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CO-OPTIMISING NETWORK AND STORAGE SYSTEMS INVESTMENTS THROUGH STOCHASTIC OPTIMISATION VIA COLUMN GENERATION ALGORITHMS

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN CIENCIAS DE LA INGENIERÍA, MENCIÓN ELÉCTRICA

MEMORIA PARA OPTAR AL TÍTULO DE INGENIERO CIVIL ELÉCTRICO

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RESUMEN DE LA MEMORIA PARA OPTAR
AL TÍTULO DE INGENIERO CIVIL ELÉCTRICO
Y GRADO DE MAGÍSTER EN CIENCIAS DE LA INGENIERÍA,
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POR: HÉCTOR ANDRÉS OTÁROLA GARCÉS
FECHA: 2019
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In the context of higher participation of renewable generation in power systems worldwide, it is critical to capture the variable nature of these energy sources in investment planning models. Furthermore, an optimal investment plan of complementary generation, transmission, and storage infrastructure for the integration of renewable generation has to recognise the flexible means necessary to deal with its variable outputs. To do so, investment planning models have to consider higher time resolution and a more detailed model of operation, which renders models intractable. Further computational complexities are needed to capture the increased levels of long-term uncertainty, due to evolving policy and market parameters, such as subsidies to renewables, investment costs of generation and storage technologies, among others.

Hence, we propose a multi-stage stochastic network expansion program and its associated decomposition algorithm, which is able to co-optimise network and energy storage assets, properly capturing long-term uncertainties through a scenario tree representation of various possible future evolutions of model's parameters. Additionally, the proposed model considers high resolution in the operation, with an hourly representation, and incorporates unit commitment constraints, to properly capture the inflexibilities of the current infrastructure. Due to these features, the model is able to plan for future flexible systems, such as energy storage systems, needed to deal with the variability of increased volumes of renewable generation. To handle the increased computational burden produced by the operational details considered, we represent the yearly operation of the system by a set of typical days/weeks, and solve the problem utilising a Dantzig-Wolfe decomposition with an improved column generation approach. The novel characteristic of our algorithm is the day/week-based decomposition utilised to generate new columns, which is beyond the classic scenario tree node-based decomposition reported in existing literature.

Through various case studies on three different power networks, we validate our model, study key features of planning network and storage facilities under uncertainty, and demonstrate the scalability of the proposed approach. In this vein, we use the IEEE 24-busbar network for validation and derivation of key insights of planning future flexible networks. Then, we test computational performance of our algorithm on the IEEE 118-busbar network, demonstrating the benefits of the day/week-based decomposition against the classic scenario tree node-based decomposition. Finally, we study the Australian power system where investments in large pumped storage hydro facilities are being coordinated with investments in key transmission corridors. Our case studies demonstrate the significant option value of storage facilities, helping to defer investments in new corridors, waiting for more information to be available in the future that will support a better decision making. Our case studies also show the distortions caused by neglecting operational details in network expansion planning, particularly, the value of flexibility is considerably decreased, as investment on flexible assets is significantly lower than case studies with higher operational details. Finally, our enhanced model of Dantzig-Wolfe decomposition is able to solve instances of multi-stage stochastic planning problem that can not be solved by the most recent version of the algorithm available in the literature.

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Dentro del contexto de una mayor participación de generación renovable, es necesario capturar la naturaleza variable de esta tecnología en modelos de planificación. Además, un plan de inversión óptimo de infraestructura de generación complementaria, transmisión y almacenamiento para la integración de energías renovables tiene que reconocer los mecanismos flexibles necesarios para lidiar con su variabilidad. Para hacerlo, modelos de planificación de la inversión tienen que considerar una mayor resolución temporal y detalle de la operación, lo que genera modelos intratables computacionalmente. Más complejidades computacionales son necesarias para incluir los elevados niveles de incertidumbre a largo plazo, debido a nuevas políticas y parámetros de mercado, tales como, subsidios a renovables, costos de inversión de generación y almacenamiento, entre otros.

Por consiguiente, proponemos un programa de expansión de redes estocástico multietapa y su algoritmo de descomposición asociado, el cual es capaz de cooptimizar redes y sistemas de almacenamiento, capturando adecuadamente la incertidumbre a largo plazo a través de una representación de árbol de escenarios de distintas posibles evoluciones de parámetros del modelo. Adicionalmente, el modelo propuesto considera alta resolución en la operación con resolución horaria, e incorpora restricciones de *unit commitment* para capturar apropiadamente las inflexibilidades de la infraestructura actual. Dadas estas características, el modelo es capaz de planificar sistemas flexibles futuros necesarios para lidiar con la variabilidad de altos volúmenes de generación renovable. Para manejar la carga computacional producida por estos detalles de operación, representamos la operación anual del sistema a través de un conjunto de días/semanas típicas, y resolvemos el problema utilizando la descomposición de Dantzig-Wolfe con un método de generación de columnas mejorado. La novedosa característica de nuestro algoritmo es la descomposición en día/semana típica utilizada para generar nuevas columnas, la cual extiende la clásica descomposición nodal reportada en la literatura.

A través de distintos casos de estudio en tres distintos sistemas de potencia, validamos nuestro modelo, estudiamos características claves de la planificación de redes y almacenamiento bajo incertidumbre y demostramos la escalabilidad de la propuesta. En este sentido, usamos la red de prueba IEEE de 24 barras para validación y derivación de información clave para planificar futuras redes flexibles. Luego se probó el desempeño del algoritmo en la red de prueba IEEE de 118 barras, demostrando los beneficios de la descomposición en día/semana típica. Finalmente, se estudió el sistema de potencia australiano, donde inversiones en grandes centrales de bombeo son coordinadas con corredores de transmisión. Nuestros casos de estudio demuestran el significativo valor de la opción del almacenamiento, aplazando inversiones en nuevos corredores, esperando por más información disponible para tomar una mejor decisión. También muestran las distorsiones causadas por desestimar los detalles operacionales en la red de transmisión, particularmente, el valor de la flexibilidad es considerablemente reducido al obtener una menor inversión en tecnologías flexibles que en casos de estudio con mayor detalle operacional. Finalmente, nuestro modelo mejorado de la descomposición de Dantzig Wolfe es capaz de resolver instancias de planificación estocástica multietapa que no pueden ser resueltos por la versión más reciente disponible en la literatura.

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Chapter 1

Introduction

1.1 Motivation

Power systems are currently evolving towards low-carbon generation systems, mainly dominated by renewable sources such as wind and solar generators. Power system operators will need to deploy flexibility in the operation to cope with the increased variability and uncertainty added by these generators [1]. In addition, the availability of flexible technologies such as energy storage, flexible AC transmission systems, demand response, among others, will provide different operational measures to improve the performance of the system. Several entities have begun to tackle this lack of flexibility by developing studies aiming to plan required measures and infrastructure to make a better and smoother transition towards low-carbon systems. Reference [2] is a plan developed by Australian Energy Market Operator (AEMO) which aims to identify transmission investments that will be necessary to develop in the Network Electricity Market (NEM) for the next 20 years, in the context of an evolving Australian power system.

The coordination of flexible technologies can have a significant impact on the operational cost and also on the investment requirements of the network infrastructure [3]. In consequence, short-term operation must be considered explicitly within long-term planning. Neglecting short term operational constraints can result in suboptimal or even infeasible solutions [4]. Moreover, considering long-term uncertainty will also be important in the context of low-carbon power systems. Network infrastructure requires longer construction time compared to renewable generation. Thus, network planners will need to anticipate investment decisions in generation, which are uncertain in terms of magnitude, location and connection times [5]. Technologies such as energy storage and FACTS devices have a considerable shorter construction time, therefore, they can provide flexibility in the planning stage by allowing to adapt the investment plan within shorter time scales, avoiding large network investments that may be needed only in a limited number of scenarios. Hence, a strategic approach, modelled by stochastic programming, will be required in order to avoid the risk of locking in to inefficient solutions [3].

We present a multi-stage stochastic transmission and storage co-optimisation model with unit commitment constraints. For realistic size systems, the model is a large-scale mixed integer programming problem. To overcome the computational burden, we develop a solution methodology based on the Dantzig-Wolfe decomposition that allows to solve large case studies efficiently. We demonstrate through different study cases the benefit of the proposed methodology. Additionally, we show the importance of considering an explicit representation of operational details in planning with renewable generation. We also present the benefits of co-optimising investment in network infrastructure and storage systems. Finally, we extend the use of this algorithm applying it to the australian NEM, solving a real-scale stochastic optimisation problem under uncertainty [2].

1.2 Proposed Hypothesis

Considering high operational details in the short-term and uncertainty in the long-term in a stochastic planning problem impact the amount, timing and diversity of the optimal portfolio of investment in comparison to traditional planning approaches.

1.3 General Objective

The general objective of this thesis is to develop a mathematical program for solving the co-optimisation of planning long-term investment in network assets and storage system. The importance features of our proposal is to recognise high operational details in the operational problem, as well as, long-term uncertainty regarding location and volume of future generation, storage costs, demand growth, fuel costs.

1.3.1 Specific Objectives

- Co-optimise network and storage systems under uncertainty considering operational details in the IEEE RTS 24-bus system, in order to validate our optimisation model and observe benefits and consequences of co-optimising in the long-term when several scenarios are considered.

- Develop a computational model able to solve a transmission and storage co-optimisation model under uncertainty that considers high operational details in a real-scale network.

- Demonstrate scalability of the computational model solving a co-optimisation problem in the IEEE RTS 118-bus system considering a larger amount of scenarios.

- Demonstrate the applicability of the computational model by employing it on a real network, specifically, to the National Electricity Market network of Australia.

1.4 Contributions

- Develop a multi-stage stochastic mathematical program to determine long-term investments in network and energy storage systems, considering long-term uncertainty and high operational resolution so as to capture the (in)flexibility levels of the generation fleet.

- Reformulate the Dantzig Wolfe Algorithm proposed in [6] to improve solution times and memory usage, by splitting the operational problem, reaching a sub-nodal level, in many smaller and decoupled subproblems by using a typical day/week-decomposition approach that can be easily paralellised.
- Demonstrate the relations between network investment and energy storage investment in a stochastic multi-stage fashion, analysing the complementarities and conflicts between both of them in future network plans.

1.5 Structure of the Document

The document is structured as follows: In Chapter 2 the co-optimisation model is presented, alongside with the necessary modifications to render the Reformulated Dantzig Wolfe Algorithm that will be applied on two study cases. Chapter 3 extends the use of the Reformulated version by utilising it in a real study case on the Australian Network Electricity Market. In Chapter 4 conclusions are drawn and further work is proposed.

Chapter 2

Co-optimising network and storage systems with high operational resolution

2.1 State of the Art

2.1.1 Transmission planning under uncertainty

Current models for power system planning which consider uncertainty are structured under different approaches. At first, different temporal frameworks might be considered, these are utilised in the model to declare how decisions are taken in time and how the uncertainty is developed throughout the expansion. A single-stage approach considers decisions only in a single period under equal information for all future periods. Whereas, a multi-stage approach decisions are made in each period facing uncertainty regarding future developments. Moreover, uncertainty can be represented by: using probabilistic models, which corresponds to stochastic programming and robust optimisation, which ensures feasibility for a user-defined set of uncertainty realisations [7].

On transmission planning, several formulations have considered uncertainty with a simplified representation of the operation. Reference [5] proposed a two-stage transmission and generation planning model. Operation was modelled through an economic dispatch with a DC representation of the network. Results showed the importance of taking into account uncertainty and the benefits of stochastic approaches compared to deterministic approaches. In [8] a solution methodology for the two-stage transmission and generation planning based on the Progressive Hedging (PH) algorithm was developed. Since PH cannot guarantee convergence to the optimal solution, several acceleration techniques are implemented, which allow to improve the quality of the solution. Authors in [9] proposed a transmission planning model with non-conventional assets, such as energy storage or FACTS devices. The problem has binary investment variables and linear operation variables. A methodology based on the Benders decomposition was used to solve the problem. Results show how non-conventional assets enable more adaptability for the system planner to overcome uncertainty.

In [3] the importance of considering uncertainty and operational flexibility in transmission planning was studied. The authors demonstrate the need for a unified framework and discuss the computational challenges that arise from it. A stochastic transmission and storage planning model with an horizon of multiple years is presented in [10]. Although different scenarios are considered, the planner cannot adapt investment decisions as more information is known about the uncertain parameters. Only 3 long-term scenarios, 5 days per year and a simplification of the UC constraints are considered to reduce the complexity of the problem. Reference [11], also studies the multi-stage stochastic transmission and energy storage planning problem. Investment decisions are binary, and the operation was represented by a DC optimal power flow with no consideration of unit commitment constraints. The authors developed a decomposition based on Nested Benders decomposition. The algorithm was compared to the Progressive Hedging algorithm, and results showed that PH has convergence issues for multi-stage mixed integer problems, failing to find a solution, while the nested decomposition allows to solve the problem, achieving a solution with a 1.11% optimality gap. Reference [12] presents a multi-stage stochastic linear generation and transmission expansion planning model with energy storage. Operation is represented by an economic dispatch. Ramp rate constraints are included, and transmission is represented by a pipeline model. The Progressive Hedging algorithm was used to solve the large-scale linear programming model. Results show that the decomposition allows to reduce solution times by 96%. Most recently, in [13] a transmission planning problem under long- and short-term uncertainty is presented. Long-term uncertainty is represented by changes across years of demand growth and generation capacity, whereas short-term uncertainty is related to seasonal changes, for example, demand and renewable power production variability. This problem was solved via a primal Benders' decomposition.

2.1.2 Flexibility in the expansion problem

Traditional methods for the expansion problem used to utilise load blocks for representing the operational model, which brought the problem of decoupling hourly chronology of demand and renewable profiles in the hope of reducing the computational burden. As renewable generation capacity increases in power systems, this simplification is not be longer useful to represent the operational model as new hourly effects were introduced by these new technologies, being necessary to use a higher operational resolution to represent operational aspects of conventional generation, such as, commitment status, as well as ramping capabilities. These features gained relevance due to variability introduced by renewables. In [14] authors declare that modelling under a low temporal resolution may have a great impact on the planning results, therefore they suggest that improving the temporal representation is suggested to be prioritised.

In the recent years, the consideration of flexibility within expansion problems has become an active area of research. References [15, 16, 1, 17] present different static deterministic generation expansion planning models including unit commitment constraints. To overcome tractability issues, using a reduced number of typical weeks to represent the year, clustering similar units or convex relaxations were proposed, as opposed to reference [4], where thirteen typical weeks were considered for each year, developing a deterministic multi-year generation expansion model with UC constraints, which utilises the Dantzig-Wolfe decomposition to solve large-scale instances with high operational resolution. Reference [18] utilised a mixed integer linear program to determine the optimal set of generation units within a generation expansion problem framework. They considered operational constraints, such as, unit commitment and startup costs, demonstrating that including these constraints have a important impact on the optimal portfolio of investments, and need being considered, especially at increasing rates of intermittent renewables. In addition to commitment, ramps and startup costs, reference [19] included minimum stable generation constraint and reserve requirements demonstrating that operating these mentioned reserves have a substancial impact on the optimal portfolio of investments, and result in a substancial increase of renewable integration costs. Most recently, in [20] was utilised an adaptive robust optimisation model for planning with operational uncertainty, by using representative days based on uncertainty sets they could consider variability and short-term uncertainty rendering a chronological representation of the system operation, and thus enabling the inclusion of key operational aspects. Authors stated that the risk of inappropriately choosing specific load an renewable profiles is reduced, as a broader range of operational conditions may be considered in the uncertainty sets.

Additionally, Transmission Expansion Problems have been coordinated with different assets to provide operational flexibility which proves to defer expansion investment in transmission lines, in [21], demand response was incorporated into the transmission planning problem for systems with a high penetration of wind energy, authors proved that demand response programs can even substitute for generation and transmission network expansion in power system with considerable amount of intermittent energy resources. Flexible AC transmission system (FACTS) and Series Compensator (SC) devices have been incorporated in the Transmission Expansion Problem to determine the minimum-cost network reinforcement schemes considering investment and congestions costs in [22]. Authors in [23] introduce the concept of flexible transmission network planning by proposing a corrective post-contingency network switching action to reconfigure the efficiently the network under contingency conditions. The approach proposed find the optimum generation dispatch as well as optimum transmission capacity along with network switching pattern in all outage circumstances.

2.1.3 Storage systems in the expansion problem

As renewable generation increases in power systems, there has been created a new interest in investigating the impact of utility scale energy storage in power system operation and planning. In [24] authors have listed the benefits of the energy storage systems (ESS) in transmission networks, such as, asset deferral, voltage regulation and system stability, and integration of renewable energy at avoiding curtailment imposed by insufficient transmission capacity and time-shifting when renewable energy is stored during off-peak interval for deploying it during on-peak interval. In [25] it is concluded that ancillary services bring more profit to ESS than arbitrage, authors modelled three different market products (day-ahead market, intraday market and regulation market) in order to asses economically ESS in energy market and ancillary services in the Nordic power market. Reference [26] presents the costs and benefits of ESS deployment in a Transmission Planning context. Authors conclude that by deploying new ESS assets the network investment costs are reduced in all their study cases. Utilising their proposed planning formulation size and location of future ESS can be obtained. Additionally, in [27] a bilevel program is used to obtain optimal location and size of ESS by reducing the system operating cost while ensuring that merchant storage recover investments in ESS assets via a minimum profit constraint.

2.1.4 Decomposing methods

Including the unit commitment constraints and hourly time-scale resolution in the stochastic transmission and storage planning problem leads to a large scale mixed integer linear problem (MILP), which often cannot be solved by commercial MIP solvers. Thus, it is necessary to use decomposition methods to break the problem into several easier-to-solve subproblems. The co-optimisation model has integer variables in the investment and operation decisions of every stage. This characteristic cannot be handled by traditional Benders decomposition, and complicates the use of methods such as the ones presented in [11] or [12]. The Nested decomposition presented [11] could lack of accuracy due to the convexification used, or require a large amount of time to achieve the desired accuracy. Moreover it does not allow to fully exploit the parallelisation of subproblems. In [20] a two-stage model was solved under the column-and-constraint generation method. The Progressive Hedging algorithm has been succesfully applied to two-stage transmission planning problems [8], and to multi-stage linear generation and transmission planning [12]. For multi-stage stochastic linear problems, the Progressive Hedging algorithm is proved to converge. However, for mixed-integer problems, there is no guarantee of convergence. This issue can be tackled by using several heuristics for two-stage problems. But for multi-stage problems, the convergence can be difficult to achieve. Moreover, since Progressive Hedging is a scenario-based decomposition, each subproblem is a multi-stage mixed integer quadratic deterministic problem. These can be very difficult to solve even without quadratic terms, as shown in [4].

Considering the structure of a planning problem which is characterised by a diagonal in block structure, The Dantzig-Wolfe decomposition presents features that make it more appealing for tackling this problem, compared with other common decomposition methods applied in planning problems, this algorithm can easily deal with integer variables at the slave subproblem level unlike the abovementioned approaches resulting in a more-suited technique for solving these large instances of MILP, [6] presented a formulation of the Dantzig-Wolfe Algorithm applied to a multi-stage stochastic capacity planning problem applying "variable splitting" to allow multiple capacity expansions of a facility over the planning horizon, authours stated that they reached optimality in a case composed of 243 different scenarios with six stages. Authors in [4] extended this work by including high operational resolution constraints in a deterministic expansion capacity problem utilising the abovementioned algorithm, the algorithm has been extended to transmission expansion problems, in [28] a multi-stage stochastic planning of a integrated power and natural gas system was proposed, this problem was solved by using an asynchronous version of the dantzig wolfe algorithm, uncertainty was related to (i) volumes of new renewable generation and (ii) new demands. Importance of a unified planning between these two networks was highlighted in this work in regard of planning the energy sector.

2.2 Co-optimisation model

We propose a stochastic mixed integer linear programming model to determine the optimal investment in energy storage and transmission assets in power systems. The model minimises the overall expected investment and operating costs across a multi-stage scenario tree.

Transmission system investment relieves congestion in existing lines and helps to integrate new generation units, among other things. On the other hand, energy storage systems open possibilities to flow management, arbitrage, peak load shaving and can defer or replace network investments. Furthermore, energy storage systems, have shorter commissioning times than transmission lines. Therefore, energy storage systems provide more adaptability, by allowing the system planner to decide its investment after the realisation of the uncertainties.

Usually, in long-term planning, the operation was represented by non-chronological models using the load duration curve. However, in order to capture benefits of energy storage systems a more detailed time-sequential modeling should be proposed. In addition, the effects of variability from renewable sources on conventional generation cycling must be considered. Therefore, the unit commitment constraints must be included to accurately capture the operational issues.

Our model decides when and where to invest in either energy storage or transmission infrastructure. In the operational stage, it decides the output power for every generation technology, which generators to commit, power flows through lines, charge and discharge power of energy storage systems and reserve provision. Long-term uncertainty can be presented through different generation investment plans, renewable penetration levels, fuel prices, hydrology, investment costs, among others.

2.2.1 Objective function

The model minimises overall expected investment and operating costs across every node in scenario tree as shown in (2.1).

$$\text{Minimise} \sum_{m \in M} \phi_m \Big[\frac{I_m + O_m}{(1+r)^{y(m)}} \Big] \tag{2.1}$$

Investment costs are the annualised cost of investing in new assets such as energy storage systems an new transmission lines, as shown in (2.2).

Operational costs, as shown in (2.3), include fuel costs, startup and shutdown costs for conventional generation. We also consider a penalisation arising from renewable generation curtailment.

$$I_m = \sum_{b\in\widehat{B}} \sum_{\mathrm{i}\in\wp_m} \Pi_b^{b\mathrm{i}} C^B w_{b\mathrm{i}}^B + \sum_{l\in\widehat{L}} \sum_{\mathrm{i}\in\wp_m} \Pi_l^{l\mathrm{i}} w_{l\mathrm{i}}^L, \qquad \forall m \in M \tag{2.2}$$

$$O_m = \sum_{\mathrm{d}\in D} \Gamma_\mathrm{d} \Big(\sum_{t\in T} \Big(\sum_{g\in G^C} \Big(\Pi_g^{OG} p_{gm\mathrm{d}t}^G + \Pi_g^{OU} u_{gm\mathrm{d}t} + \Pi_g^{OV} v_{gm\mathrm{d}t} \Big) + \sum_{g\in G^R} \Pi_g^{OC} \Big(P_{gm}^R A_{gm\mathrm{d}t}^R - p_{gm\mathrm{d}t}^R \Big) \Big) \Big), \ \forall m \in M \tag{2.3}$$

2.2.2 Main Investment Constraints

$$w_{bm}^B \in \mathbb{Z}^+, \qquad \forall b \in \widehat{B}, \forall m \in M \tag{2.4}$$

$$w_{lm}^L \in \mathbb{Z}^+, \qquad \forall l \in \widehat{L}, \forall m \in M \tag{2.5}$$

$$\sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L \leq 1, \qquad \forall l \in \widehat{L}, \forall m \in M \tag{2.6}$$

$$\sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L = \sum_{\mathrm{i}\in\wp_k} w_{l\mathrm{i}}^L, \qquad \forall l \in \widehat{L}, \forall m \in M^s, \forall k \in S_m \tag{2.7}$$

$$w_{l1}^L = 0, \qquad \forall l \in \widehat{L} \tag{2.8}$$

Investment decisions are defined as positive integer variables, as shown in (2.4)−(2.5). Thus, an asset cannot be decommissioned once invested. Transmission lines can be invested only once per scenario, as shown in (2.6). We consider that transmission lines have a lag of one stage between decision and commissioning time due to prolonged construction times. Thus, transmission investment decision in siblings nodes must be the same, this is modeled by constraint (2.7). Also, transmission lines cannot be commissioned in stage 1, as shown in (2.8).

2.2.3 Main Operational Constraints

$$\sum_{g\in G_n^C} p_{gm\mathrm{d}t}^G + \sum_{g\in G_n^R} p_{gm\mathrm{d}t}^R + \sum_{b\in B_n} p_{bm\mathrm{d}t}^B - D_{nm\mathrm{d}t} = \sum_{l\in From_n} f_{lm\mathrm{d}t} - \sum_{l\in To_n} f_{lm\mathrm{d}t}, \quad \forall n \in N, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.9}$$

$$\sum_{g\in G^C} \overline{r}_{gm\mathrm{d}t}^G + \sum_{b\in B} \overline{r}_{bm\mathrm{d}t}^B \geq \overline{R}_{tm}^S \qquad \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.10}$$

$$\sum_{g\in G^C} \underline{r}_{gm\mathrm{d}t}^G + \sum_{b\in B} \underline{r}_{bm\mathrm{d}t}^B \geq \underline{R}_{tm}^S \qquad \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.11}$$

$$-\overline{F}_{lm} \leq f_{lm\mathrm{d}t} \leq \overline{F}_{lm} \qquad \forall l \in EL, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.12}$$

$$-\overline{F}_{lm} \sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L \leq f_{lm\mathrm{d}t} \leq \overline{F}_{lm} \sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L \qquad \forall l \in \widehat{L}, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.13}$$

$$-M(1 - \sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L) + \frac{\theta_{lm\mathrm{d}t}^{From} - \theta_{lm\mathrm{d}t}^{To}}{X_l} \leq f_{lm\mathrm{d}t} \leq \frac{\theta_{lm\mathrm{d}t}^{From} - \theta_{lm\mathrm{d}t}^{To}}{X_l} + M(1 - \sum_{\mathrm{i}\in\wp_m} w_{l\mathrm{i}}^L),$$

$$\forall l \in \widehat{L}, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.14)$$

$$\frac{\theta^{From}_{lm\mathrm{d}t} - \theta^{To}_{lm\mathrm{d}t}}{X_l} \leq f_{lm\mathrm{d}t} \leq \frac{\theta^{From}_{lm\mathrm{d}t} - \theta^{To}_{lm\mathrm{d}t}}{X_l}, \qquad \forall l \in EL, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.15)$$

$$p^G_{gm\mathrm{d}t} + \overline{r}^G_{gm\mathrm{d}t} \leq \overline{P}^G_{gm} x^G_{gm\mathrm{d}t}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.16)$$

$$p^G_{gm\mathrm{d}t} \geq \underline{P}^G_{gm} x^G_{gm\mathrm{d}t} + \underline{r}^G_{gm\mathrm{d}t}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.17)$$

$$\overline{r}^G_{gm\mathrm{d}t} \leq x^G_{gm\mathrm{d}t} \overline{R}^G_{gm}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.18)$$

$$\underline{r}^G_{gm\mathrm{d}t} \leq x^G_{gm\mathrm{d}t} \underline{R}^G_{gm}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.19)$$

$$x^G_{gm\mathrm{d}t} = x^G_{gm\mathrm{d}(t-1)} + u_{gm\mathrm{d}t} - v_{gm\mathrm{d}t}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.20)$$

$$x^G_{gm\mathrm{d}t} \geq \sum_{\tau = t - t^{on}_g}^{t} u_{gm\mathrm{d}\tau}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.21)$$

$$1 - x^G_{gm\mathrm{d}t} \geq \sum_{\tau = t - t^{off}_g}^{t} v_{gm\mathrm{d}\tau}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.22)$$

$$p^G_{gm\mathrm{d}t} - p^G_{gm\mathrm{d}(t-1)} \leq x^G_{gm\mathrm{d}(t-1)} Rp_{gm} + u_{gm\mathrm{d}t} \underline{P}^G_{gm}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.23)$$

$$p^G_{gm\mathrm{d}(t-1)} - p^G_{gm\mathrm{d}t} \leq x^G_{gm\mathrm{d}(t-1)} Rp_{gm} + v_{gm\mathrm{d}t} \overline{P}^G_{gm}, \qquad \forall g \in G^C, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.24)$$

$$p^R_{gm\mathrm{d}t} \leq \overline{P}^R_{gm} A^R_{gm\mathrm{d}t}, \qquad \forall g \in G^R, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.25)$$

$$p^B_{bm\mathrm{d}t} = p^{B+}_{bm\mathrm{d}t} - p^{B-}_{bm\mathrm{d}t}, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.26)$$

$$p^{BE}_{bm\mathrm{d}t} = p_{bm\mathrm{d}(t-1)} - p^{B+}_{bm\mathrm{d}t} + p^{B-}_{bm\mathrm{d}t}\eta, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.27)$$

$$p^B_{bm\mathrm{d}t} - \underline{r}^B_{bm\mathrm{d}t} \geq -C^B \sum_{\mathrm{i} \in \wp_m} w^B_{b\mathrm{i}}, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.28)$$

$$p^B_{bm\mathrm{d}t} + \overline{r}^B_{bm\mathrm{d}t} \leq C^B \sum_{\mathrm{i} \in \wp_m} w^B_{b\mathrm{i}}, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.29)$$

$$p^{BE}_{bm\mathrm{d}t} + \underline{r}^B_{bm\mathrm{d}t}\alpha \leq C^B \zeta^B \sum_{\mathrm{i} \in \wp_m} w^B_{b\mathrm{i}} \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.30)$$

$$p^{BE}_{bm\mathrm{d}(t-1)} + \underline{r}^B_{bm\mathrm{d}t}\alpha \leq C^B \zeta^B \sum_{\mathrm{i} \in \wp_m} w^B_{b\mathrm{i}} \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.31)$$

$$p^{BE}_{bm\mathrm{d}t} - \overline{r}^B_{bm\mathrm{d}t}\alpha \geq 0, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.32)$$

$$p^{BE}_{bm\mathrm{d}(t-1)} - \overline{r}^B_{bm\mathrm{d}t}\alpha \geq 0, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \qquad (2.33)$$

$$p^{BE}_{bm\mathrm{d}1} = 0, \qquad \forall m \in M, \forall \mathrm{d} \in D, \forall b \in B \qquad (2.34)$$

$$p^{BE}_{bm\mathrm{d}t} = 0, \qquad \forall m \in M, \forall \mathrm{d} \in D, \forall b \in B \qquad (2.35)$$

Demand in each bus bar must be satisfied in every node at every moment in the system according to the nodal balance equation (2.9). System up/down reserve requirements are requested to respond to short-term perturbations, as shown in (2.10)−(2.11). Power flows in lines are bounded by their maximum capacity, according to (2.12)−(2.13). A linearized DC power flow is formulated to represent power transfers according to (2.14)−(2.15). For candidate lines the Big-M approach has been used, as shown in (2.14).

Constraints (2.16)−(2.25) pertain to the operation of generators. The output power of generators, considering upward reserves, is limited by the committed capacity, as shown in (2.16). A minimum output, considering downward reserves, is required to have a stable power production, as in (2.17). Constraints (2.18)−(2.19) model the reserve provision limits of generators. Equation (2.20) is the unit commitment state equation, which relates commitment state with startup and shutdown variables. This allows us to consider minimum up and down times along with startup and shutdown costs. Constraints (2.21)−(2.22) impose minimum operation times of generators. Ramping limits are considered for conventional generators, as shown in (2.23)−(2.24). Constraint (2.25) limits the output power of renewable generators by the availability of the resource and the installed capacity.

Batteries operation is modelled through (2.26)−(2.35). Constraint (2.26) models the battery power. Constraint (2.27) states the energy balance of batteries. The output power of batteries, considering reserve, is bounded by the maximum power capacity, as shown in (2.28)−(2.29). Equations (2.30)−(2.33) set energy limits in batteries, enough energy should remain in the battery to provide up reserve according to (2.30) and (2.31) and enough available energy capacity to provide down reserve according to (2.32) and (2.33). According to (2.34)−(2.35) batteries must start and finish the representative day with zero energy.

2.3 Column Generation Approach

To apply the decomposition, we first reformulate the problem into a diagonal block structure. To do so, we include new variables $z^B_{b,\mathrm{i}}$ and $z^L_{l,\mathrm{i}}$ that represent the total units of storage b and line l, respectively, that have been installed until node i. These variables must meet constraints (2.36) and (2.37).

$$z^B_{bm} \leq \sum_{\mathrm{i}\in\wp_m} w^B_{b\mathrm{i}}, \qquad \forall b \in B, m \in M \tag{2.36}$$

$$z^L_{lm} \leq \sum_{\mathrm{i}\in\wp_m} w^L_{l\mathrm{i}}, \qquad \forall l \in L, m \in M \tag{2.37}$$

Thus, we can replace constraints (2.13)-(2.14) by constraints (2.38)-(2.39) and constraints (2.28)-(2.31) by constraints (2.40)-(2.43).

$$-\overline{F}_{lm} z^L_{lm} \leq f_{lm\mathrm{d}t} \leq \overline{F}_{lm} z^L_{lm}, \qquad \forall l \in \widehat{L}, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.38}$$

$$-M(1-z^L_{lm}) + \frac{\theta^{From}_{lm\mathrm{d}t} - \theta^{To}_{lm\mathrm{d}t}}{X_l} \leq f_{lm\mathrm{d}t} \leq \frac{\theta^{From}_{lm\mathrm{d}t} - \theta^{To}_{lm\mathrm{d}t}}{X_l} + M(1-z^L_{lm}), \qquad \forall l \in \widehat{L}, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.39}$$

$$p^B_{bm\mathrm{d}t} - \underline{r}^B_{bm\mathrm{d}t} \geq -z^B_{bm} C^B, \qquad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.40}$$

$$p^{B}_{bmdt} + \overline{r}^{B}_{bmdt} \leq z^{B}_{bm} C^{B}, \quad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.41}$$

$$p^{BE}_{bmdt} + \underline{r}^{B}_{bmdt}\alpha \leq z^{B}_{bm} C^{B} \zeta^{B}, \quad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.42}$$

$$p^{BE}_{bmd(t-1)} + \underline{r}^{B}_{bmdt}\alpha \leq z^{B}_{bm} C^{B} \zeta^{B}, \quad \forall b \in B, \forall m \in M, \forall \mathrm{d} \in D, \forall t \in T \tag{2.43}$$

Then, the reformulated co-optimisation problem seeks to minimise the objective function (2.1) subject to constraints (2.9)-(2.12),(2.15)-(2.27),(2.32)-(2.43).

Now it is possible to apply the Dantzig Wolfe decomposition. To ease the understanding, we first present the matrix form of the reformulated co-optimisation problem (2.44). Constraint (2.44b) is the linking constraint that couples time stages by relating the available infrastructure in scenario tree node m with the investment decisions made on the predecessor nodes of m. Constraint (2.44c) restrict the operational decisions to the total available infrastructure in node m. Constraint (2.44d) summarise the investment constraints (2.7)-(2.8). The operational constraints are modelled by (2.44e). Set Υ_m is the feasible region of operating decisions in scenario tree node m. If constraint (2.44b) was relaxed, the investment problem for each node could be solved independently.

$$\min \quad \sum_{m \in M} \sum_{\mathrm{i} \in \wp_m} \phi_m \mathbf{c}_m^\top \mathbf{w}_\mathrm{i} + \sum_{m \in M} \phi_m \mathbf{q}_m^\top \mathbf{y}_m \tag{2.44a}$$

$$s.t.: \quad \mathbf{z}_m \leq \sum_{\mathrm{i} \in \wp_m} \mathbf{w}_\mathrm{i}, \quad \forall m \in M \tag{2.44b}$$

$$\mathbf{A}_m \mathbf{y}_m \leq \mathbf{z}_m, \quad \forall m \in M \tag{2.44c}$$

$$\mathbf{B}_m \mathbf{w}_m \leq 0, \quad \forall m \in M \tag{2.44d}$$

$$\mathbf{y}_m \in \Upsilon_m, \quad \forall m \in M \tag{2.44e}$$

$$\mathbf{w}_m \leq \bar{\mathbf{w}}_m, \quad \forall m \in M \tag{2.44f}$$

$$\mathbf{z}_m \leq \bar{\mathbf{z}}_m, \quad \forall m \in M \tag{2.44g}$$

$$\mathbf{w}_m \in \mathbb{Z}^+, \quad \forall m \in M \tag{2.44h}$$

$$\mathbf{z}_m \in \mathbb{Z}^+, \quad \forall m \in M \tag{2.44i}$$

We define the feasible region of available infrastructure in scenario tree node m by:

$$\Psi_m = \{\mathbf{z}_m \in \mathbb{Z}^+ \mid \exists \mathbf{y}_m \in \Upsilon_m, A_m \mathbf{y}_m \leq \mathbf{z}_m, \mathbf{z}_m \leq \bar{\mathbf{z}}_m\}$$

Note that Ψ_m is a bounded integer polyhedron, and that any point in Ψ_m can be expressed as an integer combination of a finite number of integer points $\{\ \widehat{z}_m\}_{j=1}^{j_m}$ [29]. For each vector of available infrastructure, there exist an associated optimal operational plan, $\widehat{\mathbf{y}}^j_m$. Then, $\mathbf{z}_m$ can be rewritten as:

$$\mathbf{z}_m = \sum_{j=1}^{j_m} \lambda^j_m \widehat{\mathbf{z}}^j_m, \qquad \sum_{j=1}^{j_m} \lambda^j_m = 1, \qquad \lambda^j_m \in \{0,1\}. \tag{2.45}$$

The master problem of the Dantzig-Wolfe decomposition can be obtained by substituting $\mathbf{z}_m$ and $\mathbf{y}_m$ in (2.44).

$$\min \sum_{m\in M} \phi_m \mathbf{c}_m^\top \mathbf{w}_m + \sum_{m\in M} \sum_{j=1}^{j_m} \phi_m \mathbf{q}_m^\top \widehat{\mathbf{y}}_m^j \lambda_m^j \tag{2.46a}$$

$$s.t.: \quad \sum_{j=1}^{j_m} \widehat{\mathbf{z}}_m^j \lambda_m^j \leq \sum_{\mathrm{i}\in\wp_m} \mathbf{w}_\mathrm{i}, \qquad \forall m \in M, \qquad [\boldsymbol{\pi}_m] \tag{2.46b}$$

$$\sum_{j=1}^{j_m} \lambda_m^j = 1, \qquad \forall m \in M, \qquad [\mu_m] \tag{2.46c}$$

$$\lambda_m^j \in \{0,1\}, \qquad \forall m \in M, \qquad \forall j \in \mathcal{J}_m \tag{2.46d}$$

$$\mathbf{B}_m \mathbf{w}_m \leq 0, \qquad \forall m \in M \tag{2.46e}$$

$$\mathbf{w}_m \leq \bar{\mathbf{w}}_m \in \mathbb{Z}^+, \qquad \forall m \in M \tag{2.46f}$$

$$\mathbf{w}_m \in \mathbb{Z}^+, \qquad \forall m \in M \tag{2.46g}$$

2.3.1 Column Generation Algorithm

Since it is not possible to enumerate all feasible vectors of available units and its associated operational plan, they are produced using the Column Generation approach. The idea is to work only with a subset of columns in the master problem, and add more only when needed. First, a restricted master problem is formulated with a limited number of columns. Then, the dual prices $\boldsymbol{\pi}_m$ and μ_m are obtained by solving the linear relaxation of the master problem. New columns are generated by solving the subproblem (2.47) for each node m of the scenario tree. The objective value (2.47a) is the reduced cost of the new column. Columns with negative reduced cost could improve the objective value of the master problem. If no column with negative reduced cost can be found, then the linear relaxation of the master problem has been solved to optimality.

$$\mathrm{sp}(m): \qquad \mathit{min} \quad \phi_m \mathbf{q}_m^\top \mathbf{y}_m - \mathbf{z}_m \boldsymbol{\pi}_m - \mu_m \tag{2.47a}$$

$$\text{s.t.:} \qquad A_m \mathbf{y}_m \leq \mathbf{z}_m \tag{2.47b}$$

$$\mathbf{y}_m \in \Upsilon_m \tag{2.47c}$$

$$\mathbf{z}_m \leq \bar{\mathbf{z}}_m \tag{2.47d}$$

$$\mathbf{z}_m \in \mathbb{Z}^+ \tag{2.47e}$$

The subproblems can be solved in parallel because they only require the dual price information require from the restricted master problem.

The Column Generation algorithm is described in Algorithm 1. The first set of columns is constructed by solving the subproblems (2.47) using $\boldsymbol{\pi}_m = -10^6$ for every node and candidate asset and $\mu_m = 0$ for every node.

2.3.2 Representative Day-Based Dantzig Wolfe Decomposition

The subproblems can be seen as one-stage mixed integer investment problems. They can become large and difficult to solve, depending on the size of the power system and the number of representative days or weeks used for replicating the yearly operation. Additionally, when subproblems are solved in parallel, the iteration is not completed until every subproblem is solved. Therefore, sometimes bottlenecks can be faced if a group of subproblems requires a larger computational time than the rest.

To overcome this intractability issue we propose a different approach for the Dantzig Wolfe decomposition. Instead of decomposing in yearly subproblems, we further decompose by representative days reaching a sub-nodal level. Increasing, in this way, the number of subproblems, but with much less computational effort per subproblem. Since more subproblems are being solved, the number of iterations required for convergence of the algorithm will probably increase.

Figure 2.1 depicts the representative day-based decomposition. Each node of the original scenario tree is split into several sub-nodes, representing each day of the operating stage. The investment decisions of each group of sub-nodes must be the same. This is coordinated by the master problem.

Following the reasoning presented above, the master and subproblems can be formulated. Problem (2.48) presents the master problem of the day-based decomposition. Note that now for each node of the scenario tree m and each representative day d, columns of available infrastructure and its associated daily-operational cost are modelled. On each node, investments should be performed to meet the requested available infrastructure for each day, as stated in (2.48b).

$$\min \sum_{m\in M} \phi_m \mathbf{c}_m^\top \mathbf{w}_m + \sum_{m\in M}\sum_{\mathrm{d}\in D}\sum_{j=1}^{\jmath_{m\mathrm{d}}} \Gamma_\mathrm{d}\phi_m \mathbf{q}_{m\mathrm{d}}^\top \widehat{\mathbf{y}}_{m\mathrm{d}}^j \lambda_{m\mathrm{d}}^j \tag{2.48a}$$

$$\begin{aligned}
s.t.:\quad & \sum_{j=1}^{\jmath_{m\mathrm{d}}} \widehat{\mathbf{z}}_{m\mathrm{d}}^j \lambda_{m\mathrm{d}}^j \leq \sum_{\mathrm{i}\in\wp_m} \mathbf{w}_\mathrm{i}, && \forall m\in M, \forall \mathrm{d}\in D, && [\boldsymbol{\pi}_{m\mathrm{d}}] && (2.48b)\\
& \sum_{j=1}^{\jmath_{m\mathrm{d}}} \lambda_{m\mathrm{d}}^j = 1, && \forall m\in M, \forall \mathrm{d}\in D, && [\mu_{m\mathrm{d}}] && (2.48c)\\
& \lambda_{m\mathrm{d}}^j \in \{0,1\}, && \forall m\in M, \forall \mathrm{d}\in D, && \forall j\in \mathcal{J}_{m\mathrm{d}} && (2.48d)\\
& \mathbf{B}_m \mathbf{w}_m \leq 0, && \forall m\in M && && (2.48e)\\
& \mathbf{w}_m \leq \bar{\mathbf{w}}_m \in \mathbb{Z}^+, && \forall m\in M && && (2.48f)\\
& \mathbf{w}_m \in \mathbb{Z}^+, && \forall m\in M && && (2.48g)
\end{aligned}$$

Problem (2.49) is the subproblem of the day-based decomposition. There is one subproblem per day and node of the scenario tree. Now, each subproblem can be interpreted as a daily investment problem.

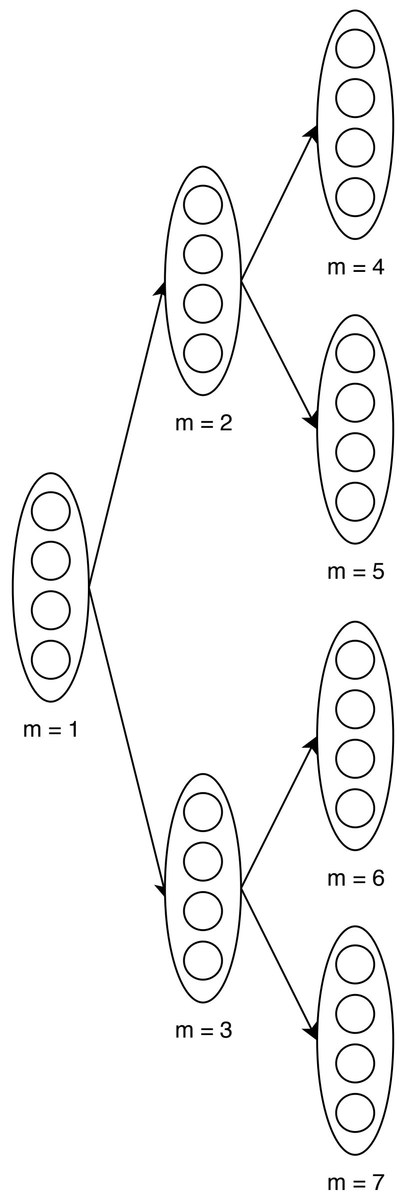

Figure 2.1: Scenario tree with 7 nodes, 4 typical days, 28 subproblems and 4 scenarios

$$\text{sp}(m, \text{d}): \quad min \quad \Gamma_{\text{d}}\phi_m\phi_m\mathbf{q}_{m\text{d}}^{\top}\mathbf{y}_{m\text{d}} - \mathbf{z}_{m\text{d}}\boldsymbol{\pi}_{m\text{d}} - \mu_{m\text{d}} \tag{2.49a}$$

$$\text{s.t.:} \quad A_{m\text{d}}\mathbf{y}_{m\text{d}} \leq \mathbf{z}_{m\text{d}} \tag{2.49b}$$

$$\mathbf{y}_{m\text{d}} \in \Upsilon_{m\text{d}} \tag{2.49c}$$

$$\mathbf{z}_{m\text{d}} \leq \bar{\mathbf{z}}_m \tag{2.49d}$$

$$\mathbf{z}_{m\text{d}} \in \mathbb{Z}^+ \tag{2.49e}$$

The problem is solved following Algorithm 1, but changing the master problem (2.46) by (2.48), and the subproblem (2.47) by (2.49). Also, the for-loop in line 16 should be over $m \in M$ and $\text{d} \in D$.

2.4 IEEE-RTS Case Study - Validation model

This section validates the optimisation model and studies the economic performance of stochastic and deterministic network expansion plans when co-optimised with battery energy storage plants. To do so, we introduce 4 case studies in which we also study the impacts of operational details on the results of co-optimised network expansion plans with storage.

2.4.1 Input Data

We modified the IEEE 24-Bus System described in [30] by reducing in 25% rate capacity for lines connected to transformers between buses: 24-3, 11-9 and 12-10. Also, we consider two types of technologies for investing: (a) Transmission investment, new lines added in parallel to existing ones with same capacity and reactance as installed: 3-10, 3-9 x2, 8-9 and 15-24 with an investment cost of 48 $/MW/km/yr and transformers 3-24 x4, 9-12 with an investment cost of 28.2k $/MW/yr. One stage lag is considered between decision and commissioning time; (b) Storage system in buses 11, 12 and 24 characterised by modules of 5MW/10MWh, 50 modules as maximum per bus, round-trip efficiency of 90% and investment cost of 80 k$/MW/yr, additionally, curtailment cost from renewables Π^{OC} is set at 50 $/MWh. Modified system with candidate assets is shown in Figure 2.2 and network parameters are presented in Table 4.1. A 8760 hours systemic Chilean demand profile and solar profile have been utilised, these profiles have been clustered into 25 typical days. Profiles have been clustered through K-means algorithm [31] by comparing a vector with 6 components, 3 components from each profile: Peak value, highest ramp (absolute value), total energy in a day. Peak load is set in 2850 MW considering a 1% demand growth per year a 10% discount rate is considered.

2.4.2 Case studies

We present 4 different cases where the modified IEEE 24-bus system is solved:

i The stochastic co-optimisation of new network and energy storage infrastructure, undertaken in a multi-stage fashion and considering the (in)flexibility levels of the generation fleet by using UC constraints.

ii The stochastic optimisation of new network infrastructure only (without energy storage plants), undertaken in a multi-stage fashion and considering the (in)flexibility levels of the generation fleet by using UC constraints.

iii The stochastic co-optimisation of network and energy storage infrastructure without UC constraints, undertaken in a multi-stage fashion and ignoring the (in)flexibility levels of the generation fleet.

iv The deterministic co-optimisation of network and energy storage infrastructure, undertaken in a multi-year fashion and considering the (in)flexibility levels of the generation fleet by using UC constraints. In this deterministic approach, optimisation of every scenario is carried out in isolation from other scenarios, assuming perfect information about how the future will evolve.

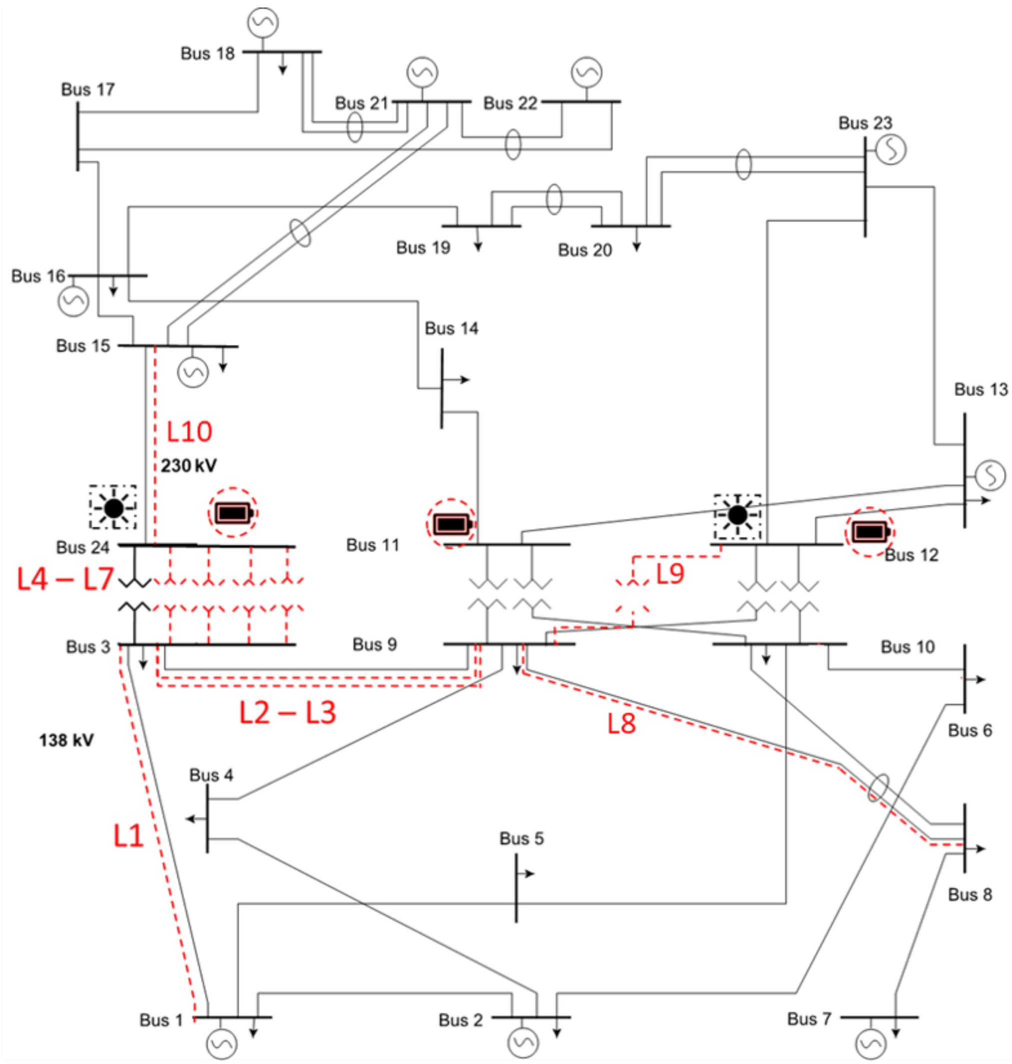

Figure 2.2: Modified IEEE 24-Bus System with candidate assets in dashed red lines

Three stages are considered for 4 scenarios, uncertainty is related to location and installed capacity of renewable generation. Scenario tree is depicted in Figure 2.3 and its data is shown in Table 2.1.

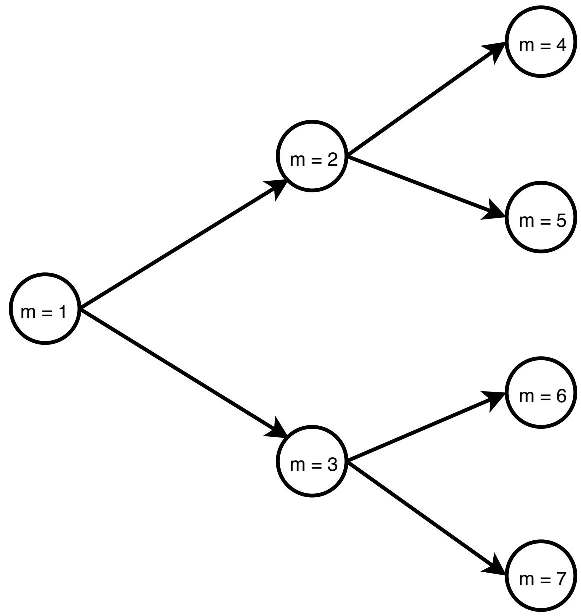

Figure 2.3: Scenario Tree - 3 Stages and 4 Scenarios

Table 2.1: Scenario data for IEEE 24-Bus case. PV 12 and PV 24 correspond to PV installed capacity in buses 12 and 24 respectively.

Node	Probability	Stage	Scenario	PV 12 [MW]	PV 24 [MW]
1	1	1	S1 - S4	0	0
2	0.5	2	S1 - S2	0	1150
3	0.5	2	S3 - S4	1150	0
4	0.25	3	S1	0	1600
5	0.25	3	S2	535	1150
6	0.25	3	S3	1150	535
7	0.25	3	S4	1600	0

All cases are coded in Julia 0.6 [32] and solved with CPLEX 12.6.1 on a server with 24 vCPU 2.3 GHz Intel Xeon E5 and 24 GB of RAM under Google Cloud Engine infrastracture [33]. 0.1% MIP_{gap} was requested. The firsts three cases solve the whole scenario tree, thus considering that every scenario tree node includes 25 subproblems, in every iteration 175 subproblems are solved parallelly using 24 workers with 1 thread each. In the deterministic case 75 subproblems are solved in every iteration.

Results

Tables 2.2 to 2.5 show the investment infrastructure (amount of modules of battery invested are presented within brackets, tables show when decision is taken) and Tables 2.6 to 2.11 the respective costs of the four case studies.

As cases i-iii are obtained in a multi-stage stochastic fashion, there are investment solutions shown in Tables 2.2 to 2.4 that are common to multiple scenarios so as to respect the non-anticipativity constraints of the stochastic problem. On the contrary, there are no non-anticipativity constraints in case iv and thus investment solutions are shown for each scenario independently as depicted in Table 2.5.

Table 2.2: Co-optimising network and storage systems

	S1	S2	S3	S4
Stage 1	L2, L3, L4, L8			
Stage 2	L1, L5, L10, B24[42]		L9, B12[24]	
Stage 3	B24[8]	B24[8]	-	B12[26]

Table 2.3: Only network investment

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Stage 1	L2, L3, L4, L8, L10			
Stage 2	L1, L5		L9	
Stage 3	-	-	-	-

In case i, various investments are undertaken in powerlines in stage 1 that are complemented later by the installation of further lines but also new battery storage plants in node 24 (for scenarios 1 and 2) and node 12 (in scenario 4). In case ii, instead, only lines are utilised in the investment plans, which is translated into lower costs of investments, but significantly higher operational cost as demonstrated in Tables 2.6 and 2.7, increasing the overall total cost. Thus, the use of battery energy storage in network expansion plans can drive, in this case, costs downwards as much as 0.8% in average. Another interesting result corresponds to the delay in the decision of installing line L10 in the stochastic program that co-optimises new line capacities and storage plants. Indeed, in case 2, note that the installation of L10 is carried out in stage 1, which is common to all scenarios. However, L10 is truly needed to deal with scenarios 1 and 2 only (when new generation is installed in node 24) and it may result stranded if scenarios 3 and 4 realises. Thus, in the co-optimisation solution, the decision to undertake L10 is delayed in order to wait and see which scenario is more likely to unfold. Hence, in the co-optimisation solution, L10 will be installed and used efficiently only if scenarios 1 and 2 realises, while battery energy storage will be preferred under the realisation of scenarios 3 and 4.

Table 2.4: Unit commitment constraints neglected - Stochastic

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Stage 1	L2, L3, L4, L8, L10			
Stage 2	L1, L5		L9	
Stage 3	-	-	-	B12[5]

Results for case iii (see Table 2.4) demonstrate that investments in storage plants are significantly reduced if the (in)flexibility levels associated with the current generation fleet are ignored. This is an important result since operational details (such as the UC constraints) are usually neglected in transmission expansion plans. Moreover, the lack of participation of battery storage plants in transmission plans creates another problem: L10 will be brought forward and installed in stage 1, altering the overall transmission plan. Note that, in this example, battery plants have a double benefit: provide operational flexibility and delay the installation of network infrastructure. In fact, investments in storage plants serve as a "buffer" while we wait to get more information about which scenario is more likely to occur. Therefore, network investment will be needed sooner rather than later (as operational flexibility is ignored, affecting the participation of energy storage plants in transmission plans), even when some of these investments may be stranded in the future due to the realisation of unfavourable scenarios (like scenarios 3 and 4, in which L10 is not needed if the appropriate amount of capacity in storage plants is installed).

Table 2.5: Co-optimising network and storage system - Deterministic

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Stage 1	L2, L3, L4, L8, L10	L2, L3, L4, L8, L10	L8	L8
Stage 2	L1, L5, B24[27]	B24[25]	B12[25]	L9, B12[25]
Stage 3	B24[23]	B24[4]	B12[4], B24[4]	B12[5]

Case iv shows investment plans for each scenario assuming perfect information about the future (see Table 2.5). Interestingly, if the network planner knew that new generation capacity was going to be installed in node 12 (scenario 4), he would build only L8 in the first stage. However, and as demonstrated in Table 2.10, a significantly higher cost will be observed is another scenario, different to scenario 4, realises. For example, Table 2.10 shows that if the solution of scenario 4 is implemented, but scenario 1 ultimately realises, then the total cost will be as high as MM$ 1,035.51. Note that this cost differs significantly from the cost of scenario 4 in Table 2.9, and this is because the latter assumes perfect information about the future, which is unrealistic when planning networks under uncertainty (in other words, it quantifies the cost of implementing the investment propositions of scenario 4 under the realisation of scenario 4).

Table 2.6: Co-optimising network and storage system - Stochastic - Costs in MM$

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Operation	770.14	761.64	767.90	767.1	766.69
Investment	46.81	46.81	33.05	39.44	41.53
Total	816.95	808.45	800.95	806.54	808.22

Table 2.7: Only network investment - Stochastic - Costs in MM$

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Operation	801.84	786.58	784.78	795.75	792.24
Investment	22.81	22.81	22.21	22.21	22.51
Total	824.65	809.39	806.98	817.96	814.75

Table 2.8: Unit Commitment constraints - Stochastic - Costs in MM$

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Operation	470.09	457.18	455.4	462.33	461.25
Investment	22.81	22.81	22.21	23.43	22.81
Total	492.9	479.99	477.61	485.76	484.07

From comparing Table 2.6 and 2.10, we can observe that the solution of the stochastic program, that features a cost of MM$ 808.22, is better than the solution of any deterministic plans and this is because although deterministic plans feature the lower costs under perfect information (see Table 2.9), in reality, the future is uncertain and thus the costs associated with the realisation of different scenarios to those used in the design of the plans, might be extremely high. Thus, although costs of deterministic plants seem to be smaller (Table 2.9), they are not (see Table 2.10).

Table 2.9: Co-optimising network and storage system - Deterministic - Costs in MM$

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Operation	772.38	769.47	769.47	767.94	769.81
Investment	43.55	31.97	17.01	26.38	29.73
Total	815.93	801.44	786.48	794.32	799.54

Table 2.10: Matrix cost by fixing deterministic solutions in different scenarios - Costs in MM$

		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Solution from	Scenario 1	815.93	807.42	812.89	842.27	819.63
	Scenario 2	825.10	801.43	807.31	836.09	817.48
	Scenario 3	1,030.28	953.27	786.48	809.46	894.87
	Scenario 4	1,035.51	957.72	790.42	794.32	894.49

Likewise, the costs of case iii displayed in Table 2.8 would not correspond to the true cost observed in reality. Indeed, in reality UC constraints must be respected and thus Table 2.11 shows the true costs of case iii, where the network and storage capacity obtained from the solution of case iii is operated by using the UC constraints, recalculating operational costs. This demonstrates that ignoring the (in)flexibility levels of the generation fleet may drive costs up, as high as 7%.

Table 2.11: Fixed solution from neglecting UC constraints - Stochastic - Costs in MM$

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Mean
Operation	803.66	786.97	785.25	793.57	792.36
Investment	22.81	22.81	22.21	23.43	22.81
Total	826.48	809.78	807.45	817.00	815.18

2.5 IEEE 118-busbar System Case Study

This section studies the scalability of our approach and the computational performance against the traditional DW node-based decomposition in terms of execution time, RAM utilisation and number of iterations.

2.5.1 Input data

We modified the IEEE 118-Bus System described in [34] by raising peak load from 3319 MW to 4500 MW. We consider two types of technologies for investing: (a) 8 candidate transmission lines added in parallel to existing ones with same capacity and reactance as installed: 8-30, 30-38, 53-54, 64-65, 77-82, 82-83, 80-99, 94-100 with an investment cost of 90 \$/MW/km/yr. One stage lag is considered between decision and commissioning time; (b) Storage system in buses 8, 15, 30, 38, 54, 59, 77, 80, 83, 100 characterised by modules of 5MW/10MWh, 50 modules as maximum per bus, round-trip efficiency of 90% and investment cost of 40 k\$/MW/yr, additionally, curtailment cost from renewables Π^{OC} is set at 150 \$/MWh.

Same demand profile as 2.4 is considered, and uncertainty is related to growth rate of systemic solar installed capacity. We include 4 solar plants in buses (initial installed capacity) 15 (270 MW), 54 (325 MW), 59 (875 MW) and 80 (475 MW) whose final installed capacity depends on the scenario, all solar plants growth at the same rate.

2.5.2 Results and discussion

In Figures 2.5 to 2.8, we show the value of the objective function and compare the computational performance in terms of execution time, use of RAM, and number of iterations for different instances of the stochastic program, in particular in terms of the number of representative days, number of stages, and number of scenarios. Hence, we study the following cases:

- 4 scenarios obtained by branching in two nodes in firsts two stages with equal probability considering 3 stages. Demand and solar profiles have been clustered in 5, 15 and 25 typical days. Same scenario tree as shown in Figure 2.3 and its data is presented in Table 2.13

- 9 scenarios obtained by branching in three nodes in firsts two stages with equal probability considering 3 stages. Demand and solar profiles have been clustered 25 typical days. Scenario tree is shown in Figure 2.4 considering firsts 3 stages and its data is presented in Table 2.14 for firsts 3 stages.

- 27 scenarios obtained by branching in three nodes in firsts three stages with equal probability considering 4 stages. Demand and solar profiles have been clustered in 5, 15 and 25 typical days. Scenario tree is shown in Figure 2.4 and its data is presented in Table 2.14.

We compared amount of integer and continuous variables and constraints from a monolithic approach, original formulation of Danztig Wolfe and the node-based decomposition from the 4 stages, 27 scenarios and 25 representative days case. From Table 2.12 it can be observed that the reformulation subproblem size is about 970 times smaller in terms of integer variables, 918 times smaller in terms of continuous variables and 1000 times smaller in terms of constraints in comparison to the monolithic approach.

Table 2.12: Subproblem size comparison

	Reformulated DW	DW	Monolithic
Integer Variables	4,014	97,326	3,893,040
Continuous Variables	31,296	782,400	28,747,200
Constraints	59,230	1,480,510	59,220,088

All cases are coded in Julia 0.6 [32] and solved with CPLEX 12.6.1 on two servers with 2 10-core Intel Xeon E5-2660 each and 48 GB of RAM each from National Laboratory High Performance Computing infrastructure [35], 0.1% MIP_{gap} was requested for every 3 stages case and 0.5% for every 4 stages case.

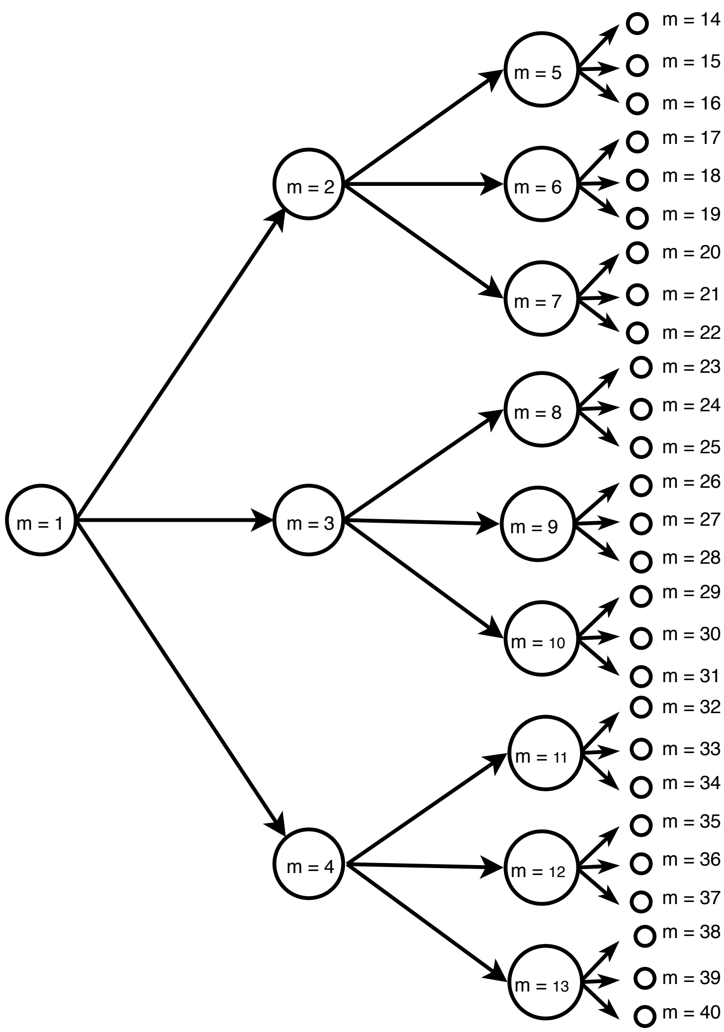

Figure 2.4: Scenario Tree - 4 Stages and 27 Scenarios - IEEE 118-Bus System

Table 2.13: Scenario tree - 3 Stages and 4 Scenarios - IEEE 118-Bus System

Node	Probability	Stage	Scenario	Solar Growth Rate
1	1	1	S1 - S4	1
2	0.5	2	S1 - S2	1.3
3	0.5	2	S3 - S4	1.1
4	0.25	3	S1	1.5
5	0.25	3	S2	1.4
6	0.25	3	S3	1.3
7	0.25	3	S4	1.2

Table 2.14: Scenario tree data - 4 Stages and 27 scenarios - IEEE 118-Bus System

Node	Probability	Stage	Scenario	Solar Growth Rate
1	1	1	S1-S27	1
2	1/3	2	S1-S9	1.5
3	1/3	2	S10-18	1.3
4	1/3	2	S19-S27	1.1
5	1/9	3	S1-S3	2
6	1/9	3	S4-S6	1.8
7	1/9	3	S7-S9	1.7
8	1/9	3	S10-S12	1.6
9	1/9	3	S13-S15	1.5
10	1/9	3	S16-S18	1.4
11	1/9	3	S19-S21	1.3
12	1/9	3	S22-S24	1.2
13	1/9	3	S25-S27	1.1
14	1/27	4	S1	2.7
15	1/27	4	S2	2.6
16	1/27	4	S3	2.5
17	1/27	4	S4	2.5
18	1/27	4	S5	2.4
19	1/27	4	S6	2.3
20	1/27	4	S7	2.2
21	1/27	4	S8	2.1
22	1/27	4	S9	2
23	1/27	4	S10	2.2
24	1/27	4	S11	2.1
25	1/27	4	S12	2
26	1/27	4	S13	2
27	1/27	4	S14	1.9
28	1/27	4	S15	1.8
29	1/27	4	S16	1.9
30	1/27	4	S17	1.8
31	1/27	4	S18	1.7
32	1/27	4	S19	1.7
33	1/27	4	S20	1.6
34	1/27	4	S21	1.5
35	1/27	4	S22	1.6
36	1/27	4	S23	1.5
37	1/27	4	S24	1.4
38	1/27	4	S25	1.5
39	1/27	4	S26	1.4
40	1/27	4	S27	1.3

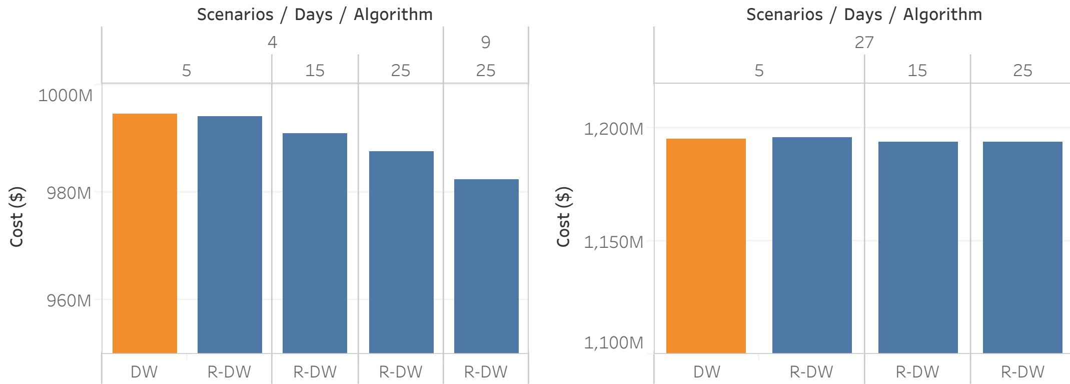

Figure 2.5: Objective Function Costs - IEEE 118-Bus System

In terms of execution time, we have information for only two instances when applying the traditional DW approach. These two cases are, as shown in Figure 2.6, (i) that of 5 days, 3 stages and 4 scenarios, and (ii) that of 5 days, 4 stages and 27 scenarios. For the other cases of 3 stages, the traditional DW approach reached the maximum allowed time of 48 hours without delivering a solution, while for those cases of 4 stages, the computer run out of memory. Instead, when we use our proposed DW approach, we obtain solutions for all studied instances, with time savings of more than a half with respect to the times utilised by the traditional DW algorithm.

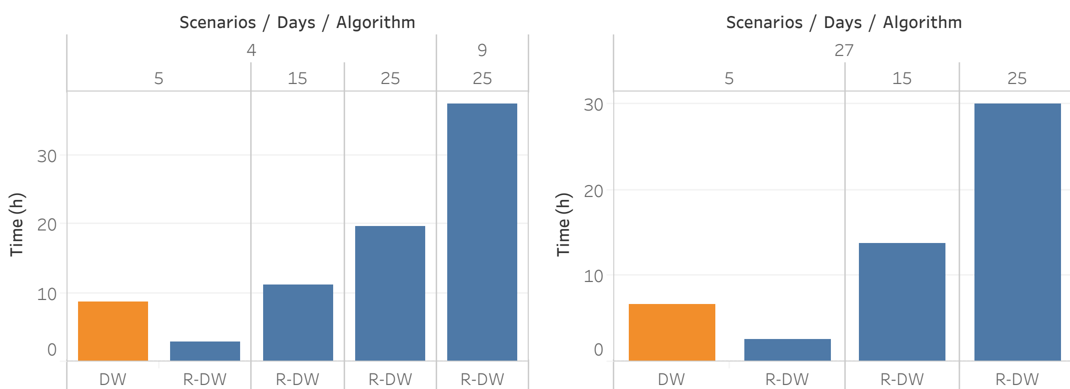

Figure 2.6: Time solution - IEEE 118-Bus System

We observe a similar situation in terms of RAM usage (see Figure 2.7, with more significant differences and advantages for the larger case study with 4 stages, in which our approach saves approximately a half of the memory utilised by the traditional DW approach. Note that, in the case of 4 stages, saving RAM is critically important to obtain investment solutions since, precisely, the other cases of 4 stages could not be solved due to RAM problems.

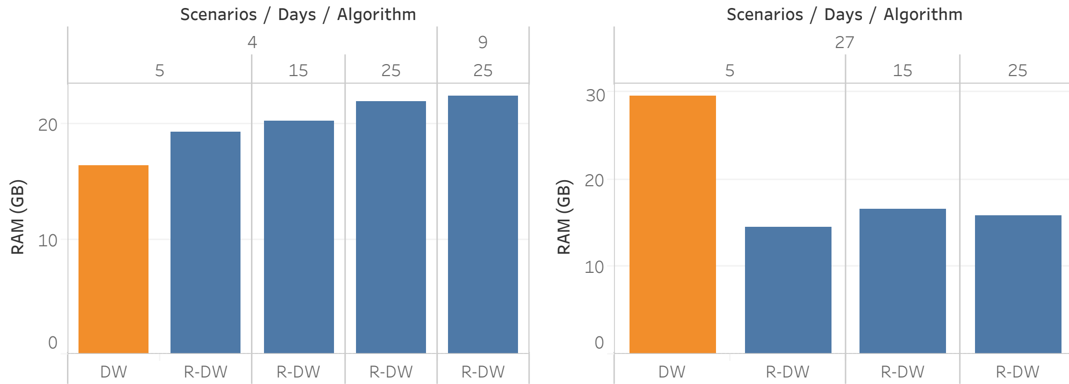

Figure 2.7: Use of Memory - IEEE 118-Bus System

Finally, in terms of the number of iterations Figure 2.8 shows that our approach features significantly more iterations due to the larger amounts of subproblems present in the iterative process. Indeed, and as mentioned, the decomposition approach in our proposal is based on typical days, while in the traditional approach, a node-based decomposition is used. Nevertheless, the larger amount of subproblems and iterations present in our approach is precisely what makes it faster and less demanding in terms of utilisation of RAM since every subproblem is significantly simpler to solve.

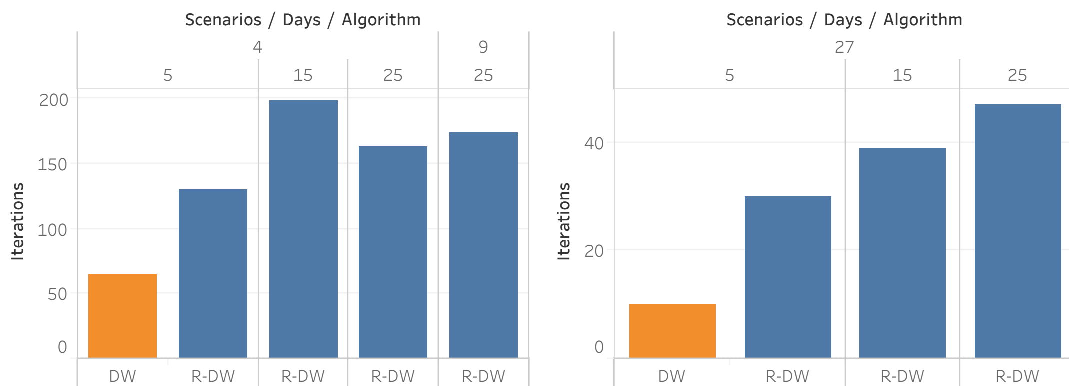

Figure 2.8: Iterations - IEEE 118-Bus System

Algorithm 1: Column Generation algorithm

Initialize MP (2.46) with initial set of columns ;
Set $j_m \leftarrow 1$, $k \leftarrow 0$, $\delta_{IP} \leftarrow \infty$, $\delta_{LP} \leftarrow \infty$, $UB \leftarrow \infty$, $LB \leftarrow \infty$;
while $\delta_{IP} > \varepsilon_{MIP}$ **do**
  while $\delta_{LP} > \varepsilon_{LP}$ **do**
    $Z^{SP} \leftarrow 0$;
    Solve the linear relaxation of MP (2.46);
    Collect solution $(Z^{MP}_{LP}, \boldsymbol{\pi}, \boldsymbol{\mu})$;
    $UB \leftarrow Z^{MP}_{LP}$;
    for $m = 1$ **to** M **do**
      Solve subproblem (2.47);
      Collect solution $(Z^{SP}_m, \widehat{x}_m, \widehat{y}_m)$;
      if $Z^{SP}_m < 0$ **then**
        $j_m \leftarrow j_m + 1$;
        $\widehat{x}^j_m \leftarrow \widehat{x}_m, \widehat{y}^j_m \leftarrow \widehat{y}_m$;
        $Z^{SP} \leftarrow Z^{SP} + Z^{SP}_m$;
      end
    end
    $LB \leftarrow Z^{MP}_{LP} + Z^{SP}$;
    $\delta_{LP} \leftarrow (UB - LB)/LB)$;
  end
  Solve integer MP (2.46);
  Collect solution (Z^{MP}_{IP});
  $\delta_{IP} \leftarrow (Z^{MP}_{IP} - LB)/(LB)$;
  $Z^{MP}_{IP\ k} \leftarrow Z^{MP}_{IP}$;
  $k \leftarrow k + 1$;
  if $k \geq 5$ **then**
    if $abs(Z^{IP}_k - \sum_{\mathrm{i}=k-4}^{k-1} Z^{IP}_{\mathrm{i}}/4) \leq \sigma$ **then**
      break
    end
  end
end

Chapter 3

Australian Case Study

3.1 Mathematical model

3.1.1 Master problem

$$\min \quad \sum_{m\in M}\gamma_m\phi_m\big(\sum_{l\in L}\Pi^L_{lm}v^L_{ml}+\sum_{p\in P^C}\Pi^P_{pm}v^P_{mp}+\sum_{b\in B^C}\Pi^B_{bm}v^B_{mb}\big) + \sum_{m\in M}\sum_{w\in W_m}\sum_{j\in\mathfrak{J}_{wm}}\gamma_m\Gamma_w\phi_m\mathbf{q}^T_{wm}\hat{\mathbf{y}}^j_{wm}\lambda^j_{wm} \tag{3.1a}$$

$$\text{s.t.} \quad \sum_{j\in\mathfrak{J}_{wm}}\hat{v}^L_{mwl}\lambda^j_{wm}\le\sum_{\mathrm{i}\in\wp_m}v^L_{\mathrm{il}} \qquad \forall m\in M,\forall w\in W_m,\forall l\in L, \quad [\pi_{mwl}] \tag{3.1b}$$

$$\sum_{j\in\mathfrak{J}_{wm}}\hat{v}^B_{mwb}\lambda^j_{wm}\le\sum_{\mathrm{i}\in\wp_m}v^B_{\mathrm{ib}} \qquad \forall m\in M,\forall w\in W_m,\forall b\in B^C, \quad [\pi_{mwb}] \tag{3.1c}$$

$$\sum_{j\in\mathfrak{J}_{wm}}\hat{v}^P_{mwp}\lambda^j_{wm}\le\sum_{\mathrm{i}\in\wp_m}v^P_{\mathrm{ip}} \qquad \forall m\in M,\forall w\in W_m,\forall p\in P^C, \quad [\pi_{mwp}] \tag{3.1d}$$

$$\sum_{j\in\mathfrak{J}_{wm}}\lambda^j_{wm}=1 \qquad \forall m\in M,\forall w\in W_m, \quad [\mu_{wm}] \tag{3.1e}$$

$$v^L_{ml}\in\mathbb{Z}^+ \qquad \forall m\in M,\forall l\in L, \tag{3.1f}$$

$$v^B_{mb}\in\mathbb{Z}^+ \qquad \forall m\in M,\forall b\in B^c. \tag{3.1g}$$

$$v^P_{mp}\in\{0,1\} \qquad \forall m\in M,\forall p\in P^C, \tag{3.1h}$$

3.1.2 Slave problem

$$\min sp_{(w,m)} : \quad \sum_{j \in \mathcal{J}_{wm}} \gamma_m \Gamma_w \phi_m \mathbf{q}_{wm}^T \mathbf{y}_{wm}^j \lambda_{wm}^j - \sum_{l \in L} v_{mwl}^L \hat{\pi}_{mwl} - \sum_{p \in P^C} v_{mwp}^P \hat{\pi}_{mwp} - \sum_{b \in B^C} v_{mwb}^B \hat{\pi}_{mwb} - \hat{\mu}_{mw} \tag{3.2a}$$

s.t.

$$v_{mwl}^L \leq \bar{v}_l^L \qquad \forall l \in L, \tag{3.2b}$$

$$v_{mwl}^B \leq \bar{v}_b^B \qquad \forall b \in B^C, \tag{3.2c}$$

$$\sum_{g \in G_n} p_{gh} + \sum_{b \in B_n^R} p_{bh} + \sum_{b \in B_n^C} p_{bh} + \sum_{g \in G_n^R} p_{gh} + \sum_{p \in P_n^E} p_{ph} + \sum_{p \in P_n^C} p_{ph} + \sum_{l \in In_n} f_{lh} - \sum_{l \in Out_n} f_{lh} + LS_{nh} = D_{nh} \qquad \forall n \in N, \forall h \in H, \tag{3.2d}$$

$$f_{lh} + fr_{lh}^{fwd} \leq \bar{F}_l + v_{mwl}^L \bar{L}_l \qquad \forall l \in L, \forall h \in H, \tag{3.2e}$$

$$f_{lh} - fr_{lh}^{rev} \leq \bar{F}_l - v_{mwl}^L \bar{L}_l \qquad \forall l \in L, \forall h \in H, \tag{3.2f}$$

$$\sum_{g \in G_n} r_{gh} + \sum_{b \in B_n^C} r_{bh} + \sum_{p \in P_n^E} r_{ph} + \sum_{p \in P_n^C} r_{ph} + \sum_{l \in In_n} fr_{lh}^{fwd} - \sum_{l \in Out_n} fr_{lh}^{fwd} - \sum_{l \in In_n} fr_{lh}^{rev} + \sum_{l \in Out_n} fr_{lh}^{rev} = \bar{R}q_{nh} \qquad \forall n \in N, \forall h \in H, \tag{3.2g}$$

$$p_{gh} + r_{gh} \leq \bar{P}_{gm} x_{gh} \qquad \forall g \in G, \forall h \in H, \tag{3.2h}$$

$$p_{gh} \geq \underline{P}_g x_{gh} \qquad \forall g \in G, \forall h \in H, \tag{3.2i}$$

$$r_{gh} \leq \alpha_g \bar{P}_{gm} x_{gh} \qquad \forall g \in G, \forall h \in H, \tag{3.2j}$$

$$x_{gh} \leq N_{gm} \qquad \forall g \in G, \forall h \in H, \tag{3.2k}$$

$$p_{gh} \leq \bar{P}_{gm} \beta_{wg} N_{gm} \qquad \forall g \in G_{ror}, \forall h \in H, \tag{3.2l}$$

$$\sum_{h \in H} p_{gh} \leq H \bar{P}_{gm} \beta_{wg} N_{gm} \qquad \forall g \in G \setminus G_{ror}, \tag{3.2m}$$

$$x_{gh} = x_{gh-1} + s_{gh} - t_{gh} \qquad \forall g \in G, \forall h \in H, \tag{3.2n}$$

$$p_{gh} - p_{gh-1} \leq x_{gh-1} \Delta_g \bar{P}_{gm} + s_{gh} \underline{P}_g \qquad \forall g \in G, \forall h \in H \tag{3.2o}$$

$$p_{gh-1} - p_{gh} \leq x_{gh} \Delta_g \bar{P}_{gm} + t_{gh} \underline{P}_g \qquad \forall g \in G, \forall h \in H, \tag{3.2p}$$

$$x_{gh} \geq \sum_{h' \in h - h_{on(g)}} s_{g,h'} \qquad \forall g \in G, \forall h \in H, \tag{3.2q}$$

$$N_{gm} - x_{gh} \geq \sum_{h' \in h - h_{off(g)}} t_{g,h'} \qquad \forall g \in G, \forall h \in H, \tag{3.2r}$$

$$p_{gh} \leq A_{gh} \bar{P}_{gm} \qquad \forall g \in G^R, \forall h \in H, \tag{3.2s}$$

$$
\begin{aligned}
p_{bh} &\leq \bar{P}^B_{mb} && \forall b \in B^R, \forall h \in H, && (3.3a)\\
p_{bh} &\geq -\bar{P}^B_{mb} && \forall b \in B^R, \forall h \in H, && (3.3b)\\
\mathrm{e}_{bh} &\leq \bar{P}^B_{mb} C^{B_r} && \forall b \in B^R, \forall h \in H, && (3.3c)\\
\mathrm{e}_{bh} &\geq 0 && \forall b \in B^R, \forall h \in H, && (3.3d)\\
\mathrm{e}_{bh} &= \mathrm{e}_{bh-1} - p_{bh}\eta_r && \forall b \in B^R, \forall h \in H, && (3.3e)\\
\mathrm{e}_{b1} = 0, &\quad \mathrm{e}_{bH} = 0 && \forall b \in B^R && (3.3f)\\
p_{bh} + r_{bh} &\leq v^B_{mwb}\zeta^B && \forall b \in B^C, \forall h \in H, && (3.3g)\\
p_{bh} &\geq -v^B_{mwb}\zeta^B && \forall b \in B^C, \forall h \in H, && (3.3h)\\
\mathrm{e}_{bh} - \xi r_{bh} &\geq 0 && \forall b \in B^C, \forall h \in H, && (3.3i)\\
\mathrm{e}_{bh-1} - \xi r_{bh} &\geq 0 && \forall b \in B^C, \forall h \in H, && (3.3j)\\
\mathrm{e}_{bh} &= \mathrm{e}_{bh-1} - p_{bh}\eta_b && \forall b \in B^C, \forall h \in H, && (3.3k)\\
\mathrm{e}_{bh} &\leq v^B_{mwb} C^B \zeta^B_b && \forall b \in B^C, \forall h \in H, && (3.3l)\\
b_{b1} = 0, &\quad b_{bH} = 0 && \forall b \in B^C, && (3.3m)\\
p_{ph} + r_{ph} &\leq v^P_{mwp}\zeta^P_p && \forall p \in P^C, \forall h \in H, && (3.3n)\\
p_{ph} &\geq -v^P_{mwp}\zeta^P_p && \forall p \in P^C, \forall h \in H, && (3.3o)\\
\mathrm{e}_{ph} - \xi r_{ph} &\geq 0 && \forall p \in P^C, \forall h \in H, && (3.3p)\\
\mathrm{e}_{ph-1} - \xi r_{ph} &\geq 0 && \forall p \in P^C, \forall h \in H, && (3.3q)\\
\mathrm{e}_{ph} &\leq v^P_{mwp} C^P_p \zeta^P_p && \forall p \in P^C, \forall h \in H, && (3.3r)\\
\mathrm{e}_{ph} &= \mathrm{e}_{ph-1} - p_{bh}\eta^P && \forall p \in P^C, \forall h \in H, && (3.3s)\\
\mathrm{e}_{p1} = \mathrm{e}_{pH} &= \frac{1}{2} v^P_{mwp} C^P_p \zeta^P_p && \forall p \in P^C, && (3.3t)\\
p_{ph} + r_{ph} &\leq \bar{P}^P_{mp} && \forall p \in P^E, \forall h \in H, && (3.3u)\\
p_{ph} &\geq -\bar{P}^P_{mp} && \forall p \in P^E, \forall h \in H, && (3.3v)\\
\mathrm{e}_{ph} - \xi r_{ph} &\geq 0 && \forall p \in P^E, \forall h \in H, && (3.3w)\\
\mathrm{e}_{ph-1} - \xi r_{ph} &\geq 0 && \forall p \in P^E, \forall h \in H, && (3.3x)\\
\mathrm{e}_{ph} &\leq \bar{P}^P_{mp} C^P_p && \forall p \in P^E, \forall h \in H, && (3.3y)\\
\mathrm{e}_{ph} &= \mathrm{e}_{ph-1} - p_{bh}\eta^P && \forall p \in P^E, \forall h \in H, && (3.3z)\\
\mathrm{e}_{p1} = \mathrm{e}_{pH} &= \frac{1}{2} \bar{P}^P_{mp} C^P_p && \forall p \in P^E && (3.4a)
\end{aligned}
$$

3.1.3 Planning Model with column generation

After validating the optimisation model and proving its scalability in real-scale networks we apply it on a real-size network system corresponding to the Australian NEM network. We extend the use of the Reformulated Day-Based Dantzig Wolfe Decomposition presented in section 2.3.2 by solving a large-scale mixed-integer linear problem, in this case, as opposed to cases solved in Chapter 2, subproblems solve a operation problem of one week long each turning the reformulation from a Day-Based to a Week-Based model. The formulation does not change but only the value of H increases from 24 to 168.

The optimisation model involves two problems, the master problem, which decides investment for all nodes of the scenario tree and operational solution coming from previous columns added from subproblems (3.1a), and the slave problem, which solves one independent investment and operational problem within one typical week in a specific scenario and stage utilising dual prices obtained from master problem (3.2a).

Constraints (3.1b) - (3.1c) ensure that investments are consistently made, and any new investment is available for all coming nodes. (3.1e) guarantees that only one column is selected for every subproblem. Line and battery investment are integer as depicted in (3.1f) and (3.1g) respectively, and candidate pumped storage decision is binary as real projects are considered (3.1h).

In slave subproblems, the operational and investment optimisation problem is modelled as follow: a maximum amount of modules can be installed in lines and batteries as shown in (3.2b)-(3.2c). Constraint (3.2d) models nodal power balance, (3.2e) and (3.2f) model power flows in lines considering reserve flow and new added capacity if modules of lines are invested, reserve balance is modelled in (3.2g) allowing to transfer reserve among electrical nodes. Conventional generators are modelled through constraints (3.2h) to (3.2r), (3.2h) reflects maximum output power, (3.2i) minimum stable generation, (3.2j) present the headroom that must be available in conventional generators for providing spinning reserve, (3.2k) limits maximum amount of machines to commit per generator, (3.2l) is applied only for run-of-river generators constraining their maximum generation according to their plant factor and (3.2m) is applied to no run-of-river conventional generators constraining the maximum energy generated within a typical week (one subproblem's duration), (3.2n) shows commited machines per generator according to startups and shutdowns, (3.2o)-(3.2p) present ramp rates per generators, and (3.2q)-(3.2r) constraint minimum up and down time per generators respectively. Renewables' power output are constrained by their installed capacity and availability of resources as shown in (3.2s), constraints (3.3a) to (3.3f) describe residential batteries' operation, (3.3a) and (3.3b) model limits for generation and load mode respectively, (3.3c) and (3.3d) present maximum and minimum energy to be stored in residential batteries respectively, and (3.3f) present their border conditions. (3.3g) - (3.3m) describe candidate battery operation, unlike residential batteries, candidate batteries can provide reserve, therefore an additional reserve variable is added in its operation, (3.3g) and (3.3h) describe power limits for generation and load mode, (3.3i) and (3.3j) present minimum energy that must be available at the beginning and at the end of one time block (one hour) for providing reserve, (3.3k) shows state of charge of a candidate battery, (3.3l) presents maximum energy capacity and (3.3m) border conditions stating that no energy must be kept at the end of the simulation. From constraint (3.3n) to constraint (3.4a) candidate and existing pumped storage plants are modelled, for candidate pumped storage plants, (3.3n) models maximum power output as generator and (3.3o) models maximum power input operating as pump, constraints (3.3p) and (3.3q) state the minimum energy that must be stored at all times for providing reserve, energy capacity is obtained according to (3.3y) and state of charge according to (3.3s), border conditions state that, in case of any investment, energy stored at the beginning and at the end of simulation period must be half of maximum capacity. Similarly, for existing pumped storage plants their maximum power as generator is modelled according to (3.3u) and maximum power input as pump is modelled according to (3.3v), minimum energy must be stored at all times for providing reserve as modelled in (3.3w) and (3.3x), energy capacity is obtained according to (3.3z) and state of charge is obtained according to (3.3y), energy at the beginning and at the end of simulation period must be half of maximum capacity as shown in (3.4a).

Accelerating methods for Column Generation

Despite solving subproblems which are fast to solve, sometimes the algorithm faces issues in converging, finding good columns or it simply takes too long. Therefore, We have implemented some accelerating methods that help the algorithm to reach convergence.

- Dynamic time limit: When solving many subproblems in parallel, sometimes a few amount of them are harder to be solved creating a bottleneck in the algorithm, this because one iteration is not completed until all of subproblems are solved. We have implemented a methodology which capture the solution time of all subproblems in one iteration and calculates the 85^{th} percentile. For the next iteration, all of subproblems must be solved within this time, otherwise the algorithm stops the subproblem and captures the best solution obtained for that subproblem. If more than 25% of subproblems are stopped before converging, a new time limit is set.

- Tunned solver: We have utilised the auto tunning feature of the solver in the subproblems.

- Warm-start: Before solving a subproblem, we provide an initial value to investment variables coming from previous master problem solution.

- Column Sharing: The investment solution obtained from a subproblem is shared among all subproblems that belong to the same scenario tree node. This applies to all subproblems of the scenario tree. Iterations will become longer to solve, but many columns will be added to master problem in each iteration accelerating convergence.

Additionally in this study case, we have relaxed the operational variables coming from conventional generators in order to reduce computational time from subproblems, yet the investment variables remained integer. It has been proven that by relaxing these variables the model still captures with relatively high precision the relevant flexibility requirements according to reference [36].

3.2 Study Case

This study aims to develop a planning model for the Network Electricity Market (NEM) under uncertainty. We merge four different scenarios described in the ISP [2] into one scenario tree branching on the root node. These scenarios differ each other in generation expansion plans, storage investment costs, load growth rate and fuel costs.

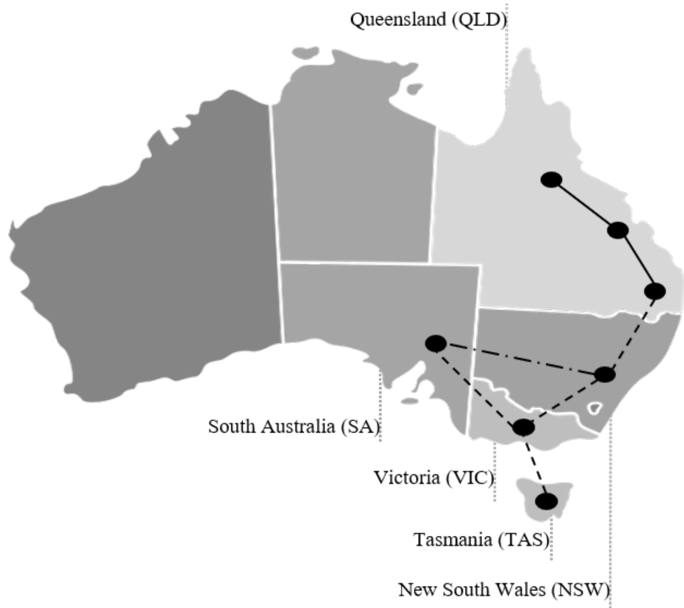

Figure 3.1: 7-bus system NEM

The network is composed by seven buses and six lines as shown in Figure 3.1, one bus for each state except Queensland which is separated in three buses. Interconnectors are shown in dashed lines and a candidate line is shown in dash-dotted line. Current capacities are shown in Table 3.1

Load profiles are obtained from [37], they increase in time by different rates according to scenario, stage and location conforming to shown in Tables 4.2 - 4.4, renewable profiles do not change in time, thus, they are repeated in every scenario tree node, additionally, generation installed capacity, storage investment prices and fuel costs depend on scenario tree node.

Table 3.1: Interconnector's capacities

Link		Capacity
From	To	[MW]
TAS	VIC	500
NSW	VIC	1000
QLDS	NSW	600
QLDC	QLDS	1900
QLDN	QLDC	2225
SA	VIC	850
SA	NSW	0

The study case is programmed in Julia 0.6, being solved utilising Gurobi 8.0 and CPLEX 12.8.1, University of Melbourne infrastructure was utilised to run the models utilising 12 8-core i7 Intel machines with 16 GB of RAM each, these computers were coordinated under OpenHPC clustering environment. 156 subproblems in parallel were solved at each iteration.

3.2.1 Operational model

Every year is represented through 12 independent subproblems of 168 hours long each. Every subproblem represent one typical week corresponding to one month of the year, these weeks are characterised by their resource availability, weight in the year and demand.

Some interconnectors in NEM are High Voltage Direct Current (HVDC) lines [38], besides that, NEM's shape is mostly radial resulting in controllable flows in the system, for this reason, angles in electrical nodes are dismissed rendering a transport model, line capacity is assumed the same for forward and reverse direction.

In order to reduce computational complexity, generators are aggregated into clusters of same technology and similar variable cost, one or two aggregated machines per technology in every bus. Wind farms, solar plants and rooftop solar are modelled as single machines constrained by their availability and installed capacity with the possibility of curtailing.

Storage systems are classified according to their energy capacity. Residential batteries' energy capacity is considered in two hours at maximum power and their installed capacity depends on stage and scenario being solved, utility-scale storage system's energy capacity is considered in two hours as well, and their installed capacity is economically optimised, finally pumped storage energy capacity depend either is existing pumped storage or candidate pumped storage, the former have energy capacities from 6 hours to 25 hours and the latter are composed by projects of either 24 hours or 168 hours with 1500 MW and 2000 MW of maximum power respectively whose installation is economically optimised. Residential batteries can only do arbitrage, although, pumped storage systems and utility-scale storage systems can provide spinning reserve and do arbitrage. Residential batteries and utility-scale storage systems have a 90% round-trip efficiency, unlike pumped storage system having a 80% round-trip efficiency.

3 + 5 rule has been utilised for reserve requirements at all times. Reserve must be equal to 3% of demand plus 5% of renewable generation at every bus at every hour and reserve can be imported/exported through transmission system. Conventional generation can provide up to 20% of commited generation as reserve and storage systems must keep enough energy to provide up to half-an-hour of reserve at maximum power.

3.2.2 Investment model

Every existing link can be reinforced by expanding their actual capacity by modules of 200 MW up to a defined maximum depending on the interconnector as shown in Table 3.2, a new line between South Australia and New South Wales is proposed with a candidate module of 700 MW. Investment costs are obtained by calculating an average cost per installed MW according to each interconnector from ISP Assumptions Workbook [39].

Table 3.2: Current line capacities and maximum reinforcement options

Link		Capacity	Maximum
From	To	[MW]	modules
TAS	VIC	500	12
NSW	VIC	1000	18
QLDS	NSW	600	30
QLDC	QLDS	1900	20
QLDN	QLDC	2225	20
SA	VIC	850	20
SA	NSW	0	1 (700 MW)

Pumped storage system and large-scale utility storage are investment options in NEM, the former can be invested in New South Wales representing Snowy 2.0 project characterised by a 2000 MW storage system with 168 hours of duration at maximum power with an estimated cost of 4 billion of Australian dollars and in Tasmania representing Battery of The Nation project characterised by a 1500 MW storage system with 24 hours of duration at maximum power with an estimated cost of 2.25 billion of Australian dollars, pumped storage system have an efficiency set at 80% and 50 years of lifetime as AEMO considers, they also have one stage lag between decision and commissioning time, the latter can be invested in any of the seven buses as modules of 200 MW up to 15 GW with 2 hours of duration at maximum power, no lag in considered between decision and commissioning time and efficiency is set at 90%.

3.2.3 Scenarios

Four different scenarios are solved simultaneously under a stochastic approach considering the root node as base for all of them (see Figure 3.2), each scenario has a 25% probability of occurrence. A 6% of discount rate is considered.

Scenarios as described as follows, any comparison is referred to Neutral scenario:

- Neutral: Business as Usual
- Slow: Economic growth is weak reducing generation investment along with a strong large-scale demand side participation. Wind and utility PV show a slower cost reduction in comparison to Neutral scenario.
- Fast: Strong economic growth along with a weak large-scale demand side participation. Wind and utility PV show a rapid cost reduction in comparison to Neutral scenario.
- High DER: Neutral economic growth along with a strong large-scale demand side participation and distributed storage aggregation.

All scenarios consider a initial generation installed capacity which varies depending on the scenario and stage being solved (see Figure 3.3), thermal generation reaching their lifespan are retired from the system, new base load generation such as high efficiency low emissions

(HELE) coal-fired generation is added into the system to deliver low-cost, reliable and secure supply of synchronous generation and renewable technologies penetration increases according to build prices and policies. Moreover, scenarios are characterised by different demand forecasts projected to increase in time at different rates, however, net demand is expected to remain flat due to new DER supplying new energy into the system. Finally, investment costs may differ among scenarios depending on economical and technologic development.

Planning horizon is set in 20 years beginning in 2020, every scenario is composed by 4 stages of 5 years long each. Each year is represented by a representative time frame of 12 weeks, these weeks are obtained utilising K-medoids clustering algorithm [40] by comparing a large matrix with demand and renewable profiles for every electrical node and obtaining a representative week for every month of the year.

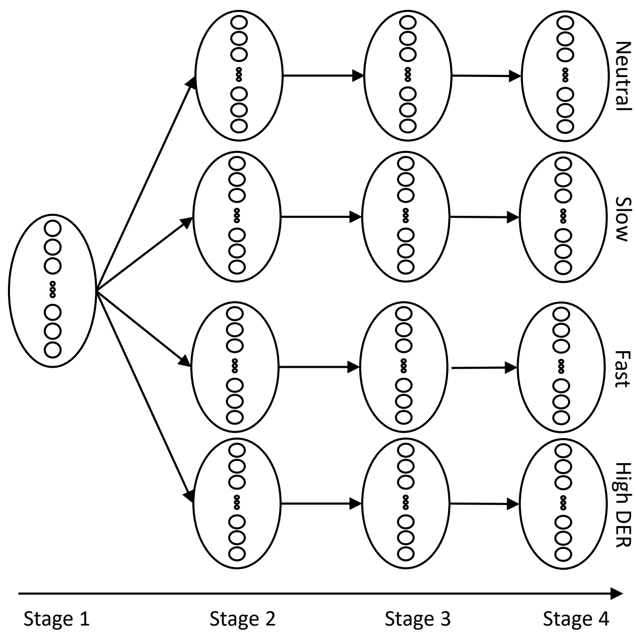

Figure 3.2: Scenario tree node composed by 4 scenarios and 4 stages

3.2.4 Results

Investment decisions for stochastic study case are shown in Tables 3.4 and 3.5 (it is shown when new investments are operating), a darker background in some cells mean that decision must be the same for all scenarios within same stage due to longer construction times of pumped storage plants and transmission lines.

From Table 3.4 it can be observed that two important investments are made being commissioned at the second stage, $NSW - VIC$ link is reinforced by 2.2 GW and $TAS - VIC$ link is reinforced by 400 MW, additionally, $SA - NSW$ new link is invested in the fast scenario at the fourth stage, creating a new interconnection with 700 MW of capacity between two buses that were not connected before. From Table 3.5 it can be observed when Battery of The Nation investment is obtained at stage 4 in the Fast scenario the $TAS - VIC$ link is considerably reinforced, likewise when Snowy 2.0 is invested, links connecting NSW are reinforced as well. Moreover, it is important to note that no utility storage asset were

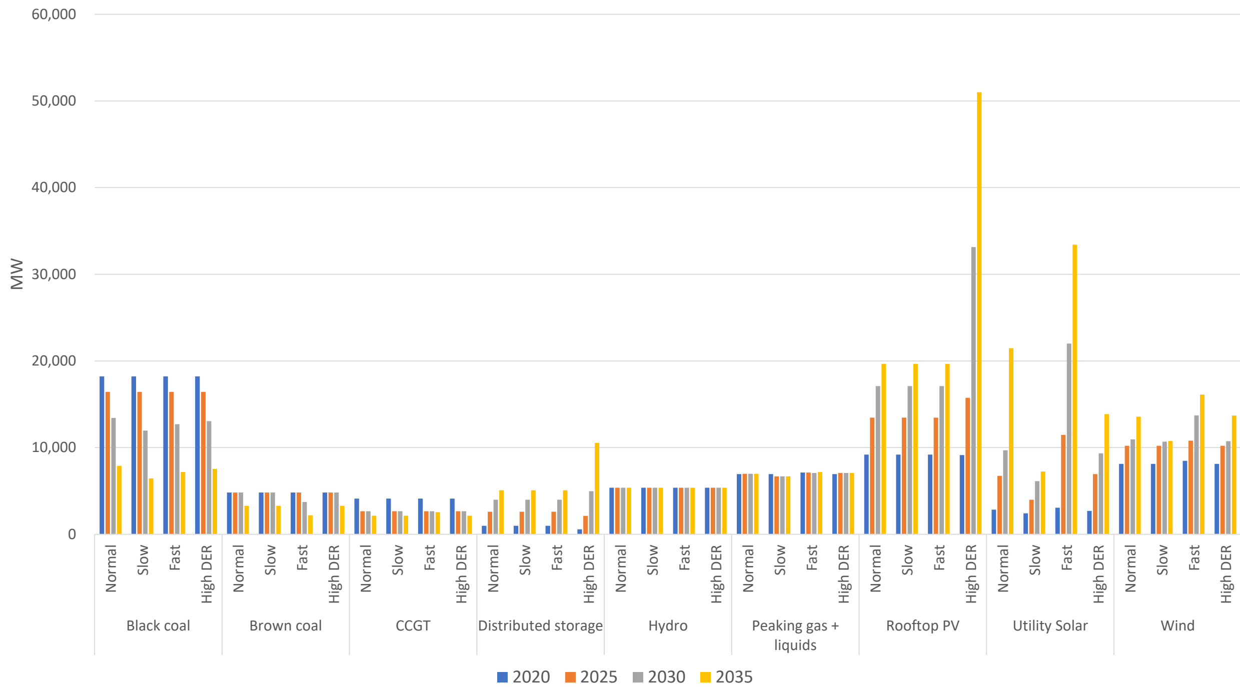

Figure 3.3: Installed capacity by technology, stage and scenario of NEM

invested.

Transmission investment

Due to the presence of lead time in transmission investments, all scenarios at the second stage share the same transmission investment decision. $NSW - VIC$ link by the second stage is reinforced in more than two times its initial capacity ending up with 3.2 GW of transfer capacity. This major investment is justified by its operation in the first stage where this link, most of the time, remained importing energy from VIC to NSW at maximum capacity according to the load duration curve depicted in Figure 3.4. During the firsts two stages, NSW, in average, is the most expensive bus of the system as shown in Table 3.3, therefore it is expected to be importing energy rendering $NSW - VIC$ link to be highly congested.

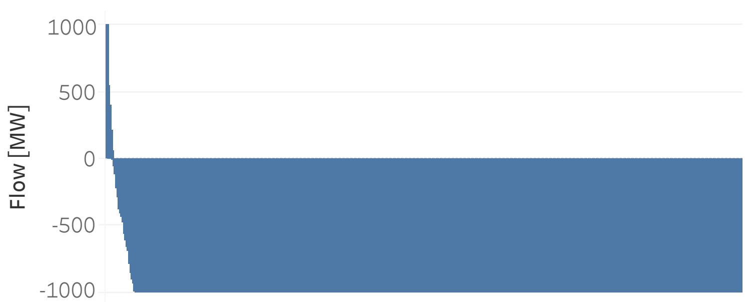

Figure 3.4: Load duration curve of $NSW - VIC$ link at Stage 1

After reinforcing the link at the second stage, its load duration curve for the different scenarios are shown in Figure 3.5, the fast scenario is the only scenario with forward flows in

Table 3.3: Marginal costs in stage 1 and stage 2

	Marginal Cost [$/MWh]				
	Stage 1	Stage 2			
Location	Root node	Fast	HighDER	Neutral	Slow
NSW	21.5	14.4	15.56	16.04	16.04
QLDN	19.79	16.05	16.05	16.04	15.92
QLDC	19.79	16.05	16.05	16.04	15.92
QLDS	19.79	16.05	16.05	16.04	15.92
SA	15.42	16.49	12.72	14.75	11.24
TAS	0.89	5.61	3.77	6.60	3.08
VIC	9.94	11.17	9.4	10.27	7.90

NSW to VIC direction, additionally in this scenario NSW bus is cheaper than Queensland's. For the rest of scenarios, this link still remains exporting at maximum capacity.

Links connecting Queensland's buses are not reinforced during the firsts stages, it is important to note from Table 3.3 that marginal costs of Queensland's buses are the same for every stage, therefore links connecting Queensland are not as congested as NSW's links obtaining no investments.

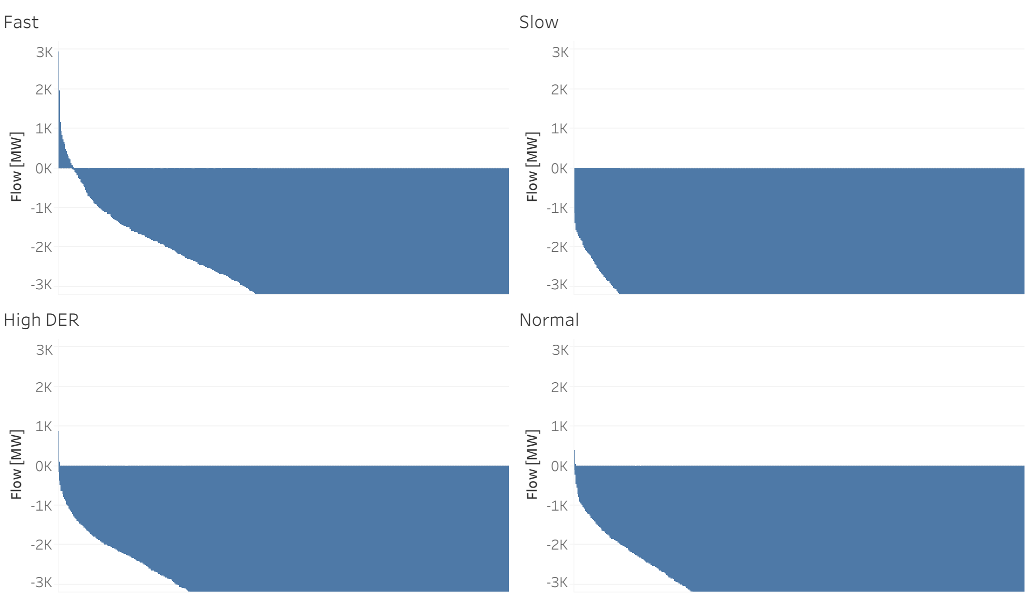

Figure 3.5: Load duration curve of $NSW - VIC$ link at Stage 2

Table 3.4: Stochastic - Line Investment

Line	Scenario	Stage 1	2	3	4
NSW - VIC	Fast	0	2200	2200	3000
	HighDER	0	2200	2200	2400
	Normal	0	2200	2200	2200
	Slow	0	2200	2600	2600
QLDC - QLDS	Fast	0	0	0	1000
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
QLDN - QLDC	Fast	0	0	0	0
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
QLDS - NSW	Fast	0	0	0	2000
	HighDER	0	0	0	0
	Normal	0	0	0	600
	Slow	0	0	0	0
SA - NSW	Fast	0	0	0	700
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
SA - VIC	Fast	0	0	0	0
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
TAS - VIC	Fast	0	400	600	1800
	HighDER	0	400	400	600
	Normal	0	400	400	800
	Slow	0	400	400	800

Storage Investments

From Table 3.5 it can be observed at the fourth stage Battery of The Nation was invested only in the Fast Scenario and Snowy 2.0 was invested in the Fast, HighDER and Neutral scenarios. Their investment were triggered mostly by providing arbitrage, avoiding curtailment and providing reserve.

From Figure 3.6 it can be observed the input/output power of existing and invested pumped storage plants on the top and the amount of stored water (state of charge) on the bottom of New South Wales. Both pumped storage do arbitrage at pumping during PV generation time and they generate during no PV generation time. From the bottom chart it can be observed that the storing capacity of the existing pumped storage is fully utilised at some times, leaving the pumped storage with no energy left, on the other hand, the invested pumped storage capacity is not fully utilised due to its energy capacity which is large enough to generate at maximum power as long as the time simulation, besides that, it is set to start and finish the operation at half of capacity so it is not possible to take advantages of its large energy capacity.

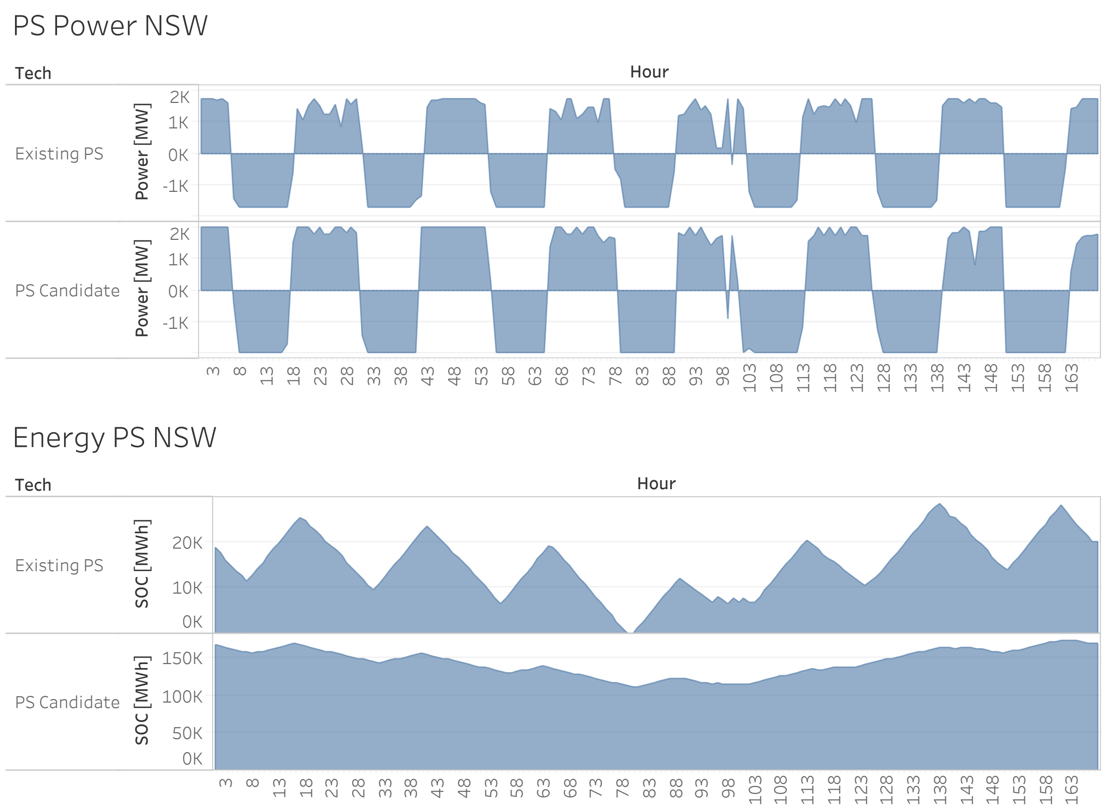

Figure 3.6: Power and State of Charge of Pumped Storage plants - NSW Neutral Scenario at Stage 4

In addition to arbitrage, at the same time pumped storage supports the system to avoid curtailment during high renewable generation, from Table 3.6 curtailment for all stages and scenarios are shown. Battery of The Nation project was invested at the fourth stage in the Fast Scenario reducing curtailment from 15.6 GWh in the previous stage to zero, it is important to keep in mind from Figure 3.3 that renewable installed capacity increases in time and the Fast Scenario involves the highest Utility Solar and Wind installed capacity among all scenarios.

Table 3.6: Curtailment in Tasmania

	Scenario [MWh]			
Stage	Fast	HighDER	Neutral	Slow
1	0			
2	2402	3019	665	1225
3	15647	8153	2897	3545
4	0	38503	20574	11937

Table 3.5: Stochastic - Storage Investment

			Stage			
Location	Tech	Scenario	1	2	3	4
NSW	Pumped Storage	Fast	0	0	0	1
		HighDER	0	0	0	1
		Normal	0	0	0	1
		Slow	0	0	0	0
	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDN	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDC	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDS	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
SA	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
TAS	Pumped Storage	Fast	0	0	0	1
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
VIC	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0

Furthermore, pumped storage systems are big reserve contributors to the system, most of the reserve requirements are provided by either new plants or existing plants (see Figure 3.7). With this in mind, less conventional generators must be commited to fulfill reserve requirements decreasing marginal costs in the system. Moreover, importing reserve nodes become exporting reserve nodes according to Figure 3.7 where provided reserve, in average, becomes higher than average reserve requirements (blue line in Figure 3.7).
Specifically, Tasmania at the third stage in the Fast Scenario, in average, has 57.3 MW of required reserves, and only 6.3 MW, in average, of provided reserve, on the contrary, at the fourth stage still in the Fast Scenario, the required reserve increased to 65.3 MW in average, but Battery of The Nation project provided in average 131.5 MW of reserve, therefore $TAS - VIC$ link end up transferring reserve at the fourth stage as a consequence of the Battery of The Nation investment as shown in Figure 3.8.

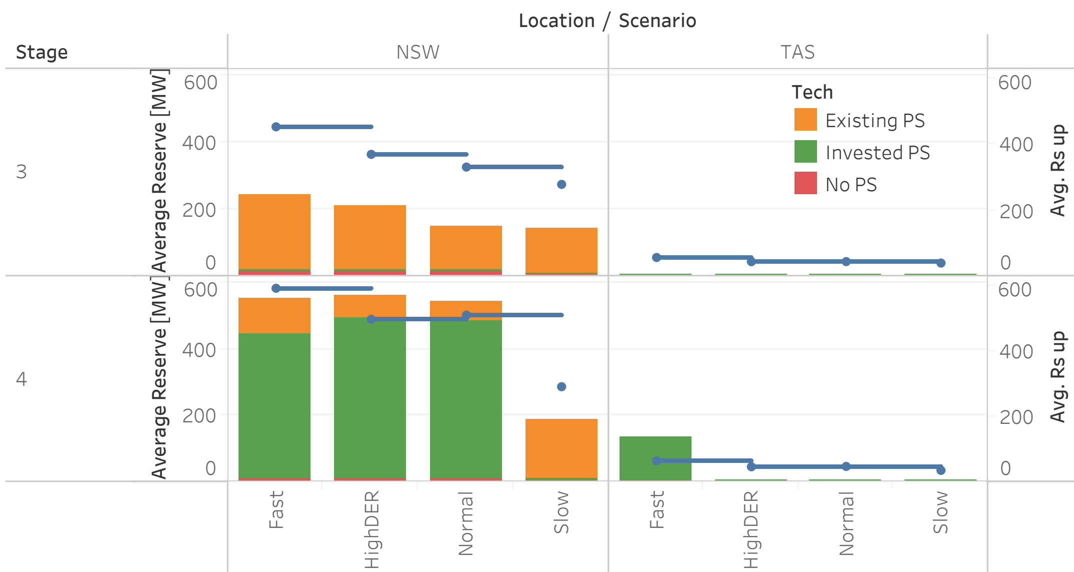

Figure 3.7: Average provided reserve in buses with new pumped storage plants

Deterministic Results

After solving the stochastic model, every scenario is solved separately in order to observe which investments are triggered by a single scenario, or which investments suit all scenarios, results are shown in Tables 3.7 and 3.8.

At first, it can be observed from Table 3.7 that storage investments do not change in comparison to stochastic's results from Table 3.5.

Considering the deterministic shape of the scenario tree of all scenarios after the second stage, it could be expected to obtain the same storage investment at the fourth stage like the stochastic results. Whereas, stochastic results present line investments right after the branching at the second stage, so it is expected to obtain differences at the second stage. From Table 3.8, $NSW - VIC$ link has different investments in each scenarios, the Fast scenario has the lowest investment in comparison to the rest of scenarios, and only the

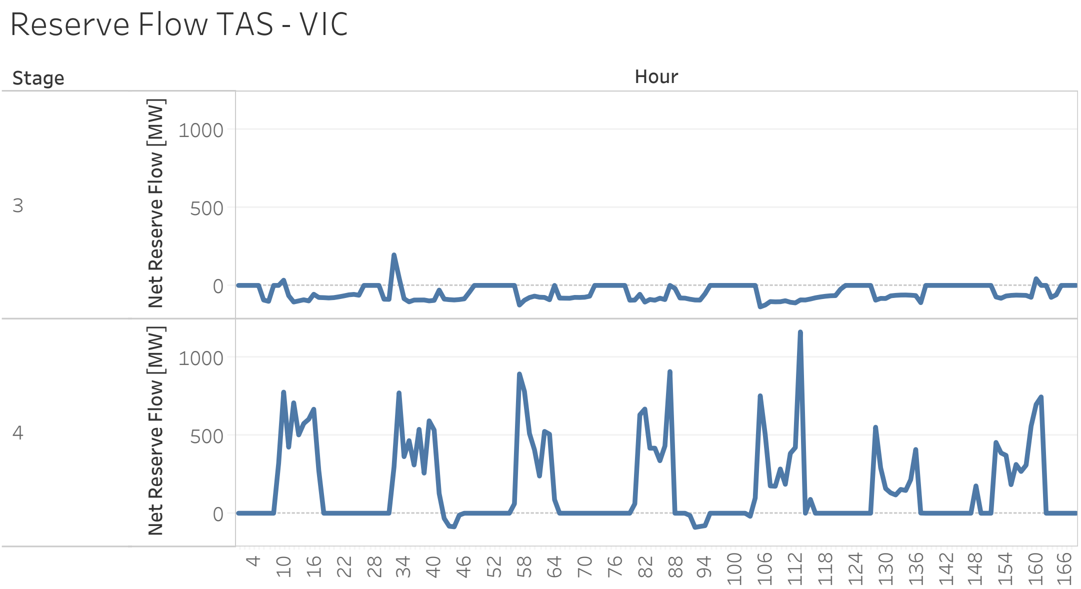

Figure 3.8: Reserve flow in $TAS - VIC$ link in the Fast Scenario

Slow Scenario reaches the 2200 MW obtained previously in the stochastic result, moreover, $TAS - VIC$ investment at the second stage is deferred in three out of four scenarios, thus, the corridor between Tasmania and New South Wales is not as reinforced as the stochastic results. Despite having differences at the second stage, as mentioned before, the deterministic shape of the scenarios from the second stage renders similar investments at the fourth stage, having big investment in links connecting NSW when Snowy 2.0 is invested, as well as big investment in $TAS - VIC$ link when Battery of The Nation is invested.

System Security

In the previous planning exercise, the only consideration of security modelled was the spinning reserve, therefore, this security aspect were ensured at all times for every scenario. Furthermore, according to Fig. 3.7 and Fig. 3.8 when new pumped storage capacity are installed in the system, these new assets change how reserve flows are distributed around the system, fulfilling not only the reserve requirements of the bus where these assets were installed but also by exporting reserve to the system.

Utility storage batteries have been modelled to do arbitrage and provide secondary reserve only. Considering that conventional generation and pumped storage systems can provide secondary reserve as batteries can, the latter type of storage system can not stand out against those technologies due to all reserve requirements were already satisfied during the first stages of the exercise by existing capacity of the system. Hence, no investment was obtained in utility storage batteries.

If the planning exercise would have been done within a security-constrained context, whereby different security requirements were presented, such as, ROCOF, nadir requirements, fast frequency response, among others. Batteries could have stood out against different technologies because of their characteristics which make them more attractive to invest on.

Table 3.7: Deterministic - Storage Investment

			Stage			
Location	Tech	Scenario	1	2	3	4
NSW	Pumped Storage	Fast	0	0	0	1
		HighDER	0	0	0	1
		Normal	0	0	0	1
		Slow	0	0	0	0
	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDN	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDC	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
QLDS	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
SA	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
TAS	Pumped Storage	Fast	0	0	0	1
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0
VIC	Utility Storage	Fast	0	0	0	0
		HighDER	0	0	0	0
		Normal	0	0	0	0
		Slow	0	0	0	0

Table 3.8: Deterministic - Line Investment

		Stage			
Line	Scenario	1	2	3	4
NSW - VIC	Fast	0	800	800	3000
	HighDER	0	2000	2000	2000
	Normal	0	1800	1800	1800
	Slow	0	2200	2400	2400
QLDC - QLDS	Fast	0	0	0	800
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
QLDN - QLDC	Fast	0	0	0	0
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
QLDS - NSW	Fast	0	0	0	1600
	HighDER	0	0	0	200
	Normal	0	0	0	800
	Slow	0	0	0	0
SA - NSW	Fast	0	0	0	700
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
SA - VIC	Fast	0	0	0	0
	HighDER	0	0	0	0
	Normal	0	0	0	0
	Slow	0	0	0	0
TAS - VIC	Fast	0	0	200	2000
	HighDER	0	0	200	600
	Normal	0	0	0	600
	Slow	0	0	200	400

Chapter 4

Conclusions and Further Work

4.1 Conclusions

We have presented through this thesis a large-scale mixed-integer program applied to a planning problem in the context of co-optimising network and storage systems under uncertainty with high operational resolution through a column generation approach. We have been able to formulate a methodology to solve this program by applying advanced decomposing techniques in the field of optimisation. Besides the contribution of the reformulation of the technique, we can conclude several statements about the planning problem by solving three different study cases.

After validating the optimisation model through a co-optimisation problem under uncertainty considering high operational resolution on the IEEE 24-bus system and utilising the reformulated algorithm on the NEM system we can state that: (a) Neglecting unit commitment constraints in the planning problem leads to inefficient solutions when flexibility requirements are not considered when high penetration of renewable generation is presented in the system. (b) Storage system can defer or replace investments in transmission system, we have proved that a transmission expansion problems with no consideration of storage systems leads to more and earlier transmission investments, in addition to higher overall costs. (c) Investment in batteries depends on the systemic capacity of providing flexibility and the flexibility requirements on the system. In the IEEE 24 bus case, when flexibility requirements were dismissed by neglecting unit commitment constraints, investment in batteries were reduced considerably in comparison to a higher operational resolution. However, in the Australian case, no investments in batteries were obtained as the system had high capability of providing the required flexibility. We could have expected to obtain investments in batteries in the Australian case if different types of flexibility were required where batteries could over-perform against conventional assets. (d) Co-optimising network and storage systems permits to avoid uncoordinated large investments. We have shown that investments in pumped storage assets come along with reinforcement in the transmission system, e.g. if one pumped storage plant were decided to be installed unilaterally, it might face unsuitable transmission system around it. (e) Investments in storage systems with high energy capacity support considerably to reduce curtailment levels. We have shown how pumped storage system performs during a week by displacing energy from cheaper moments of the day to more expensive moments reducing curtailment. (f) When a pumped storage system is installed, it can not only change power flows around it, but it can also change the reserve distribution around the system. We have shown that importing-reserve buses become exporting-reserve ones when a pumped storage system with high energy capacity is installed. (g) It is not possible to take all advantages of the energy capacity from large pumped storage systems if the operation problem is as long as the energy capacity. We have shown that new pumped storage state of charge was far from being fully utilised during a week operational problem. This should affect the investment cost of this asset. This effect was not considered in this work.

Regarding the use of The Dantzig Wolfe Algorithm applied to stochastic planning problems it can be concluded that: we have proposed and applied a reformulation for the Dantzig Wolfe Algorithm based on splitting the scenario tree nodes (reaching a sub-nodal level) into a number of independent subproblems which are smaller and faster to solve. We have demonstrated through solving a planning problem in the IEEE 118-bus system that the accuracy of results is ensured, the use of computational resources is considerably reduced as well as the computational time required for solving this problem in comparison to original formulation. Furthermore, this reformulation of the algorithm allow to solve instances of the stochastic planning problem that can not be solved by the most recent version available in the literature.

4.2 Further Work

We propose to focus on the operational problem by adding new considerations in the model, such as inertia constraints, fast-frequency response, ROCOF and nadir constraints. It would be interesting to observe differences in investments when these security constraints are involved in the planning problem. Moreover, another interesting topic to study would be to extend the duration of subproblems to a couple of weeks or a month, in order to observe how this large pumped storage performs, and if it moves energy from one week to another. Additionally, it could be study how investment changes if the amount of typical representations of the year are reduced.

Furthermore, the algorithm can be improved by utilising the computational resources that are not being used while harder subproblems are being solved. We propose to study a methodology to assign dynamically the computational resources on the subproblems while a iteration is being completed in order to increase the average use of CPUs.

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Appendix

Nomenclature

Chapter 1 - Indices

b Index of battery.

d Index of typical day.

g Index of generator.

j Index of columns.

l Index of lines.

m Index of scenario tree node.

t Index of hour.

Chapter 1 - Sets

$\mathfrak{J}_m$ Set of total columns added in scenario tree node m.

ς_m Set of all predecessors of m, not including m.

$\widehat{B}$ Set of candidate batteries.

$\widehat{L}$ Set of candidate lines.

$\wp_m$ Set of all predecessors of m, including m.

B_n Set of batteries in node n.

B Set of batteries.

D Set of typical days.

EL Set of existing lines.

$From_n$ Set of lines that start from node n.

G_n^C Set of conventional generators in node n.

G^C Set of conventional generators.

G_n^R Set of renewable generators in node n.

G^R Set of renewable generators.

G Set of generators.

M^S Set of the scenario tree nodes that contains one child node of each parent node in the scenario tree.

M Set of scenario tree nodes.

S_m Set of sibling nodes of scenario tree node m.

To_n Set of lines that go to node n.

T Set of time periods (hours).

Chapter 1 - Parameters

α Duration for reserve in storage.

Γ_{d} Weight for typical day d.

$\widehat{\mathbf{x}}_m^j$ Investment solution for column j in scenario tree node m.

$\widehat{\mathbf{y}}_{m\mathrm{d}}^j$ Operational solution for column j in scenario tree node m in typical day d.

$\mathbf{A}_m$ Matrix that couples operational and investment decisions in scenario tree node m.

$\mathbf{c}_m^\top$ Investment costs in scenario tree node m.

$\mathbf{q}_m^\top$ Operational costs in scenario tree node m.

$\overline{F}_{lm}$ Maximum capacity in line l in scenario tree node m.

$\overline{P}_{gm}^G$ Capacity of generator g in scenario tree node m.

$\overline{P}_{gm}^R$ Capacity of renewable generator g in scenario tree node.

$\overline{R}_{gm}^G$ Maximum up secondary reserve of generator g in scenario tree node m.

$\overline{R}_{mdt}^S$ Up reserve requirements in scenario tree node m in typical day d at time t.

ϕ_m Probabliity of scenario tree node m.

Π_b^{bi} Investment cost for candidate battery b in scenario tree node i. (annuitized)

Π_g^{OG} Operational cost for generator g.

Π_g^{OU} Start-up cost for generator g.

Π_g^{OV} Shut-down cost for generator g.

Π_l^{li} Investment cost for candidate line l in scenario tree node i. (annuitized)

Π_{gm}^{OC} Curtaliment cost of renewable generator g in scenario tree node m.

$\underline{P}_{gm}^{G}$ Minimum capacity of generator g in scenario tree node m.

$\underline{R}_{gm}^{G}$ Maximum down secondary reserve of generator g in scenario tree node m.

$\underline{R}_{mdt}^{S}$ Down reserve requirements in scenario tree node m in typical day d at time t.

ζ^B Duration for a single module of storage battery.

A_{gmdt}^r Renewable avaliabliity of renewable generator g in scenario tree node m at time t.

C^B Capacity of one battery module.

D_{nmdt} Demand in node n in scenario tree node m in typical day d at time t.

M Sufficiently large positive constant.

$p(m)$ Parent node of scenario tree node m.

Rp_{gm} Maximum ramp rate in of generator g in scenario tree node m.

r Discount rate.

t_g^{off} Minimum down time of a generator g.

t_g^{on} Minimum up time of a generator g.

X_l Reactance of line l.

$y(m)$ Year according to scenario tree node m.

Chapter 1 - Variables

f_{lmdt} Power flow of line l in scenario tree node m in typical day d at time t.

λ_m^j Binary variable that selects column j for each scenario tree node m.

$\mathbf{x}'_m$ Vector of investment in scenario tree node m.

$\mathbf{x}_m$ Investment decisions in scenario tree node m.

$\mathbf{y}_{md}$ Operational decisions in scenario tree node m in typical day d.

$\overline{r}^{B}_{bmdt}$ Up reserve of battery b in scenario tree node m in typical day d of at time t.

$\overline{r}^{G}_{gmdt}$ Up reserve of generator g in scenario tree node m in typical day d at time t.

$\theta^{From/To}_{lmdt}$ Voltage angle in From/To node of line l in scenario tree node m in typical day d at time t.

$\underline{r}^{B}_{bmdt}$ Down reserve of battery b in scenario tree node m in typical day d at time t.

$\underline{r}^{G}_{gmdt}$ Down reserve of generator g in scenario tree node m in typical day d at time t.

p^{B}_{bmdt} Power output of battery b in scenario tree node m in typical day d at time t.

p^{G}_{gmdt} Power output of generator g in scenario tree node m in typical day d at time t.

p^{R}_{gmdt} Power output of renewable generator g in scenario tree node m in typical day d at time t.

p^{B+}_{bmdt} Discharge power of battery b in scenario tree node m in typical day d at time t.

p^{B-}_{bmdt} Charge power of battery b in scenario tree node m in typical day d at time t.

p^{BE}_{bmdt} Energy stored of battery b in scenario tree node m in typical day d at time t.

u_{gmdt} Startup of generator g in scenario tree node m in typical day d at time t.

v_{gmdt} Shutdown of generator g in scenario tree node m in typical day d at time t.

w^{B}_{bi} Installation of candidate battery b in scenario tree node i.

w^{L}_{li} Installation of line l in scenario tree node i.

x^{G}_{gmdt} Commitment of generator g in scenario tree node m in typical day d at time t.

x_{bm} Investment variable in scenario tree node m for candidate battery b.

x_{lm} Investment variable in scenario tree node m for candidate line l.

Chapter 2 - Sets

$\mathfrak{J}_{wm}$ Set of added columns of typical week w in scenario tree node m.

$\wp_m$ Set of nodes from root-node to m-node.

B^C Set of candidate batteries(B^C_n for residential batteries in electrical node n).

B^R Set of residential batteries (B^R_n for residential batteries in electrical node n).

G^R Set of renewable generators (G^R_n for renewable generators in electrical node n).

G_{ror} Set of run-of-river generators. ($G_{ror} \subset G$).

G Set of conventional generators (G_n for conventional generators in electrical node n).

L Set of lines.

M Set of scenario tree nodes.

N Set of electrical nodes.

P^C Set of candidate pumped storage plants.(P_n^C for candidate pumped storage plants in electrical node n)

P^E Set of existing pumped storage plants (P_n^E for existing pumped storage plants in electrical node n).

P_c Set of candidate pumped storage plants.

W_m Set of subproblems in scenario tree node m.

Chapter 2 - Parameters

α_g Available headroom for reserve of generator g.

$\bar{L}_l$ Capacity of one module in line l.

$\bar{P}_b^B$ Maximum power of battery b.

$\bar{P}_p^P$ Maximum power of pumped storage plant p.

$\bar{P}_{gm}$ Capacity of generator g in scenario tree node m.

$\bar{v}_b^B$ Maximum modules to be installed of candidate battery b.

$\bar{v}_l^L$ Maximum modules to be installed in line l.

β_{wg} Plant factor in typical week w of generator g.

Δ_g Ramp limit of generator g

η^B Round-trip efficiency for candidate batteries.

η^P Round-trip efficiency for pumped storage plants.

η^{B_r} Round-trip efficiency for residential batteries.

γ_m Discount factor in scenario tree node m.

Γ_w Weight of typical week w.

$\hat{\mathbf{y}}_{wm}^j$ Operational solution of column j of typical week w in scenario tree node m.

$\mathbf{q}_{wm}^T$ Operational cost of typical week w in scenario tree node m.

ϕ_m Probability of node m.

Π^B_{bm} Investment cost of candidate battery b in scenario tree node m.

Π^L_{lm} Investment cost of line l in scenario tree node m.

Π^P_{pm} Investment cost of pumped storage p in scenario tree node m.

$\underline{\mathrm{P}}_g$ Minimum generation limit of generator g.

ξ Minimum reserve duration of batteries.

ζ^B Power of one module of battery.

ζ^P_p Maximum power of candidate pumped storage plant p.

A_{gwh} Availability of renewable resource of generator g in typical wee w at hour h.

C^P_p Duration at maximum power of pumped storage plant p.

C^{B_r} Duration at maximum power of residential batteries.

D_{nh} Demand in electrical node n at hour h.

$h_{off(g)}$ Minimum down time of generator g.

$h_{on(g)}$ Minimum up time of generator g.

H Duration of one subproblem.

N_{gm} Total available units of generator g to perate in scenario tree node m.

Chapter 2 - Variables

$\bar{R}q_{nh}$ Reserve requirement in electrical node n at time h.

λ^j_{wm} if 1, column j is selected in scenario tree node m in typical week w.

μ_{wm} Dual variable from convexity constraint of typical week w in scenario tree node m.

π_{mwb} Dual variable from battery investment constraint in scenario tree node m in typical week w of battery b.

π_{mwl} Dual variable from line investment constraint in scenario tree node m in typical week w of line l.

π_{mwp} Dual variable from pumped storage investment constraint in scenario tree node m in typical week w of pumped storage plant p.

e_{bh} State of charge of battery b at time h.

e_{ph} State of charge of pumped storage plant p at time h.

f_{lh} Power flow in line l at time h.

fr_{lh}^{fwd} Forward reserve flow in line l at time h.

fr_{lh}^{rev} Reverse reserve flow in line l at time h.

LS_{nh} Load shedding in electrical node n at hour h.

p_{bh} Power of battery b at time h.

p_{gh} Generation output of generator g at time h.

p_{ph} Power of pumped storage plant p at time h.

r_{bh} Reserve provided by battery b at time h.

r_{gh} Reserve provided by generator g at time h.

r_{ph} Reserve provided by pumped storage plant p at time h.

s_{gh} Number of startups of generator g at time h.

t_{gh} Number of shutdowns of generator g at time h.

v_{mb}^{B} Investment decision of battery b in scenario tree node m.

v_{ml}^{L} Investment decision of line l in scenario tree node m.

v_{mp}^{P} Investment decision of pumped storage plant p in scenario tree node m.

x_{gh} Commited machines of generator g at time h.

Table 4.1: Network parameters - Modified IEEE 24-Bus system

From node	To node	X [p.u.]	Rating [MW]	Length [km]
1	2	0.014	175	5
1	3	0.211	131.25	89
1	5	0.085	175	35
2	4	0.127	175	53
2	6	0.192	175	80
3	9	0.119	131.25	50
3	24	0.084	300	0
4	9	0.104	131.25	43
5	10	0.088	175	37
6	10	0.061	131.25	26
7	8	0.061	175	26
8	9	0.165	131.25	69
8	10	0.165	131.25	69
9	11	0.084	300	0
9	12	0.084	300	0
10	11	0.084	300	0
10	12	0.084	300	0
11	13	0.048	500	53
11	14	0.042	375	47
12	13	0.048	375	53
12	23	0.097	375	108
13	23	0.087	500	97
14	16	0.059	500	43
15	16	0.017	500	19
15	21	0.049	500	55
15	21	0.049	500	55
15	24	0.052	375	58
16	17	0.026	500	29
16	19	0.023	500	26
17	18	0.014	500	16
17	22	0.105	500	117
18	21	0.026	500	29
18	21	0.026	500	29
19	20	0.04	500	44
19	20	0.04	500	44
20	23	0.022	500	24
20	23	0.022	500	24
21	22	0.068	500	76

Table 4.2: Slow scenario demand growth comparing to Neutral Case

Stage	NSW	QLD	SA	TAS	VIC
2020-21 Stage 1	0%	0%	0%	0%	0%
2025-26 Stage 2	-7%	-14%	-6%	-5%	-16%
2030-31 Stage 3	-19%	-17%	-7%	-6%	-16%
2035-36 Stage 4	-25%	-33%	-13%	-16%	-24%

Table 4.3: Fast scenario demand growth comparing to Neutral Case

Stage	NSW	QLD	SA	TAS	VIC
2020-21 Stage 1	0%	0%	0%	0%	0%
2025-26 Stage 2	6%	5%	6%	8%	5%
2030-31 Stage 3	12%	11%	11%	10%	11%
2035-36 Stage 4	17%	15%	17%	14%	16%

Table 4.4: High DER scenario demand growth comparing to Neutral Case

Stage	NSW	QLD	SA	TAS	VIC
2020-21 Stage 1	0%	0%	0%	0%	0%
2025-26 Stage 2	0%	0%	0%	0%	0%
2030-31 Stage 3	0%	0%	0%	0%	0%
2035-36 Stage 4	0%	0%	0%	0%	0%

Table 4.5: Utility storage investment cost for Australian Case [$/MW/yr]

Stage	Neutral Scenario	Slow Scenario	Fast Scenario	High DER Scenario
2020-21 Stage 1	$ 146,717	$ 146,717	$ 146,717	$ 146,717
2025-26 Stage 2	$ 119,311	$ 119,311	$ 97,540	$ 141,081
2030-31 Stage 3	$ 108,089	$ 108,089	$ 80,707	$ 135,470
2035-36 Stage 4	$ 98,621	$ 98,621	$ 66,505	$ 130,736

Table 4.6: NEM Installed capacity by technology - Neutral Scenario

Technology	2020-21	2025-26	2030-31	2035-36
Black coal	18,219	16,419	13,419	7,899
Brown coal	4,808	4,808	4,808	3,280
Hydro	5,364	5,364	5,364	5,364
CCGT	4,111	2,649	2,649	2,139
Peaking gas + liquids	6,944	6,971	6,971	6,971
Wind	8,118	10,211	10,943	13,563
Utility Solar	2,839	6,728	9,686	21,472
Distributed storage	977	2,588	3,980	5,066
Rooftop PV	9,186	13,459	17,092	19,655
Total	**60,566**	**69,197**	**74,912**	**85,408**

Table 4.7: NEM Installed capacity by technology - Slow Scenario

Technology	2020-21	2025-26	2030-31	2035-36
Black coal	18,219	16,419	11,959	6,439
Brown coal	4,808	4,808	4,808	3,280
Hydro	5,364	5,364	5,364	5,364
CCGT	4,111	2,649	2,649	2,139
Peaking gas + liquids	6,944	6,669	6,669	6,669
Wind	8,118	10,211	10,676	10,763
Utility Solar	2,839	3,990	6,126	7,224
Distributed storage	977	2,588	3,980	5,066
Rooftop PV	9,186	13,459	17,092	19,655
Total	**60,566**	**66,157**	**69,323**	**66,599**

Table 4.8: NEM Installed capacity by technology - Fast Scenario

Technology	2020-21	2025-26	2030-31	2035-36
Black coal	18,219	16,419	12,689	7,169
Brown coal	4,808	4,808	3,718	2,190
Hydro	5,364	5,364	5,364	5,364
CCGT	4,111	2,649	2,649	2,539
Peaking gas + liquids	6,944	7,119	7,072	7,180
Wind	8,118	10,801	13,708	16,107
Utility Solar	2,839	11,462	22,002	33,412
Distributed storage	977	2,588	3,980	5,066
Rooftop PV	9,186	13,459	17,092	19,655
Total	**60,566**	**74,669**	**88,273**	**98,681**

Table 4.9: NEM Installed capacity by technology - HighDER Scenario

Technology	2020-21	2025-26	2030-31	2035-36
Black coal	18,219	16,419	13,054	7,534
Brown coal	4,808	4,808	4,808	3,280
Hydro	5,364	5,364	5,364	5,364
CCGT	4,111	2,649	2,649	2,139
Peaking gas + liquids	6,944	7,070	7,070	7,070
Wind	8,118	10,211	10,747	13,700
Utility Solar	2,839	6,932	9,328	13,867
Distributed storage	977	2,111	4,969	10,537
Rooftop PV	9,186	15,736	33,136	51,014
Total	**60,566**	**71,300**	**91,125**	**114,504**