ all generation and storage plant $\}$
r		$r \in R = \{$ all regions $\}$
t		$t \in T = \{$ all timesteps $\}$
	L_r	$L_r \subseteq L = \{$ all links connected to region r $\}$
	M_w	$M_w \subseteq M = \{$ all working modes, operating at msg, srl, cap and fill$\}$
	P_h	$P_h \subseteq P = \{$ all hydro plant $\}$
	P_r	$P_r \subseteq P = \{$ all plant within region r $\}$
	P_s	$P_s \subseteq P = \{$ all storage plant $\}$
	T_d	$T_d \subseteq T = \{$ all timesteps in day d $\}$

Table A2
Input Parameters Used by MEGS

Parameter	Units	Description
$DEM_{r,t}$	MW	Demand in region r , at timestep t §
$GHIS_{p,d}$	MWh	Historic generation of hydro plant p , on day d
IRQ_r	MW	Inertia requirement in region r
$LCAP_l$	MW	Capacity of link l
$LIMP_{l,r}$	1,0,-1	Link Import indicator: 1 if link l imports to region r , -1 if link l exports from region r, and 0 otherwise
$LVOC_l$	$/MWh	Variable operating cost of link l
$PAVL_{p,t}$		Availability of plant p , at timestep t §
$PCAP_p$	MW	Capacity of plant p
$PINC_p$	MW s	Inertia constant of plant p
$PINR_{p,m}$	MW s	Inertia provided by plant p, operating in mode m *
$PPWR_{p,m}$	MW	Power produced by plant p , operating in mode m *
$PRES_{p,m}$	MW	Reserve produced by plant p , operating in mode m *
$PSUC_p$	$/MW	Start-up cost of plant p per MW of capacity. Shut-down cost is not modelled directly but can be added in here
$PVOC_{p,m}$	$/MWh	Variable operating cost of plant p , operating in mode m * (derived from fuel, carbon and non-fuel variable costs)
$RES_{r,t}$	MW	Reserve requirement in region r , at timestep t §
$SEFF_{p,m}$	0–1	Set as turnaround efficiency for filling mode for storage plant p , set as 1 for all other modes.
TSD	hour	Time step duration = time between one step and the next
$TSPD$		Time steps per day = No. of timesteps solved together, does not have to be exactly one day.

* See Table 1 for list of operational modes.
§ Time series data based on historic values.

Table A3
Variables Used by MEGS

Variable	Units	Description
$gbud_{p,d}$	MWh	Generation budget for hydro or storage plant p , for day d. Set as historic generation for hydro, or as reduction in storage level by algorithm
$prolpow_{l,t}$	0 to 1	Proportion of link l , transmitting power, at timestep t
$prolres_{l,t}$	0 to 1	Proportion of link l , carrying reserve, at timestep t
$proplant_{p,m,t}$	0 to 1	Proportion of plant p , operating in mode m , at timestep t
$propshutd_{p,t}$	0 to 1	Proportion of plant p , shutting down at timestep t
$propstart_{p,t}$	0 to 1	Proportion of plant p , starting up at timestep t
$srcday_d$	$	System short run cost for day d

Constraint equations

The main constraint equations are given in Box 3, the following are included in the code and are supplementary:
Proportion of plant in each mode sum to 1

$$1 = \sum_{m \in M} proplant_{p,m,t} \forall p, \forall t$$

Define start up and shutdowns by linking relevant variables

$$0 = \sum_{m \in M_w} proplant_{p,m,t} - proplant_{p,m,t-1} - propstart_{p,t} + propstop_{p,t} \; \forall p, \forall t$$

Circularity is enforced at end of year by setting. $proplant_{p,m,0} = proplant_{p,m,tmax}$
Ensure links do not exceed their capacity carrying power and reserve

$$1 \geq prolpow_{l,t} + prolres_{l,t} \forall l, \forall t$$

Ensure storage meet their energy budget

$$gbud_{p,d} = \sum_{t \in T_d} \sum_{m \in M} SEFF_{p,m} PAVL_{p,t} PPWR_{p,m} proplant_{p,m,t} \; \forall p \in P_s, \; \forall d$$

Ensure hydro meet their energy budget

$$GHIS_{p,d} = \sum_{t \in T_d} \sum_{m \in M} PAVL_{p,t} PPWR_{p,m} proplant_{p,m,t} \; \forall p \in P_h, \; \forall d$$

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