INCORPORATING OPERATIONAL FLEXIBILITY INTO ELECTRIC GENERATION PLANNING

Impacts and Methods for System Design and Policy Analysis

by

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ABSTRACT

This dissertation demonstrates how flexibility in hourly electricity operations can impact long-term planning and analysis for future power systems, particularly those with substantial variable renewables (e.g., wind) or strict carbon policies. Operational flexibility describes a power system's ability to respond to predictable and unexpected changes in generation or demand. Planning and policy models have traditionally not directly captured the technical operating constraints that determine operational flexibility. However, as demonstrated in this dissertation, this capability becomes increasingly important with the greater flexibility required by significant renewables (>=20%) and the decreased flexibility inherent in some low-carbon generation technologies. Incorporating flexibility can significantly change optimal generation and energy mixes, lower system costs, improve policy impact estimates, and enable system designs capable of meeting strict regulatory targets.

Methodologically, this work presents a new clustered formulation that tractably combines a range of normally distinct power system models, from hourly unit-commitment operations to long-term generation planning. This formulation groups similar generators into clusters to reduce problem size, while still retaining the individual unit constraints required to accurately capture operating reserves and other flexibility drivers. In comparisons against traditional unit commitment

formulations, errors were generally less than 1% while run times decreased by several orders of magnitude (e.g., 5000x). Extensive numeric simulations, using a realistic Texas-based power system show that ignoring flexibility can underestimate carbon emissions by 50% or result in significant load and wind shedding to meet environmental regulations.

Contributions of this dissertation include:

1. Demonstrating that operational flexibility can have an important impact on power system planning, and describing *when* and *how* these impacts occur;
2. Demonstrating that a failure to account for operational flexibility can result in undesirable outcomes for both utility planners and policy analysts; and
3. Extending the state of the art for electric power system models by introducing a tractable method for incorporating unit commitment based operational flexibility at full 8760 hourly resolution directly into planning optimization.

Together these results encourage and offer a new flexibility-aware approach for capacity planning and accompanying policy design that can enable cleaner, less expensive electric power systems for the future.

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ACRONYMS

AC	Alternating current
ADP	Approximate Dynamic Programming
AGC	Automatic Generation Control
CAISO	California ISO
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Sequestration
CO_2	carbon dioxide
CPS	Control Performance Standard
DC	Direct current
DP	Dynamic Programming

EFOR	Effective Forced Outage Rate
EIA	Energy Information Administration
ELCC	Effective Load Carrying Capacity
EPA	Environmental Protection Agency
ERCOT	Electric Reliability Council of Texas
EWITS	Eastern Wind Integration and Transmission Study
FACTS	Flexible Alternating Current Transmission System
FAST	Flexibility ASsessmenT
GAMS	the General Algebraic Modeling System
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
IGCC	Integrated Gasification Combined Cycle
IRRE	Insufficient Ramp Resource Expectation
ISO	Independent System Operator
ISO-NE	ISO New England
LDC	Load Duration Curve
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LP	Linear Program
MILP	Mixed Integer Linear Program
NERC	the North American Electric Reliability Corporation
NG-CC	Natural Gas fired Combined Cycle Gas Turbine
NG-GT	Natural Gas fired Combustion Gas Turbine
NOx	Nitrogen Oxides

O&M	operations and maintenance
OPF	Optimal Powerflow
RE Futures	Renewable Electricity Futures
RMILP	Relaxed Mixed Integer Linear Program
RMS	Root Mean Square
RPS	Renewable Portfolio Standard
RTS	Reliability Test System
SOx	Sulfur Oxides
UC	Unit Commitment
WACC	Weighted Average Cost of Capital
WECC	Western Electricity Coordinating Council
WWSIS	Western Wind and Solar Integration Study

1 INTRODUCTION

1.1 SUMMARY

This dissertation explores the impacts of operational flexibility on electricity generation planning. It seeks to demonstrate *when* and *how* flexibility impacts planning and to explain *why* these impacts occur. This chapter motivates this work, defines operational flexibility, provides a brief introduction to power systems and associated modeling, and describes relevant work from the literature.

Operational flexibility describes a power system's ability to respond to predictable and unexpected changes in generation or demand. It is of growing concern in power systems today due to 1) the additional flexibility required by high penetrations of variable renewables and 2) the potentially reduced operational flexibility available from low-carbon plants (e.g., traditional nuclear, geothermal, or coal with carbon capture). Previous studies have demonstrated important *operations* changes in flexibility-challenged scenarios, particularly with significant variable renewables. These studies also postulate that operational flexibility should, therefore, also impact the optimal generation mix during expansion *planning*.

Yet, few studies to date have looked directly at the combined flexibility-planning problem, let alone demonstrated how operational flexibility impacts of planning or explained why such differences occur. Available operational flexibility is determined by technical unit-level operating parameters—such as minimum power output, startup costs, minimum up and down time, ramp rates, and reserve capabilities. These parameters are typically ignored or highly simplified in the initial phase of traditional planning processes.

In utility power system planning flexibility considerations may only captured later, during detailed simulations used to estimate power generation and associated production costs. This opens the possibility of selecting a suboptimal generation mix during the initial planning phase and then carrying this error through subsequent detailed simulations and eventually into the generation plan. Moreover, if flexibility challenges are encountered, planners must manually adjust capacity to correct them.

In policy analysis the second detailed simulation stage is typically omitted, meaning that operational flexibility may be omitted entirely or only considered using simplified representations that may not capture realistic dynamics. This can lead to misrepresentations of policy impacts or suboptimal policy design.

In either case, if additional operating constraints can be included initially, when first evaluating investments, one might expect to design generation mixes and policies better able to cope with operational flexibility challenges. However the large size and long run times required to simulate flexibility in operations have traditionally made the required combined model intractable. So the key methodological contribution of this thesis is a new modeling approach that effectively merges flexibility-aware operations simulations, previously only available through production costing tools, directly into early phase generation investment optimization.

Taken together the results of this dissertation should be useful to stakeholders from across the electric power system, including:

POWER SYSTEMS PLANNERS, who stand to benefit both from 1) improved recognition and intuitive understanding of operational flexibility impacts on planning, and 2) new modeling methods for capturing operational flexibility within planning. By directly including flexibility within planning, these methods enable optimizing for flexibility when identifying configurations to simulate in-depth. Such flexibility screening can produce generation mixes that are lower cost and/or more reliable in actual operations, even though they might have been eliminated as sub-optimal using today's simpler screening tools. In the end, this reduces the system cost and improves reliability for the generators that are actually built;

ENERGY AND ENVIRONMENTAL POLICY ANALYSTS, who typically omit detailed operations simulations and therefore may miss flexibility challenges resulting in suboptimal policy designs. Ignoring flexibility can potentially grossly under-estimate the emission reductions from a carbon tax or identify the wrong set of technologies to incentivize. Understanding the need to and then incorporating a rich set of operating technical constraints will enable setting effective taxes, incentives, and other policy measures for modern power systems;

EMERGING TECHNOLOGY DEVELOPERS whose products derive value from providing operational flexibility (e.g., energy storage, demand response, thermal plant retrofits). Such developers need to understand when their products will have the most value. They can use these methods to quickly and accurately assess technical and economic outcomes of deployment scenarios and to understand competition from other sources of flexibility;

RENEWABLE INTEGRATION RESEARCHERS, who currently do not have an efficient way to identify the non-renewable generation resources for future scenarios and hence may spend considerable effort analyzing renewable impacts with a sub-optimal non-renewable balance of system. This may also cause over or under estimates of reserve needs, energy adequacy, and costs for variable renewable integration; and

POWER SYSTEM FLEXIBILITY RESEARCHERS, who are attempting to develop metrics for operational flexibility, but are currently faced with deciding between quick to compute but inaccurate estimates and very data and computationally expensive full operations analysis. My methods enable a middle ground where rich operations analysis can be tractably used to provide good estimates for these metrics. Moreover, a better understanding of how flexibility impacts planning can lead to more refined metrics and possibly identify missing dimensions worthy of inclusion.

At a broader level, society stands to benefit from new power system infrastructure and corresponding policies that provide a cleaner, less expensive electric power system better able to meet the energy needs of future generations, to incorporate advanced technologies, and to meet the challenges of a carbon-constrained future.

Society stands to benefit from... a cleaner, less expensive electric power system

1.2 2050 CLIMATE TARGETS START NOW

Scientists overwhelming suggest a need to reduce greenhouse gas emissions, particularly carbon dioxide (CO_2), to avoid the worst impacts of global climate change [1, 2]. As one of the largest sources of greenhouse gas emissions, our entire energy system, and the electric power production in particular,[1] will require important changes to achieve these reductions. As a result, three recent high level roadmap exercises from Europe, the US, and California have produced similarly ambitious targets for the year 2050. Despite other differences, the European Union "Energy Roadmap 2050" [4, 5], the NREL RE Futures Study for the US [6], and the work of Williams, et al. for California [7] all suggest that significant reductions in economy-wide carbon emissions (e.g. 80% below 1990 levels) will involve:

- Aggressive energy efficiency,
- Significant electrification of transportation,
- An electric power system that produces near zero carbon emissions, and
- Well over 50% of electricity from renewable sources.

Each of these alone represents a radical departure from today's energy system. Together they will require a fundamental change in the worldwide economy.

For the electric power system, perhaps the most urgent message of these reports is the recognition that we are one investment cycle away from 2050. Given the 40+ year lifetimes of electric power facilities, the power generation planned today and built tomorrow will still be operational in 2050. Hence, any generation investments today must be able to interact with future technology deployments as part of a carbon-constrained power system, or risk being stranded as expensive, but under-used, investments.

This thesis focusses on planning for a very low carbon power system with significant generation from renewable sources, including semi-dispatchable variable sources such as wind and solar. As described below, this combination requires new methods for representing technology interactions in operations and the resulting impacts on planning. Even without the pressures of climate change, the tremendous transformations already underway in the electric power system may also require similar changes to operations and planning.

1 In the US, electricity production accounted for approximately 40% of nation-wide carbon dioxide emissions [3]

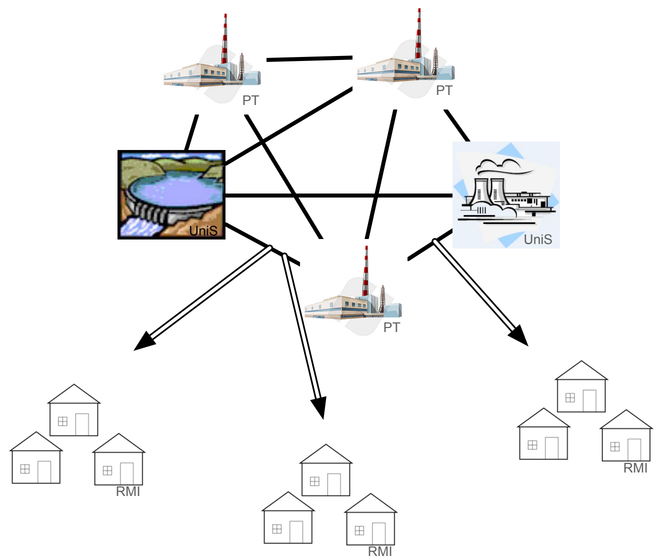
1.3 POWER SYSTEMS IN TRANSITION

The current power systems closely resembles those built by Westinghouse and others in the early part of the 20th century. Fossil fuel fired generation provides the bulk of electricity worldwide, and for the most part, this electricity flows outward from transmission linked centralized generation for distribution to passive consumers. However, current environmental, technical, economic, and political factors are driving a worldwide transition to advanced electric power systems, increasingly characterized by:

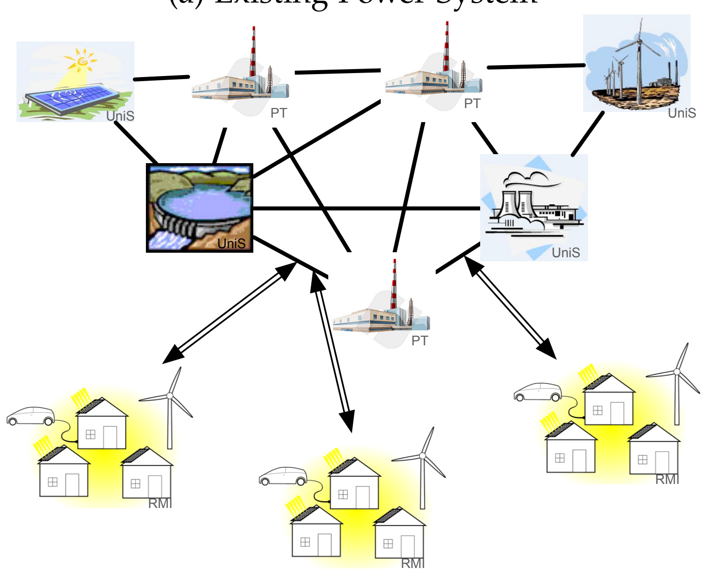
- Intermittent renewable generation—e.g., wind & solar photovoltaic [8];
- Distributed generation—e.g. co-generation, solar photovoltaic [9];
- Active demand resources—e.g., high-performance buildings, distributed generation, and demand response [10]; and
- Novel storage technologies—e.g., electric drive vehicles and thermal storage [11, 12, 13].

Simultaneously, structural changes in recent decades have shifted a growing amount (currently about half) of power systems away from centralized regulated monopolies to deregulated competitive markets, and ubiquitous communication/computing promises a forthcoming "Smart Grid." Figure 1.1 shows a conceptual picture of this transition.

These changes introduce new dynamics across multiple timescales, forcing power systems planners and policy makers to revisit the long-standing question of how much operational detail must be captured to adequately assess long-term planning options. In the short term, these new technologies each increase uncertainty and variability in the hour-to-hour operational dynamics. Designing the power system that can manage this uncertainty and integrate these emerging technologies with the still evolving mix of traditional generation requires new paradigms for capacity expansion planning [14, 15, 16]. In particular, these technologies are all inextricably linked to operational "flexibility"—the ability of a power system to respond to changes in operations at timescales from sub-second to hourly, daily, and longer due to predictable and unexpected variations in demand and variable renewable generation, outages of generation plants, other network induced disturbances or environmental constraints [17]. This thesis



(a) Existing Power System



(b) Advanced Power System of the Future

Figure 1.1: A power system in transition. Showing a shift from (a) centralized, largely fossil generation with passive consumers to (b) a distributed "smart grid" with bi-directional power and data flows.

Icon sources: PT = PoweredTemplates, RMI = Rocky Mountain Institute, UniS = http://science.uniserve.edu.au/school/sciweek/2005/

presents a novel way of integrating flexibility directly into capacity planning models.

1.4 OPERATIONAL FLEXIBILITY

1.4.1 *The electricity balancing act*

The need for operational flexibility[2] in the power system begins with the fact that electricity cannot easily be stored in bulk which in turn requires generation to match demand at all times. As a result, generation must increase and decrease with every flick of a light switch or start/stop of an aluminum smelter. Conveniently, when aggregated across an entire power system - which typically span a scale from cities to multiple states or even multiple nations - the resulting fluctuations are both slowly varying and predictable to within a few percent [25].

On the supply side, generators increase or decrease their outputs, primarily[3] in response to an Automatic Generation Control (AGC) signal from the system operator. However, technical constraints may limit a generators ability to respond to these changes. These technology and facility specific constraints include: minimum and maximum stable output power; ramp limits, which restrict the rate of output change; and startup/shutdown constraints such as minimum up (and down) time to ensure plants run (and stay off) long enough to avoid excessive thermal stresses.

Traditionally, these operating constraints are seldom limiting due to the combination of slow, predictable changes in demand and a correlation of operational flexibility with the natural plant dispatch "merit order:" The least flexible units - nuclear, geothermal, and coal - also have the lowest operating costs and hence run nearly all the time as

2 Note that in this thesis, and currently in the power systems community [18, 19, 17, 20, 21], the term "flexibility" considers the operational flexibility described in this section. This usage is distinct from the concept of designing for expansion or reconfiguration that has also been called flexibility by the real-options/engineering-design community [22]. Confusingly, such design flexibility has also been used in the past for power systems [23, 24]. For clarity, I have tried to specifically specify "operational flexibility" throughout this thesis.

3 Smaller plants, many renewables, and co-generation currently do not receive such signals. They produce whatever power they can as long as their local sensors see the power grid is operating normally. In addition large thermal plants also use a combination of rotating inertia and "droop" control to respond to faster changes (less than a few seconds) [26]

"baseload" units, thereby largely avoiding operations limits. At the other extreme, the most flexible units - aero-derivative natural gas turbines and internal combustion generators fueled by oil or natural gas - are also most expensive and hence they are used as "peakers" that only run for brief times during the highest demand periods. This high cycling regime with frequent ramps is well matched to peakers higher operational flexibility.

1.4.2 *Challenges of variable renewables*

Increased use of variable renewable sources - wind and solar - increases both the variability and uncertainty in the "net load." The net load is defined as consumer demand minus generation by variable renewables and represents the power that must be generated by other units on the system. The existing power system is already designed to handle some variability and uncertainty in (net) demand and hence can readily accommodate moderate[4] amounts of variable renewables with little to no changes [27]. However, as illustrated schematically in Figure 1.2 at higher penetration levels, these dynamics and uncertainty can cause operational flexibility challenges such as those described in the following three examples:

1. MINIMUM OUTPUT LIMITS Increased variable renewable capacity can meet most or all of demand during some time periods, causing baseload coal, geothermal, and particularly nuclear plants to reach minimum output constraints, which can be as high as 50 or 90% of their maximum output [28]. Further reductions beyond these levels requires shutting down. And after shutdown, the large thermal mass of these units can require hours (combined cycle), days (large steam plants) or even weeks (nuclear) of minimum down time before the the facility can again be restarted. Such cycling is also costly in terms of fuel, manpower, and increased maintenance. Moreover, once a unit restarts it may encounter minimum up time constraints and be unable to shutdown during the next dip in net load. More flexible units are able to lower their outputs further and can be started and stopped sooner and at lower cost.

4 The meaning of "moderate" varies by power system ranging from about 5-20%

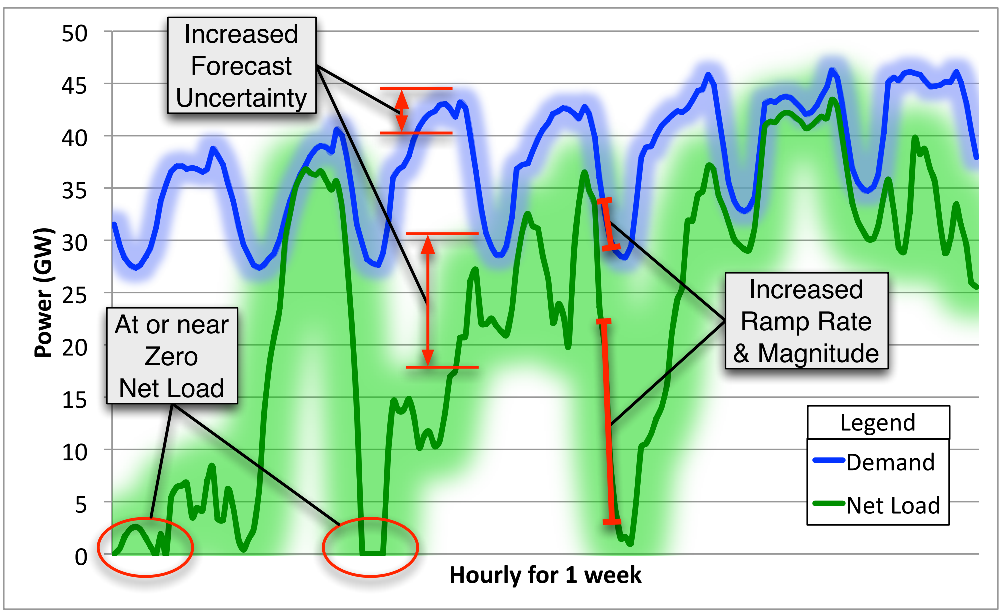


Figure 1.2: Conceptual diagram of increased dynamics of net load as a result of increased renewable generation. Net load is demand minus production from non-dispatchable resources such as wind. Based on actual ERCOT load and wind data scaled to provide 40% of annual energy.

2. INCREASED RAMPING REQUIREMENTS The increase in magnitude of hour-to-hour net load changes and related sub-hourly dynamics require increased ramping by the rest of the system, potentially forcing thermal plants, particularly steam units, up against their ramp rate limits. This can require the increased operation of more flexible combined cycle and combustion turbine units to accommodate ramping needs.

3. INCREASED RESERVE NEEDS Uncertainty in demand and in availability of supply is largely managed with reserves. Reserves are the extra capacity maintained to account for the possibility that there may be insufficient generating capability when demand is higher than expected or if some generation is unexpectedly unavailable. Concepts of reserves span timescales from years - planning reserves for unexpected load growth - down to seconds - regulating reserves that adjust for the inherent stochasticity in usage over short time scales. In operations, electricity's traditional lack of bulk storage can also require downward reserves to account for unexpected decreases in generating requirements. At high penetrations of renewable generation, the uncertainty in net load due to imperfect renewable forecasting can increase reserve requirements for the system. In addition, the ability of a generating unit to provide reserves is a function of its ramping capability over the corresponding timeframe. This further complicates the ramp limit challenges described in the previous example.

1.4.3 *Challenges of emission limits, particularly carbon*

Binding limits on pollutant emissions - or equivalently emission taxes or other costs [29] - can impact the operational flexibility of power systems. Such limits for Sulfur Oxides (SOx) and Nitrogen Oxides (NOx) have existed in the US since 1990s due to the Environmental Protection Agency (EPA) Acid Rain Program [30] and NOx Budget Trading Program [31]. And similar markets for carbon dioxide and other greenhouse gases have been established (e.g. Europe [32], California [33]) or proposed (e.g. US [34]) in efforts to limit the extent of global climate change. For simplicity, this thesis focuses on the impacts from limits on carbon emissions on operational flexibility across a number of time frames. Exploring the impact of other environmental constraints is left for future research.

In the short term, carbon emissions limits or carbon prices can alter the marginal cost based merit order, reducing the relative cost of generation from lower carbon intensity Natural Gas fired Combined Cycle Gas Turbine (NG-CC) plants and raising the relative cost of generating from coal steam as baseload. Such a swap would improve system-wide ramping capability since NG-CC output can change more rapidly. However during peak periods when coal must also run to meet demand, the altered merit order could impact reserves. This is because coal steam plants are now the marginal generator, but they have lower ramping, and hence reserve, capability. Coal steam units as marginal generators create additional challenges for operating dynamics, because they cannot start and stop frequently to meet the daily demand cycles. As a result, startup and shutdown constraints may require consideration when assessing carbon policy impacts.

In the long-term, carbon restrictions will encourage investment shifts toward low-carbon baseload technologies such as nuclear, geothermal, and Carbon Capture and Sequestration (CCS). Many existing and proposed configurations[5] for such facilities have limited operational flexibility due to high minimum output levels and limited ramping rates [36, 28]. This decrease in operational flexibility can be particularly problematic in combination with variable renewables - whose increased adoption is also encouraged by emission limits of all kinds. As described in the previous section, high penetrations of variable renewables require more, not less, flexibility to account for increased variability and uncertainty. The least cost generation mix with low carbon emissions, if determined without considering operational constraints, would be unable to meet a realistic pattern of demand.

1.4.4 *Other sources of operational flexibility*

In addition to adjusting thermal plant output, non-thermal generation, storage, and demand side resources can provide operational flexibility as described below:

5 Operational flexibility of CCS is unknown given limited experience for power generation. Some suggest the carbon capture equipment itself may require steady operation to be effective [28], while others have suggested that the ability to throttle the CCS equipment might increase operational flexibility by enabling a reduction the plant's internal load and hence an increase its output [35]. In addition Integrated Gasification Combined Cycle (IGCC) could allow coal plants to use more operationally flexible Combined Cycle Gas Turbine (CCGT) technology.

HYDROPOWER turbines can ramp rapidly and have few technical startup and shutdown constraints making the inherent energy stored by hydropower reservoirs a potentially large source of operational flexibility. However, such systems are not as flexible as they first seem. Large hydro systems such as those of the pacific northwest and Brazil consist of interlinked cascades of dams with minimal storage in intervening reservoirs such that water entering the upper part of the system must continue on to the end. Some short-term variations such as the seconds to minutes changes of regulation are possible, if facilities are so equipped, but large hour-to-hour changes to adjust for uncertainty are not always possible. More importantly, agriculture, recreation, and environmental habitat considerations[6] can force hydro to follow a rigid pre-planned operating schedule, potentially eliminating any contribution to operational flexibility [38].

WIND CURTAILMENT, or "shedding," can be used when wind levels are higher than forecast or demand is lower than anticipated. In addition to correcting day ahead forecast errors, curtailment can also be used to reduce the rate of thermal plant ramp down in the event of rapid increases in available wind.[7] However, curtailment only helps for these downward flexibility requirements. Other sources of upward operations flexibility are still required. Furthermore, regulations in many regions prioritize wind, preventing wind shedding. Furthermore, in market environments, wind incentives enable wind producers to bid negative prices for extra wind output in short term balancing markets, making such curtailment financially unattractive.

DEMAND RESPONSE—THE ability for demand to respond to signals from the power grid - provides operational flexibility by adjusting the other side of the energy balance equation. Historically, demand response involves large customers who receive lower electricity rates in exchange for the system's ability to cut power

6 For example, the Pacific Northwest's hydro dominated Bonneville Power Administration (BPA) was forced to shed wind output in order to run more water through its hydro turbines in the springs of 2011 and 2012. Both were high snowmelt years and despite rules giving dispatch priority to wind, the water needed to run through the turbines since diverting it through the spillway would introduce unhealthy levels of nitrogen for fish populations [37].

7 For example, limits to renewable ramping are imposed by the grid codes in Hawaii [39].

when required by the grid, such as following a generator loss. Today, a large number of variations exist including price-based programs run by operators [40], and companies that offer reserve services by aggregating mid-sized customers who are linked with manual and automated energy control systems [41]. Most existing demand response programs provide the equivalent of upward operations flexibility provided by generators by lowering net load needs. In addition, large customers may also bid directly into energy markets, including the 5-15min balancing markets, thereby offering some bi-directional flexibility. In the future, real-time pricing, enabled by smart-grid communication, could extend this to all customer classes, potentially providing bi-directional operations flexibility to compensate for outages or renewable forecast errors in the minutes to hours timescale. Faster reserve classes might be provided by locally sensed frequency[8] responsive loads [42]. However, particularly with price based programs, uncertainty in customer responses, the need to coordinate across large areas, and the potential for rebound and oscillations will require care if the power system relies on large-scale demand response for operational flexibility.

ENERGY STORAGE could offer a solution to many of the power systems challenges discussed here, if only it were not so expensive. Within its power and energy capacity limits, energy storage can readily provide bi-directional operational flexibility across a wide range of timescales from sub-second to days and longer. Today, pumped hydro storage operates in some power systems to help smooth daily demand cycles by pumping water uphill during periods of low demand and running as a traditional hydro facility during peak hours. Just like traditional hydro, such systems can also provide operational flexibility. Moreover, pumped storage facilities are typically less constrained by political and environmental limits. In addition, emerging technologies including flywheels, stationary batteries, and plug-in electric vehicles not only are capable of providing operations flexibility, but may partially rely on providing reserve services for supplemental income [43, 44].

In addition, the physical and regulatory structure of a power system can also impact available flexibility. For example, transmission con-

8 Deviations in the grid's frequency provide the first indicator to supply-demand mismatches

straints can limit the ability of resources in one region of a power system to provide power or reserves to another, thereby restricting operational flexibility. In contrast, transmission inter-connections may enable one power system to share operational flexibility resources with its neighbors. On the regulatory side, the timing of market closing can have a large impact on the amount of operational flexibility required by a system. The closer to operating time that market bids are due, the more accurate are the forecasts for variable renewables and load . As a result, markets which accept bids more frequently and closer to times of operation offer a form of operational flexibility by reducing the total quantity of flexibility required from generators or other resources.

1.4.5 *Quantifying Flexibility*

Growing awareness of the need to consider operations flexibility has sparked an interest in developing metrics to quantify it [38, 45]. For example, Lannoye, et al.'s proposed Insufficient Ramp Resource Expectation (IRRE) metric [46] estimates the expected percentage of ramping events during a year that exceed a power system's capabilities. These deviations are then plotted as a function of time for horizons from 0 to 24 hours to identify short versus long term flexibility needs. The International Energy Agency (IEA)'s Flexibility ASsessmenT (FAST) method [36] uses simple accounting to estimating the maximum ramping capabilities for a system from a variety of sources, and relies on system-specific judgement to qualitatively assess how much of this maximum is actually available.

These efforts point out the difficulty of accurately computing the operational flexibility for a power system. The FAST method falls back on qualitative methods for assessing system flexibility adequacy due to data and modeling limitations that prevent accounting for all the constraints, such as startup effects, that impact flexibility. With IRRE, Lannoye, et al. show examples where simplified methods that do not include relevant operating constraints can mis-represent system flexibility by a factor of 3x [46] and argue for the importance of conducting fully detailed operations modeling to adequately assess power system operations flexibility [45].

This thesis addresses this need by presenting a computationally efficient method for computing complex operations within capacity planning. Specifically, it integrates the basic power systems models of unit

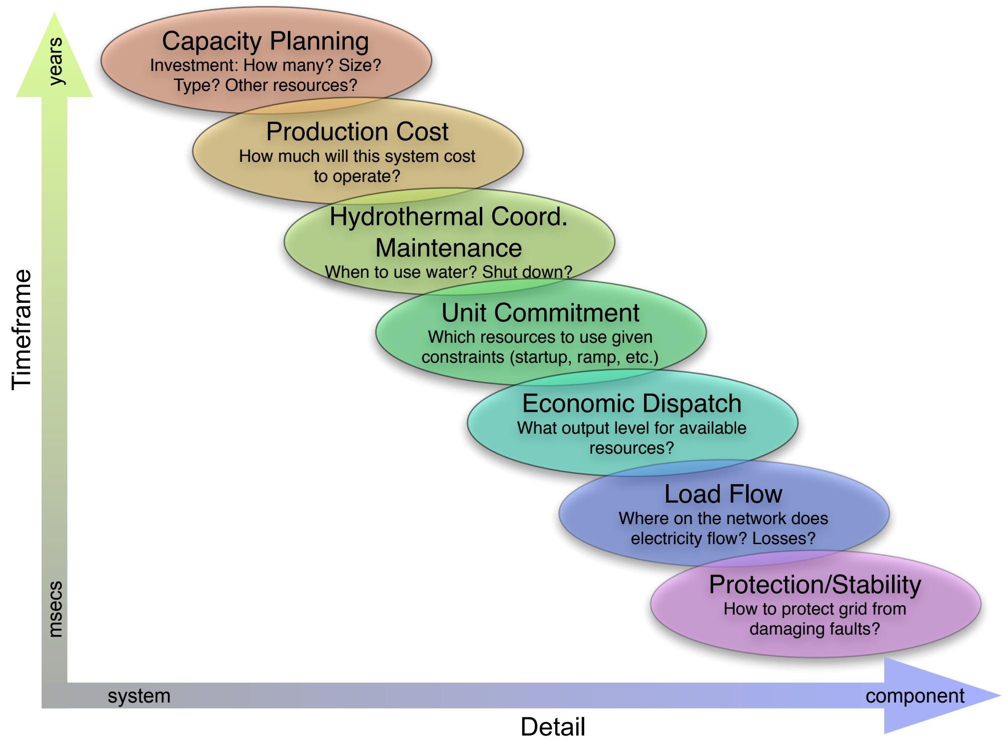


Figure 1.3: Electricity Modeling Types: different model types cover overlapping timeframes from milli-seconds to years, but there is a trade-off with the feasible level of modeling detail.

commitment-based operations, maintenance scheduling, and capacity planning into a single optimization model. These basic model types are described in more detail in the following section.

1.5 OVERVIEW OF POWER SYSTEMS MODELS

1.5.1 *Basic model types*

Given the scale and complexity of the electric power system, a wide range of model types have evolved to address basic system needs. Figure 1.3 shows a cascading chain of these models working across a range of timescales from milliseconds to years with an associated trade-off in the level of engineering detail captured. As the overlapping bubbles suggest, the boundary between types is not precise and many sub-types and variations exist. Moreover, when working up the model chain, ever simpler versions of each model serve as sub-models for the larger types that cover longer time-frames at lower technical resolution.

- **PROTECTION/STABILITY:** At the fastest timeframes, engineering models are used to ensure reliable system operation during normal operations and in the fractions of a second following a disturbance. For example models are used to design set points for circuit breaker relays as part of over-voltage and line/phase trip protection schemes. Other models examine the precise stability of control systems for individual controls and generators and for wide-area coordination [47].

- **LOAD FLOW,** or power flow, captures many of the unique challenges of the power system. It not only checks the instantaneous balance of supply and demand (see section 1.4.1) but also models the key fact that, unlike water flowing in pipes, electricity flows through the power grid cannot be directly controlled[9]. Rather, the flow depends on the physics of the lines and components as described by Kirchhoff's and Ohm's laws [26].

- **ECONOMIC DISPATCH** attempts to find the least cost combination of generator power output levels to meet the load. This combination of economics and engineering enters into the realm of socio-technical modeling as required by all later model types. The important sub-type of Optimal Powerflow (OPF) explicitly combines economic dispatch with load flow to find the least cost dispatch considering power system losses and respecting transmission constraints. In many market based systems, OPF provides location-based energy price based on the marginal value[10] of power demand at each transmission node/bus [48].

- **UNIT COMMITMENT** looks ahead a few hours to a few days to determine which generators to turn on and have available for output. This requires considering a large number of technical con-

9 There are some limited exceptions to this lack of controllability. Input power can be controlled for the small fraction of transmission lines that use steady Direct current (DC) power rather than sinusoidal Alternating current (AC) power. Also in recent decades there has been growing academic interest and some limited utility deployment of Flexible Alternating Current Transmission System (FACTS) devices that use power electronics to exert control over how power flows on the system.

10 These marginal values, also known as dual variables for linear formulations, represent the change in overall system cost per unit change in power input/output at each point in the system.

straints on generators leading to a challenging optimization problem. This difficulty combined with the potential for large cost savings from even minor improvements in optimality has encouraged extensive research in unit commitment methods [49, 50, 51, 52, 53] as described in more detail in Section 2.2. In many market based power systems, unit commitment is used to clear the day ahead market. Unit commitment plays a central role in this thesis because its ability to capture the full range of generator technical constraints makes it the best tool for accurately modeling the operating flexibility of power systems.

MAINTENANCE: Thermal generators typically require from one to five weeks of scheduled maintenance per year during which time they are unavailable to provide power or reserves. Typically maintenance is scheduled during periods of low demand, to keep plants available during peak periods, but even during low demand periods, sufficient capacity must be available to provide energy and reserves. Maintenance optimization must therefore balance system reliability with other constraints such as maintenance crew availability [54].

HYDRO-THERMAL COORDINATION Typically, traditional hydropower resources are not limited by peak power capacity but by water availability. As a result, water usage is allocated over the year to ensure its availability for both energy and other uses during dryer seasons. Given the uncertainty in future weather and the topological complexity of many hydropower systems, the challenging hydro-thermal coordination problem has spawned extensive research [55] and even development of new optimization algorithms [56].

PRODUCTION COST As the timeframe extends beyond weeks and out to a full year (8760 hours), modeling enters into the realm of production costing and the mid-term considerations of maintenance and hydro-thermal coordination must be included along with shorter-term economic dispatch and unit commitment. Typically the objective of production cost models is to determine the expected cost of operating the power system for an extended period of time [57].

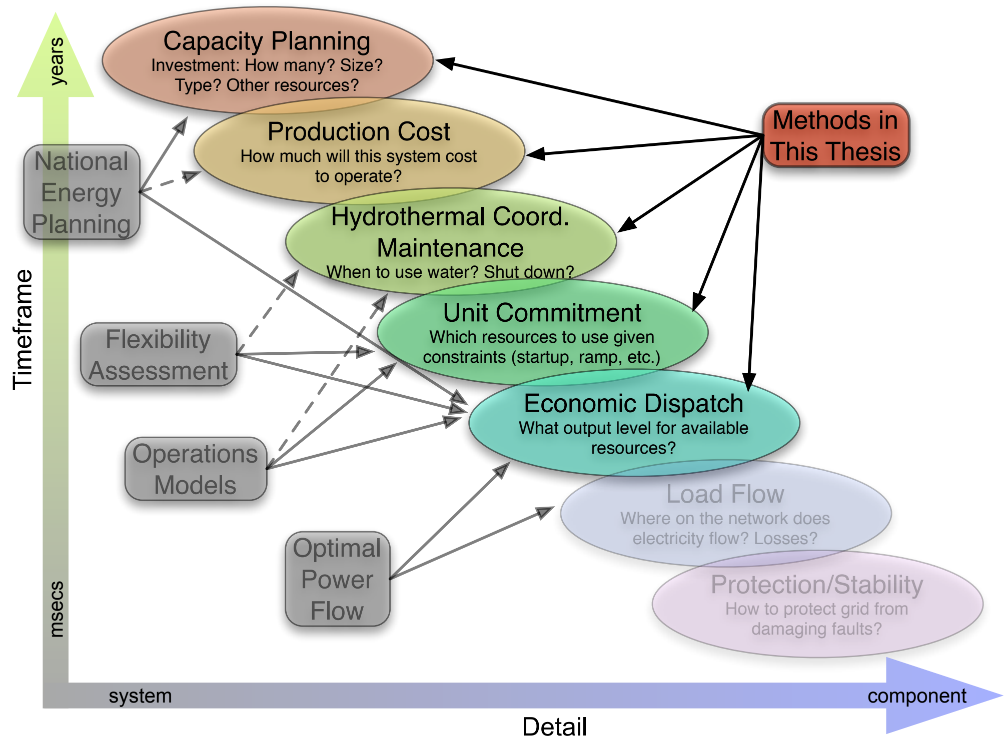


Figure 1.4: Modeling types integrated by the methods of this thesis. Some other common classes of combined models are shown for comparison.

CAPACITY PLANNING attempts to optimize investments to provide the least cost power system while maintaining reliability and meeting environmental and other constraints. There are two interlinked sub-types: transmission and generation planning, which are historically kept separate due to computational complexity [58, 59]. Capacity planning is described in more detail in the next section (1.6).

1.5.2 *This thesis*

In order to capture operations flexibility directly within capacity planning models, this thesis combines unit commitment-based methods and capacity planning optimization. In addition, as seen in Figure 1.4, the full range of power systems models from economic dispatch to capacity planning is included . This is in contrast to most national energy planning models that cover a comparable span of power systems models[11], but typically omit unit commitment, maintenance, and hydro-thermal coordination issues.

1.6 ROLE OF PLANNING AND PLANNING MODELS

1.6.1 *How planning fits in*

Centrally planed systems

Beginning in the mid-1900s most electricity was provided by large state-owned or heavily regulated monopoly utilities. These utilities used capacity planning to determine the type, size, and technology of generation plants to build. Although these utilities had to justify their decisions to regulators and/or customers, the question of who was in charge of planning was fairly straight-forward since the utilities owned and operated all of the facilities. For the US, things changed somewhat with the Public Utilities Regulatory Act (PURPA) of 1978 [60], that enabled small independent power producers to provide power the grid. More importantly, starting in the late-1990s the deregulation of the electricity sector meant that some or all of generation was no longer controlled—or planned—by central utilities, as described in the next paragraph. However, even today, the role of centralized planning remains largely unchanged in those utilities that remain regulated monopolies.

Markets and planning

The advent of markets for electric power over the past few decades has made the role of planning less clear. Theoretically in an idealized energy market that correctly prices non-served energy, marginal-cost-based market clearing[12] will enable all generators to recover their fixed costs. This will, in turn, provide adequate signals to investors to build an identical generation mix to that under a centrally planned

11 In addition, national energy planning and related models typically cover multiple-energy sectors, a dimension not shown on this graphic and not covered by the methods of this thesis. Conceptually, the methods of this thesis could be used as part of a multi-sector combined model. This extension is left as an area for future research.

12 Marginal-cost-based market clearing sets the energy price equal to the bid of the most expensive unit that is actually used to meet demand. All generators who operate in the same time period are paid this energy price. Technically, there are also some price variations based on location due to transmission constraints and non-linear components of generator cost functions.

system [61]. However, in reality this has not been the case [62]. . Price caps, system specific combinations of environment/social considerations (economic externalities), imperfect information, market power, mis-matched risk profiles, and even generator technical constraints can individually or together prevent socially "optimal" investments [63, 64].

Planning and policy

As a result, there has been growing need for indicative planning conducted by system operators and/or regulators. Indicative planning uses a planning process from a centralized perspective to inform the design of incentives and/or supplemental markets [65]. Such planning can target Renewable Portfolio Standard (RPS) or forward capacity market[13] design..

But, perhaps more importantly, policy makers also directly or indirectly consider electricity planning when analyzing broader energy and/or climate policy. In this setting, capacity planning is used to estimate the electricity infrastructure investments and their costs that result from potential policy changes. In this setting, shortcomings in the planning-for-policy process can be particularly problematic. Often electricity is but one of many sectors under consideration, encouraging the use of (highly) simplified representations of the power system. Such simplifications may miss key interactions that can drive actual power system behavior. Furthermore, as described next, policy analysts may only consider the "initial" planning phase—one that historically lacks operational flexibility considerations—potentially leading to sub-optimal policy design. An important component of this dissertation is illustrating and describing such problems and offering methods for capturing operational flexibility when conduction planning for policy.

1.6.2 *Modeling for planning*

The resource planning problem consists of two primary components: (1) Investment decisions to determine what types of power plants and demand resources to deploy and when; and (2) a rich operations subproblem that determines the cost and other impacts that result from

13 In a forward capacity market generators bid into an auction years in advance and are paid to supply firm capacity to the system

a given resource mix. Given this complexity, planning methodologies traditionally apply one of two model types:

1. Exploring a rich planning decision (investment) space using highly simplified operations models, e.g. [66, 67, 68, 69];or

2. Capturing detailed operating dynamics for a limited set (e.g. 1 to 3) of pre-determined capacity mixes, e.g.[70, 71].

In practice, energy planners may use both approaches sequentially. Simplified type-1 models are used to screen for promising results to study in detail using type-2 models (e.g., [72]). However, as shown later in this thesis, when designing advanced power systems, the interactions among dynamics, uncertainties and constraints from both the planning decisions and detailed operations may need to be examined simultaneously. The assumptions exploited by traditional planning models in order to decouple operations from planning no longer hold. For instance, type-1 planning models typically simplify operations using non-sequential, highly aggregated demand distributions called load-duration curves [73, 57, 74, 75]. This simplification ignores operational flexibility by implicitly relying on the fact that, historically, demand varied smoothly and predictably at a rate slower than the response time of most power plants. But, as described in the Operational Flexibility section above, interactions among intermittent renewables, demand-side resources, and storage occur at these faster operating timescales requiring consideration of the sequence of energy and demand variations , their weather dependent correlation [76, 70], and operating constraints for the complimentary traditional thermal generation such as ramping limits & startup costs of traditional thermal plants [77, 78]. Neglecting these faster dynamics and constraints in longer term planning may misrepresent the true cost and performance of a particular generation mix and result in solutions that are suboptimal or infeasible.

1.6.3 *Planning and Flexibility*

As described in Section 1.4, operational flexibility can have important implications in the operating timeframe. Not surprisingly, operational flexibility can in turn impact capacity planning decisions. This section describes a few such interactions to increase intuition about operational flexibility impacts on planning:

- Nuclear power facilities typically are designed to run at a nearly constant output level and hence have very high minimum output levels. Stopping and restarting these plants can literally take weeks so is typically avoided, except for scheduled maintenance. As a result, the total capacity of nuclear facilities is effectively limited to be less than the minimum net load. This creates a potential conflict as strict carbon policy may encourage increased nuclear investment, while increased variable renewable generation simultaneously reduces the minimum net load. As a result, operational flexibility concerns could limit the optimal investment in nuclear.

- This scenario and related challenges with inflexible generation, such as those based on coal, are further complicated when operating reserves are considered. If the inflexible baseload units are unable to provide sufficient quantities of reserves, it becomes necessary to supplement flexibility by running alternative, flexible units all the time. This causes a reduction in the run-time and/or energy output for the baseload plants to the point that operating revenues may no longer offset high up-front construction costs. This phenomenon may exist in the future even for systems where baseload is able to provide sufficient low demand period reserves today, since high penetrations of variable renewables will increase reserve requirements. As a result, investments in more reserve capable units will displace less flexible baseload if operational flexibility is considered during planing.

- Partially counteracting this shift is the fact that less flexible units (e.g. coal) may still be required to meet daily peak loads. Even though high carbon prices might restrict operation to peak periods, the more limited start-up flexibility of these units may require running the units throughout the entire peak season, rather than just for the peak hours. This out of merit order operation would decrease the run-time, revenues, and hence installed capacity of intermediate units (e.g. NG-CC).

- Even maintenance can represent an important dimension for operational flexibility impacts on capacity planning. Maintenance causes a temporary reduction in available capacity and thereby reduces available reserves and hence system reliability. As a result, capacity planning tools that consider both maintenance and reserves may favor investment in technologies with less demanding maintenance schedules.

These interactions are not captured by traditional capacity planning models, particularly those used for the first screening phase and those used by policy makers. This thesis uses numeric modeling to confirm these intuitive interactions by mapping out some situations where operations flexibility can drive planning decisions. In addition, this thesis describes methods for tractably including operational flexibility directly into early planning decision tools.

1.7 LITERATURE REVIEW: PLANNING AND FLEXIBILITY

This section reviews the literature related to power systems planning and operations flexibility. It adds to the references presented already in this introduction. In addition, literature reviews for specific subtopics are incorporated into corresponding sections elsewhere in the thesis. Specifically:

- Section 1.4 introduces operational flexibility in power systems and Section 1.4.5 describes recent efforts to define and measure it,
- Section 2.2 describes the unit commitment problem formulation and optimization technique literature, and
- Section 2.4.2 reviews past work in clustered unit commitment formulations.

1.7.1 *A Brief History of Least Cost Electric Generation Planning*

Even without the complexity of capturing operational flexibility, electricity generation capacity investment planning represents a challenging optimization problem. The full problem is a stochastic, multi-period decision problem with lumpy (integer) investments [79]. Because of the large scope of the problem, typically only a subset of these attributes are included as required by the application. This subsection highlights key developments in the long and rich history of least cost electricity generation planning. These developments describe the long-standing tension between simulating realistic operations and tractably optimizing investment decisions. As described in Sections 1.5 and 1.6, this tension results in the use of two different styles of models for planning: investment optimization models, with simplified representations of operations, and production cost models, that simulate more sophisticated operations for a fixed generation mix. Developments in both are intermingled in this discussion. Furthermore, even though awareness of the need to capture additional system aspects during planning typically precedes modeling/computational ability; it is often the model advances themselves that get published. As a result, much of this history refers to model developments in which a new algorithmic insight allowed the inclusion of an additional dimension of the planning problem. For interested readers, the combination of reviews by Anderson [73], Nakamura [80], Hobbs [79], and Kagiannas, et al. [81], each published about a decade apart, provide additional detail for different stages in the history of electricity capacity planning and associated models.

Early History: 1940s, 50s, and 60s

In the 1940s and 50s researchers and planners began to formalize methods for optimizing least cost investment plans in electric power. Although methodologies ranged from graphical methods (e.g. [82, 83]) to formalized mathematical optimization problems (e.g. [84]), all of these methods solved the same core problem of minimizing the sum of investment and operations costs—one that is relevant today. Anderson [73] provides an in-depth review and summary of at these first three decades of electricity planning while Sasson and Merrill [85] puts these planning optimizations in context with other contemporary electricity optimization approaches including discussing the difficulty long-term operations optimization for production costing. Early work also established the distinction between detailed operations simulation and investment optimization described in Section 1.6.2, with graphical methods dominating for operation simulation and mathematical programming (or heuristics) for investments [73].

In 1957, Massè and Gibrat presented perhaps the first representation of capacity planning investments as a Linear Program (LP) [84]. This model was soon solved via computer, corrected to account for the key role of time varying demand, and expanded for use in helping plan the French power system [86]. Though limited by the scope of computers at the time, this marked the beginning of a trend that continues today where rapidly advancing algorithms and computers are used to solve ever more complex electricity investment planning problems. In the 1960s solving practical problems first used interactive semi-automated heuristics (e.g. [87]) but later was replaced with non-linear optimization models such as [86] that included hydropower and simple spatial detail, yet captured operation costs with only two time periods per year.

The Load Duration Curve

Of the early graphical methods, those built around the Load Duration Curve (LDC) became the most widely used and today still continue to evolve and provide valuable intuition into production costing. In 1955, Kirchmeyer, et al. used LDCs to explain the economic value of having a distinct type of low capital cost, high operating cost thermal plants—known as peaking units or "peakers" today—that only run during the highest ten to hundred hours of the year to supplement other "baseload" units with higher capital cost but lower operating costs [82]. Five years later, Galloway, et al. extended this analysis to include a third "intermediate" plant type and use the intuition from the LDC as the basis for a heuristic computer model [88]. During the same time, Marsh and Wright introduced angled availability in the LDC method to partially adjust for the fact that maintenance occurs during non-peak periods [89] while Schroeder and Wilson introduced additional simple operating considerations including partial unit loading through multi-segment cost curves. Later, Jacoby presented a systematic method to include hydro in the LDC [90] (as detailed in [73])

In 1972, a landmark paper by Booth [91] popularized a technique published (in French) five years earlier by Baleriaux, et al. [92] for LDC based probabilistic production costing. This approach recognized the LDC as a cumulative distribution function and convolved it with generator outage distributions to estimate system reliability, while also allocating energy production to generators. Ten years later, Caramanis extended Booth and Baleriaux's work for use with non-dispatchable resources (e.g. wind) by using Gram-Schmidt Orthogonalization to modify the net LDC and account for correlations between these resources and demand [93, 76].

More recently, Ramos, et al. use the LDC as a basis for non-linear investment optimization with storage [94]. Ramos, et al.'s work also highlights the value of 1) single period expansion results for providing insight into capacity planning dynamics and 2) using commercial general purpose solvers to decouple the problem formulation from the optimization algorithm. Both of these approaches are adopted in this dissertation. Today, improvements in computing power have largely replaced these direct uses of LDC with mathematically equivalent constraints embedded in optimization problems[14]. However, the LDC is still widely used as a tool for illustrating concepts.

Modern methods: 1970s and 80s

By the mid 1970s and early 1980s computers had evolved sufficiently to afford greater temporal resolution in operations, ushering in the modern style of capacity planning models. Evolved forms of some of these tools are still in use today. These tools co-optimize investment decisions and mathematical representations of the LDC for operations thereby capturing variations in daily, weekly, and seasonal electric demand in a non-sequential manner. These models use a variety of algorithmic approaches including LP (e.g., MARKAL [66]), Bender's decomposition (e.g., [96, 97]) and Dynamic Programming (DP) (e.g., WASP [98]; EGEAS [99, 100]).

MARKAL extended the capacity planning problem to include national scale, multi-sector energy systems, while maintaining a fairly simple (e.g. 12 periods/year) representation of operations [66, 101]. MARKAL itself [102], and similar national energy planning tools, are actively used today by analysts for assessing policy impacts and identifying optimal energy pathways.

For utilities, EGEAS represented a major advance by providing a compatible suite of separate tools for both investment planning and more detailed operations simulation, EGEAS use the Fourier transform of the LDC to capture unprecedented temporal resolution directly in the initial investment planning phase [99]. Moreover, EGEAS's use of DP enabled directly capturing discrete investment choices. And its inclusion of Caramanis's LDC adjustments [93, 76] made it suitable for optimizing investment in low to moderate quantities of non-dispatchable resources (e.g. wind). Today, evolved forms of EGEAS are still used for capacity planning [72] and in renewable integration analysis [70].

14 Recent work by Batlle and Rodilla[95] may present a modern revival of graphically derived approaches for modern planning problems. It uses the results of an extended LDC analysis as the basis for developing computationally efficient heuristics to approximate cycling and ramping behaviors that result from renewable variations.

Extensions: 1990s through today

The forward-looking 1995 review by Hobbs [79] both summarizes and foreshadows the primary developments in electricity planning in recent decades. These represent extensions the the core methods described above and include:

- Demand resources as alternatives to supply, through Demand Side Management (DSM) programs [103, 104] or more holistic Integrated Resources Planning (IRP) [105]. Advances are still being made in this area, including De Jonghe, et al.'s current work [106, 107] that extends a traditional LP-based model to include price-elastic demand[15] along with a small subset of operational flexibility constraints;

- Markets and competition, which require moving away from centralized least cost planning to consider the impacts of market dynamics on capacity mix. Cazalet [108] and Lucas and Taylor [109] represent early efforts in this area that have since continued in tools such as WILMAR [110] and research by Botterud [111]; Graves, et al. [59]; and many others, including those reviewed in Ventosa [112];

- Transmission expansion which ideally would be co-optimized with generation, but doing still remains computationally prohibitive for large power systems. Wenyuan and Billinton [113] represents early work in this area, while Latorre, et al. [58] describe and categorize more recent developments;

- Multiple decision criteria to recognize that cost is but one of many competing objectives that also include environmental impacts, reliability, and siting. Hobbs and Meier's earlier work [114] compared a number of different multi-criteria approaches in a case study with Seattle City Light. More recently, multiple decision criteria are included in the NETPLAN model [115] and work by Tekiner [116]; and

- Uncertainty in both the operational and planning time scales. Hirst and Schweitzer [117] describe how by 1990 many utilities

15 This extension makes the problem an Mixed Complementary Problem (MCP) that can also be solved as a Quadratic Program (QP) or with iterative procedures.

were already using scenarios, sensitivity analysis, and probabilistic methods such as decision trees to analyze long-term uncertainties. Later, Kanudia and Loulou [118] used the stochastic programming[16] version of MARKAL to describe potential responses to uncertainty in climate policy. More recently Powell, et al.'s SMART model [119] demonstrates how Approximate Dynamic Programming (ADP) can significantly speed computations compared to MARKAL's LP formulation for stochastic resource planning with a high (hourly) temporal resolution, and simplified, merit order operations.

Each of these extensions required associated algorithmic advances. In addition, the difficulty of the capacity planning problem continued to attract the application of emerging large-scale optimization techniques that promise to speed calculations. These included expert systems, fuzzy logic, and neural networks [120]. In particular, modern evolutionary metaheuristics, such as genetic algorithms, have seen significant research attention (e.g., [121, 122, 123]). However, as commercial solvers for LPs, Mixed Integer Linear Programs (MILPs), and Non-Linear Programs (NLP) have continually improved, increasing numbers of researchers, planners, and analysts are turning to such tools e.g. [94, 66, 19, 124, 125, 107]. As a result, the focus for capacity planning has increasingly shifted to problem formulation, higher-level algorithm development, and the resulting insights rather than low-level optimization methods .

But, most relevant to our discussion is that nearly all of these techniques use highly simplify operating constraints during the investment optimization phase of planning[17]. The next section reviews some exceptions and describes examples and tools of how flexibility has been incorporated into planning. A major thrust of this research is to address this gap by exploring the impacts of operational flexibility within initial planning.

16 Deterministic equivalent formulated as a larger LP

17 That is not to say operating constraints are entirely ignored in planning... they come at a later stage in the multi-phase planning process and hence may not be well reflected in the generation mixes chosen for additional study.

1.7.2 *Operations Flexibility in Planning*

Growing Awareness

A number of recent reports and articles have identified the importance for systems to have sufficient operational flexibility when managing relatively large quantities of variable renewables; yet, these reports highlight the inability of current planning tools to adequately capture flexibility effects. For example, the the North American Electric Reliability Corporation (NERC) Integration of Variable Generation Task Force (IVGTF) describes how increased system variability will significantly alter operations and states "planning approaches must consider needed system flexibility" [15]. The International Energy Agency (IEA) describes flexibility and how it "empowers" variable renewables, yet continues to point out that flexibility is only "indirectly" included in current planning [14]. Lannoye, et al. [17] look specifically at flexibility in planning and effectively articulate many basic flexibility concepts. They also succinctly state that "to date, no method exists to determine the degree to which a system is [operationally] flexible or inflexible in a long term planning context." ([17] p1). In the past two years, each of these teams have introduced metrics for assessing flexibility [38, 36, 46], yet have stopped short of integrating flexibility directly into the planning problem or associated tools. Furthermore, little previous work has been done to consider the complimentary flexibility-supply reductions due to inflexible, low-carbon baseload units[18]. Perhaps most importantly, to the author's knowledge, the hypothesis that operational flexibility will impact optimal generation mixes during planning—though intuitively compelling—has not been carefully tested. Nor, have there been systematic attempts to understand when or how such planning impacts occur. This research addresses these gaps.

"To date, no method exists to determine... flexibl[ity]... in long term planning..." – Lannoye, et al. 2011

Production Cost Tools

In the current multi-step planning process (Section 1.6.2) operations-only production cost tools are the primary method used for assessing flexibility. As described above (Section 1.5), these large simulation models capture tremendous detail about the power system, including

18 An important exception is the Western Wind Integration and Solar Study (WWIS) [126] that performed a sensitivity analysis on minimum output levels of coal from 40% to 70% and found that the increased minimum output levels caused increased operating costs.

complex generator operating details, transmission constraints, power flows, and the daily decision/market processes of operators. Given the complexity of the required simulation, many planning processes use commercial products such as Ventyx's PROMOD [127], ABB's GridView [128], or GE Energy's MAPS [129]. However these tools have a number of short comings. They are expensive—in financial, personnel, and computational terms. They require tremendous amounts of data, much of which is proprietary. And, while these tools are quite adapt at modeling the nuances of todays power systems, their structure can make it difficult to adequately model the large-scale adoption of new technologies—including renewables, storage, and demand-side technologies—that may form the foundation of future power systems.

To overcome these difficulties, researchers have recently developed production costing tools that simplify data requirements, while also more readily incorporating advanced technologies at scale. For example, Ramos's ROM model (described in [130] and used in e.g. [125]) and Meibom, et al.'s WILMAR model (described in [131] and used in e.g. [132, 20]) both provide chronologic annual simulations based on rolling unit commitment. In this structure, for each simulation day generators are first committed using a forecast-based stochastic unit commitment, and then dispatched based on simulated "actual" events. This approach effectively captures operational flexibility and other considerations for advanced technologies.

Still, these research efforts only address part of the challenge. They have partially overcome the shortcomings of proprietary data, tool access, and long solution times. But they only consider the operations portion of the planning process. They still require an external process to select generation expansion plans, and typically these tools do not consider operational flexibility. Furthermore, attempting to directly incorporate the production costing models described here directly into a planning tool, remains impractical due to resulting prohibitively long run times. Moreover, production cost tools are typically not used at all by policy analysts, meaning that operational flexibility considerations are not included or are highly simplified in policy design. This dissertation addresses this methodological gap.

Renewable Integration Studies

A number of recent research efforts have looked explicitly at the integration of renewables into the US electric power system[19]. All highlight the importance of operational flexibility for renewables using detailed production costing. Yet, flexibility is highly simplified in corresponding capacity planning.

- The Western Wind and Solar Integration Study (WWSIS) [126, 133] explored the impacts of 35% renewables (30% wind plus 5% solar) in the Western US. Its main finding is that with reasonable system changes it is possible to accommodate this 35% penetration level. It also suggests that increased variable renewables might push the generation mix to be more operationally flexible, but "WWSIS is an operations study" [133, p6] that does not consider planning decisions. Its analysis uses the MAPS production cost tool for detailed operations simulations and assumes existing non-renewable generation mixes. It also specifically highlights the need for future research that characterizes the capabilities of non-renewable generation, includes technical operating constraints, and looks at changes in the non-renewable generation portfolio.

- The complementary Eastern Wind Integration and Transmission Study (EWITS) [70] explored similar impacts for the Eastern US. Its findings are similar, although additional emphasis is placed on the role of transmission to transport renewable energy to load centers. In contrast to WWSIS, EWITS does explicitly model generation capacity expansions using EGEAS. EGEAS does not directly capture operational flexibility. Operational simulations to capture flexibility are instead modeled using PROMOD.

- Most recently, the NREL Renewable Electricity Futures (RE Futures) study [134, 6] looked at the potential for moderate to high renewable penetrations (30-90% energy) in the US by 2050. It focusses in depth on a range of 80% renewable cases. It found that such high percentages of renewables are possible and would rely on a diverse mix of renewable sources, flexible generation, sufficient transmission, extensive storage, and other plausible changes. Unlike the previous studies—or this thesis—dispatchable renewable

19 Additional studies have been done for Europe and other locations.

sources such as biomass and geothermal are included. Still, variable renewables (e.g. wind and solar) provide about 50% of the 2050 supply in the core 80% scenario. The NREL ReEDs model [124] (described below) was used for planning expansion of both generation and transmission. RE Futures also highlights the importance of operational flexibility in operations. Production cost simulations with ABB's GridView reveal the value of flexibility from storage, and highlight the difficulty of operations during low net demand periods. Interestingly, GridView's rolling simulation horizon does not allow an the renewable target fraction to be enforced. As a result, renewables supply only 75% of energy during simulation for the 80% target case. [20]

ReEDS [124] is a recursive dynamic (rolling) long-term national electricity model with 2-year decision stages each implemented as a large LP. ReEDS has an extensive set of capabilities including energy balance for hundreds of nodes and approximated transmission flows. However, it relies on a highly stylized representation of operations by using only 17 annual time slices—four seasonally representative days with four sub-periods each plus a super peak. Several operating reserve classes are included, but the lack of integer on/off decisions means these estimates are based on power output, rather than committed capacity As described later (Section 4.7.1), this can over estimate available reserves. Minimum output levels are also used for baseload, but again without commitment these are likely overly restrictive. Inter-period constraints such as startup and ramping are not included.

All of these studies describe the critical roll of operational flexibility with renewables; yet in the capacity planning phase of these studies, flexibility is either ignored (EWITS) or roughly approximated (RE Futures). As a result, the additional, in-depth analysis of renewable impacts may be based on a sub-optimal generation mix. This dissertation begins to address this gap by integrating flexibility considerations directly into planning through unit-commitment.

20 As described in Section 4.7.1, this shortcoming could also have resulted from ReEDS' optimistic assessment of operating reserve requirements.

Integrated Flexibility and Planning

Despite the widespread awareness of operational flexibility and *operations* simulations just described, little previous literature exists that directly considers the impacts of operational flexibility on *planning*. Rosekrans, et al. offer a rare and early (1999) exception in [135]. This work compares results from WASP [67, 98], which uses merit order economic dispatch operations, with the Environmental Defense Fund's (EDF's) ELFIN planning tool that heuristically captures unit commitment constraints. The paper finds important differences between the investment plans proposed by typical planning tools, represented by WASP, that ignore operational flexibility; and the plan proposed by ELFIN. ELFIN uses an iterative non-optimal heuristic to estimate discrete unit commitment and capture operating reserves, minimum up times, and minimum output constraints. In a Philippines based case study, considering operational flexibility shifts the generation mix partially away from coal to more flexible NG-CC and Natural Gas fired Combustion Gas Turbine (NG-GT). The paper also qualitatively describes how in some situations it may be more efficient to run a high marginal cost peaker during a daily peak, rather than starting up a low marginal cost baseload unit that would have to run for extra hours due to minimum run times. However, the paper's analysis does not consider impacts with renewables. The model's ability to do so is somewhat limited by its relatively coarse time blocks (14 periods per week). It also does not look at CO_2 or nuclear. This dissertation verifies this early work and expands it significantly by considering renewables, a larger power system, a richer thermal technology set, additional technical constraints, a provably optimal solver, a finer-grained time series, and wider range of scenarios[21].

A few years, later Deng and Oren [136] looked at the impact of realistic operating constraints on a different planning-scale question: the real option valuation of a single plant facing stochastic prices. Though not capacity planning, it is interesting to note that they compared unconstrained versus constrained operations across a full year at a daily resolution. They found that inefficient plants faced a larger cost increase (7-8% vs 1-2%) for detailed operations over simpler operations.

21 Note that the work in this thesis was developed independently from ELFIN, largely since the ELFIN model remains relatively unknown, In fact,his work is not cited by any of the other references in this thesis and was only available by special request from the library

In the example, startup costs and startup delays had a bigger impact than small variations in output efficiency. They used stochastic DP with multinomial lattice prices. The discrete nature of this method limited the model time resolution and required the use of stylized daily operations with only 3 output levels: off, minimum, and maximum.

More recently, Shortt and O'Malley [137] explore the impact of variable renewables—and hence increased operational flexibility need—on generation planning. They primarily motivate the need for special consideration of the resulting uncertainty and variation within generation planning. It also presents a heuristic production cost approach with special emphasis on minimum output constraints and maintenance. With this approach, the model horizon (e.g. a year) is first divided between periods (e.g. hours) where units that avoid starts (baseload) are marginal, and those where max output (peakers) must also operate. The minimum output portion of the baseload units is dispatched first, using the maximum number of units able to stay on-line during the subsequent demand trough (to avoid shutdowns/startups). The remaining capacity of on-line baseload units plus any required peakers is then dispatched to meet residual net demand. For maintenance a reliability based Monte Carlo method is used to iteratively schedule maintenance during periods of expected minimum output. Though an interesting heuristic for production costing, the associated capacity planning "approach," hardly qualifies as it simply suggests manually adjusting the capacity iteratively based on the production costing output—no further guidance is offered.

Other efforts have accepted the qualitative reasoning that operational flexibility can impact planning and attempted to incorporate it. For example, NETPLAN and the model by De Jonghe both join ReEDS in heuristically estimating reserves and a limited set of additional constraints within an LP optimization. Specifically, the Iowa State NETPLAN model, under development by McCalley, et al. [115] for integrated planning of the transportation and energy systems, captures a similar set of reserve classes and fixed minimum output levels as ReEDs. It it is partially built to over come the shortcomings of the MARKAL family of models by integrating a more detailed power system representation. At its core, the model uses a network flow optimization structure that can also be solved by LP modeling tools. In addition, NETPLAN can automate multi-objective runs to compare trade-offs among competing stakeholder concerns using the NSGA-II genetic algorithm [123]. Similarly, De Jonghe, et. al present a model

[106, 18, 107] that further simplifies the heuristic reserves into two groups, up and down, and adds ramping constraints while maintaining the LP structure. For all of these models, the LP structure is attractive since enables the use of very powerful commercial solvers for large scale problems but as described by De Jonghe, "unit commitment constraints, such as startup-costs, minimum up and down times, and minimum output levels require the use of integer variables" [106, p11]. This prompts the questions of *if* and *when* this LP approximation is sufficient, both of which are addressed later in this dissertation.

A more comprehensive attempt to capture operational flexibility within planning is presented by Kirschen and Ma, et al. [19, 138]. This effort along with my own paper presented with Webster at the same conference [139] demonstrate the first known efforts to incorporate optimal long duration unit commitment and capacity planning without decomposition. Kirschen and Ma, et al. use a priority order to speed unit commitment and apply it to a small test system, with a limited time resolution. Their work compares the results of simple prototypical wind patterns: flat vs time varying to demonstrate how increased variability encourages investment in more peaking generation. In contrast Palmintier and Webster study a larger power system at full 8760 hour time resolution using an early version of the clustered, combined unit commitment and capacity planning model described in this dissertation. With it, we show that not only can renewable-driven operational flexibility prompt important changes to the capacity and energy mixes, but also 1) that these are a function of carbon policy and 2) that ignoring flexibility may lead to large emission errors or infeasible generation mixes. This dissertation presents many extensions to this preliminary work including explaining at the causes of these impacts; demonstrating when these impacts are most important; comparing clustering to other approaches including Kirschen and Ma, et al's priority list; and adding maintenance, minimum up and down time, and other technical constraints.

1.8 READERS GUIDE

The remainder of this thesis is organized as follows: Chapter 2 describes a novel model formulation that uses clustered unit commitment modeling to capturing operational flexibility during capacity planning optimization. It also provides additional background information and literature review. Chapter 3 looks at the trade-offs between errors and computational savings associated with clustering in the operations-only context. Chapter 4 uses the full model to examine the interaction between operational flexibility and planning results. It characterizes when operational flexibility does and does not impact investment decisions and which aspects of flexibility drive the decisions. Chapter 5 discusses the results, suggests areas of further research, and offers conclusions. The Appendixes include additional figures, data tables, and selected model code listings.

2 MODEL FORMULATION-CAPACITY PLANNING WITH UNIT COMMITMENT

2.1 INTRODUCTION

This chapter introduces a new model formulation that tractably captures operational flexibility within capacity planning optimization and thereby enables the analyses of flexibility impacts presented later in this dissertation. It simply would not have been practical to conduct the analyses presented later without this key methodological advance.

The formulation presented here uses unit clustering to tractably co-optimize three interlinked power systems decision models:

1. Capacity planning,
2. Production costing with maintenance scheduling, and
3. Unit commitment operations.

As described in the INTRODUCTION, combined flexibility and planning analysis would have previously required resorting to a two step process. In the first step, investment decisions are made using simplified operations. The second step would then simulate operational flexibility with unit-commitment-based production costing. This formulation enables modeling operational flexibility impacts on capacity planning in a single, monolithic optimization problem.

The use of optimization models to solve the investment, production costing, or operations problems alone is well established (e.g. [85, 57, 75]), but no known previous works have combined integer optimal unit commitment directly into capacity planning, let alone integrated all three subproblems. The integrated model described here leverages the fact that all three problems share a similar structure that can be readily modeled as a Mixed Integer Linear Program (MILP), a mathematical optimization problem with linear and discrete variables and constraints. As described below, MILP's ability to represent individual, discrete units enables link the model components using simple inequality constraints. However, a straightforward binary implementation of this approach would be computationally prohibitive, due to the combinatorial explosion of the large number of binary variables and constraints on them. Instead, this formulation uses clustering to combine similar, but not identical, units into groups that use 0 to *n* integer variables to represent decisions and dynamics at the unit level while drastically reducing the problem size.

This chapter reviews the traditional binary formulations of each of these problems, and presents the alternative clustered formulation for each. Additional sections describe important considerations, including operating reserves, additional planning constraints, and software implementation. It then presents the formulation for the combined problem, including capacity expansion, maintenance, and operations. The final section describes details of the implementation.

2.2 UNIT COMMITMENT BACKGROUND

2.2.1 *What is Unit Commitment?*

Unit commitment represents one of the fundamental optimization problems in power systems. Its importance goes far beyond simply determining which generating units to commit (run) by also including important technical and reliability constraints necessary for successful power systems operations. Historically, vertically integrated utilities and market operators have used unit commitment models to plan the next 24 to 72 hours of operations. And unit commitment is used to clear the power markets based on complex bids (e.g. ISO New England (ISO-NE), PJM, Ireland). Recently, however, there has been growing interest in power systems models that represent detailed unit commitment constraints for mid to long-term planning by considering time horizons of a few weeks up to a year or more. In this context, unit commitment can provide improved strategies for managing constrained resources over time, such as allocating emissions under a cap, maintenance scheduling, and hydrothermal coordination. During investment planning and policy analysis, unit commitment enables more accurate assessment of systems with operational flexibility challenges such as significant penetrations of variable renewables, emissions caps, or less flexible generating units including traditional nuclear designs and potentially carbon sequestering plants.

However, even for short time horizons, the unit commitment problem is inherently difficult to solve because of the combination of the large number of discrete decisions – one for each generator for each time period – and the number and complexity of the constraints. The increased problem size for long-term optimal unit commitment alone can make traditional formulations computationally intractable for realistically sized systems and attempting to also include mid to long term decisions compounds the combinatorial challenge. As a result, planners have historically separated the mid to long term decisions or used simplifications to the unit commitment operations problem that could lead to suboptimal designs .

2.2.2 *Modeling Approaches to Unit Commitment*

In the operational context, extensive studies of the unit commitment problem have been motivated by the fact that even small improvements in the quality of the solution (e.g. ~1%) can result in huge operational cost savings (millions of dollars). This section presents highlights from this broad literature.Interested readers are refered to [49, 51, 53] for additional reviews.

In the early days of electric power , unit commitment was handled by a combination of operator judgment and simplified non-optimal heuristics such as a merit order startup lists [140, 141]. In the 1960's, growing access to computers, larger more complex power systems, and increased financial pressures drove efforts to optimize unit scheduling [142, 143, 144]. Over the following decade, advances lead to improving commitment solutions for larger power systems with increasingly detailed constraints [85, 145]. The combined practical importance and theoretical complexity lead the optimization and power systems communities to use the latest optimization techniques and to refine existing techniques, including dynamic programming [146], branch-and-bound [147], genetic algorithms [148], and meta-heuristics such as ant colony and tabu search [149, 150]. However, in practice, Lagrange relaxation methods [57, 50, 151] have dominated utility and market operator implementations of unit commitment until recently. Today there is a growing trend toward implementing unit commitment as a MILP that is then passed to a general-purpose commercial solver [152, 153, 154, 155]. In addition to reducing computation times, MILP also greatly simplifies formulating and adding additional constraints, a task that requires significant effort with Lagrange relaxation.

2.2.3 *Mixed-Integer Linear Programming (MILP) for Unit Commitment*

MILP was first proposed for unit commitment in the 1960's by Garver [156] and later demonstrated and further refined by Muckstadt & Wilson [157] and Dillan & Egan [147]. Early MILP implementations used the branch-and-bound approach, in which integer variables are ordered into a tree that is explored and pruned to find the optimum. At each node, bounds on the upper and lower limits for the sub-branches are found using the Linear Program (LP) relaxation and the LP-dual respectively. These bounds enable pruning portions of the tree that can't possibly offer the optimum. However this approach was not practical at the time for full-sized unit commitment. Today's shift to MILP was partially enabled by advances in available computer hardware, but more importantly by algorithmic advances [158], notably branch-and-cut approaches that use cutting planes to guide the solver toward feasible integer solutions before (and during) the branch-and-bound optimization.

With the use of state-of-the-art, general-purpose commercial solvers, modelers now largely rely on these packages to implement the latest algorithm developments and instead improve performance through solver option tuning, parallelization, and/or software/hardware upgrades. In addition dramatic improvements can sometimes be made by adjusting the problem formulation itself [159]. Generically, such reformulations have one or more of three objectives:

- TIGHTENING the relaxed integer (linear) equations to more closely approximate the non-convexities inherent in MILP problems. Ideally, the relaxed equations form the *convex hull*, the linearly constrained representation of the problem that minimally contains the feasible integer solution space, such that the LP vertices fall at integer solutions. With such a representation the LP closely matches the MILP allowing for more efficient branch-and-cut tree pruning by the solver;

- REDUCING INTEGER VARIABLES to take advantage of the significantly more powerful (faster) algorithms available for continuous equations with purely linear variables (LP) relative to those with discrete variables (e.g. MILP)[1]; and

1 Note: as described below, recent research suggests that in some cases fewer integers can lead to longer solution times. This can occur when the additional integers pro-

REDUCING OVERALL PROBLEM SIZE by reducing the total number of variables and equations required to be solved in the problem. Not surprisingly, overall problem size reductions can directly speedup solution times since all known classes of LP algorithms - including both Dantzig's simplex method [160] and interior-point barrier methods (starting with Karmarkar [161]) - scale with at least polynomial time as a function of problem dimension [162].

Each of these techniques have been used for unit commitment. Rajan & Takriti [163] and Hedman, et al. [164] demonstrate constraint tightening to approach the convex hull for minimum up and down time formulations. Carrion & Arroyo [165] demonstrate improved performance by reducing the number of integer variables in unit commitment, although recent work by Ostrowski, et al. [166] demonstrate the surprising result that modern MILP solvers can actually solve unit commitment problems faster when the full set of integer variables are included. Many researchers rely on various simplifications to reduce overall problem size.out of computational necessity. For example pure unit commitment research studies are often limited to small demonstration power systems [167, 168, 166] or use only a sub-set of weeks for production cost models with unit commitment (e.g.[19]). As outlined below, the clustering formulations described below for unit commitment, maintenance, and capacity planning; employ all three reformulations, but most importantly rely on reducing the problem size through clustering to speed up performance.

2.2.4 *Distinguishing similar MILP solutions*

The literature also describes a number of solution tuning approaches aimed at the difficult challenge of distinguishing very similar, near-optimal solutions. Such similar solutions are common in the unit commitment problem, because many units in a large system have similar (or identical) operating characteristics. This can cause MILP branch-and-cut (and other combinatorial optimization), to waste considerable time finding and attempting to improve on such (nearly) equivalent solutions. As a result, a number of heuristics to distinguish similar solutions have been employed:

vide additional structure of the branch-and-bound tree that helps eliminate more branches than it adds.

- In the branch-and-bound phase of branch-and-cut algorithms, the ε-optimal heuristic, informally known as "cheat," can improve solution times by only considering branches of the node tree that have the potential to improve the solution by more than a tunable parameter, ε; [169]

- For truly identical units, perturbing key parameters (variable cost) can introduce small artificial differences; and

- To help structure the problem, a merit order priority list may be imposed to ensure that certain units always start before others, unless it would violate other constraints. [19]

However, the sophisticated algorithms employed by modern solvers reduce the gain from such heuristics. More importantly, while these approaches may reduce computation time by an order of magnitude in the best cases, unit commitment for long time horizons remains intractable.

2.3 TRADITIONAL UNIT COMMITMENT FORMULATION

2.3.1 *Core model*

The generic unit commitment problem finds the minimum cost combination of generator commitment and power output to meet demand over time. This section linearizes and adapts the standard basic formulation [57, 50], for a thermal-only system and simultaneously introduces the nomenclature used in this dissertation. The resulting optimization problem is a large MILP that can then be solved by powerful commercial solvers as is done by a growing number of power system operators [152]. For clarity, uppercase is used for variables, bold uppercase for sets, and lowercase for parameters and set elements.

THE OBJECTIVE FUNCTION minimizes total operations costs:

$$C^{\mathsf{total}} = \min \sum_{g \in \boldsymbol{G}} \sum_{t \in \boldsymbol{T}} \left(C^{\mathsf{var}}_{g,t} + C^{\mathsf{start}}_{g,t} \right) \tag{2.1}$$

computed as the sum of variable costs, $C^{\mathsf{var}}_{g,t}$, and startup costs, $C^{\mathsf{start}}_{g,t}$, for all units, g, and time periods, t.

THE VARIABLE COSTS, $C^{\mathsf{var}}_{g,t}$ include fuel costs, $c^{\mathsf{fuel}}_{g,t}$, and variable operations and maintenance (O&M) costs, $c^{\mathsf{varO\&M}}_{g}$:

$$C^{\mathsf{var}}_{g,t} = \mathrm{F}_{g,t}(P_{g,t})\, c^{\mathsf{fuel}}_{g} + P_{g,t} c^{\mathsf{varO\&M}}_{g,t} \quad P_{g,t} \geq 0, F_{g,t} \geq 0 \tag{2.2}$$

Where $\mathrm{F}_{g,t}(P_{g,t})_{g,t}$ is the fuel usage as a function of the instantaneous power output, $P_{g,t}$. Startup costs are treated separately below.

STARTUP AND SHUTDOWN EVENTS , $S_{g,t}$ and $D_{g,t}$, are computed using the state equation:

$$U_{g,t} = U_{g,t-1} + S_{g,t} - D_{g,t} \tag{2.3}$$

$$with \quad U_{g,t}, S_{g,t}, D_{g,t} \in \{0, 1\} \tag{2.4}$$

Where $U_{g,t}$ represents the commitment (on/off) state of each unit and is set to 1 when the unit is running. This formulation therefore sets $S_{g,t}$ (or $D_{g,t}$) to 1 only during time periods when the unit starts up (or shuts down). Some state equation formulations relax the integral constraints on $S_{g,t}$ and $D_{g,t}$ in (2.4) because the binary restriction on $U_{g,t}$forces them to take only take binary values [165]; however, with modern solvers, enforcing the binary constraints for all three variables can provide considerable computational speed up in practice [166]. In numeric testing for this thesis, I observed approximately five times faster runtimes with all three variables constrained to discrete values.

STARTUP COSTS, $C^{\mathsf{start}}_{g,t}$, assume a constant fuel use per startup, f^{start}_{g} and include an additional fixed cost per start, $c^{\mathsf{fix\,start}}_{g}$ to include maintenance and personnel costs:

$$C^{\mathsf{start}}_{g,t} = S_{g,t} \cdot \left(f^{\mathsf{start}}_{g} c^{\mathsf{fuel}}_{g} + c^{\mathsf{fix\,start}}_{g} \right) \tag{2.5}$$

Note that this formulation uses fixed values for c_g^{fuel} and $c_g^{fixstart}$ and therefor deviates from startup formulations that distinguish warm and cold startup costs, e.g. [57]. This constant startup cost simplification is commonly used for this class of long-term unit commitment problem [19, 170, 168].

A PIECEWISE LINEAR FUEL USAGE function, $\mathrm{F}_{g,t}(P_{g,t})_{g,t}$, captures the non-linear relationship between fuel usage and power output, represented using a unit-specific convex piecewise linear approximation with segments, $\boldsymbol{X_g}$:

$$\mathrm{F}_{g,t}(P_{g,t})_{g,t} \geq h_{g,x}P_{g,t} + U_{g,t}f_{g,x}^{\mathsf{P=0}} \quad \forall x \in \boldsymbol{X_g} \tag{2.6}$$

For each piecewise linear segment, x, the slope, $h_{g,x}$, represents the incremental heat rate and the intercept, $f_{g,x}^{\mathsf{P=0}}$, indicates the projected fuel use if hypothetically running at zero power. Since fuel has a positive cost, the optimizer will minimize fuel usage forcing the inequality to equality for the highest piecewise segment. When a unit is not running, the commitment variable, $U_{g,t}$, brings fuel use to zero.

THE SYSTEM BALANCE CONSTRAINT ensures that the sum of instantaneous power, $P_{g,t}$, equals total load, L_t, at all times[2]:

$$\sum_{g \in \boldsymbol{G}} P_{g,t} = L_t \quad \forall t \in \boldsymbol{T} \tag{2.7}$$

UNIT MINIMUM AND MAXIMUM OUTPUT CONSTRAINTS use the binary commitment variable to imply that each generating unit is either off and outputting zero power (when $U_{g,t} = 0$), or on and running within its operating limits, from its minimum output level, p_g^{min}, up to its maximum, $p_g^{\mathsf{max}}(t)$ (when $U_{g,t} = 1$):

$$U_{g,t}p_g^{\mathsf{min}} \leq P_{g,t} \leq U_{g,t}p_g^{\mathsf{max}}(t) \tag{2.8}$$

Note that the maximum power, $p_g^{max}(t)$, is a function of time. This is enables capturing the time varying resource availability for renewable generators[3] and enables exogenous maintenance scheduling.

2 This relation is updated later to allow for non-served energy.

3 To be precise, as described later, variable renewables typically do not have an associated unit commitment variable since their minimum output is zero. This is equivalent to treating $U_{g,t}$ as always equal to one; however, the concept of time varying maximum power still applies.

2.3.2 *Additional Constraints*

A more realistic model includes additional cost components and generator and system reliability imposed technical constraints [50]. I focus on the most common extensions:

RAMPING LIMITS capture limitations on how fast thermal units can adjust their output power:

$$\begin{aligned} P_{g,t-1} - P_{g,t} &\leq U_{g,t}\Delta p_g^{\mathsf{downmax}} \\ &\quad + \max(p_g^{min}, \Delta p_g^{\mathsf{downmax}}) D_{g,t} \qquad (2.9) \\ P_{g,t} - P_{g,t-1} &\leq U_{g,t}\Delta p_g^{\mathsf{upmax}} \\ &\quad + \max(p_g^{min}, \Delta p_g^{\mathsf{upmax}}) S_{g,t} \qquad (2.10) \end{aligned}$$

where the Δp's are the ramp limits up or down. The right-hand sizes enforce the simple ramp rates during normal operations, but enable higher up/down ramps during startup/shutdown events if the ramp rates would otherwise be too low.

MINIMUM UP AND DOWN TIMES are represented using the formulation found to be most efficient by [163] [164] and [166]. This formulation sums startup (shutdown) events to allow at most one startup (or shutdown) during the preceding minimum up (down) time interval if the unit is running (stopped):

$$U_{g,t} \geq \sum_{\tau=t-a_g^{\mathsf{minup}}}^{t} S_{g,\tau} \qquad (2.11)$$

$$1 - U_{g,t} \geq \sum_{\tau=t-a_g^{\mathsf{mindown}}}^{t} D_{g,\tau} \qquad (2.12)$$

Where a_g^{minup} and a_g^{mindown} are the minimum up and down times, respectively.

2.3.3 *Operating Reserves*

Because power generated on the grid must match demand instantaneously, a number of operating reserves are maintained by allowing slack between generator output levels and corresponding limits. Reserves provide on-line capacity that can rapidly increase (or decrease) in order to compensate for generation or transmission outages, forecast errors, etc.:

PRIMARY RESERVES operate on a timescale of a few seconds to compensate for rapid changes:

$$\sum_{g \in \boldsymbol{G}} R_{g,t}^{\text{primaryup}} \geq \mathrm{r}^{\text{regup}}(L_t) \tag{2.13}$$

$$\sum_{g \in \boldsymbol{G}} R_{g,t}^{\text{primarydown}} \geq \mathrm{r}^{\text{regdown}}(L_t) \tag{2.14}$$

Where $R_{g,t}^{\text{primaryup}}$ and $R_{g,t}^{\text{primarydown}}$ are the quantity of primary reserve supplied by unit g in time period t. The totals of which must exceed the exogenously determined system-level frequency reserve requirements, $\mathrm{r}^{\text{regup}}$ and $\mathrm{r}^{\text{regdown}}$.

SECONDARY RESERVES operate on a timescale of a few minutes for contingencies (spinning reserves) and for load following. I allow a fraction of the reserve-up supply, k^{nosync}, to be supplied by non-synchronized resources such as offline quick starting units or demand response:

$$\sum_{g \in \boldsymbol{G}} R_{g,t}^{secondaryup} \geq \left(\mathrm{r}^{lfup}(L_t) + r^{\text{outage}}\right)(1 - k^{\text{nosync}}) \tag{2.15}$$

$$\sum_{g \in \boldsymbol{G}} R_{g,t}^{secondarydown} \geq \mathrm{r}^{lfdown}(L_t) \tag{2.16}$$

The $R_{g,t}$'s are the quantity of on-line secondary reserves supplied by each unit. $\mathrm{r}^{lfup}(L_t)$ and $\mathrm{r}^{lfdown}(L_t)$ are the system load following requirements, a function of load/wind forecast error. r^{outage} is the additional reserve required for contingencies, typically set to the largest unit or transmission tie capacity.

TERTIARY OR QUICK START RESERVES are off-line but ready to run units that can be brought on-line quickly when needed:

$$\sum_{g \in \boldsymbol{G}} R_{g,t}^{\text{tertiary}} + R_{g,t}^{\text{secondaryup}} \geq \mathrm{r}^{\text{lfup}}(L_t) + r^{\text{outage}} + r^{\text{replace}} \tag{2.17}$$

The left-hand side includes both tertiary and secondary up reserves to both capture the fraction of the secondary reserve allowed by (2.15) from off-line units, and to enable tertiary reserves to be met by on-line units when appropriate.

UNIT RESERVE CAPABILITIES are dictated by a unit's ability to provide each type of reserve, a_g^ρ:

$$R_{g,t}^{\rho} \le U_{g,t} a_g^{\rho} p_g^{\mathsf{max}} \quad \forall \rho \in \{primarydown, secondarydown, primaryup, secondaryup\} \tag{2.18}$$

For tertiary reserves, quick start capable units can only be drawn from the pool of non-active units:

$$R_{g,t}^{\mathsf{tertiary}} \le \left(1 - U_{g,t}\right) a_g^{\mathsf{quickstart}} p_g^{\mathsf{max}} \tag{2.19}$$

where $a_g^{\mathsf{quickstart}}$ represents the fraction of the unit capacity, p_g^{max}, that can be deployed fast enough.

UPDATED UNIT OUTPUT CONSTRAINTS capture the need for a unit to run below maximum for upward and above minimum for downward reserves. These supplement[4] (2.8) with the pair:

$$P_{g,t} \ge U_{g,t} p_g^{\mathsf{min}} + R_{g,t}^{\mathsf{primarydown}} + R_{g,t}^{\mathsf{secondarydown}} \tag{2.20}$$

$$U_{g,t} p_{g,t}^{max} \ge P_{g,t} + R_{g,t}^{\mathsf{primaryup}} + R_{g,t}^{\mathsf{primarydown}} \tag{2.21}$$

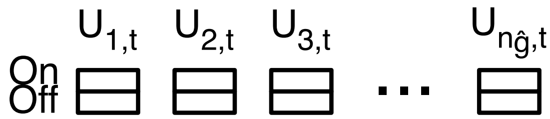
2.4 CLUSTERED UNIT COMMITMENT

2.4.1 *The Concept of Clustering*

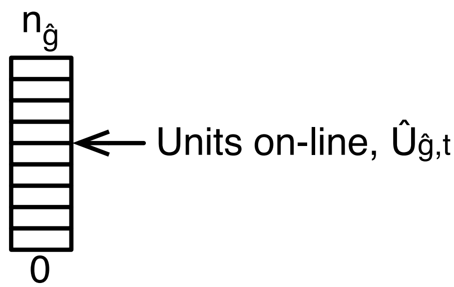
For problems with simplified or non-binding transmission constraints, it is possible to combine similar generating units into clusters. As seen in Figure 2.1, this replaces the large set of binary commitment decisions, one for each unit, with a smaller set of integer commitment states, one for each cluster. The distinction between binary and integer variables is important: in traditional binary unit commitment, each unit is either on or off. With clustering, the integer commitment state varies from zero to the number of units in the cluster, $n_{\hat{g}}$. In this way, clustering still captures commitment decisions and associated relations

4 Both sets of equations are maintained to prevent the optimizer from attempting to supply non-quickstart reserves from a unit that is off.

at the individual plant level. All of the other variables – such as power output level, reserves contribution, etc. – and constraints are then aggregated for the entire cluster.



(a)



(b)

Figure 2.1: Conceptual comparison between traditional and clustered unit commitment for a single type of unit in a single time period. In the traditional formulation (a), each unit has a separate binary commitment variable, $U_{g,t}$. With clustering (b), the entire cluster of $n_{\hat{g}}$ units has only a single integer commitment variable, $\hat{U}_{\hat{g},t}$.

Computationally, the integer variables provide structure that both reduces the dimensionality of and guides the search through the combinatorial commitment state space by eliminating a large number of identical or very similar permutations of binary commitment decisions. The number of possible discrete combinations of commitment variables with the traditional formulation scales exponentially with the number of units: $2^{n_{\hat{g}}}$. Clustering dramatically reduces this dimensionality to the product of the cluster sizes: $\prod n_{\hat{g}}$. For example in a system with 100 units clustered into three groups as 10/70/20 this reduces the number of discrete combinations[5] in each time period from $\approx 10^{30}$ to $\approx 10^{4}$.

At least as importantly, clustering also reduces the number of continuous equations and variables, since the unit commitment constraints now apply over the smaller number of clusters rather than the full set

5 Modern MILP solvers use sophisticated branch-and-cut algorithms to explore only a tiny fraction of this combinatorial space. Still, the speedup with reduced dimensionality can be dramatic.

of individual units. In our example, this reduces the problem size by 97%. This savings applies to both the full, discrete MILP solution and the relaxed LP equivalent. A faster LP equivalent implies faster MILP solutions by speeding both the root-node solution and the sub-nodes of the branch-and-cut tree. Moreover, in some situations, the LP equivalent formulation can be used directly, provided it sufficiently captures operational constraints and dynamics.

2.4.2 *Clustering Literature Review*

The concept of aggregating units is not new. As early as 1966, pioneering studies in computer based unit commitment, grouped generators together to illustrate simple solution techniques with limited computer hardware [142]. More recently, examples of combining *identical* units has also appeared in the literature. For example, Gollmer, et al. [151] also use grouped integer commitment for identical thermal plants and Garcia-Gonzalez, et al. [171] use a grouped integer on/off state when modeling banks of identical hydro turbines for optimal combined bidding with wind. It is likely that other implementations have also clustered identical units, but remain unpublished since the computational advantages of binary aggregation to integers is well recognized in the operations research community [159]. For example in his dissertation, Cerisola describes homogeneous aggregation into "generalized" units with integer commitment variables [172], yet this formulation is not described in related journal articles [173]. Clustering identical, co-located units can provide identical solutions in faster times.

The formulation used hereextends this aggregation so that *similar*, but not identical, units are clustered together and assigned an integer commitment state. Conceptually, this approach is similar to that of Sen & Kothari [174], who also group units. However, their treatment assumes a binary commitment state for the entire group: all on or all off. This is computationally helpful, but is much less flexible and less realistic than an integer formulation that allows some of the generators within a group to run while others are off. The all or none approach also prevents properly computing startup costs, minimum output levels, and reserve capability. Recent work on heterogeneous clustering, including that by the author, has demonstrated efficient unit-commitment-based computations over long time horizons (e.g. full year as 8760 sequential hours) as part of price estimation [175] and planning studies [139].

These two types of clustering serve subtly different purposes. Clustering identical units causes little to no loss of fidelity and in most cases will produce identical results[6] in less time by avoiding unnecessary, duplicate computations. In contrast, clustering similar, but not identical, units is an approximation that assumes all of the units in the resulting cluster have identical technical characteristics. This also speeds computation, but introduces some approximation error. For capacity planning, both types of clustering may occur simultaneously. Clustering existing generation will most typically involve grouping similar, but not identical, units. In contrast, candidate new units for each technology are typically assumed to have identical technical characteristics, such that clustering can provide identical results to separate units.

2.4.3 *Clustering Formulation*

Mathematically, clustering introduces fairly simple changes to the traditional formulation. Clustering replaces the individual unit index, g, with the cluster identifier, $\hat{g}$, and uses a corresponding expanded range for the commitment, startup, and shutdown variables replacing (2.4) with:

$$\hat{U}_{\hat{g}}, \hat{S}_{\hat{g}}, \hat{D}_{\hat{g}} \in \{0, 1, \cdots, n_{\hat{g}}\} \qquad \forall \hat{g} \tag{2.22}$$

In all cases the clustered variables are distinguished by a hat, " ˆ ".

Relations With No Change Needed

Beyond the above substitutions, no further changes are required for the objective (2.1), variable costs (2.2), commitment state (2.3), startup costs (2.5), piecewise linear fuel use (2.6), system balance (2.7), unit output constraints (2.8), (2.20), & (2.21), minimum up time (2.11), system reserve requirements (2.13) – (2.17), and non-tertiary reserve capabilities (2.18). The relations requiring additional modification are described below.

6 At least in most cases. For units with highly non-linear fuel cost functions, identical clustering still introduces the approximation that all units in the cluster are operating on the same piecewise linear segment.

Updates for Clusters

RAMPING LIMITS require the most extensive changes since hour-to-hour output for the entire cluster must account for unit start up, $\hat{S}_{\hat{g},t}$, and shut down, $\hat{D}_{\hat{g},t}$. The ramp rates for on-line generators also scale by the number of on-line units within the cluster, $\hat{U}_{\hat{g},t}$. These modify (2.9) & (2.10) to:

$$\begin{aligned} P_{\hat{g},t-1} - P_{\hat{g},t} \ \leq \ & \left(\hat{U}_{\hat{g},t} - \hat{S}_{\hat{g},t}\right) \Delta p_{\hat{g}}^{downmax} \\ & - p_{\hat{g}}^{min} \hat{S}_{\hat{g},t} \\ & + \min(p_{\hat{g}}^{max}(t), \max(p_{\hat{g}}^{min}, \Delta p_{\hat{g}}^{downmax})) \hat{D}_{\hat{g},t} \quad (2.23) \\ P_{\hat{g},t} - P_{\hat{g},t-1} \ \leq \ & \left(\hat{U}_{\hat{g},t} - \hat{S}_{\hat{g},t}\right) \Delta p_{\hat{g}}^{upmax} \\ & + \min(p_{\hat{g}}^{max}(t), \max(p_{\hat{g}}^{min}, \Delta p_{\hat{g}}^{upmax}, p_{\hat{g}}^{quickstart})) \hat{S}_{\hat{g},t} \\ & - p_{\hat{g}}^{min} \hat{D}_{\hat{g},t} \quad (2.24) \end{aligned}$$

where $p_{\hat{g}}^{quickstart} \equiv a_{g}^{\mathsf{quickstart}} p_{g}^{\mathsf{max}}$.

THE MINIMUM DOWN TIME requires finding the number of units currently off as the difference between $n_{\hat{g}}$ (as opposed to one) and the current commitment state, $\hat{U}_{\hat{g},t}$, replacing(2.12) with:

$$n_{\hat{g}} - \hat{U}_{\hat{g},t} \geq \sum_{\tau = t - m_{\hat{g}}^{mindown}}^{t} \hat{D}_{\hat{g},\tau} \quad (2.25)$$

TERTIARY RESERVE CAPABILITIES change similarly replacing (2.19) with:

$$R_{\hat{g},t}^{\mathsf{tertiary}} \leq \left(n_{\hat{g}} - \hat{U}_{\hat{g},t}\right) a_{\hat{g}}^{\mathsf{quickstart}} p_{\hat{g}}^{\mathsf{max}} \quad (2.26)$$

2.4.4 *Clustering Methodology*

With the heterogeneity of existing generation units in real systems, the exact basis for clustering is a decision with important tradeoffs[7]. This thesis considers four different approaches to aggregation:

7 As described in Section 2.4.2, during capacity planning, candidate new units for each technology are typically assumed to be identical, and clustering does not introduces minimal approximation. There is no approximation, if the fuel cost curve has a single segment.

1. Separate units – no clustering. This is the traditional formulation with binary commitment decisions for each unit and is used as the baseline for comparison.

2. Full clustering by unit type only – In this case all units with the same combination of fuel type and prime mover (e.g., coal steam, open cycle gas turbine, natural gas combined cycle) are combined into clusters.

3. Clustering by type and additional characteristics. This clustering approach sub-divides full clusters using an additional characteristic. For example, Section 3.4.3separately compares sub-dividing by size, age, and efficiency (heat rate). Cluster membership can be determined manually to provide roughly equal distributions of units between sub-clusters (as was done here), or by using a formal clustering algorithm, such as k-means [176].

4. Clustering by plant. This approach clusters all units of the same type at the facility or plant level. Often, but not always, such units are identical.

For all clustering approaches, the representative unit for each cluster is assumed to have a size (nameplate capacity) equal to the average of cluster members. Technical characteristics such as heat rate, ramp rates, minimum output, etc., are taken as the size-weighted average. This representative plant is effectively duplicated such that the number of units in the cluster, $n_{\hat{g}}$, matches the original number of individual units.

2.4.5 *Key Assumptions*

In general, clustering assumes homogeneity of units within a cluster. When clusters consist of identical units with constant incremental heat rates – i.e., only a single piecewise linear segment – the clustered solution exactly matches the traditional solution. For similar, but not identical, generators in the same cluster, they are assumed to have uniform technical characteristics such as minimum and maximum output levels, ramp rates, etc. In addition, power output levels for all of the units in the cluster are assumed to lie on the same piecewise-linear segment for fuel usage. This assumption is always met with constant incremental heat rates – i.e., a simple affine (linear with offset) fuel use function

– or under the somewhat stricter assumption that all units operate with the same power output.

2.4.6 *Additional Assumptions*

WRAP-AROUND COMMITMENT The unit commitment problem requires establishing the initial conditions for commitment state and elapsed up and down times. To simplify this complication, this research assumes that for each operations time block (e.g., week or year) the first hour follows the last hour and enforces ramping and minimum up and down times accordingly. This assumption implies that the initial sub-periods (e.g., hours) in the subsequent block are effectively the same as the initial hours in the current block. In data selection, this also requires care to prevent a sudden jump in demand between the last and first hours that might violate ramp rate limits. In all simulations described in this work, time series data was selected such that the difference in demand between the last and first demand periods is= of the same magnitude as the differences already observed between adjacent operating hours in the data.

CONSTANT INCREMENTAL HEAT RATE WITH OFFSET This assumption replaces the piecewise linear fuel usage with a single affine (linear with offset) constraint for each generator or cluster. This is equivalent to assuming a constant incremental heat rate with an offset for projected fuel usage at hypothetical zero power output. This shrinks the problem by reducing the number of constraint equations. For many units, this assumption is fairly mild since fuel use is typically close to collinear. Section 3.4.3 compares this assumption with the full piecewise linear results.

2.5 ADDITIONAL SPEED-UP STRATEGIES

In addition to clustering, this research explores other strategies for speeding up long-term unit commitment computations. These strategies fall into two categories: generic MILP heuristics, described earlier in Section 2.2.4, and problem-specific simplifications, described below. Both categories can be used with either traditional or clustered formulations and therefore offer comparisons of clustering with other strategies and methods to further speed up very large problems.

2.5.1 *Relax integer constraints for units with low minimum outputs*

In MILP optimization, the number of discrete variables has a much larger impact on solution time than the number of continuous variables since continuous linear programming solvers are far more powerful than the combinatorial solvers required for discrete variables. Any discrete variables that can be treated as continuous typically reduce the computation time. Such a relaxation is obvious with commitment variables for units, such as wind turbines, that are modeled with a minimum output levels of zero and no fuel use at minimum power. For these units, a fractional commitment state causes no loss of fidelity. But for long-term unit commitment, one can extend this concept further to eliminate integer decisions for units with small non-zero minimum output levels. For example, in many systems, there are a considerable number of peaking units with small size and even smaller minimum output such that extending the relaxation to small minimum output units can considerably decrease the solution time. These relaxed constraints also apply to the corresponding startup and shutdown variables.

2.5.2 *Combined Reserves*

Computing the multiple separate classes of reserves introduces a large number of equations for each unit (or cluster) in each time period. With the five classes of reserves described above, system requirements and unit capability for each reserve class result in ten types of equations for each time period. However, the major driver for both system reserve requirements and unit reserve capability is ramp limits. Therefore, this approximation explores combining the reserves into three classes: offline (tertiary), flexibility up, and flexibility down (both sums of the primary & secondary), thereby reducing the total number of reserve equation types to six.

2.5.3 *Limit start-ups per time*

Minimum up and down time constraints also require a large number of equations: two per unit (or cluster) for each time period. Furthermore, they are some of the most computationally difficult constraints since they link decisions across as many time periods as the minimum up and down time durations. As an alternative, this approximation limits the total number of startups allowed for each unit or cluster. This replaces a large number of multi-period constraints, one per time period, with a single larger constraint for each generator that sums across all time periods.

2.6 OPERATING RESERVES: MANAGING SHORT-TERM UNCERTAINTY

Power systems must manage a wide range of uncertainties during operation including:

- Load short-term variations and forecast errors,
- Renewable generation short-term variations and forecast errors, and
- Thermal generator inability to respond to rapidly changing control signals,
- Contingencies including unexpected generation or transmission outages.

These uncertainties are managed using a range of operating "reserves" that correspond to different time horizons [177]. Reserves are sometimes used interchangeably with the larger concept of ancillary services [178, 179], which includes all non-energy services necessary to operate the power system including reserves along with generator control signals, market operation, etc. As described in Section 2.3.3 reserves are divided into types based on time horizon and are generally provided by nominally operating generation below its maximum output level to enable increasing output as required to meet routine and contingency "up" reserve requirements. Similarly, some units are kept above their minimum output levels to provide complementary "down" reserves. In addition, off-line units that can be started on short notice, such as load shedding or storage, can also provide certain classes of reserves.

A complete discussion of power system reserves is far beyond the scope of this thesis; instead this section seeks only to motivate and describe the simplified reserve assumptions used in this formulation and analysis. A recent report by Ela, et al. [177] provides an excellent in-depth discussion and extensive reference list for readers interested in more information.

2.6.1 *Reserve requirements*

Power systems use a wide range of methods to calculate the required operating reserve levels for each reserve type [177]. Historically, this involved rule-of-thumb metrics and operator judgement that have proven in practice to meet the reliability targets set out by reliability organizations such as the North American Electric Reliability Corporation (NERC).

For instance, at the fastest time scale of seconds to minutes , each of the major Independent System Operator (ISO)s has a distinct approach to quantifying the required reserves, despite being governed by the same requirements: Control Performance Standard (CPS) 1 and CPS-2. Specifically, PJM (the ISO for Pennsylvania, New Jersey, Maryland, and ten other eastern states) simply requires 1% of maximum and minimum loads for on-peak and off-peak regulation respectively. In contrast, ISO-NE and California ISO (CAISO) use formulas based on the month, day of the week, and hour of the day; while the Electric Reliability Council of Texas (ERCOT) uses the 98.8 percentile of historic reserve deployments over the past 30 days [177].

By analyzing the CAISO ancillary service market data at an hourly resolution for all of 2006, I obtained a estimate of the average capacity required for each class of reserves [180]. The load following "reserve" is based on the average volume of trades in the 5-minute balancing market. As seen in Table 2.1, these results match PJM's rule of thumb guideline of 1% of load for regulating reserves. As described below, they also approximately equal the zero wind intercept for the 80% confidence curve fit of wind net load and the proposed Western Electricity Coordinating Council (WECC) guideline of 3% of the load for contingency reserves.

2.6.2 *Reserves for Wind*

The question of how increased variable renewables impact reserve requirements has received considerable attention in the literature. A recent search on IEEE Xplore found over 100 articles for "operating reserves for wind" alone and this does not include countless reports by consultants, from national labs, and in non-IEEE-indexed publications. In summary, the increased variability and uncertainty require additions of all types of reserves; however, the smoothing effects of aggre-

SERVICE	PERCENT OF ON-LINE GENERATION
Regulation (Up& Down)	1.3%
Load Follow	4.0%
Spin-Reserves	3.0%
Non-Spin	3.0%
Total Reserves	*11.3%*
Energy	*88.7%*

Table 2.1: Approximate ancillary service requirements. Source: analysis of CAISO 2006 hourly average ancillary service and balancing markets.

gation and spatial diversity reduce the increase in variability compared to linearly scaling a single renewable plant. In general, reserve requirements with moderate amounts of renewables (10-15% of energy) are comparable to those already maintained by the power system for contingencies and load uncertainty [177, 27, 181, 182, 183, 184, 77, 185].

Regulation

For regulation, it was once argued that output variations between geographically scattered wind farms canceled each other out, so that wind required no increase in regulation reserves [186]. However, a recent report by GE Energy that analyzed ERCOT's ancillary serves needs with increased wind shows on average a slight increase of 3.58MW for regulation up and 3.21MW for regulation down per GW of additional wind capacity [187]. Although these figures vary on monthly and diurnal cycles, for simplicity and without loss of formulation generality, this analysis takes them as constant.

Spinning/Net Load Following Reserve

At the operational timescale of a few minutes, wind uncertainty combines with load uncertainty and generator outages to produce stochastic variations in net demand. Wind has three primary reserve drivers in this timeframe, two related to forecast errors (uncertainty) and a third that captures the increased ramping (dynamics) even with perfect forecasting. In practice, the reserve requirements procured in the ancillary service market can be reduced through the routine operations of short-term (5 minute) balancing markets; however, the hourly time step used

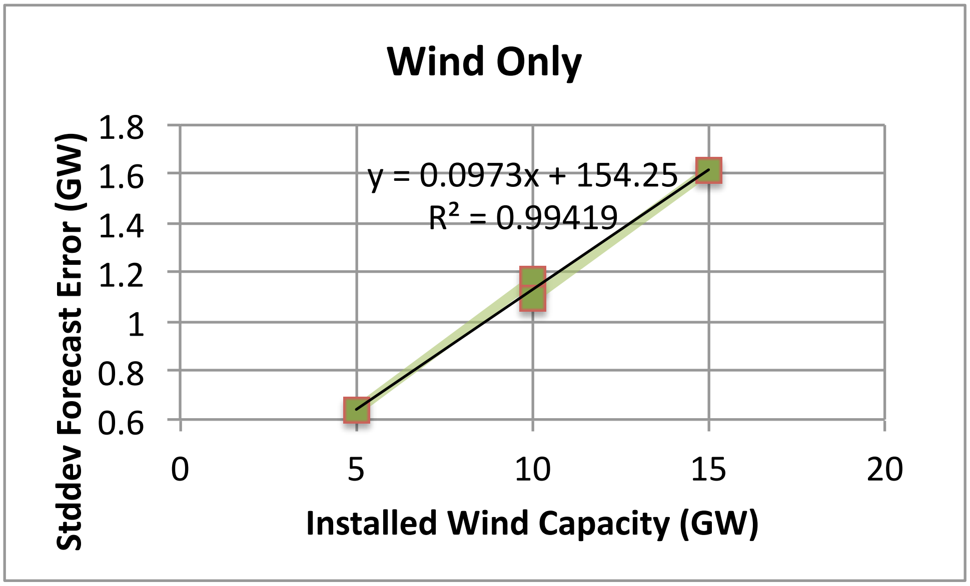


Figure 2.2: Variation in average wind forecast error for ERCOT showing the linear relation between standard deviation and installed capacity. Data from [187]

in this analysis hides these details. Even if the economic transactions are settled in a balancing market, the commitment generation mix still must have sufficient operational flexibility to meet the associated output changes. As a result, this analysis requires the full forecast error and 10-minute dynamics be met with reserves.

FORECAST ERROR AS A FUNCTION OF WIND CAPACITY Conceptually the purpose of reserves is to keep the probability of an under (or over) generation event low. Doherty & O'Malley [188, 189] make this probabilistic connection explicit by pointing out that the standard deviation, σ, of variability at the corresponding timescale provides a good starting point for reserve calculations. If the distributions are (approximately) Gaussian, a value of 3σ corresponds to a 99.7% of the variability. In practice, a range of 2-5σ has been used in studies [190]. As seen in Figure 2.2, the same GE Energy report on wind on ancillary services in ERCOT [187] describes a linear relation between the standard deviation of wind forecast error σ_{wind} and installed wind capacity. However, the relevant uncertainty for load following reserves also includes demand forecast errors. If wind and load are assumed to be uncor-

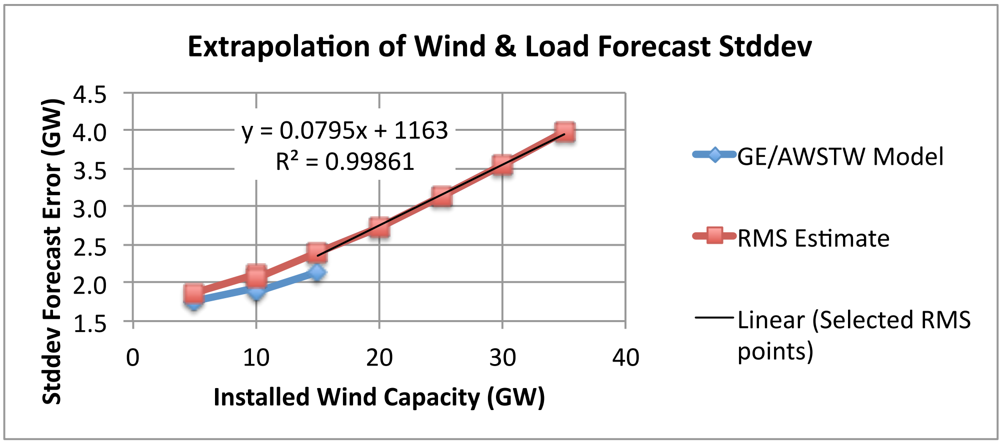


Figure 2.3: Extrapolation of combined wind & load forecast standard deviation, σ_{total}, showing near linear trend for higher wind penetration levels. Load following reserve requirements can be estimated based on the desired multiple of σ.

related, their combined variances, σ^2, can be added resulting in the following relation for the combined standard deviation [190]:

$$\sigma_{total} = \sqrt{\sigma_{load}^2 + \sigma_{wind}^2} \tag{2.27}$$

This assumption is consistent with the very low correlation between wind and load observed in ERCOT [187]. Using the reported standard deviation for load-only forecast of 1755MW and assuming that the standard deviation of wind follows a linear function of installed capacity described above, it is possible to extrapolate the combined standard deviation as a function of installed wind capacity beyond the 5 to 15GW range studied in the GE Energy report.[8] As seen in Figure 2.3, for higher penetrations of wind, the combined standard deviation, σ_{total} becomes dominated by the wind component and can be reasonably approximated with another linear fit. For comparison, the "actual" standard deviation for combined wind and load from the GE simulations is also shown. Note that an installed wind capacity of 24GW corresponds to a 20% energy penetration of wind at 2008 demand levels. Also, even though it only corresponds to a single standard deviation, 1 σ, the intercept value of 1163MW

8 Note I have some trepidation about such large extrapolations, but without better data for higher wind penetrations, they are used here as an illustrative placeholder.

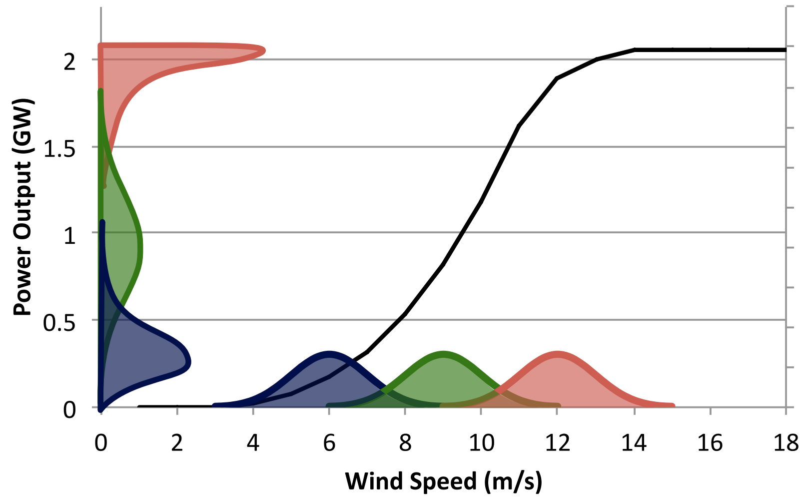


Figure 2.4: Conceptual relation between wind speed forecast error distributions (normal) and corresponding wind power error distributions (skewed) due to the highly non-linear wind turbine production curve. Enercon E-82 production curve [192] shown in solid black. Based on [191] figure 2.1.

represents 3.3% of the average load for 2008, a value consistent with the 2006 CAISO data (4%) and WECC rule of thumb (3%) described above. In this analysis, this linear fit is combined with the estimate of forecast uncertainty as a function of power described below to capture the reserve requirements as a function of wind capacity and load.

FORECAST ERROR AS A FUNCTION OF WIND POWER The (in)accuracy of wind forecasts, and hence requirements for reserves, are also known to be a function of the wind power. As described by Pinson, et al. [191] the forecast error for wind *speed* tends to be normally distributed, but because wind power increases with the cube of windspeed, the resulting distributions of wind *power* forecast error are no longer normal. As shown in Figure 2.4, the relation is further complicated by actual wind turbine production curves that level-off at the maximum capacity of the generator equipment at high wind speeds. Using this idea and the publicly available production curves for an Enercon E-82 2GW wind turbine [192], I estimated the 80% confidence interval of wind speed forecast errors assuming wind speed errors are normally

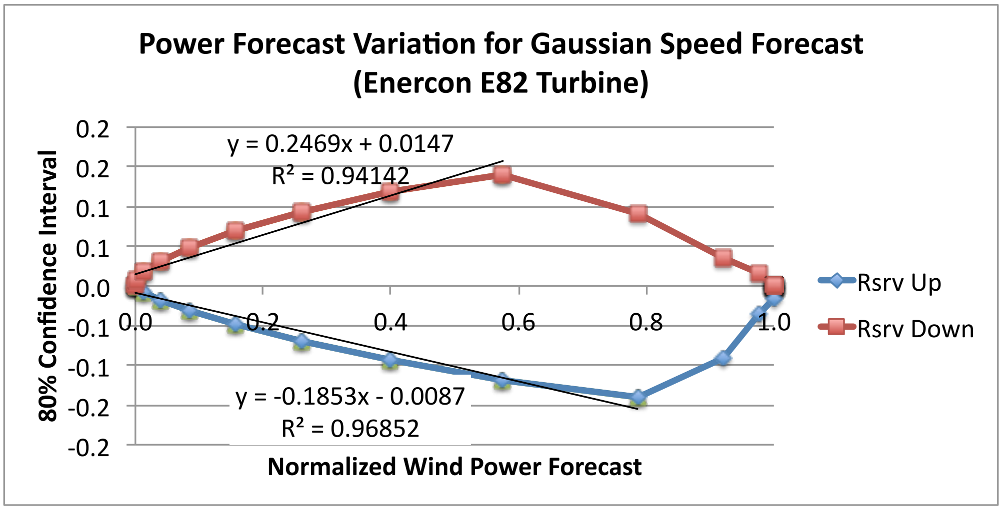


Figure 2.5: Eighty percent (80%) confidence interval for wind power forecasts showing asymmetry due to non-linear production function and near linear fits for lower output forecasts.

distributed with mean zero and standard deviation of 0.5m/s. As seen in Figure 2.5, the up and down forecast errors are not symmetric, but can be separately fit to a linear approximation for forecasts up to about 80% of the turbine rating. I assume a similar relationship holds for a collection of wind farms rather than a single turbine to approximate the forecast component of reserve up requirements. The limited range (0-80% power) of this approximation is partially justified by the observation that the ERCOT system-wide wind production from 2007-2010 was always below 80% of the installed capacity (Historic data from [193] and similar). This is a conservative estimate, since individual turbines may frequently operate near 100% outputs, even though the aggregated wind production never exceeds 80%.

10-MINUTE WIND RAMP DYNAMICS Since the uncertainty requirements of the reserve down service can be provided by curtailing wind if required, the load following reserve requirement is based on the less stringent 10-min ramping dynamics assuming a perfect forecast. The capacity normalized average standard deviation of 10-minute step power changes from 2006-2009 as reported by Wan [194] is $\sigma_{wind_{10min}} = 0.709\%$, which, assuming a normal distribution of changes provides a 99.5% confidence interval (2.8σ) with

2% of wind capacity for reserves. This value is used for reserve down requirements.

2.6.3 *Reserve Capabilities*

A generation unit's maximum ramp rate largely determines its ability to provide reserves, with each class of reserve having an associated ramp duration. Spinning reserves must reach full deployment in under 10min, and hence a generators spinning reserve capability is based on its maximum 10min ramp rate [177]. The faster regulating reserves are computed differently. Although regulation is designed to deal with ~1min variations, longer period ramp rates from 5-15min are used in practice [195]. This implies that the total cumulative excursions for regulation are larger than the minute-to-minute variations. However, independent of ramp rate, not all types of generation are capable of providing reserves. For example, current US nuclear reactors and renewable generation are not capable of providing reserves, though technically both could be configured to do so, albeit with a decrease in efficiency and increase in up-front costs.

2.6.4 *Summary of Reserve Assumptions*

Although the test system used in this thesis is loosely based on ERCOT, for the sake of simplicity and data availability, some reserve assumptions are adopted from CAISO, PJM, and WECC as described in Table 2.2.

The Reserve capabilities of generators are provided in Table 2.3

2.7 CLUSTERED PRODUCTION COSTING

2.7.1 *Introduction*

Because the simulation time horizon extends beyond weeks to as much as a full year (8760 hours), production costing and a number of mid-term considerations become important. Again, clustering can simplify model formulation. As described in section Section 1.5.1 this thesis only considers maintenance scheduling. Extensions for hydro scheduling, reserve deployment and other considerations are left for future work.

Table 2.2: Reserve requirements used in this thesis

Type	Requirement	Source
Reg. Up	1% of load + 3.58MW/GWwind	PJM guideline [177] + ERCOT annual avg. for wind [187]
Reg. Down	1% of load + 3.21MW/GWwind	
Outage	2.3 GW	Loss of two largest generators [187]
Net Load Up	3.3% of load + 7.95% wind capacity + 13.9% wind power	See discussion.
Net Load Down	3.3% of load + 2% of wind capacity	See discussion.
QuickStart	50% of Secondary can be met by off-line	WECC guideline [177]
Replacement	1.28 GW	Replacement reserves for largest generator

Table 2.3: Basis for reserve capabilities of generators

Type	Actual Duration	Ramp Rate Basis
Regulation	1sec-1min	5min
Spinning/Load-follow	10min-2hr	10min
Quick Start	10min	Only NG-GT Aero & Internal Combustion

2.7.2 *Hierarchical time indices*

Dividing the operating time period into a hierarchy of time periods - such as years, weeks, hours – can make the model more efficient in two ways:

1. Enabling a reduced number of time periods (e.g., 14 weeks to represent a year) while still maintaining high temporal resolution (hourly), and

2. Simplifying the formulation of mid-term decisions for production costing by limiting the decision domain to mid- or high-level time dimensions. (e.g. decide maintenance at a weekly resolution)

Mathematically, this simply requires expanding the indexing for all time varying variables and parameters to include not only time periods (e.g., hours) with subscript t, but also time blocks (e.g., weeks) indexed with, b. For example the objective function (2.1) becomes

$$C^{\mathsf{total}} = \min \sum_{\hat{g} \in \boldsymbol{G}} \sum_{b \in \mathbf{B}} l_b^{duration} \sum_{t \in \boldsymbol{T}} \left(C^{\mathsf{var}}_{\hat{g},b,t} + C^{\mathsf{start}}_{\hat{g},b,t} \right) \tag{2.28}$$

where the block duration (in weeks), $l_b^{duration}$, recognizes that time blocks, b, may be scaled to represent multiple weeks and enable representative seasonal, monthly, etc. blocks to replace an entire annual sequence of (e.g. hourly) subperiods. For intra-period constraints such as unit commitment state, ramping, and minimum up and down time constraints, the wrap-around commitment assumption described in section 2.4.6 applies to each time block.

2.7.3 *Maintenance Scheduling*

The full generator maintenance scheduling problem considers a large number of constraints on both power system reliability and maintenance logistics - such as work crew availability, probabilistic generator outages, shared fuel constraints, etc. - and quickly becomes a challenging optimization problem in itself [54]. To balance tractability and accuracy, I use a simplified formulation to capture the most important constraints as described below. As with unit commitment, clustering enables replacing individual maintenance decisions and schedules for each unit with a decision on the number of units in each cluster under maintenance for each time block. The clustered maintenance scheduling formulation includes:

UNIT AVAILABILITY A unit on scheduled maintenance is not available for commitment/dispatch. Conceptually this introduces a additional limit to the committed number of units for each cluster as seen in Figure 2.6.
Mathematically this becomes:

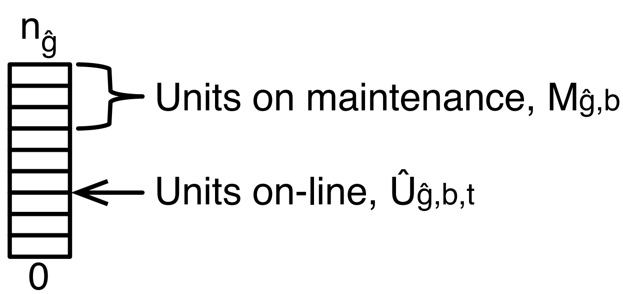


Figure 2.6: Conceptual diagram of clustered maintenance for a single type of unit in a single time block.

$$0 \leq \hat{U}_{\hat{g},b,t} \leq n_{\hat{g}} - M_{\hat{g},b} \tag{2.29}$$

where $M_{\hat{g},b}$ represents the number of units within the cluster under going maintenance in time block, b.

MAINTENANCE SUFFICIENCY ensures that each unit undergoes the required maintenance by ensuring the sum-product of block duration, $l_b^{duration}$, and units on maintenance, $M_{\hat{g},b}$ meet or exceed the annual maintenance required per unit, $a_{\hat{g}}^{maint}$, times the number units in the cluster, $n_{\hat{g}}$:

$$\sum_{b \in \mathcal{B}} M_{\hat{g},b} l_b^{duration} \geq a_{\hat{g}}^{maint} n_{\hat{g}} \tag{2.30}$$

where the block duration (in weeks), $l_b^{duration}$, recognizes that taking a unit down for maintenance during block, b, may allow for more than a single week of maintenance. For example, if a type of generation requires two weeks of annual maintenance per unit ($a_g^{maint} = 2$), a four week time block - or a representative week from a 4 week month - ($l_b^{duration} = 4$) can support the back-to-back maintenance of two of the units in the cluster while only keeping a single unit off-line at any given time ($M_{\hat{g},b} = 1$).

MAINTENANCE COST updates the objective function, 2.28, with an additional maintenance term:

$$C^{\text{total}} = \min \sum_{\hat{g} \in \boldsymbol{G}} \sum_{b \in \mathbf{B}} \left[C^{\text{maint}}_{\hat{g},b} + l_b^{duration} \sum_{t \in \boldsymbol{T}} \left(C^{\text{var}}_{\hat{g},b,t} + C^{\text{start}}_{\hat{g},b,t} \right) \right] \tag{2.31}$$

where the maintenance cost, $C^{\text{maint}}_{\hat{g},b}$ for each technology cluster, $\hat{g}$, for time block, b, is given by

$$C^{\text{maint}}_{\hat{g},b} = M_{\hat{g},b} \frac{c_{\hat{g}}^{fixO\&M} a_{\hat{g}}^{MaintFractOfO\&M}}{a_{\hat{g}}^{maint}} l_b^{duration} \tag{2.32}$$

CONTIGUOUS MAINTENANCE ensures that once a unit begins scheduled maintenance, it remains off-line until the maintenance is complete. This constraint is analogous to the minimum up time constraint from unit commitment and may be captured similarly using both 1) a maintenance state equation:

$$M_{\hat{g},b} = M_{\hat{g},b-1} + M_{\hat{g},b}^{begin} - M_{\hat{g},b}^{end} \tag{2.33}$$

$$with \quad M_{\hat{g},b}, M_{\hat{g},b}^{begin}, M_{\hat{g},b}^{end} \in \{0, 1, \cdots, n_{\hat{g}}\} \tag{2.34}$$

Where $M_{\hat{g},b}^{begin}$ and $M_{\hat{g},b}^{end}$ represent the number of units in the cluster that begin and end maintenance respectively in time block b. And 2) a minimum maintenance duration constraint:

$$M_{\hat{g},b} \geq \sum_{b - a_{\hat{g}}^{maint} \leq \beta \leq b} M_{\hat{g},\beta}^{begin} \tag{2.35}$$

As with commitment states, all three of the maintenance state variables are constrained to take integer values for improved performance (see discussion under Startup and Shutdown Events on page 67).

CREW LIMITS recognize that there are a finite number of maintenance crews and equipment capable of maintaining each plant type. As a result, only a fraction, $w_{\hat{g}}^{maintfract}$ of each facility type can undergo maintenance at a time:

$$M_{\hat{g},b} < w_{\hat{g}}^{maintfract} n_{\hat{g}} \tag{2.36}$$

2.8 TRADITIONAL CAPACITY PLANNING

2.8.1 *Basic Generation Expansion Planning*

This section describes the generation expansion problem and the traditional formulation used. Centralized generation expansion planning attempts to minimize the total lifecycle cost of the entire generation fleet while still maintaining sufficient capacity to reliably supply the demand. These costs are a combination of investment plus discounted operations costs. Traditionally, unit commitment constraints are ignored and for a given capacity mix, the facilities with the lowest operating costs are used first. This simple operations model is sometimes called "merit order" or economic dispatch based operations costs.

For a single decision period, this generation expansion problem with simple operations can be solved graphically using "screening curves" [74]. These curves illustrate how a mix of generation types provides the lowest total cost for meeting a non-constant demand. Specifically, expensive to build and cheap to operate "baseload" facilities run most to all of the time, while less capital intensive, but more expensive to operate, "intermediate" and "peaker" plants run only during higher demand periods. In a screening curve analysis each generator's costs are plotted as straight lines of total annualized cost versus number of operating hours. Each line has a slope equal to the sum of variable operating costs, c_g^{var}, and intercept equal to the sum of fixed costs (annualized investment, O&M, etc.), c_g^{fix}. The intersection of these lines for different technologies correspond to the transition points where it is more cost effective to use a higher fixed cost generator due to savings in operating costs. These intersections are then projected onto a cumulative distribution function of demand, or "load duration curve," to determine the optimal capacity investment as illustrated in Figure 2.7. Although significantly more sophisticated formulations looking at reliability, multiple time-periods, multi-criteria objectives, etc. have been developed, the humble load duration curve (or its numeric equivalent) remains at the heart of most large capacity planning models including

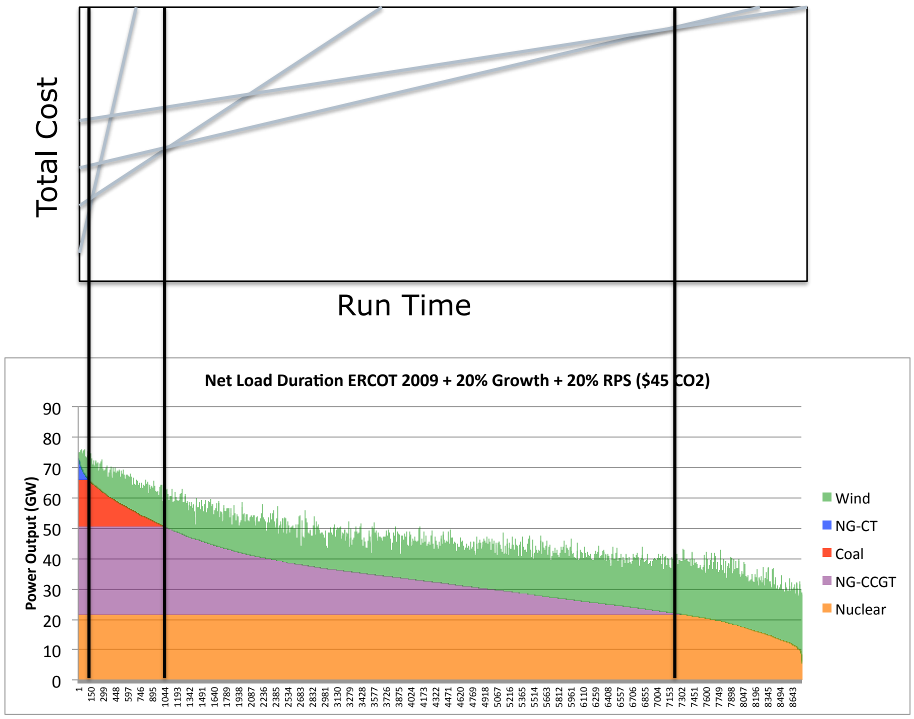


Figure 2.7: Example of Screening Curve Approach to Capacity Planning

MARKAL [66], EGEAS [100], etc. that despite having been initially developed 30 years ago, have updated versions that are still considered state-of-the-art and remain in active use today [102, 70, 196].

The same results can be obtained using a Linear Program (LP), which is easier to extend to include additional operating constraints. The simplest form of the objective function for the LP formulation is:

$$C^{\text{total}} = \min \sum_{g \in \mathbf{G}} \left(I_g c_g^{fix} + \sum_{t \in \mathbf{T}} P_{g,t} c_g^{var} \right) \tag{2.37}$$

Where I_g represents the capacity investment and, as before, $P_{g,t}$, is the power output of generator, g, in time period, t. This simple optimization is subject to generator output constraints:

$$0 \leq P_{g,t} \leq I_g \quad \forall t \in \boldsymbol{T}, g \in \mathbf{G} \tag{2.38}$$

which limit production to be less than the installed capacity. It is also subject to a requirement to meet the demand through a system balance constraint, which is identical to that from unit commitment (2.7). This equation is duplicated here for completeness:

$$\sum_{g \in \boldsymbol{G}} P_{g,t} = L_t \quad \forall t \in \boldsymbol{T}$$

2.8.2 *Annualized Capital Cost*

Generation facilities are highly capital intensive and require decades of operation to amortize the total investment. They are typically financed through a combination of debt and equity that translates into a percentage weighted effective interest rate known as the Weighted Average Cost of Capital (WACC). For single period capacity planning, capital costs are annualized using a capital recovery factor [74] that captures the capital costs and interest payments over the economic lifetime, a_g^{life}, of the facility:

$$a_g^{CRF} = \frac{WACC}{1 - \left(\frac{1}{1+WACC}\right)^{a_g^{life}}} \tag{2.39}$$

This enables computing fixed cost as a function of its components using:

$$c_g^{fix} = a_g^{CRF} c_g^{capital} + c_g^{fixO\&M} \tag{2.40}$$

2.8.3 *Availability, Derating, Firm Capacity and Planning Reserves*

Derating

Simply because a GW of capacity is built does not mean it will be available to meet demand. For example, in the unit commitment discussion above, some generating capacity is held in reserve to accommodate unexpected changes in the load, generator output or outages. In addition, large centralized plants may be unavailable due to maintenance or unforeseen breakdowns known as "forced outages." For these reasons, simplified capacity planning typically "derates" the production of facilities by replacing (2.38) with:

$$0 \leq P_{g,t} \leq I_g a_g^{derate} \quad \forall t \in \boldsymbol{T}, g \in \mathbf{G} \tag{2.41}$$

Below, I will incorporate these constraints using an integrated unit commitment and capacity planning model, such that derating will no longer be necessary.

Planning Reserve Margin

Of particular concern is the availability of a generation mix to meet demand with minimal loss of load. Probabilistic methods exist for planning based on reliability metrics such as Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE); but, the simplest approach requires a "planning reserve," $a^{PlanReserve}$, of "firm" capacity to be built beyond that required by the peak demand:

$$\sum_{g\in\mathbf{G}} a_g^{firm} I_g \geq (1 + a^{PlanReserve}) \max_{t\in\mathbf{T}} L_t \tag{2.42}$$

The planning reserve accounts for both the peak period operating reserve requirements and uncertainty in load growth projections. The firm capacity ratio, a_g^{firm}, represents the fraction of installed capacity that can be counted on to reliably provide energy during the peak. For thermal plants the firm capacity is taken as 100% minus the Effective Forced Outage Rate (EFOR). Conceptually, firm capacity is similar to derating in that both adjust the installed capacity to account for times the unit is not available. The difference is that derating considers the average unavailability throughout the year, including planned (maintenance) and unplanned outages, and reserve provisions. But since planned maintenance is typically not scheduled during the peak, firm capacity is typically higher.

Variable Renewable Availability

For most variable renewables - e.g. wind or solar PV - even centralized facilities are composed of a large number of small units - wind turbines or solar arrays. As a result, maintenance and forced outages - which occur at the individual unit level - only take a small fraction of generation off-line at any time. However, variability of the renewable resource limits the power generation potential at each hour based on the "availability" of the renewable resource. This updates the power limit (2.38) for renewables to

$$0 \leq P_{g,t} \leq I_g a_g^{avail}(t) \quad \forall t \in \boldsymbol{T}, g \in \mathbf{G}^{\mathbf{renew}} \tag{2.43}$$

For firm capacity, the probabilistic nature of resource availability coincident with the peak must be considered when computing the planning margin. There has been considerable research into methods for estimating this "capacity credit" for wind and other renewables. See the excellent pair of reviews by Milligan and Porter [197, 198]. These values are highly dependent on the existing generation mix and the correlation between renewable output and load. In this analysis the capacity credit for wind is taken as 10.5%, based on the average of two recent studies of the Effective Load Carrying Capacity (ELCC) for wind in ERCOT [199].[9]

2.8.4 *Additional Planning Constraints*

A number of additional long-term capacity planning considerations are sometimes included:

EXISTING GENERATION is readily included without any formulation changes by allowing I_g to capture the total installed capacity for each generator type:

$$\begin{aligned} I_g &= I_g^{exist} + I_g^{new} \\ with \quad & I_g^{exist}, I_g^{new} \geq 0 \end{aligned} \tag{2.44}$$

RETIREMENT is captured by updating (2.44) to include the retirement of a simple fraction of existing generation:

$$I_g = (1 - a_g^{retire}) I_g^{exist} + I_g^{new} \tag{2.45}$$

RENEWABLE PORTFOLIO STANDARDS (RPS) require that a minimum fraction of generation, a^{RPS}, must come from renewable energy sources:

$$\sum_{g \in \mathbf{G}^{renew}} \sum_{t \in \mathbf{T}} 1 \cdot P_{g,t} \geq a^{RPS} \sum_{g \in \mathbf{G}} \sum_{t \in \mathbf{T}} 1 \cdot P_{g,t} \tag{2.46}$$

9 The capacity credit for wind is a function of wind capacity and is both controversial and system specific. ELCC is the preferred method [200], but this metric depends on both the other generation on the system and the correlation of wind and load. The most recent ERCOT study (2010) found a wind capacity credit of 12.2%, while the older (2007) study found only 8.7% using similar methods. Both results are reported in [199]. However, the controversial nature was underscored by votes of both the ERCOT Board and Technical Advisory Committee to continue using the old value (8.7%) until a more detailed analysis could be conducted.

In this relation, the set, $\mathbf{G}^{renew}$, only includes renewable sources such as wind, solar, etc. The factor 1 recognizes the need for unit scaling from units of power (e.g. GW) to energy (e.g. GWh). With hourly time periods and $P_{g,t}$ defined to express the average power output per time period, only a unity conversion factor is required.

DISCRETE UNITS The traditional expansion planning model assumes continuous capacity investment decisions; however, it is not possible to construct arbitrary capacity for each generation type. Instead, facilities consist of a number of discrete generating units each with a discrete size determined by the prime mover and fuel type. Although a small range of off-the-shelf options exist for each unit type, for simplicity, this analysis assumes a single representative unit size for each type of new generation unit, thereby requiring investment decisions to take discrete values:

$$I_g^{new} \in \{0, a_g^{size}, 2a_g^{size}, \cdots, n_g^{max} a_g^{size}\} \tag{2.47}$$

This naturally leads to clustering in the capacity planning model, and enables integrating unit commitment and operations as described in the next section.

2.9 CLUSTERED EXPANSION PLANNING

A key contribution... is using clustering to directly... integrate unit commitment operations into capacity expansion optimization models

Although clustering provides considerable performance improvements for long-term unit commitment optimization, perhaps its greatest advantage is for capacity planning with integrated flexibility analysis. As described in the INTRODUCTION, such analyses in the past have relied on either highly simplified models or a two-step approach where investments were first optimized using simple operations and later analyzed using sophisticated production cost tools. A key contribution of this thesis is using clustering to directly and tractably integrate unit commitment operations into capacity expansion optimization models.

Conceptually, this adds a third clustered variable that captures investment decisions to the clustered combination of unit commitment and maintenance as seen in Figure 2.8.

Mathematically this updates the clustering relation (2.29) to include the number of units actually built:

$$0 \le \hat{U}_{\hat{g},b,t} \le N_{\hat{g}} - M_{\hat{g},b} \le N_{\hat{g}} \le n_{\hat{g}}^{max} \tag{2.48}$$

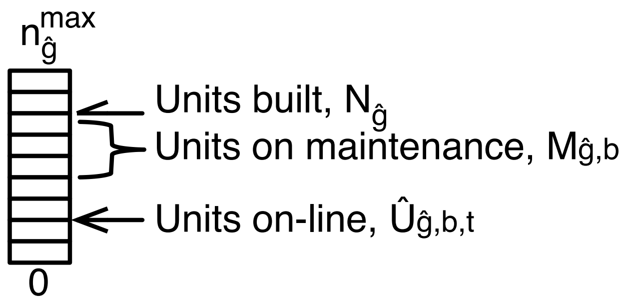


Figure 2.8: Conceptual diagram of clustered capacity planning with integrated unit commitment and maintenance for a single type of unit in a single time block.

where the number of units built for each cluster, $N_{\hat{g}}$, relates to clustered capacity investment decisions, $I_{\hat{g}}$, via the representative plant size, a_g^{size}:

$$N_{\hat{g}} = \frac{I_{\hat{g}}}{a_{\hat{g}}^{size}} \tag{2.49}$$

The combined objective function integrates the capacity planning objective (2.37) with that from the combined maintenance/unit commitment (2.31) to give:

$$C^{\text{total}} = \min \sum_{\hat{g} \in \boldsymbol{G}} \left(N_{\hat{g}} a_{\hat{g}}^{size} + \sum_{b \in \mathbf{B}} \left[C_{\hat{g},b}^{\text{maint}} + l_b^{duration} \sum_{t \in \boldsymbol{T}} \left(C_{\hat{g},b,t}^{\text{var}} + C_{\hat{g},b,t}^{\text{start}} \right) \right] \right) \tag{2.50}$$

Since all three components of this combined model - unit commitment, maintenance, and capacity planning - were developed above using clustering, minimal additional changes are required. The only required changes are to correct for the accounting of maximum units in minimum down time replacing (2.25) with:

$$\left(N_{\hat{g}} - M_{\hat{g},b}\right) - \hat{U}_{\hat{g},t} \geq \sum_{\tau = t - m_{\hat{g}}^{mindown}}^{t} \hat{D}_{\hat{g},\tau} \tag{2.51}$$

and tertiary reserve capabilities replacing (2.26) with:

$$R_{\hat{g},t}^{\text{tertiary}} \leq \left[\left(N_{\hat{g}} - M_{\hat{g},b}\right) -_{\hat{g}} - \hat{U}_{\hat{g},t}\right] a_{\hat{g}}^{\text{quickstart}} p_{\hat{g}}^{\text{max}} \tag{2.52}$$

2.10 ADDITIONAL RELATIONS

2.10.1 *Carbon Policy*

Simplified representation of the two primary types of carbon policies under consideration, taxes and caps, are included by computing the quantity of carbon dioxide equivalent emissions, $Q_f^{CO_{2eq}}$, for each fuel type, f, by multiplying the fuel-specific emissions rate, $a_f^{CO_2 rate}$, by the sum of fuel use in operation and fuel use for startup by generator for each time period, t, in each time block, b, scaled by block duration, $l_b^{duration}$:

$$Q_f^{CO_{2eq}} = a_f^{CO_2 rate} \sum_{g:f=a_g^{fuel}} \sum_{b \in \mathbf{B}} l_b^{duration} \sum_{t \in \mathbf{T}} \left(\mathrm{F}_{g,b,t}(P_{g,b,t}) + S_{g,b,t} f_g^{\mathsf{start}} \right) \tag{2.53}$$

This quantity can then be limited to enforce a sector-wide carbon cap, $q_{max}^{CO_{2eq}}$:

$$\sum_{f \in \mathbf{F}} Q_f^{CO_{2eq}} \leq q_{max}^{CO_{2eq}} \tag{2.54}$$

and/or added to the objective function to compute carbon tax costs as described in Section 2.10.3.

2.10.2 *Penalty Functions*

Penalty functions provide an alternative to some of the energy and reserve related constraints by allowing violations of the constraints at relatively high costs to more realistically capture the market and regulatory structure of modern power systems. The costs must be set high enough that violations are reserved for rare or extreme events. The added costs are included in the updated objective function described in Section 2.10.3. Each penalty function also updates a constraint as follows:

NON-SERVED ENERGY allows shedding some load if more economic than investing in additional capacity. This updates the system balance equation (2.7) to allow non-served energy, $E_t^{nonServe}$:

$$\sum_{g \in \boldsymbol{G}} 1 \cdot P_{g,b,t} + E_{b,t}^{nonServe} = 1 \cdot L_{b,t} \quad \forall t \in \boldsymbol{T}, b \in \mathbf{B} \tag{2.55}$$

In this relation, the factor 1 recognizes the need for unit scaling from units of power (e.g. GW) to energy (e.g. GWh). With hourly time periods and $P_{g,t}$ defined to express the average power output per time period, only a unity conversion factor is required.

UNMET (PLANNING) RESERVES provides an economic alternative to the planning reserves by expanding (2.42) to include unmet reserves, R^{unmet}:

$$\sum_{g\in\mathbf{G}} a_g^{firm} I_g + R^{unmet} \geq \left(1 + a^{PlanReserve}\right) \max_{b\in\mathbf{B},t\in\mathbf{T}} L_{b,t} \tag{2.56}$$

RPS NON-COMPLIANCE mimics the actual design of many Renewable Portfolio Standard (RPS) regulations by providing a penalty for not meeting the standard [8]. This updates the RPS requirement (2.46) to include unmet renewable energy,$E^{rpsUnmet}$:

$$E^{rpsUnmet} + \sum_{g\in\mathbf{G}^{renew}} \sum_{b\in\mathbf{B}} \sum_{t\in\mathbf{T}} 1 \cdot P_{g,b,t} \geq a^{RPS} \sum_{g\in\mathbf{G}} \sum_{b\in\mathbf{B}} \sum_{t\in\mathbf{T}} 1 \cdot P_{g,b,t} \tag{2.57}$$

2.10.3 *Updated Objective Function*

To account for these additions the objective function must be updated to include penalty and carbon costs:

$$\begin{aligned} C^{\mathsf{total}} = \min \Bigg\{ & c^{CO_{2eq}} \sum_{f\in\mathbf{F}} Q_f^{CO_{2eq}} + c^{nonServe} \sum_{b\in\mathbf{B}} \sum_{t\in\mathbf{T}} E_{b,t}^{nonServe} \\ & + \sum_{\hat{g}\in\boldsymbol{G}} \left(N_{\hat{g}} a_{\hat{g}}^{size} + \sum_{b\in\mathbf{B}} \left[C_{\hat{g},b}^{\mathsf{maint}} + l_b^{duration} \sum_{t\in\boldsymbol{T}} \left(C_{\hat{g},b,t}^{\mathsf{var}} + C_{\hat{g},b,t}^{\mathsf{start}} \right) \right] \right) \\ & + c^{planUnmet} R^{unmet} + c^{rpsUnmet} E^{rpsUnmet} \Bigg\} \end{aligned} \tag{2.58}$$

2.11 SOFTWARE IMPLEMENTATION

2.11.1 *Structure & Environment*

For this thesis, the author developed the Advanced Power family of models from scratch using the General Algebraic Modeling System (GAMS) [201]. Advanced Power is a modular suite of highly configurable models including UnitCommit for unit commitment and StaticCapPlan for capacity planning. The configurability comes from a combination of a rich set of command-line options, and the separation of data into include files distinct from the model files.

Each model consists of the core model, helper utilities, and a collection of "shared" model pieces. The files are structured to minimize duplication and share code (and hence enhancements, bug fixes, and documentation) as much as possible. For example, the UnitCommit model can either be used standalone for operations and production cost modeling or it can be called as the operations submodel by StaticCapPlan. Both models also share identical data sets, input functions and output reporting functions.

Command line options control pre-compile flags to use different data, model simplifications and solver configurations. For example, these options allow the same UnitCommit model to be used at a range of fidelity levels from simple economic dispatch up to full unit commitment production costing including startup, minimum up/down times, ramping, operating reserves, optimized maintenance, minimum output levels, piecewise linear fuel costs, and more. This same range of constraints can in-turn be used within capacity planning with StaticCapPlan since it relies on UnitCommit for operations. A complete listing of these model files is included in Appendix D.

The resulting problems are then solved using the state-of-the-art CPLEX 12.3[10] LP/MILP solver [202]. The high-performance barrier solver was used for all[11] LP, MIP root node relaxation, and MIP final solutions. In testing for this thesis (not reported) barrier provided generally faster, sometimes dramatically so, solutions to this class of problem. The solver was instructed to conserve memory when possible (memoryemphasis=1) to prevent out-of-memory errors for the large problems considered here. The LP tolerance (epopt) was tightened to 1e-9 to ensure that the final LP solve matches the MILP branch-and-cut solution. Except as noted, all model runs were conducted as a single thread running on a single 64-bit core (Intel Nehalem) at 2.67GHz clock speed. Up to 6-10 runs were run in parallel as sub-tasks of exclusive jobs on iden-

10 In some cases a different version of CPLEX is used. This variation are noted in the text.

11 As noted in the text, a few runs employed the parallel features of CPLEX. These runs used the default behavior of racing barrier against the dual and primal simplex solvers, using any spare cores for multi-threaded barrier and taking the fastest solution method.

tical 8-12core machines (keeping 2+ cores idle) with 24-48GB of shared RAM. Although run on a high performance cluster, the resulting resources allocated to each process are roughly equivalent to a modern personal computer.

2.11.2 *Additional Model Strategies*

The full integrated model formulation described above is included with some adjustments and extensions to streamline the software implementation. These adjustments are carefully selected to maintain identical solutions, while removing extraneous relations. Adjustments include:

SELECTIVE INTEGER RELAXATION to allow some or all of the integer constraints to relax and take on continuous variables. When all integers are relaxed (ignore_integer=1) the problem becomes a Relaxed Mixed Integer Linear Program (RMILP) directly solvable as an LP. This can greatly reduce computation times while still maintaining some aspects of the full unit commitment problem - notably capacity available for reserves - in ways not possible without commitment variables. As an in-between, only units with small, but non-zero, minimum output levels can use relaxed commitment variables (uc_int_unit_min > 0).

SUB-SETS to capture the fact that not all constraints are relevant for all generation units. For example, units with zero minimum output levels, $p_g^{min} = 0$, such as renewables, are typically not subject to unit commitment constraints (uc_ignore_int=0) because the optimal solution is equivalent to involve keeping them committed/on at all times (except for maintenance). This is because unlike most facilities which must consume fuel to run at a non-zero minimum output level, there is no operational cost penalty for zero minimum units to run all the time.

Subsets used in the formulation include $\mathbf{G}^{UC}$, generators subject to unit commitment; $\mathbf{G}^{UCint}$, generators subject to integer unit commitment; $\mathbf{G}^{rps}$, generators that contribute to the rps; $\mathbf{G}^{PWLcost}$, generators using piecewise-linear fuel usage functions; etc. In addition virtual subsets only create constraint equations for generation units that meet certain criteria. For example, minimum up time constraints are only considered for units with minimum up times greater than one hour.

MODULAR EQUATIONS to include only appropriate portions of equations such as the objective function and min/max output constraints. The additional terms introduced in these equations as the formulation unfolded in the discussion above exist inside conditional statements ($if and $ifthen) and only become active when required.

SCALING to improve numerical performance of the solver by presenting relations closer to 1.0 in magnitude. In general the model uses units of GW for power, capacity, and demand; TWh for energy; $million for costs; and Mt for emissions.

DATA CALCULATIONS manipulate the standardized data files for scaling, unit conversion, default values for generator parameters based on fuel type, etc. In particular, these calculations allow generator data specified in engineering terms such as fuel type, heatrate, emission rate, startup fuel use, variable operations and maintenance (O&M) costs, etc. to be mapped into variable costs, total emissions, and other factors as required.

SCENARIOS Although not used in this thesis, all of the model code includes an additional index in all parameters, variables, and equations to enable scenarios for multi-year and stochastic analysis. Mathematically this simply implies that all time period, t, and timeblock, b, indexed variables and relationships also have the scenario index, s. The scenario index enables stochastic unit commitment - by fixing commitment decisions across scenarios - and stochastic static planning - with fixed investments across scenarios - with no software changes. These capabilities are demonstrated in the StocUC and StocCapPlan models.

3 PERFORMANCE OF CLUSTERED UNIT COMMITMENT

3.1 OVERVIEW AND CONTRIBUTION

This chapter seeks to validate the clustering approach by comparing it to both traditional, full (binary) unit commitment and alternative simplification strategies. To do so, operations-only comparisons are made among binary, clustered, and alternative unit commitment optimization models. The chapter also explores the trade-off between accuracy and run-time for different levels of aggregation used in clustering[1]. For objective comparison, a set of performance metrics applicable to wide range of decision objectives are also introduced. In addition, the performance of the other simplifying long-term UC assumptions described in Section 2.5 are included in the comparison with and without clustering.

To the author's knowledge this is the first side-by-side comparison of clustering to full separate unit formulations for power systems, the first attempt to compare methodologies for aggregating units into clusters, and the first to compare clustering to other simplifying heuristics.

3.2 EXPERIMENTAL SETUP

3.2.1 *Metrics of comparison*

Unit commitment can be used to inform a range of policy and planning questions. Depending on the application, some solution outcomes may be more important than others. To provide results relevant to a range of applications, multiple comparison metrics are computed, one for each outcome of potential interest. In all cases, these metrics compare

1 In contrast to traditional separate unit formulations, clustering groups similar units into clusters and assigns an integer, rather than binary, commitment decision to the group. As described in more detail in Section 2.4, clustering allows capturing full unit commitment constraints – including ramping, start up costs, minimum output levels, piecewise linear fuel usage and minimum up and down times – at an individual unit level under the key assumption that all units within a cluster are identical.

experimental runs to the full traditional binary unit commitment formulation, indicated with subscript "baseline":

TOTAL COST is the objective function value for the optimization and includes all operations costs. For comparison, a scalar percent difference is computed using:

$$\Delta C^{total} = \frac{C^{total} - C^{total}_{baseline}}{C^{total}_{baseline}} \tag{3.1}$$

CO2E EMISSIONS: carbon dioxide (CO_2) equivalent emission are computed system-wide based on fuel usage for both power generation and startup. A scalar percent difference is computed in the same manner as total cost.

ENERGY MIX is based on total annual production by generator class divided in the same way as for clustering. The energy mix for each class is computed by summing the product of power output and duration for all time periods and dividing by the total system energy production:

$$\hat{E}^{fraction}_{\hat{g}} = \frac{\sum_{t \in \mathbf{T}} \hat{P}_{\hat{g},t} \cdot 1hr}{\sum_{\hat{g} \in \hat{\mathbf{G}}} \sum_{t \in \mathbf{T}} \hat{P}_{\hat{g},t} \cdot 1hr} \tag{3.2}$$

The mean absolute difference of this vector provides a scalar comparison metric:

$$\Delta E^{mix} = \underset{\hat{g} \in \mathbf{G}}{\text{mean}} \left| \hat{E}^{fraction}_{\hat{g}} - \hat{E}^{fraction}_{\hat{g}} \Big|_{baseline} \right| \tag{3.3}$$

COMMITMENT PLAN differences are first computed as an array of differences with one element for each time period for each group of units aggregated to the cluster level. Two scalar comparisons are then made: a) The total count of differences between plans, computed as the number of non-zero elements in this array and b) the normalized mean absolute difference where commitment difference values for each time are normalized based on the total number of units committed for that time period in the baseline:

$$\Delta U = \underset{\hat{g} \in \mathbf{G}, t \in \mathbf{T}}{\text{mean}} \left| \frac{\hat{U}_{\hat{g},t} - \hat{U}_{\hat{g},t}\big|_{baseline}}{\sum_{\hat{g} \in \mathbf{G}} \left(\hat{U}_{\hat{g},t}\big|_{baseline} \right)} \right| \tag{3.4}$$

HOURLY POWER OUTPUT differences are computed identically to commitment, except that for the count of differences, power levels are first rounded to the nearest 0.5MW.

COMPUTATION TIME is reported as total solver (CPLEX) run time and excludes model setup and output processing by GAMS.

3.2.2 *Implementation Notes*

As further described in Section 2.11, all runs were conducted with the highly configurable "UnitCommit" model from my Advanced Power toolset. UnitCommit is implemented in the General Algebraic Modeling System (GAMS) [201] and run using the state-of-the-art CPLEX 12.2[2] Linear Program (LP)/Mixed Integer Linear Program (MILP) solver [203].

These results are also based on a slightly older version of UnitCommit with the following formulation differences:

- The use of relaxed (non-integer) startup and shut-down variables, and
- Maintenance not included
- Different reserve requirements than those reported in Table 2.2. The exact values used are included in the corresponding test system description.

3.3 TEST SYSTEM #1: IEEE RELIABILITY TEST SYSTEM

3.3.1 *System description*

The Institute of Electrical and Electronics Engineers (IEEE) Reliability Test System (RTS) was initially defined in 1979 [204], updated in 1986 [205], and again in 1996 [206]. It includes detailed unit data for ten types of generators, with between one and six units of each type, to describe a basic system with 32 total units. The dataset includes tables for demand dynamics up to a full year at an hourly resolution.

This analysis uses the 1996 revision [206] for demand data and most unit data including heat rates, minimum up/down times, cycling, ramp-

2 Note: the use of a slightly older version of CPLEX in this chapter

ing, emissions, and startup fuel usage. For each unit, the baseline formulation uses a three segment piecewise linear fuel use function with intersections at each of the provided net heat rate data points. Unit cost data is only reported in the 1979 definition [204].

System reserve requirements were taken as 1% of the load for regulation up and down, and 2% of load for load following up and down plus spinning reserves equal to the largest single unit, 400MW. Quick start reserves are not used.

The system was simplified by ignoring transmission and assuming all units are located at a single node. The six hydro units were removed, leaving 26 units of eight different types. To compensate for the removed hydro, demand data was scaled uniformly by 92%, the annual ratio of hydro energy to total demand. Runs were conducted using data for the week of peak demand.

3.3.2 *Clustering Approach*

The inherent duplication of identical units in the IEEE RTS system provides straightforward clustering by grouping identical units. For perturbed runs, each unit's variable operations and maintenance costs are adjusted slightly (up to 0.01%).

3.3.3 *Results*

Mixed Integer Heuristics

As seen in Figure 3.1, most of the heuristics for streamlining similar MILP results can provide some computational speedup, but only clustering provides speed up in all cases. Clustering is also significantly more effective than the other techniques, providing 100-10,000 times faster performance than the next closest heuristic. In all cases, the aggregate errors are minimal: below 0.1% for most metrics, with the only exception of approximately 0.3% errors for separate units with a 0.1% relative cheat[3].

Unit Commitment Simplifications

As seen in Figure 3.2, most of the unit commitment simplifications also

3 "Cheat" refers to the ε-optimal MILP heuristic described in Section 2.2.4.

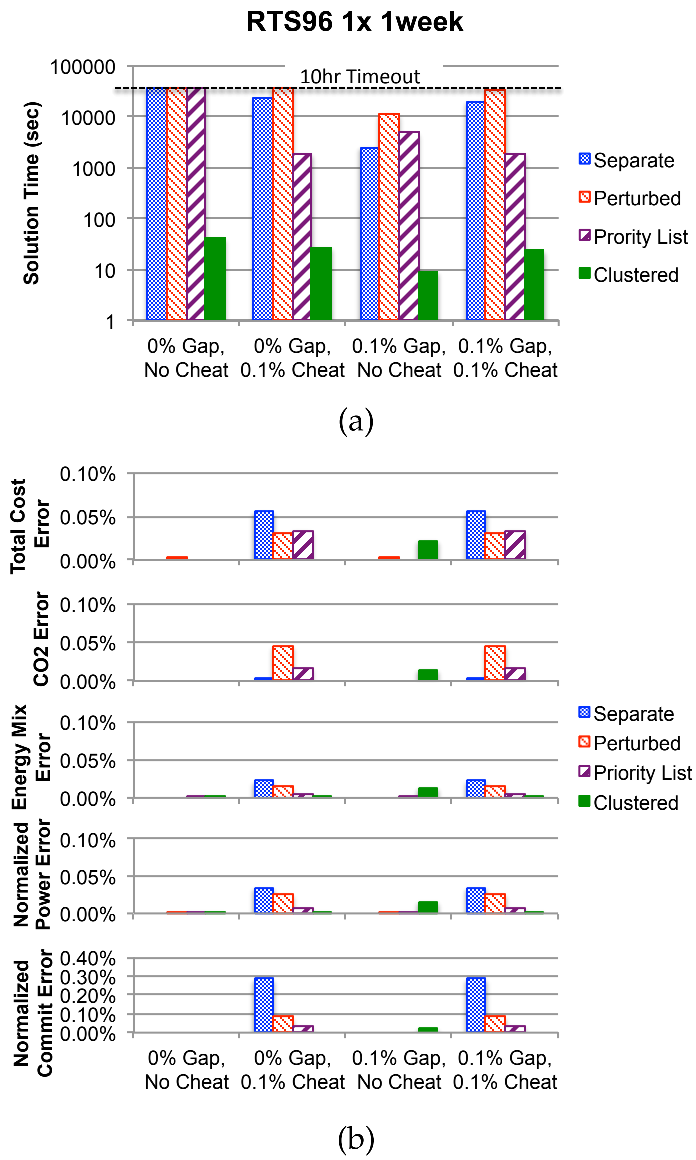
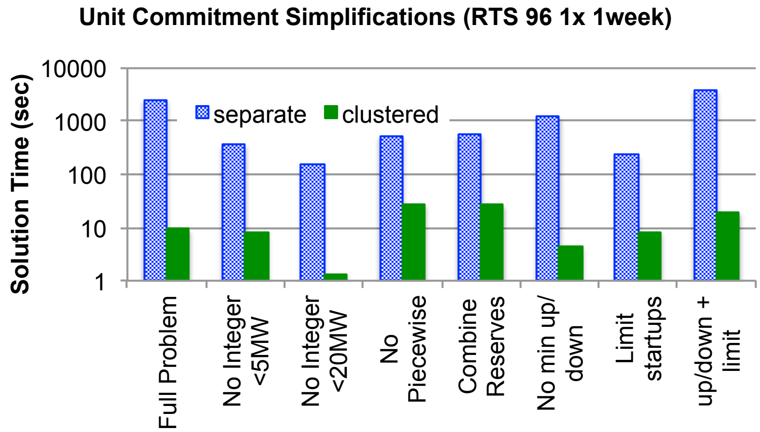
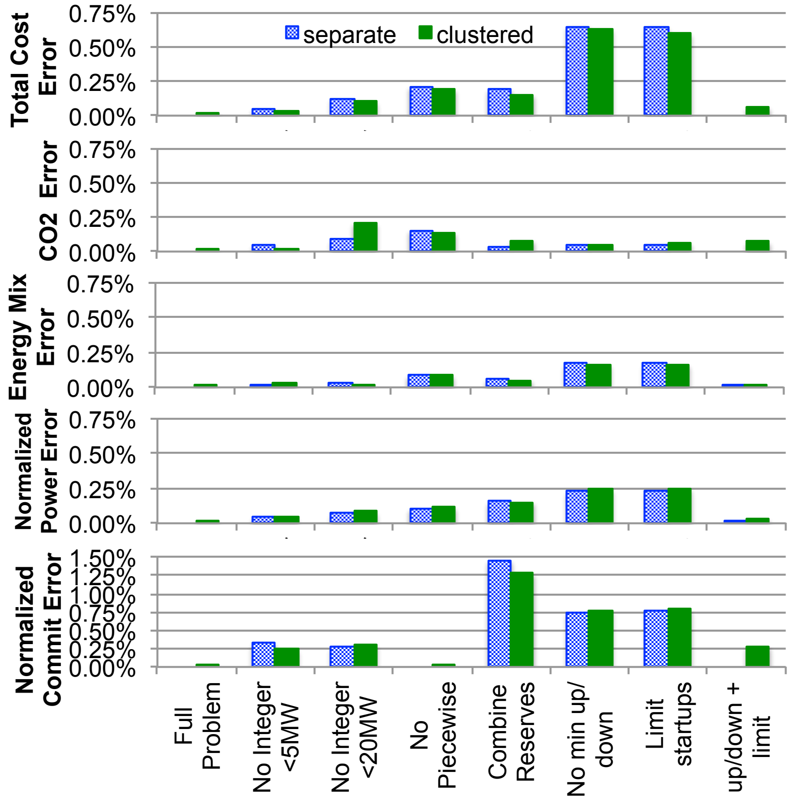


Figure 3.1: Mixed integer heuristic comparison for IEEE Reliability Test System 1996 (a) shows solver run times for different heuristic combinations (note logarithmic time axis). (b) Shows key error metrics. "Cheat" refers to the ε-optimal MILP heuristic described in Section 2.2.4. In all cases, the "Separate, 0% MIP gap, No Cheat" configuration was used as a baseline.



(a)



(b)

Figure 3.2: Unit Commitment simplification comparison for IEEE Reliability Test System 1996 (a) Shows solver run times for different simplifications. Note logarithmic time axis. And (b) shows key error metrics. In all cases, the full problem with separate units was used as a baseline. All runs used a MIP gap of 0.1% with ε or "cheat" set to 0 for the ε-optimal MILP heuristic.

provide some speed up to the problem, with reasonably small aggregate errors, but none are as effective as clustering alone, which is about 20 times faster than any other approximation technique. Furthermore, the combination of clustering with the other simplifications provided additional speed-ups of 20 to over 250 times, while still maintaining small errors. With all simplifications, the aggregate errors are all less than 1.5%, and most are below 0.25% with the exception of normalized commitment errors from 0.75% to 1.5% for combined reserves and runs without minimum up and down times. And total cost errors around 0.6% for runs without minimum up/down times.

Complete result tables for these and other figures, as well as additional run configurations are provided in Appendix B.

3.4 TEST SYSTEM #2: ERCOT

3.4.1 *System Description*

To test the impact of clustering on a more realistic system, the Electric Reliability Council of Texas (ERCOT) balancing area was modeled using hourly historic demand and wind data from 2007. This system includes the entire Texas Interconnect, which covers the majority of the state of Texas and has negligible power exchange with other systems. ERCOT had a 2007 peak load of 62GW [193] supplied by a total of 92.5GW of generation capacity from 672 units [207].

To simplify the problem, following unit types are ignored:

- Non-dispatchable combined heat and power facilities (15GW in 204 units)
- Hydro (an additional 0.5GW in 41 units)
- Units with uncommon fuel types (an additional 0.1GW in 72 units), and
- Units with less than 50MW nameplate capacity (1GW in 56units).

In addition, combined cycle facilities were modeled as 36 groups instead of 115 individual combustion and steam turbines. This resulted in a total of 205 units in our model system.

For wind, expansion during the year was ignored by assuming a fixed wind capacity equal to the final 2007 capacity of 3.7GW. Since

Table 3.1: Additional Reserve Assumptions used in this chapter (updated assumptions used in other chapters)

Reserve Type	Additional Quantity
Up for forecast	12.5% of wind power
Up for capacity	6.5% of wind capacity
Down for forecast	8.75% of wind power
Down for capacity	6.25% of wind capacity

wind shedding is allowed, the wind dispatch is treated as a decision variable, rather than using net Load Duration Curve (LDC). Hourly wind production was taken as this capacity times the actual percent production based on the installed capacity in each time period. Historic hourly wind production and demand data from 2007 was obtained from ERCOT [193].

The week of Saturday Mar 17, 2007 was used for 1-week (168hr) analyses. This week contains both the peak wind and minimum demand. Thirteen week data includes this peak week plus one week for each month.

Plant-level heat rate and unit nameplate (maximum) capacity data was taken from eGrid 2010 v1.1 [207], which contains 2007 emission and plant data. Since only average heat rate information is available in eGrid, piecewise linear fuel use functions are not used. Additional generator technical parameters were taken from the Sixth Northwest Power Plan appendix I [208] for corresponding plant types.

Fuel costs were based on EIA 2007 data for south central west electric power sector use [209]. Reserve requirements were taken as 1% of load for regulation up and down, 1350MW for spinning reserves, and 2% of load for load following up and down. As a simple proxy for additional reserves required for wind uncertainty, load following requirements were increased as a function of both installed capacity and wind production using the factors in [18]. These values are summarized in Up to 50% of the spinning reserve and load following up requirements can be met by quick start open cycle natural gas units.

Complete generator data tables are provided in Appendix A. Hourly demand and wind profile data is available by request from ERCOT. Based on the RTS results, these experiments used a 0.1% MIP gap and did not use the ε-optimal MILP heuristic. for all ERCOT runs and focus our comparisons on unit commitment simplifications.

Table 3.2: Problem Size and Runtimes For 1-week (168 Hr) ERCOT Operations

	Problem Size (before CPLEX pre-solve)					
Aggregation	clusters	equations	variables	discretes	non-zeros	Time (sec)
Separate	205	446,394	349,960	34,272	2,068,949	4517.2
By plant	90	197,922	151,048	14,952	943,685	435.3
By size	17	37,650	27,400	2,688	186,173	10.2
Full cluster	7	14,802	10,264	1,008	74,957	2.2

3.4.2 *Clustering Approach*

Units were clustered using the range of approaches as described in Section 2.4.4 and summarized below:

SEPARATE: no clustering used;

FULL CLUSTER: units are aggregated by type based on fuel and of prime-mover combination alone;

TYPE & ADDITIONAL CHARACTERISTIC: the following additional characteristics are used (one at a time) in addition to fuel/prime-mover combination:

- Unit size: nameplate capacity,
- Unit age: first year in service, and
- Unit efficiency: the heatrate of the units; and

BY PLANT: units of the same type are aggregated.

Appendix A provides complete details on clustering, including resulting cluster lists and cut-off ranges for size, age, and efficiency. Table 3.2 compares the resulting number of clusters and corresponding problem sizes and run times for each of clustering approaches. The problem size for each of the intermediate, type and additional characteristic, clusters matches that for "By size."

3.4.3 *Results*

Unit Commitment simplifications

As seen in Figure 3.3, the unit commitment simplifications provide

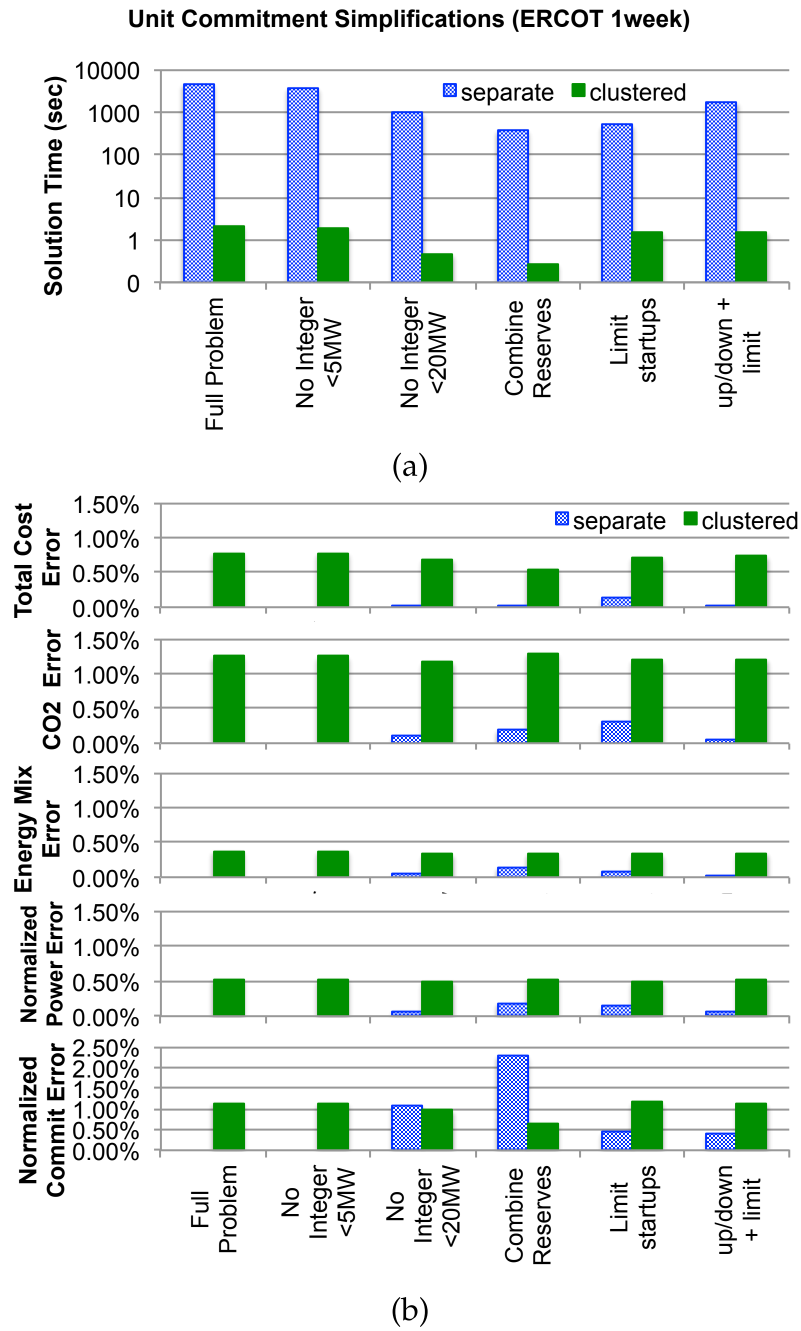


Figure 3.3: Unit Commitment simplification comparison for ERCOT 2007 (a) Shows solver run times for different simplifications. Note logarithmic time axis. And (b) shows key error metrics. The full problem with separate units was used as a baseline. All runs used a MIP gap of 0.1% without the ε-optimal heuristic.

some performance improvement, although less dramatically than for the RTS system. With separate units, combined reserves and constraining the number of startups - rather than using the minimum up and down time - provided the most significant speed-up of around 10 times faster calculation. But, as before, none of the simplifications were as effective as clustering alone, which was 200 times faster than any other simplification. In all cases, clustering further reduced computation time by a factor of between 350 to more than 2000.

Errors were still minimal, below 0.5% for separate units and near or below 1% for clusters. The only exception was with separate units and combined reserves where normalized commitment error rose to 2.3%. In contrast to the RTS system, the observed errors are larger with clustering, due to the heterogeneity of units with each cluster. This heterogeneity is also likely the cause of relatively large (~1.25%) errors in CO_2 emissions with full clustering. The CO_2 errors are notably reduced with less aggregated clustering (next section) and longer model periods (see Appendix B).

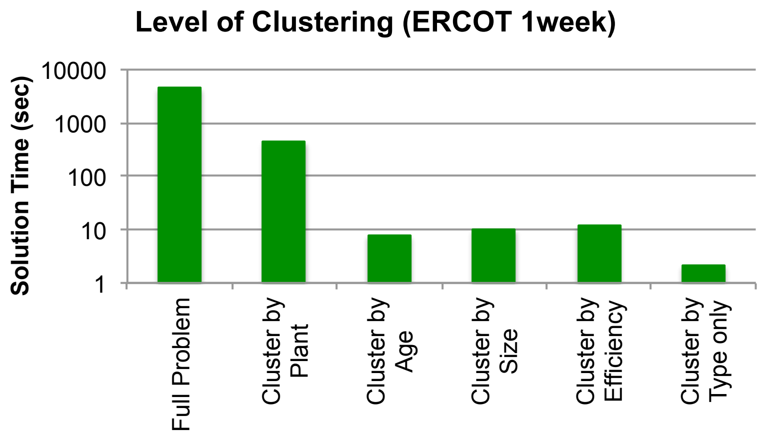
Comparison of Cluster Strategies

Figure 3.4 shows how most sub-clustering schemes result in small errors (around or below 1%) with the exception of clustering by age, which had larger errors (2.3-4.5%) for all metrics except CO_2 emissions. Clustering by efficiency resulted in the lowest errors among the 17-cluster runs, for all other metrics, often close to or slightly better than the larger clustering by plant formulation (90 units). Clustering Error Comparison (ERCOT 1week)

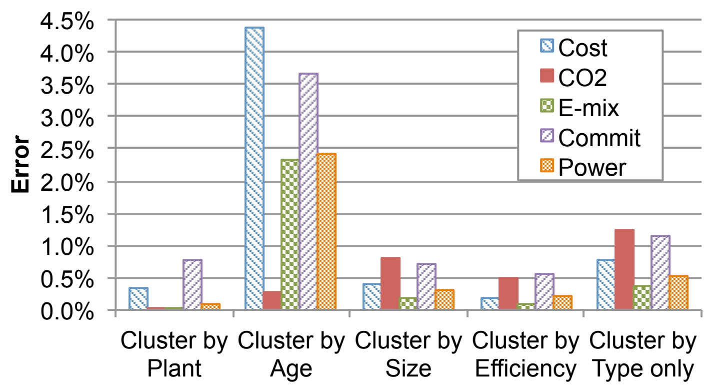
Cluster Scaling

Figure 3.5 shows how the total solver time is greatly reduced by clustering, enabling tractable computation of a full year, 8760 hour, optimal unit commitment for both 17 clusters (under 3 hours) and 7 clusters (130 seconds). The primary driver for these speed-ups is a drastic reduction in the numbers of variables and equations which both scale roughly proportionally to the number of clusters.

Complete result tables for these and other figures, as well as additional run configurations are provided in Appendix B.



(a)



(b)

Figure 3.4: Level of clustering comparison for ERCOT 2007 (a) Shows solver run times for different clustering levels. Note logarithmic time axis. And (b) shows key error metrics. In all cases, the full problem with separate units was used as a baseline. All runs used a MIP gap of 0.1% without the ε-optimal heuristic.

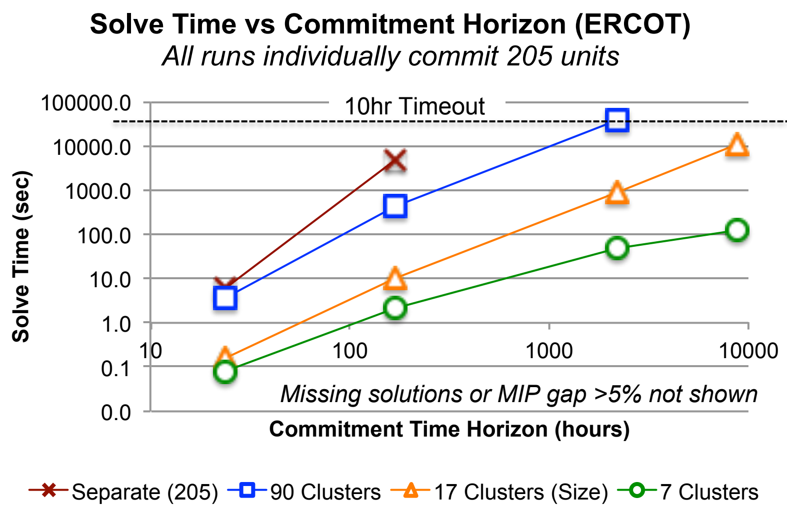


Figure 3.5: Impact of clustering and model time horizon on solution time. Note both axes are logarithmic. All runs conducted with a 0.1% MIP gap without the ε-optimal heuristic. Due to data limitations, constant heat rates are assumed. No other simplifications were used.

3.5 SUMMARY

The experiments here show the effectiveness of clustering for unit commitment operations. In comparison to traditional separate unit formulations, clustering provides orders of magnitude faster computation – 10 to over 1000 times faster depending on configuration with small errors for a wide range of metrics. The numeric examples with both the IEEE Reliability Test System (RTS) and an ERCOT-based 205-unit system show that careful aggregation (17 clusters) introduces errors of 0.05-0.2% for total cost, co2 emissions, energy mix, and dispatch schedule while providing several orders of magnitude faster solution times (400x) compared to traditional binary formulations. The unit commitment metric showed higher errors around 0.9%. More aggressive aggregation (seven clusters) increases errors slightly (~2x) with further speedup (2000x). The results also demonstrate a full year (8760 hour) unit commitment for the 205-unit system in less than three minutes with personal computer hardware. Additional unit commitment simplifications – notably combining reserves and relaxing integer constraints for units with small minimum output levels – are also compared. These additional simplifications can provide an additional order of magnitude speed-up for some problems.

4

INTEGRATED OPTIMIZATION OF UNIT COMMITMENT AND PLANNING

4.1 OVERVIEW AND CONTRIBUTIONS

This chapter highlights the importance of capturing operational flexibility during generation capacity planning for strict carbon policies and/or moderate-to-high Renewable Portfolio Standard (RPS) levels. The chapter considers the perspectives of both policy analysts and utilities in an extended set of examples with a high carbon dioxide (CO_2) price and moderate RPS level. These examples compare the results of capturing versus ignoring operational flexibility and walk through explanations of how ignoring flexibility can produce poor forecasts or difficult/expensive to operate capacity plans. With this motivation, the chapter explores the impact of flexibility for other carbon & renewable scenarios to produce a map of which combinations are most influenced by operational flexibility. The chapter closes by demonstrating how the clustering-based methods[1] proposed in Chapter 2 capture operational flexibility more realistically than alternative formulations in the literature.

Each of these components represents a contribution to the literature, specifically:

1. Demonstrating that operational flexibility has an important impact on planning;
2. Mapping *when* and *to what extent* operational flexibility changes planning results;
3. Presenting a side-by-side comparison of different approaches for capturing operational flexibility within planning models; and

1 Clustering groups similar units into clusters and assigns each group an integer, rather than binary, decision variables for investment, maintenance, and unit-commitment-operations. As described in more detail in Section 2.4, clustering allows capturing full unit commitment operations constraints at an individual unit level under the key assumption that all units within a cluster are identical. For production costing with maintenance (section 2.7) and capacity planning (section 2.9) the same clustering approach enables tractably combining the problems into a single optimization model.

4. Demonstrating that Unit Commitment (UC) details can be tractably incorporated directly into capacity planning optimization models. This chapter's very existence underscores this point: Without the clustering approaches presented in this thesis, the analyses in this chapter would not have been practical due to computational expense.

4.2 EXPERIMENTAL SETUP

4.2.1 *Test System*

All of the simulations in this chapter use a test system based on the Electric Reliability Council of Texas (ERCOT). The base system is largely the same as the ERCOT test system from Section 3.4, but it has been adapted for system expansion planning. All of the runs in this chapter model a static (single period) deterministic future year assumed to be a few decades in the future. Since only a single year of operations is considered, the capital investment costs are annualized using the capital recovery factor described in Section 2.8.2 using Equation (2.39). The Weighted Average Cost of Capital (WACC) was assumed to be 9% to match the ERCOT reported interest rate [210].

For demand, the test system assumes aggressive energy efficiency programs have kept load growth to 0% and that the savings from energy efficiency are distributed such that the load shape remains unchanged and still matches that of 2007. Effects of different load shapes and emerging technologies such as electric vehicles are left for future research. In order to introduce maintenance, the single sequential 8760 hour demand time series is broken up into 52 week-long time blocks (see Section 2.7.2) each with a full set of 168 hours. This still simulates the full year at an hourly resolution; however, since $52wks \times 7days = 364days$, I remove December 31st and scale the resulting total operations costs up by a factor of $365/364 \approx 1.00275$. This captures the year as 8736 hours, rather than 8760.

For generators, half of the existing simplified set of 204 thermal units[2] are assumed to have retired, such that despite the constant demand, significant additional capacity must be built. These generators are clustered by fuel and prime mover (full clustering). Existing gen-

2 The 205 units reported in Section 3.4 include an additional combined "unit" for all of the wind capacity.

erators and candidate new generators are assumed to have different technical characteristics and are therefore kept in separate clusters. The baseline wind capacity has been scaled up to the 2010 installed capacity of 9.4GW, of which 50% is assumed to have retired by the analysis year leaving 4.7GW of existing wind capacity. Only wind and six types of thermal units are eligible for investment. The complete set of technologies available for investment includes:

WIND: Assumed to to follow the same power production profile as the aggregated actual wind production from 2007. Using actual power production as a reference implicitly assumes the future mix of turbine types will be similar to that of today. It also conservatively over-estimates the amount of variability in power output for high RPS cases since spatial diversity has been shown to reduce variability since wind conditions typically vary across larger geographic areas [27]. For simplicity, wind investments are assumed to occur in 200MW increments. Since wind investment in the case studies are on the order of tens of GW, this assumption results in negligible loss of fidelity.

NEW COAL FIRED STEAM: Supercritical pulverized coal units using sub-bituminous fuel. These high capital cost, low variable cost plants have moderate efficiency and low to moderate operational flexibility. Similar plants provide much of the baseload generation in the US today. Their very high carbon intensity greatly increases the effective variable costs under carbon policies;

NEW COAL WITH CCS: Assumed to be similar to the new pulverized coal units but with a post combustion Carbon Capture and Sequestration (CCS) system[3]. The carbon capture rate is 90%. The CCS system increases capital costs and decreases efficiency relative to the non-CCS coal units, but generator technical constraints that determine flexibility are assumed to remain the same[4]. Only

3 This pulverized coal based CCS plant was chosen instead of a coal Integrated Gasification Combined Cycle (IGCC) facility because the Energy Information Administration (EIA) estimated capital costs for the IGCC facility were significantly higher ($5.35/W vs $4.58/W), such that other low carbon technologies, including both Natural Gas fired Combined Cycle Gas Turbine (NG-CC) with CCS ($2.06/W) or even Nuclear ($5.34/W) would always be preferable on a capital cost basis IGCC.

4 The impact of CCS on operating constraints remains uncertain. Some sources suggest that the additional equipment will restrict operational flexibility [208] while others suggest it can enable new modes of operational flexibility by turning CCS equipment

demonstration plants of this type exist today, but the technology represents an option for continuing to use inexpensive coal as a fuel in a carbon constrained future.

NEW NG-CC: Natural gas fired combined cycle gas turbine units, sometimes referred to as CCGT. Similar units provide a majority of intermediate generation in the US today and low natural gas prices have prompted significant recent investments in this type of plant. The combined-cycle system enables very high thermal efficiency since the heat from the combustion products of a gas turbine are re-used to drive a conventional steam turbine. Such units provide a moderate to high level of operational flexibility, and their combination of high efficiency and lower carbon fuel (compared to coal) provide a moderate carbon intensity.

NEW NG-CC WITH CCS: Similar to the new NG-CC units, but with a 90% capture post combustion CCS system. Such units are not in operation today, but have been receiving growing attention as an option for a carbon constrained future. As with coal, the CCS system raises capital costs and lowers thermal efficiency, while flexibility is assumed to remain at the same moderate to high level as the NG-CC units without CCS.

NEW NG-GT: Natural gas fired aero-derivative simple cycle combustion turbines. Such units are common in the power system today. Of the new generation considered in this analysis, these generators have the lowest capital cost and the highest non-carbon operating costs making them the "peakers" that may only run during a small number of the highest demand hours[5]. Their jet engine heritage also enables very high operational flexibility making them especially suited for providing large operating reserves. They are also assumed to be the only generator type capable of providing quick start off-line replacement reserves. However, their lower thermal efficiency and hence higher carbon intensity can make them less attractive than NG-CC under strict carbon policies.

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down/off — increasing CO_2 emissions — or delaying processing[35]. Using non-CCS technical constraints, as done here, represents a middle ground between these extremes.

5 For simplicity other peaking units such as reciprocating diesel units are not included

NEW NUCLEAR: Assumed to be generation III+ (Advanced) pressurized light water reactors. All currently operating US nuclear plants began construction before 1979[211] and hence use older technologies. But nuclear's effectively zero carbon emissions in operation has increased interest in the technology and this more advanced class of reactor has been proposed in most of the recent US nuclear applications [212]. As built in the US, nuclear power plants have strict technical operating constraints making them the least flexible of all generation types[6]. Nuclear power does pose some significant challenges with accidents, such as the recent events at Japan's Fukishima; non-proliferation; and waste disposal. As a result, exploring the operational flexibility impacts of low-carbon systems in the event public opinion prevents nuclear investment represents an important line of follow-on research.

New generator capital costs, operations and maintenance (O&M) costs, and efficiencies (heatrates) are taken from [213]. Where applicable, the lower costs for dual co-located units are used. As before, generator unit commitment and other technical data are taken from [208]. Complete clustering information and generation data tables can be found in Appendix A.

4.2.2 *Metrics*

As described in Section 1.6, the capacity planning model can be used to inform a range of policy and planning questions. Depending on the application, some solution outcomes may be more important than others. Therefore, as was done in Chapter 3, multiple comparison metrics are computed, one for each outcome of potential interest.

When comparing predicted to actual results, the predicted results are used as a baseline. In all other cases, the capacity planning results

6 Nuclear power is not inherently inflexible, as evidenced by the special design of some nuclear power facilities in France to have high ramp rates. These units, along with pumped hydro storage and transmission interconnection with Germany enable France to obtain 75% of its power from nuclear. The navy also operates ships and submarines that use highly throtable nuclear-electric power sources. However, this operational flexibility requires re-engineering some key plant components, further increases the already high capital costs, and has not yet been licensed in the US. Exploring the impacts of flexible nuclear is left as an area of future research.

based on full, clustered unit commitment operations were used as the baseline.

Metrics shared with Operations

Many of the metrics from the operations-only comparisons are also useful for capacity planning:

TOTAL COST is the objective function value for the optimization and includes all operations and investment costs. A scalar percent difference is computed for comparison.

CO2 EMISSIONS: CO_2 equivalent emissions, also written as CO2e, are computed system-wide based on fuel usage for both power generation and startup. A scalar percent difference is computed for comparison.

ENERGY MIX is based on total annual production by generator cluster. In this chapter, the Root Mean Square (RMS) difference of the energy production — rather than its mean average difference of energy fraction— is used as a scalar comparison metric replacing (3.3) with:

$$\Delta E^{mix} = \frac{\sqrt{\underset{\hat{g}\in\mathbf{G}}{\text{mean}} \left(\hat{E}_{\hat{g}} - \hat{E}_{\hat{g}}\big|_{baseline} \right)^2}}{\underset{\hat{g}\in\mathbf{G}}{\text{mean}}\ \hat{E}_{\hat{g}}\big|_{baseline}} \tag{4.1}$$

COMPUTATION TIME is reported as total solver (CPLEX) run time and excludes model setup and output processing by GAMS.

Refer to Section 3.2.1 for additional equations and further explanation.

Basic Capacity Planning Metrics

In addition, this chapter uses the following capacity planning specific metric:

NORMALIZED NEW CAPACITY MIX presents a normalized estimate of the similarity of the new capacity additions between two planning models. This value is taken as the coefficient of variation of the RMS difference in capacity. The coefficient of deviation is normalized based on the average baseline investment in new capacity by type:

$$\Delta I^{normalizedMix} = \frac{\sqrt{\underset{\hat{g}\in\mathbf{G}}{\text{mean}}\left(\hat{I}_{\hat{g}} - \hat{I}_{\hat{g},baseline}\right)^2}}{\underset{\hat{g}\in\mathbf{G}}{\text{mean}}\hat{I}_{\hat{g},baseline}} \tag{4.2}$$

4.2.3 *Implementation notes*

As further described in Section 2.11, all runs were conducted with the highly configurable "StaticCapPlan" and "UnitCommit" models from the Advanced Power toolset. These models are implemented in the General Algebraic Modeling System (GAMS) [201] and run using the state-of-the-art CPLEX 12.3 Linear Program (LP)/Mixed Integer Linear Program (MILP) solver [203]. All runs were conducted with a target MILP tolerance or "MIP gap" of 0.1%; however some planning model runs did not reach this tolerance before timeouts of 60 hours for planning runs and 24 hours for operations-only runs. In such cases MIP gaps below 1.5% were considered solved. Larger MIP gaps were rerun using longer timeouts and/or the CPLEX parallel facilities[7] to achieve acceptable tolerances. Since the unit commitment enabled capacity planning model results were also used as the simulation of "actual" power system operations (see Section 4.3.1), once the capacity was determined, an additional operations-only run was conducted to optimize dispatch, commitment, and maintenance decisions.

In addition, the following modeling assumptions are used:

- Maintenance is included in all operations simulations and in unit commitment based planning using the formulation described in Section 2.7.3. All other planning models derate generator output power to account for maintenance unavailability.

- Generators with minimum outputs below 80MW — which includes only Natural Gas fired Combustion Gas Turbine (NG-GT) units — use relaxed (non-integer) unit commitment variables to speed computation. Unit commitment and related constraints, such as startup and reserves, are still captured, but the corresponding commitment state can take a fractional value. Such frac-

7 Surprisingly, in some cases longer runs using a single thread outperformed parallel runs, even when the parallel runs had equally long timeouts.

tional states are not physically possible, but the results in Chapter 3 show that the resulting errors are small for these highly flexible units.

4.3 A CARBON POLICY EXAMPLE

4.3.1 *Example setup*

This section considers the impacts of capturing operational flexibility when using a capacity planning model to estimate the the outcomes of proposed carbon policies[8]. In this example, a policy analyst uses an expansion planning model to estimate a future year's electric-sector CO_2 emissions for a given carbon tax. A planning model, rather than an operations-only one, is used to capture electric sector generation capacity investments during the intervening years between the time of the estimate and actual operations.

The example then compares the accuracy of the policy analyst's estimate depending on whether or not operational flexibility is captured by the model. To do so two planning models are compared:

STANDARD (STD) A standard capacity planning model that uses simple merit order economic dispatch for operations and does not capture operational flexibility, and

ADVANCED (ADV) An advanced planning model that uses clustering to include Unit Commitment (UC) operations, including the full set of generator constraints described in Chapter 2, and thereby captures operational flexibility.

The "actual" power system operations assume that the electric utility[9] builds the optimal generation mix considering unit commitment with

8 This section updates and expands on an earlier version of this analysis that appeared in Palmintier & Webster (2011) [139]. Important assumption changes in this analysis include allowing non-served energy, revised operating reserves requirements, an expanded set of generators, and updated costs. This analysis also uses an a significantly evolved version of the StaticCapPlan and UnitCommit models that includes maintenance, minimum up and down time constraints, and many other enhancements. Still the overall message is the same.

9 For simplicity, these examples assumes a centrally planned utility. As described in Section 1.6, in a competitive electricity market, a similar role might be played by the electricity regulator who could then use the results to design regulatory instruments, such as forward capacity markets, to achieve the same or similar generation mixes. Such use would involve further analysis of the capacity impacts of these regulations

	Standard	Advanced
Maintenance	Derated Generator Output	Optimal Schedule by Week
Unit Commitment	None	Integer
Startup Costs	-	Yes
Minimum up/down times	-	Yes
Operating Reserves	Extra capacity from planning margin	1) Regulation Up&Down 2) Load/Renewable Follow Up/Down 3) Contingency Reserves 4)Quick-Start Reserves
Minimum Output	-	Yes

Table 4.1: Operations sub-model assumptions used in this chapter. Dashes indicate that the corresponding technical constraint is not included in the Standard model.

the Advanced model with full knowledge of the carbon tax level. In this setup, since the Advanced capacity planning model is able to capture the full set of generator operating constraints, these "actual" operations are the same as those computed using the Advanced planning model. As a result, only a single Advanced model result is reported and it corresponds to both the UC-planning model predictions and the corresponding "actual" operations[10].

Table 4.1 compares the operations sub-model assumptions for the two models.

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and of the resulting market based operation of the electric system. Such analysis is left for future research.

10 Further testing to compare the results of both models to an independent operations simulation using a commercial production cost tool represents an important area of future work. Such a tool was not available for this research.

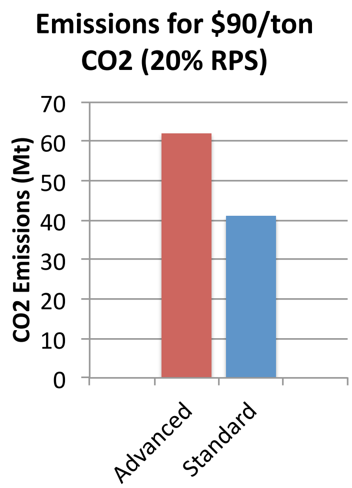


Figure 4.1: CO_2 emissions prediction using the Standard (Std), merit order operations based, planning model in comparison to the predicted—and equivalently simulated "actual"—emissions from the Advanced (Adv) unit commitment based, planning model.

4.3.2 *Emissions Level for $90/ton CO2 tax*

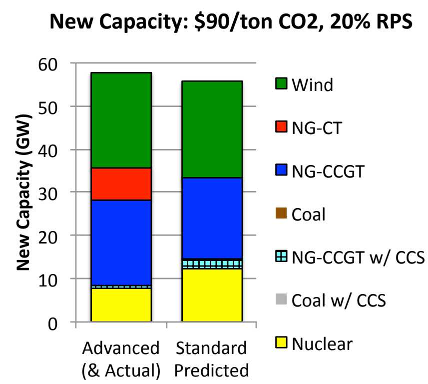
The first example assumes the policy analyst wants to estimate the electric sector carbon emissions for a $90/ton CO_2 tax. It compares the quality of the estimates from the Standard model to the results of the flexibility-aware Advanced, UC based model. The comparison assumes the following sequence of events:

1. The carbon policy analyst uses one of the two electricity generation capacity planning models, Standard or Advanced, to estimate the carbon emissions resulting from the $90/ton CO_2 tax.

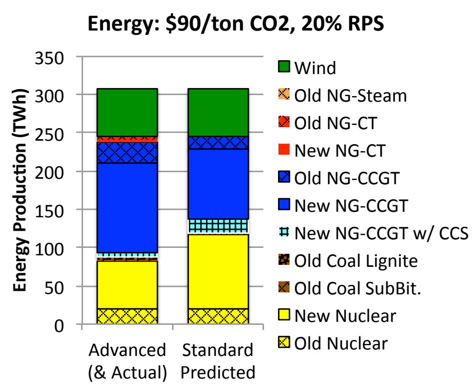
2. The electric power sector plans and builds generation to meet this $90/ton CO_2 tax on a least cost basis. The required additional generation capacity is assumed to be selected with a planning process that considers operational flexibility as simulated using the Advanced model.

3. The generator capacity is then operated, subject to the $90/ton carbon tax, and the resulting carbon emissions are evaluated.

Figure 4.1 shows that the Standard planning model underestimates the CO_2 emissions by over 50%. This error is due to operational flexibility.



(a)



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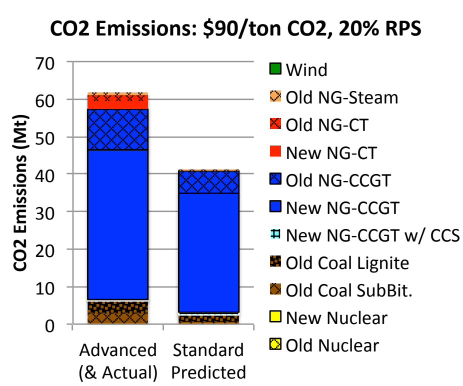


(c)

Figure 4.2: (a) Capacity additions, (b) energy mix, and (c) CO_2 emissions predicted using the Standard, merit-order based, planning model in comparison to the Advanced, unit commitment based , predictions—and equivalent simulated “actual” results, for a $90/ton CO2 cost.

As seen in Figure 4.2(a), when operating constraints are omitted in the Standard model, the predicted capacity includes significantly more inflexible nuclear while the Advanced model recognizes the need to provide additional operational flexibility by replacing some of the nuclear with highly flexible NG-GT units.

Figure 4.2(b) shows how the new NG-GT plants only contribute a small amount of the total energy in the Advanced model; but, as described in the next section, their presence is critical to providing the required operational flexibility. Figure 4.2(b) also shows a small increase in power generation by old coal facilities when operating constraints are included in Advanced model. As is also described in the next subsection, this increase comes from the inability of these coal units to shutdown between those daily peaks when their output is required to meet the demand.

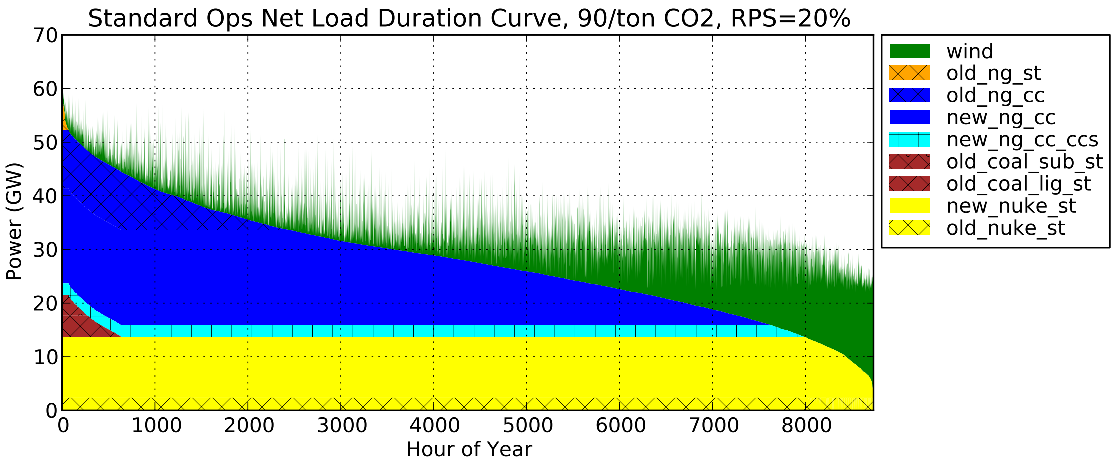
Figure 4.2(c) shows how these differences in predicted energy production between the Standard and Advanced model result in the large differences in total carbon emissions seen above. The carbon emissions by source appear different than the energy mix due to variations in generation carbon intensity. The energy contributions by carbon-free wind and nuclear do not create any CO_2 emissions. In contrast, the relatively inefficient NG-GT and carbon intensive coal units together contribute over 15% of the emissions, despite a combined energy contribution of under 4%.

4.3.3 *Flexibility Impacts*

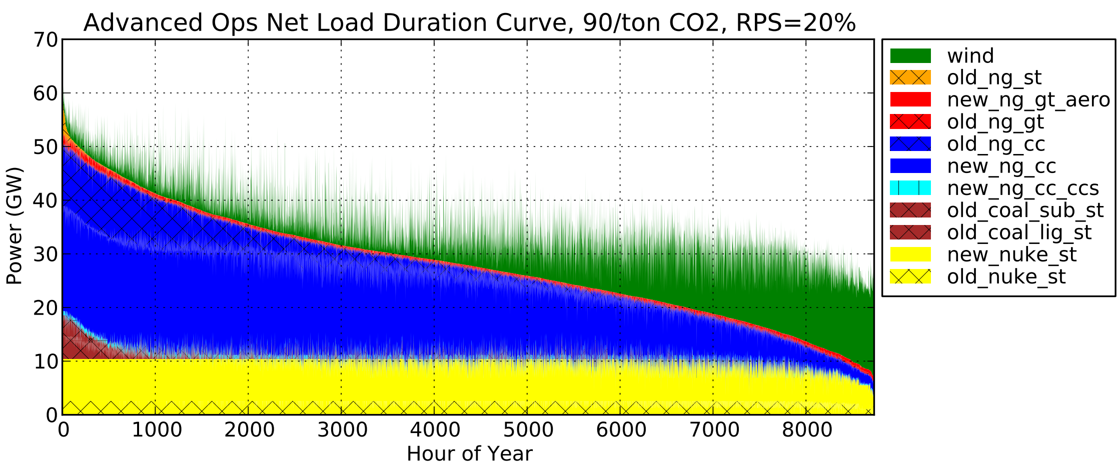
As described in Section 1.6.3 operational flexibility impacts operations, which can in turn impact planning. This section explores the impact of operational flexibility on the capacity and energy mix for the $90/ton Carbon Policy example to help further explain how actual emissions exceed those predicted by the Standard model.

Annual Net Load Duration Curve

Figure 4.3 illustrates many of the impacts of operational flexibility by comparing the net load duration curves between the Standard and Advanced models. In the net load duration curve, the hours of the year are re-arranged in order of decreasing "net load," the demand minus wind production. It is analogous to a rotated cumulative distribution function showing the probability, in number of hours, that the net load



(a)



(b)

Figure 4.3: Net load duration curves and associated power production for (a) merit order operations (Standard) and (b) unit commitment operations (Advanced). Differences in generation mix explain the differences in maximum power for nuclear, NG-CC with CCS, and to a lesser extent, NG-CC without CCS, but other variations are due to operations constraints associated with flexibility.

exceeds a given level along the smooth curve at the base of the wind block. The inclusion of wind generation above net load results in the jagged upper surface. The area of each shaded region correspond to the total energy production seen in Figure 4.2(b).

In Figure 4.3(a), the banded structure with Standard operations results from not capturing the generator technical constraints that drive operational flexibility. Instead, the model follows a "merit order" where the units with the lowest variable operations costs are dispatched fully until exhausted before moving on to the next most expensive generation type. Coal breaks this banded structure since it is shown in its traditional baseload location, yet the high carbon price increases its variable costs of operation above that of the NG-CC facilities, causing it to behave like a peaker and only run during a small number of hours of the year.

As seen in Figure 4.3(b), operational flexibility constraints create more complex patterns that begin to explain the differences in predicted energy mix between the two models. During the periods of lowest net demand, the Advanced model continues to operate NG-GT and NG-CC units and maintain the operating reserves required to compensate for wind forecast errors. This reduces the total nuclear output during these times which in turn impacts the optimal nuclear capacity. The lower nuclear capacity using the Advanced model comes partially from technical operating constraints that limit the minimum output from nuclear and partially from economic factors that recognize that with even \$90/ton CO_2, nuclear needs to run for over about 8000 hours each year to offset its high capital costs. With standard merit order operations, it appears that around 14GW of nuclear would run sufficiently long, but with advanced UC based operations, the additional NG-GT and NG-CC operation for reserves mean that only about 10GW of nuclear are economic. These changes increase carbon emissions since the zero carbon nuclear energy is partially replaced by carbon emitting, natural gas.

In addition to emission increases due to less nuclear, Figure 4.3(b) also shows an increase the annual run times for carbon intensive coal units and NG-GT peakers. The increased use of NG-GT appears as a thin red line over the entire year, while increased coal use is variable across the net load duration curve as evident by the presence of brown in the noisy region between nuclear and NG-CC. These increased run times further increase total carbon emissions because they have higher carbon emissions than the sources they displace: carbon-free nuclear and more efficient NG-CC. To understand the cause of these increases it is helpful to look at a single week of operations, as described in the next section.

One week time series

Figure 4.4 shows the impact of flexibility driven operations constraints during the week beginning just after midnight on August 14th. As seen in Figure 4.4(a) and (b), the demand peaks in the late afternoon of each of the seven days before falling to a daily minimum in the very early hours of the morning. In both cases, most of this change is handled by ramping or cycling NG-CC facilities. The first differences between the models can be seen in the nuances of these adjustments. In the Standard model, the older, less efficient NG-CC facilities, shown with cross-hatching on a blue background, only run when the net load is greater than about 33GW. However, the Advanced model recognizes that such cycling incurs a cost with each startup and instead keeps some of these older facilities running at/near their minimum output levels through the low nighttime demand periods during the first four days. This increases carbon emissions because the older facilities are less efficient and hence burn more fuel than if the newer facilities were run instead. Furthermore, during the last two demand troughs, the high wind output reduces the net load enough that the Standard model cycles all of the NG-CC, while the Advanced model maintains some of the new NG-CC plus some NG-GT at all times. This change by the Advanced model avoids startup costs, and maintains operating reserves as described below. The resulting shift away from the very low carbon NG-CC with CCS and Nuclear facilities to more carbon intensive NG-CC (without CCS) and NG-GT units further increases carbon emissions.

A similar increase in Coal operations under the realistic constraints of the Advanced model explains an even larger increase in carbon emissions. Understanding how, first requires a some additional background. Today, coal facilities run (almost) all the time as baseload generation due to their low variable operating costs. However, at a \$90/ton CO_2 price, the variable operating costs for carbon-intensive coal increase dramatically, making them nearly as expensive to run as the peaking units and precluding baseload operation. In combination with high capital costs, this prevents any new coal construction, but since they have already been built, the remaining legacy units can still be useful during peak periods.

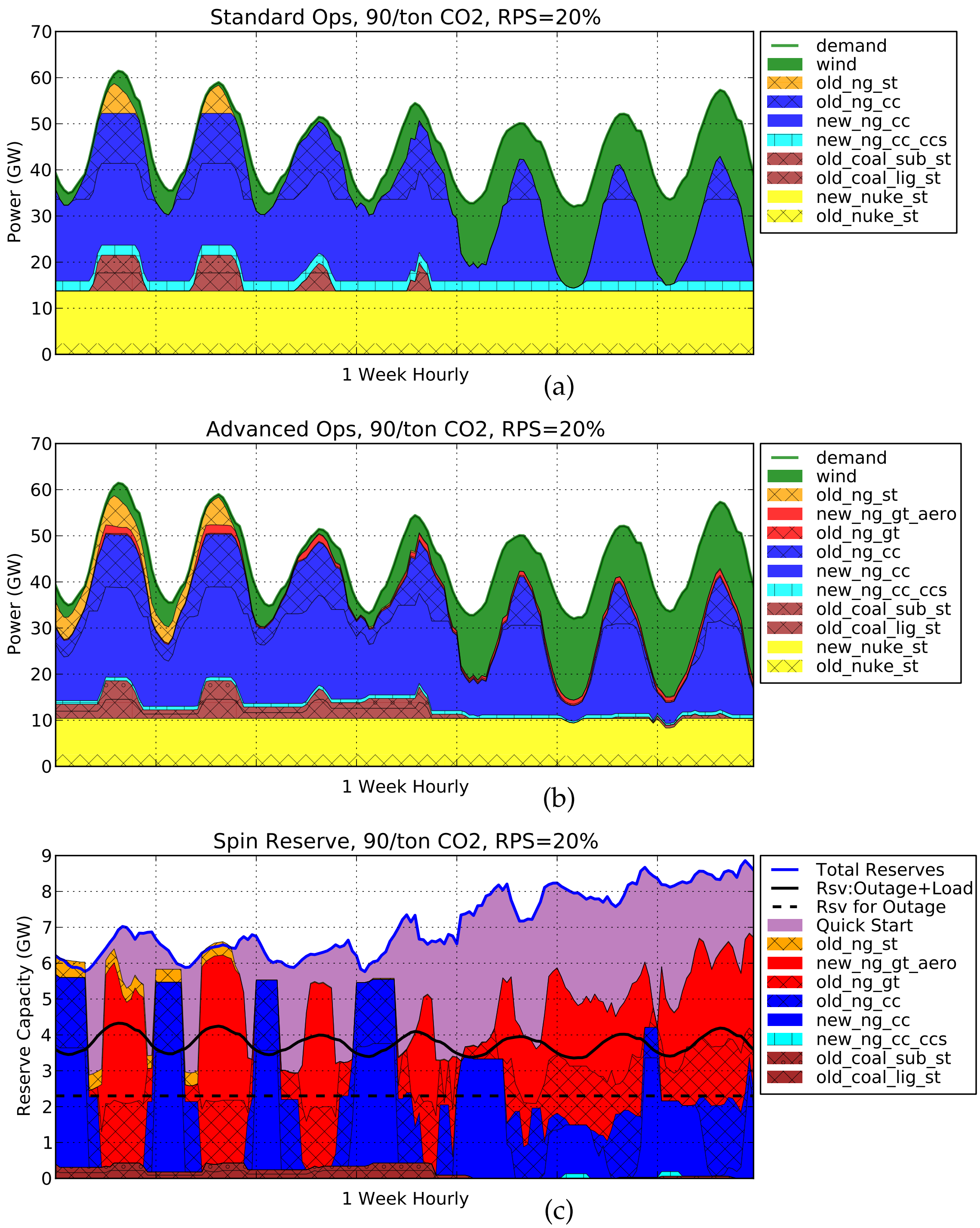


Figure 4.4: Comparison of one week of operations in August as modeled using (a) Standard, merit order operations versus (b) Advanced, unit commitment based, operations. (c) shows the corresponding secondary reserve up capacity.

In this example week, both models use legacy coal facilities during the peak periods of the first four days, but differences in operating constraints create very different dispatch profiles. As seen in Figure 4.4(a), the Standard operations model assumes coal acts like a peaker because coal's carbon-adjusted variable output costs are higher than those of NG-CC. However, Figure 4.4(b) shows how the Advanced model captures the realistic situation that coal's minimum up and down time constraints of 24 and 12 hours respectively prevent this peaker-like cycling behavior. Instead the coal units needed during the peaks continue to run at or near their minimum stable output level during the nighttime low net load periods. This additional coal displaces the far less carbon intensive NG-CC facilities resulting in an increase in carbon emissions. A similar phenomena occurs with the inefficient and hence relatively carbon intense legacy natural gas steam facilities that are also used to meet the even higher peaks of the first two days. Similar to coal steam, the realistic operations of the Advanced model captures how the units must continue to run at night thereby displacing additional NG-CC and further increasing carbon emissions.

Operating Reserves

An additional source of increased carbon emissions captured by the Advanced model comes from the need to maintain operating reserves to compensate for unexpected outages and errors in load and wind forecasts. As described in Section 2.6, operating reserves fall into a number of different categories depending on their required deployment time and their direction of compensation: up or down. For illustration, this section examines the impact of only one of these classes of reserves: secondary up reserves, which includes both spinning reserves to compensate for unexpected outages and (net) load following up reserves to compensate for load and wind forecast errors. The other reserve classes have similar, though somewhat smaller, impacts.

Figure 4.4(c) shows the quantity and source of the total secondary up reserves for the same week of operations described above. Early in the week, the influence of load on total reserve required is seen in the daily reserve peaks corresponding to demand. The peak to valley ratio is smaller than for power because of the constant requirements to maintain 2.3GW for the largest contingency and to match just under 8% of the installed wind capacity. Later in the week, the increased wind output (and forecast) — which is assumed to require 13.9% reserves —

increases total reserve requirements enough to mask the diurnal load influence. The sub-figure also shows how up to 50% of the secondary reserve can be provided by off-line quick start aero-derivative natural gas combustion turbines. Since this is an inequality constraint, the off-line eligible portion of reserves are instead met by on-line spinning generation whenever excess capacity exists, such as when the NG-CC units are kept operating at low output levels during nighttime troughs to avoid incurring startup costs during the morning pickup[11].

Unlike power generation, the upward reserve capacity shown in Figure 4.4(c) does not create any direct emissions. However, in order to provide upward reserves, a unit must 1) be running at or above its minimum stable output, 2) maintain enough headroom between its current and maximum power output to provide the reserve if needed and 3) have sufficient ramping speed to change output to meet the reserve in the required time horizon: 10 minutes for secondary reserves. The first requirement can drive out of merit order operation by keeping flexible, but potentially higher carbon emitting, units running solely for reserves, while the other two requirements favor the most operationally flexible units — those with the lowest minimum output and fastest ramping capability — for providing these reserves. In this test system, the most flexible units are the new aero-derivative NG-GT which have higher carbon emissions than the NG-CC they typically displace. This impact is evident during the night time lows later in the week when NG-GT units output increase slightly at night to use their very high reserve capabilities to meet the increased reserve needs of the high wind output levels. This nighttime NG-GT operation increases carbon emissions by displacing lower carbon NG-CC and Nuclear.

During the highest peaks on the first two days, reserve requirements again increase carbon emissions. During these periods, merit order dispatch for the Advanced generation mix would choose to max out the NG-GT before operating the less efficient legacy natural gas steam units. However, the need to maintain operating reserves requires reducing the NG-GT output which in turn uses more natural gas steam and creates higher CO_2 emissions.

11 These units also are kept running to provide downward reserves to handle situations when the actual net demand is lower than forecast. This use requires maintaining output sufficiently above the minimum stable load to be able to reduce output if required.

4.3.4 *Summary*

This example demonstrates the importance of capturing operational flexibility when assessing carbon policy impacts for moderately high carbon costs. In these examples using a Standard planning model that ignores operational flexibility created large errors in the estimated carbon emissions for a $90/ton carbon tax (51% error). In contrast, the clustered unit commitment based planning model proposed in this thesis is able to directly include the complex operating constraints important for flexibility constrained operations and produce realistic estimates for the emissions. In addition, a detailed look at the corresponding output patterns (Section 4.3.3) examines exactly how the operating constraints that drive flexibility impact operations and planning and thereby increase carbon emissions.

Looking ahead, Section 4.5 explores how important operational flexibility is when estimating the impacts of other carbon tax levels. But first, the next section examines the utility perspective of flexibility impacts on planning for the same $90/ton CO_2 policy.

4.4 THE UTILITY PERSPECTIVE

4.4.1 *Introduction*

Operational flexibility can also impact the utility capacity planning problem, particularly under a strict carbon policy. Analogous to the policy maker perspective above, this section explores the impacts of including or ignoring operational flexibility during the utility planning process. As before, the utility can also choose between two types of planning models: one based on merit order operations (Standard) that implicitly ignores operational flexibility and the other that uses the clustered combined unit commitment, maintenance and capacity planning formulation presented in Chapter 2 (Advanced).

However, unlike the policy analyst, the utility uses these planning models to decide what types of generation to actually build. As a result this example assumes the utility is less interested in predicting carbon emissions or prices and more interested in minimizing total operations cost and the ability to reliably provide energy to meet demand while still complying with RPS and carbon policies.

This example revisits the \$90/ton CO_2 case from the utility perspective assuming the following steps:

1. The utility plans and builds generation to meet the \$90/ton CO_2 tax on a least cost basis using one of the two electricity generation capacity planning models, Standard or Advanced. These model runs make predictions of the total costs, anticipated non-served energy, and required wind shedding for the system.

2. The "actual" operations for the two generation mixes are then simulated under a \$90/ton carbon tax using realistic, unit commitment–based operating constraints. As before, the "actual" operations match the Advanced model predictions so only a single Advanced result is presented. For the Standard model, the resulting actual costs, non-served energy, and required wind shedding are compared to the predictions from step 1.

4.4.2 *Results*

Figure 4.5(a) shows that the generation mix proposed by the Standard model is predicted to be slightly less expensive than that from the Advanced model; but, if built, the Standard model's mix would actually be considerably more expensive than the Advanced model's mix. The other sub-figures begin to explain the Standard model discrepancy: in actual operations, the Standard generation plan results in large quantities of both non-served energy (b) and wind shedding (c). The very high costs for the Standard model actual operations come from the high penalty cost for non-served energy[12], while the large quantity of shed wind suggests a flexibility problem.

Indeed, as seen in the last section and repeated in Figure 4.6(a), the Standard model includes significantly more inflexible nuclear capacity while the Advanced model recognizes the need to provide additional operational flexibility by replacing some of the nuclear with highly flexible NG-GT units. However, unlike the policy analyst example, it is assumed that the results of the capacity planning model are used directly for capacity expansion decisions. As illustrated in Figure 4.6(b) the Standard model omission of operational flexibility causes large differences between predicted and actual energy mixes. More importantly,

12 The non-served energy cost is set to \$50k/MWh

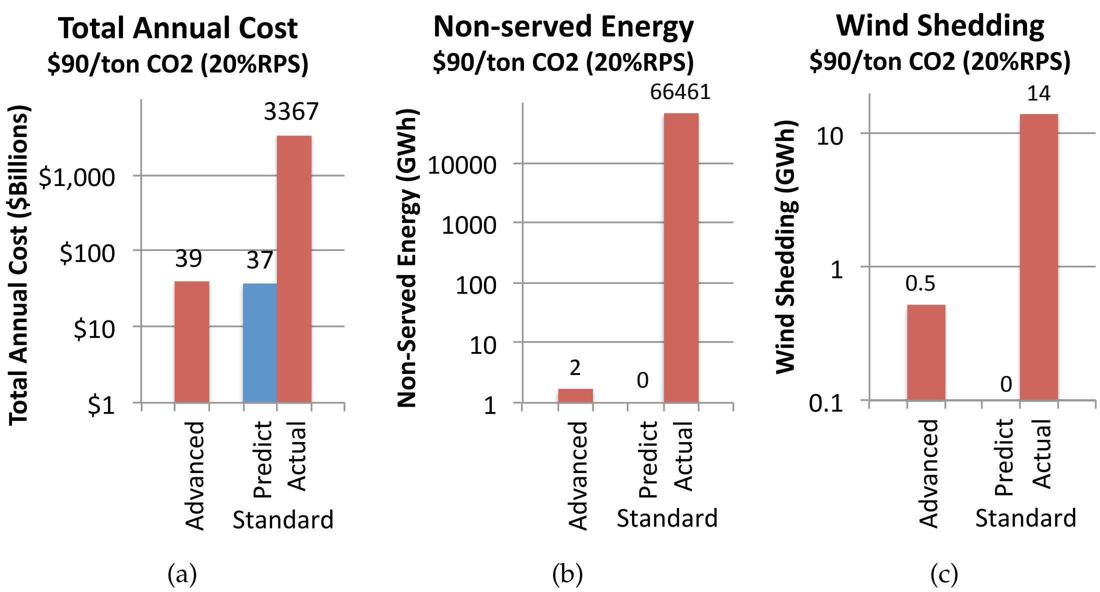
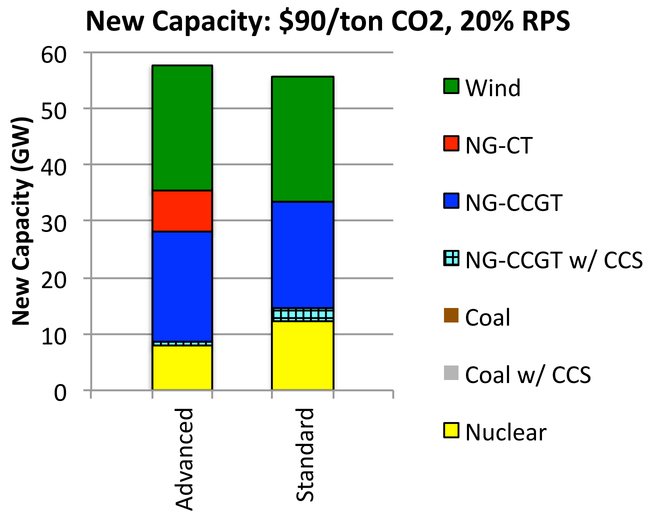


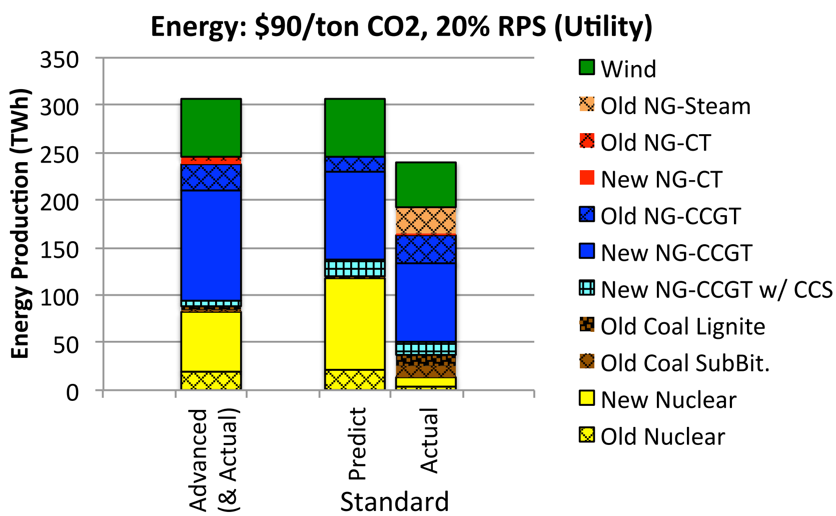
Figure 4.5: Predicted versus actual (a) costs, (b) non-served energy, and (c) wind shedding for Advanced, unit commitment based and Standard planning models. Note logarithmic y-axes. Total costs include annualized capital payments for existing and new generation plus annual operating expenses including fuel, startup, O&M, carbon cost and costs of non-served energy. The total annual Standard-Actual non-served energy represents over one fifth of the annual energy demand of just over 300TWh, and unacceptably high fraction for modern utilities.

the quantity of non-served demand in the Standard-Actual case would be unacceptably high for any modern electric utility.

With the Standard generation mix, it is not possible to simultaneously meet demand and RPS. Instead, the total energy output is reduced to meet the RPS and corresponding reserve requirements. The lost load results from a chain-reaction that begins with insufficient operational flexibility. In practice, the utility would likely keep the lights on and instead miss the RPS requirement. But for the sake of illustration, consider what would happen if the RPS was truly binding: Without the highly flexible NG-GTs to provide upward reserves for wind, the Standard generation mix must instead back-off NG-CC output. The legacy NG-Steam and coal units are also brought on-line to help replace the lost generation and to provide additional reserves during high demand periods. However, these steam units have high



(a)



(b)

Figure 4.6: (a) Capacity additions, and (b) energy mix using unit commitment based (Advanced) or standard merit order based (Standard) planning models in comparison to the simulated actual results for a \$90/ton carbon price. Note that unlike the policy analyst examples, the Standard generation mix is assumed to have been actually built for the Standard Actual case, resulting in unacceptably high levels of lost load.

minimum output levels and long minimum up/down time constraints such that they must be kept running with significant power production even during night time lows. This in turn, means that when high wind production coincides with these low demand periods, the significant minimum thermal output plus available wind power is greater than demand. As a result, some of the available wind must be shed (i.e. go unused). The wind shedding helps slightly by reducing the required operating reserves, but because the Standard model's wind capacity was built assuming all of the wind could be used, this wind shedding causes problems in relation to the RPS. Since the RPS standard requires 20% of the annual energy to come from renewables (i.e. wind in this example) shedding some of the available wind means that the only way to meet the RPS is to also reduce the total energy. And lower total energy causes a feedback loop that further squeezes the ability of the system to simultaneously provide reserves, meet minimum output and up/down time constraints and utilize available wind, causing more wind shedding and loss of load.

While this downward spiral of loss-of-load ensues, the Standard planning model's nuclear generation capacity goes underutilized due to its low operational flexibility. Traditional nuclear's minimum output and up/down constraints are even stricter than the legacy natural gas and steam facilities. This reduced flexibility means that the nuclear facilities can no longer operate during many of the nighttime lows because the minimum thermal output from the NG-CC and steam units is already causing wind shedding. With its very long minimum cycle times[13] nuclear can only provide output power during the few long-lasting periods of high demand and low wind.

The Standard generation mix requires more operational flexibility in order to make more effective use of its nuclear facilities, reduce wind shedding, curb the loss of load, and reduce operating costs. The next section explores the potential of adjusting the planning margin to increase operational flexibility with the Standard model.

4.4.3 *Planning margin adjustments*

As described in section 2.8.3, the planning reserve increases the total firm capacity investment to account for uncertainty in the peak demand. When standard, merit-order operations are used for planning,

13 assumed to be 48hr up and 24hr down, see Appendix A

	Planning Margin	
	Minimum Constraint	Effective Actual
Advanced	13.75%	17.26%
Standard	13.75%	14.12%
Adjusted-Standard	17.26%	17.99%

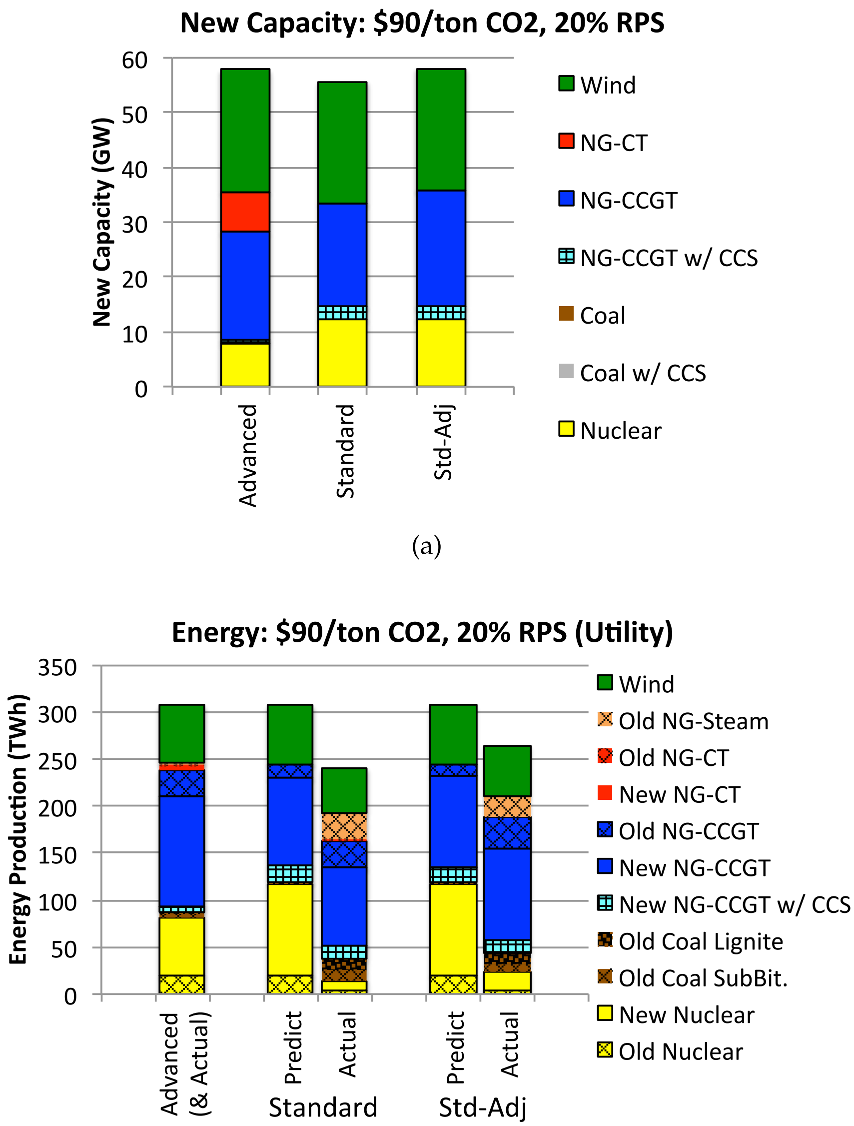
Table 4.2: Minimum required and actual planning margin for the Advanced, Standard, and Adjusted-Standard models. The Adjusted Standard model minimum is forced to match the UC actual margin to test if planning margin adjustments could fix the Standard model's operational flexibility shortage.

the planning reserve also ensures sufficient capacity to provide operating reserves during the peak period. As a result, if the planning reserve is set too low, the Standard model may not build sufficient capacity to meet reserves, potentially resulting in the challenges described in the last section.

In both the Advanced and Standard model runs, the planning margin was set to 13.75%, the current value used by ERCOT planners [199]; however, as seen in Table 4.2, the actual effective planning margin from the Advanced capacity expansion plan was 17.3%. The additional capacity was added by the Advanced model as a result of operational flexibility restrictions. Could it be that the planning margin alone is responsible for the shortage of operational flexibility in the Standard model mix? With the Standard model's merit order operations assumption, increasing the planning margin will invest in low capital cost technologies. By fortunate coincidence, low capital cost technologies tend to be highly flexible natural gas units. As a result, the increased planning margin should help the Standard model's operational flexibility problem.

This example tests this hypothesis using the heuristic of adjusting the minimum planning margin for the Standard model to match the effective planning margin built by the Advanced model[14]. Figure 4.7 shows that the increased planning margin of the Adjusted Standard

14 The example ignores the chicken and egg problem of this heuristic. After all, if the results of the Advanced model were available it would be possible to use its complete results rather than just the firm capacity. However, as described below, this is a moot point, since the adjusted planning margin is not enough to compensate for ignoring operational flexibility.



(b)

Figure 4.7: (a) Capacity additions, and (b) energy mix for the planning margin adjusted merit order operations model (Std-Adj) compared to the Advanced and non-adjusted Standard planning models for a $90/ton carbon price.

	Total System Cost ($Billions)		Non-Served Energy (GWh)		Wind Shedding (GWh)	
	Predict	Actual	Predict	Actual	Predict	Actual
Advanced	$39.0		1.7		0.5	
Standard	$37.2	$3,367.2	0	66461.4	0	13.8
Adjusted Standard	$37.4	$2,187.2	0	42848.1	0	9.1

Table 4.3: Cost, non-served energy, and wind shedding for the Advanced, Standard, and Adjusted Standard models.

planning model run increases the quantity of NG-CC built, which increases the overall system flexibility and decreases the loss of load relative to the non-adjusted Standard operations. As seen in Table 4.3, this in turn reduces the total annual costs and wind shedding. However, despite the improvements, the system remains relatively inflexible making the total costs for the Standard operations based planning model with adjusted planning margin still unacceptably high and quite different than predicted. Apparently the heuristic of adjusting the planning margin, though helpful, is not enough to ensure sufficient operational flexibility. In this scenario, the Advanced model, which does capture operational flexibility, still does a much better job of designing the system.

4.5 WHEN DOES OPERATIONAL FLEXIBILITY IMPACT PLANNING?

4.5.1 *Experiment Setup*

Motivated by the examples above, the next two sections further map out *when* operational flexibility impacts planning. Two additional dimensions are considered:

STRICTNESS OF CARBON POLICY, in terms of either carbon price or emission limits. As described in Section 1.6.3, the strict carbon policies can prompt a shift toward inflexible low-carbon baseload generation (e.g. traditional nuclear) if operational flexibility is ignored. This potentially leaves the system without the operational flexibility required to manage the uncertainty and variability of wind; and, QUANTITY OF RENEWABLES, captured by adjusting the RPS. Higher levels of variable renewables require increased operational flexibility from the system. Hence, failing to capture operational flexibility in planning models could suggest a generation mix incapable of providing the necessary operating reserves, and/or could assume that optimistically low levels of renewables are required, resulting in difficulty meeting the RPS without shedding demand.

In the first set of experiments, Section 4.5.2 looks at only variations in carbon policy by examining the sensitivity of errors in the policy analyst's forecasts as a function of carbon price. This first set of experiments also explains how the generation mix and energy mix alone can be used as proxies for concerns of both the policy analyst and the utility. With this background, Section 4.6, looks at capacity mix and energy differences as a function of both renewable quantity and carbon policy, this time in the form of electric sector emission limits.

4.5.2 *Sensitivity to CO2 price*

Carbon emission estimates

The previous examples showed how ignoring operational flexibility by using a standard, merit order based operations based capacity planning model can produce undesired results for both policy analysts and utilities in the case of a $90/ton CO_2 price. In both examples, capturing operational flexibility using a unit commitment based model provided much better results. This section explores whether or not the same problems exist for other CO_2 prices, and identifies the regions where the errors from the Standard model would be large.

Figure 4.8 and Table 4.4 shows that for prices up to and including $60/ton, the Standard merit order based model provides good estimates of the resulting CO_2 emissions, with errors ranging from 0-4%. At and above $75/ton, however the Standard model creates significant errors of up to 51%.

Interestingly, the emissions forecast errors for the Standard, merit order based model are greatest around $90/ton and then begin to fall, dropping to 10% at $120/ton. Figure 4.9(a) shows how this pattern can be partially explained by the mix of new capacity additions, particularly differences in carbon emission intensities. In all cases, both models build 22GW of wind to meet the RPS. Up to $60, both the

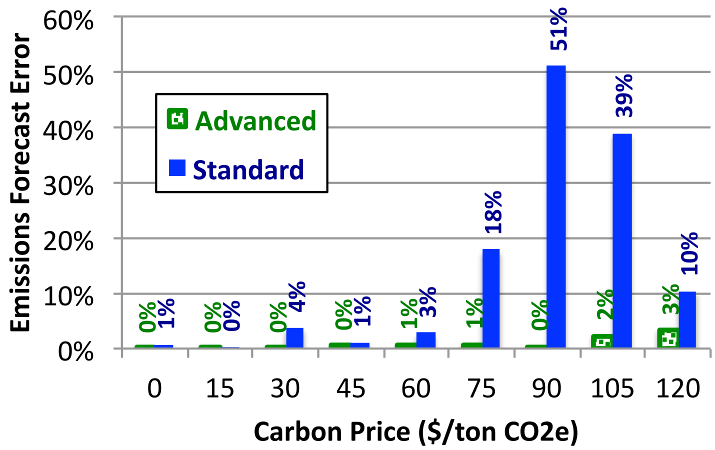
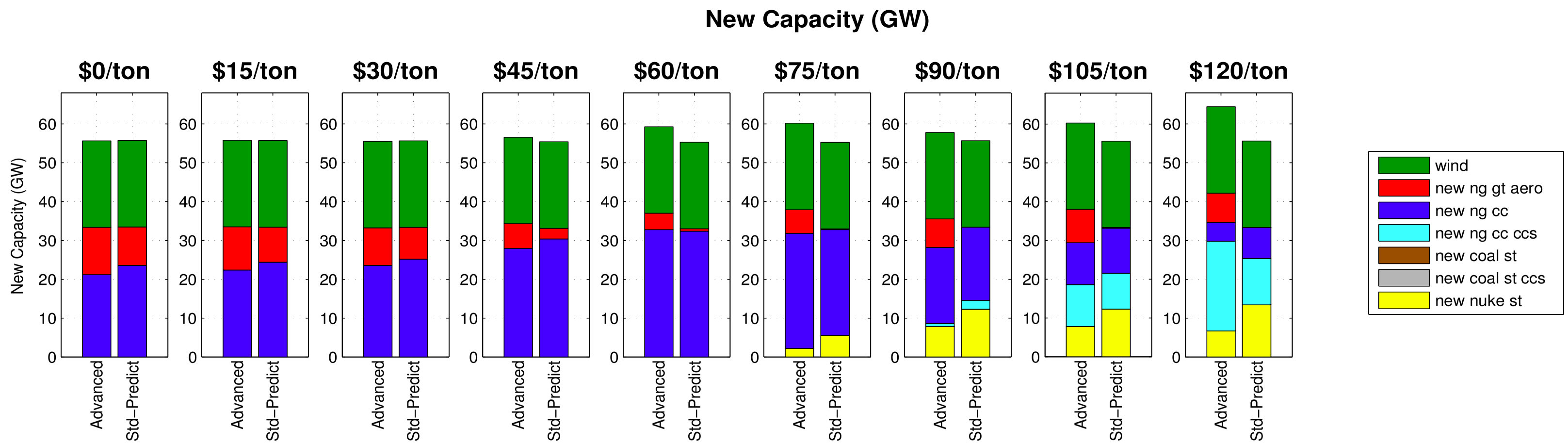


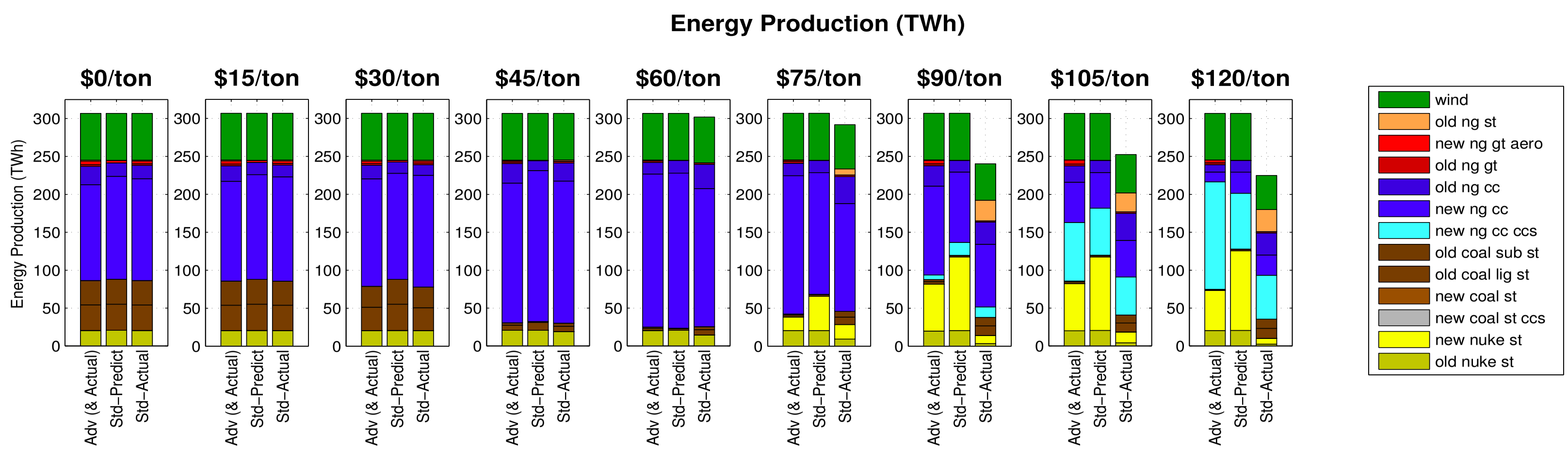
Figure 4.8: Variation in CO_2 emissions forecast errors as a function of carbon price. Policy maker predictions from Standard merit order operations and Advanced unit commitment based planning models are compared to simulated actual emissions for a system built using the Advanced generation mix.

Table 4.4: Carbon emissions predictions for Standard operations versus the more realistic Advanced planning model that captures the "actual" emissions.

	Emissions (Mt CO2e)	
Carbon Price ($/ton)	Advanced (& Actual)	Standard Predict
0	127	126
15	126	126
30	121	126
45	87	86
60	82	80
75	76	64
90	62	41
105	38	28
120	19	21



(a)



(b)

Figure 4.9: (a) New capacity and (b) energy production as function of carbon price for standard, merit order (Std) and advanced, unit commitment (Adv) based capacity planning models. Energy production in (b) includes both predicted and simulated actual assuming the generation mix was actually built. Actual simulations include maintenances and a full set of realistic, unit commitment based operating constraints.

Standard and Advanced models also build similar mixes of NG-CC and NG-GT, resulting in only minor differences in emission forecasts. At and above \$75/ton, both models also include nuclear, but in different quantities and augmented by different technologies. The largest emissions forecast errors occur for \$75-\$105/ton CO_2 where the Standard model predicts significantly more nuclear, while the Advanced model restricts nuclear investment due to nuclear's operational inflexibility. The emissions estimate errors result from replacing the zero carbon nuclear with carbon emitting natural gas. At \$120/ton, the Standard model still builds significantly more nuclear, but here the high carbon price prompts the Advanced model to add CCS to the NG-CC facilities, thereby bring their carbon emissions down considerably and reducing the difference between the Standard forecast and actual emissions.

The policy analyst perspective in terms of Capacity & Energy

In addition to the carbon emissions estimates, the policy analyst is also interested in predicting these capacity mixes and the corresponding energy production by source. These results are important for understanding the wider impacts on the energy supply chain and overall economy. For the policy analyst perspective, this thesis assumes the "actual" capacity mix will be built by the utility using the Advanced model, and that the "actual" emissions correspond to the Advanced results. Thus, for capacity, as seen in Figure 4.9(a), the analyst is interested in whether or not the Standard merit order based model reasonably matches the Advanced model mix. As described above, the Standard model does an acceptable job at estimating capacity up to \$60/ton, but at and above \$75/ton the models diverge considerably. Unlike for carbon emissions forecasts, the accuracy of capacity mix forecasts gets continually worse with higher carbon prices.

For accuracy of predicting energy mixes, the policy analyst is concerned with the comparison between the first 2 bars in each subplot in Figure 4.9(b). These compare the Advanced model results with the predictions from the Simp model. Here again, the Standard model predictions (2nd column) do a reasonable job of matching the "actual" Advanced results (1st column) up to \$60/ton but begin to steadily diverge for CO_2 prices of \$75/ton and above.

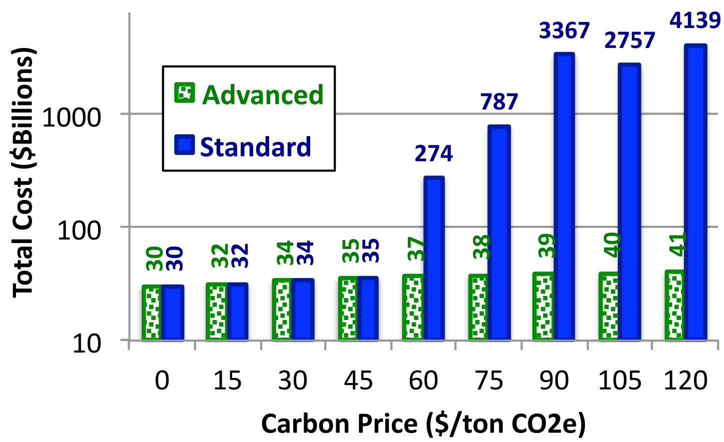


Figure 4.10: Variation in annual total costs (capacity payments plus operations) as a function of carbon price. Results assume the utility builds new capacity based on the output of the Standard or Advanced planning models. The corresponding mix is then simulated using a unit commitment based operations only model to estimate "actual" operating costs. Note logarithmic y-axis.

The Utility Perspective

Returning to the utility perspective, the scenario and metrics are different, but again the Standard, merit order based capacity planning model does poorly for stricter carbon policies as anticipated by the differences in capacity and energy mix. Figure 4.10 shows that for carbon prices up to $45/ton, the total annual cost for the systems designed by the Standard operations and Advanced UC-based capacity planning models are indistinguishable. But, at and above $60/ton the Standard model produces unsatisfactory generation mixes that if built and operated in compliance with the RPS requirements would result in extremely high costs. As described in Section 4.4 these problems with the Standard generation mix result from insufficient operational flexibility that cause a cascade of problems resulting in loss of load and associated expensive penalty costs.

These problems from the utility perspective can be seen in the capacity and energy differences between the Standard and Advanced models in Figure 4.9. Sub-figure (a) shows that the Standard model's omission of operational flexibility causes an underinvestment in total new capacity at $60/ton and above. This in turn forces the system to shed load in order to provide reserves and meet the RPS. This loss of load appears as a drop in the total quantity of energy produced for the Simp-Actual cases (3rd bar of each subplot) in sub-figure (b).

As described in Section 4.4.3, these flexibility driven problems could partially be alleviated by increasing the planning reserve used with the Standard model beyond the current requirement of 13.75% to meet the higher effective reserve levels built by the Advanced model. For the $60/ton case this heuristic might work since the resulting increase in either NG-CC or NG-GT would likely provide enough operational flexibility to overcome the observed loss of load that is driving the high total costs. But as is was seen in Section 4.4.3, the heuristic of increasing the planning margin fails when the Standard generation mix relies on significant quantities of inflexible nuclear generation, as is the case for $75/ton and higher carbon costs.

4.6 RENEWABLES AND CARBON POLICY

This section expands the carbon sensitivity analysis by considering both sides of the operationally flexibility balance: carbon policy that can restrict available flexibility and renewables that demand increased flexibility. Specifically this section compares all combinations of five RPS levels - 0%[15], 20%, 40%, 60%, and 80% - with four carbon emission limits - No limit, 141Mt, 94Mt, 47Mt. These emissions limits were chosen based on a policy-free baseline with no carbon policy and no RPS. The baseline emissions were 188Mt CO_2, such that these four carbon caps correspond to 100%, 75%, 50%, and 25% of the baseline emissions.

4.6.1 *Capacity and Energy*

Figure 4.11 compares the capacity mix suggested by both the Standard and Advanced models across this array of RPS and CO_2 limits. There is a lot if information in this chart so let us begin with the most familiar. The second column (20% RPS) is analogous to the sensitivity analysis preformed in the last section under varying CO_2 prices. As before, the two models produce very similar capacity mixes for relatively

15 Even at 0% RPS, there is still some wind on the system. As described in Section 4.2.1, 50% of the 2010 installed wind is assumed to be still operational, resulting in an installed capacity of 4.7GW which, if fully utilized, corresponds to 3.5% of the total annual energy demand.

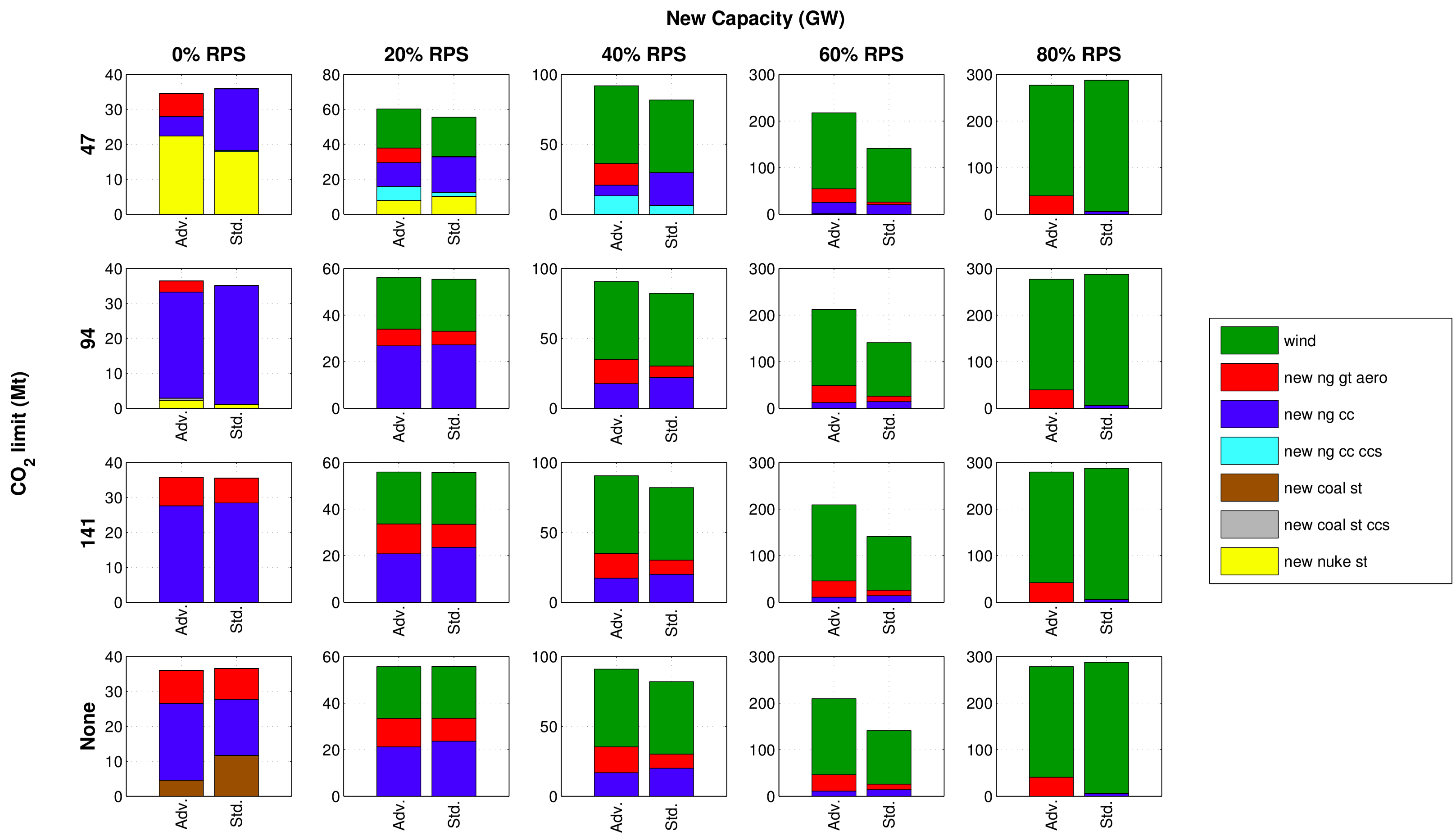


Figure 4.11: Comparison of new capacity differences between planning models that use 1) Advanced unit commitment based operations (Adv) versus 2) Standard merit order dispatch (Std).

loose carbon policies. At 20% RPS, the Advanced and Standard capacity mixes only diverge for the 47Mt CO_2 limit. As before, the differences result from operational flexibility: The Advanced model recognizes the need to balance the inflexible nuclear generation with NG-GT. This is not surprising considering the duality of carbon limits and prices. According to the earlier results reported in Table 4.4, an emissions level of 47Mt (at 20% RPS) falls between \$90/ton and \$105/ton CO_2, and not surprisingly comparing Figure 4.9(a) with Figure 4.11 the generation mixes are similar. Analogously, the 94Mt limit at 20% RPS corresponds to under \$45/ton, a point at which as is evident here only minor differences are observed in capacity between the Advanced and Standard models.

Moving laterally to the 0% and 40% RPS levels reveals similar patterns, with the operational flexibility of the Advanced model again drives an increase in highly flexibility NG-GT under strict carbon limits. These additional facilities balance the inflexible nuclear capacity in the 0% RPS case or the increased flexibility required by the extra wind in the 40% RPS case.

In addition, at 0% RPS with the 94Mt CO_2 limit, both models build some nuclear capacity, a technology that was previously only seen under the stricter 47Mt carbon limit with the 20% (or higher) RPS. This additional need for carbon-free generation results directly from the lower RPS. By definition, under the 20% RPS, 20% of the annual energy must come from carbon-free renewable sources (wind in this test system). Hence, without the RPS, additional low/no-carbon sources are required to stay under the carbon emissions limit. And again, operational flexibility causes a difference in the resulting capacity mix. The Advanced model builds significantly greater amounts of highly flexible NG-GT to more easily provide the reserves required by the system.

Interestingly, even without an RPS constraint, the reduced operational flexibility of the Standard generation mixes for the 47Mt-0% and 94Mt-0% cases still cause a loss of load similar to that seen in the strict carbon policy 20% cases, including 47Mt-20%. The reasoning is similar to that from Section 4.3.3: with insufficient operational flexibility, the Standard model's generation mix must shed load in order to provide adequate reserves and honor generator technical constraints. These cases can be seen[16] in Figure 4.12, , which compares the pre-

16 The comparatively small quantity (1.9TWh) of lost load for 94Mt-0% is not discernible in the graphs b/c it represents less than 1% of the total energy demand.

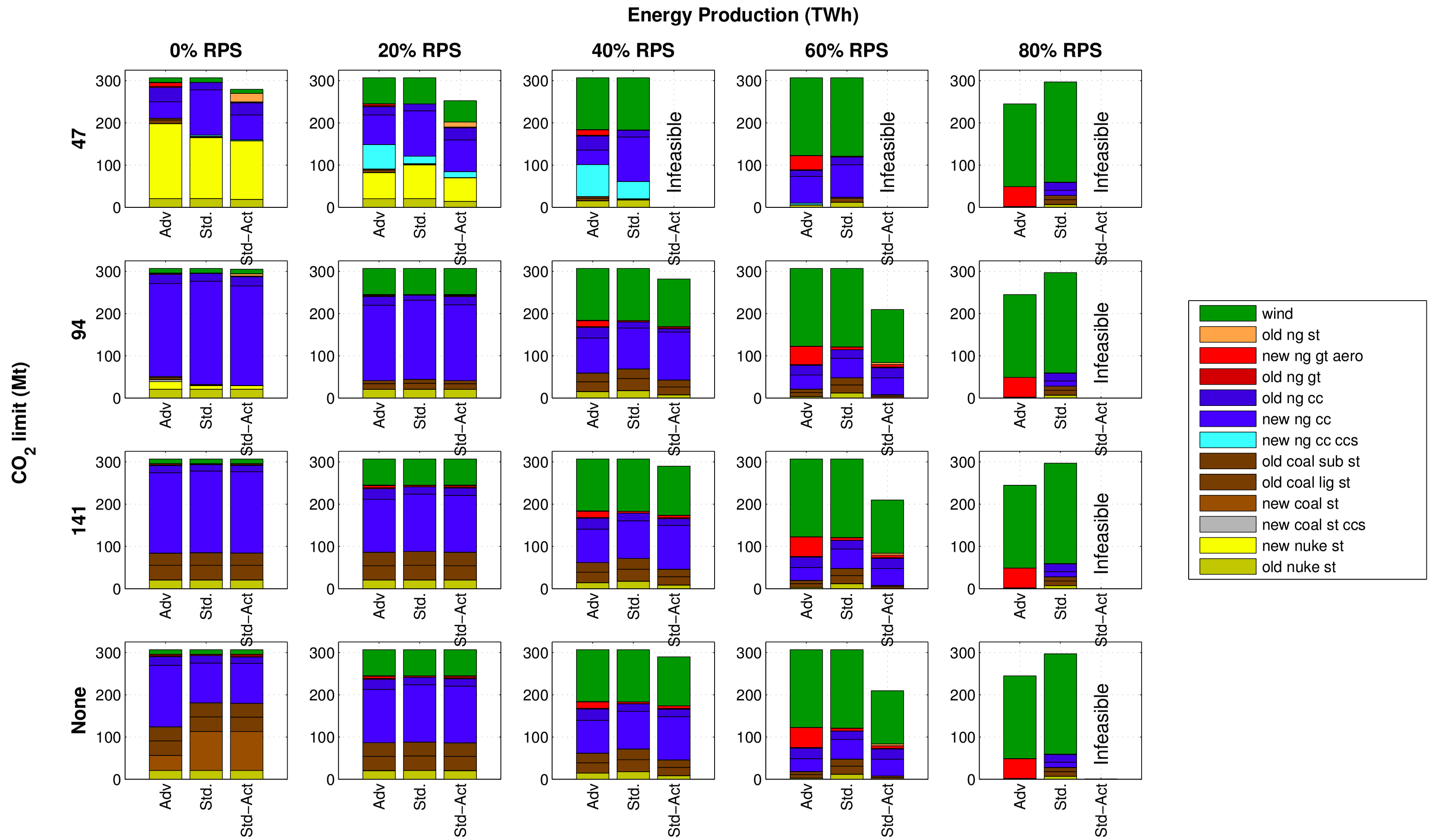


Figure 4.12: Energy production as function of RPS and carbon limit for standard merit order (Std) and advanced unit commitment (Adv) based capacity planning models. Both predicted and simulated "actual" — assuming the generation mix was actually built — are shown. For policy analysis the relevant comparisons are columns 1&3 (Advanced and Standard predictions) versus column 2 (Adv-Actual). In contrast a utility is interested in whether or not the Standard model predictions can be realized in actuality (Std vs. Std-Actual).

dicted and actually Standard model energy mixes with the Advanced model results across this array of RPS and CO_2 limits.

The situation is even worse for higher RPS levels, where the lack of flexibility from the Standard model makes the generation mix *infeasible* to operate for RPS levels of 40% and above under the 47Mt limit. In these situations, it is not possible to simultaneously meet the carbon limit and RPS requirement while still providing adequate reserves and complying with generator technical constraints[17]. In contrast, the mix suggested by the Advanced model complies with both the carbon and RPS policies.

4.6.2 *Flexibility and Renewable Capacity*

Returning to the capacity mix in Figure 4.11, shows that total renewable capacity presents another significant difference for high RPSs. In all of the 40% and 60% cases, and the 47Mt-20% case, the Standard generation planning model installs significantly less wind capacity than the Advanced model. As seen in Figure 4.12, this results in considerable loss of load or infeasible operations. At this high penetration of wind, the total available wind power exceeds demand for over 1/3 of the year. Without storage to redistribute this extra energy to other times[18], the system must over-invest in wind capacity to compensate for this wind shedding by providing extra wind at other times. Both models recognize this, but by not capturing operational flexibility, the Standard model fails to recognize that even more wind must be shed during these high wind periods since some non-renewable capacity must be kept on-line to provide operating reserves, making periods of 100% wind impossible.

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17 Again, in practice, the utility and policy makers would likely find a way to keep the lights on, likely by ignoring the RPS or carbon requirements. However, neither of these results are desirable, and more importantly can be avoided if an operational-flexibility-aware planning process is used.

18 Exploring the impacts of storage on these results represents a promising area of future research. In these situations storage could help in two ways: 1) saving wind energy for use at other times, thereby requiring less investment in underutilized wind capacity; and 2) serving as a highly operationally flexible supply resource capable of providing operating reserves, potentially requiring less investment in thermal capacity while also reducing thermal operations associated costs and emissions. The combination of these three cost savings could provide a revenue source large enough to justify the comparatively high capital cost of storage.

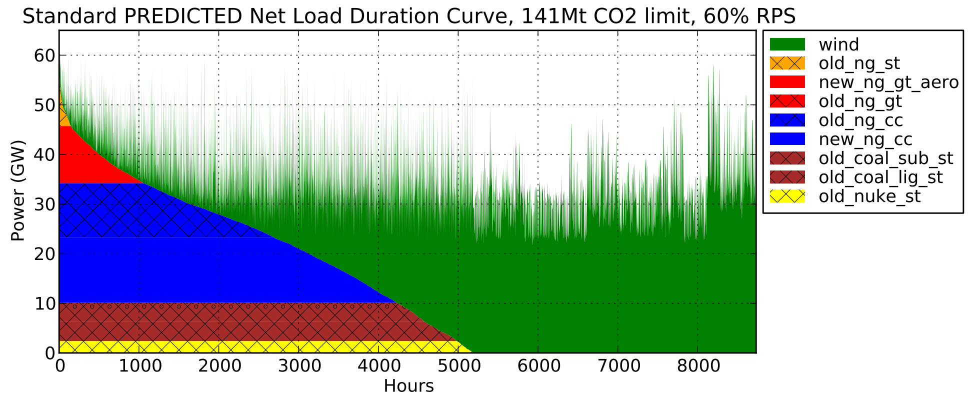
The Standard model's problems with lost load and infeasible operations come from simply not having enough installed wind capacity to accommodate the additional wind shedding required for reserves while still complying with the RPS. Figure 4.13 shows this effect by comparing the predicted annual net load duration curve with actual "simulated" operations for the Standard model under a 141Mt carbon limit with 60% RPS. In Figure 4.13(a) standard, flexibility-ignorant operations predict many hours of 100% renewables; however, as seen in (b), significant thermal capacity must be kept on-line at all times to provide reserves. The additional non-renewable generation for reserves causes significant reserve shedding, making the minimally overbuilt wind capacity unable to provide the 60% RPS without the system shedding load.

Furthermore, the increased thermal operations to provide reserves increase carbon emissions. With the 141 Mt CO_2 limit these increases are still acceptable, but as seen in Figure 4.12 with the 60% and the strict 47Mt carbon limit, the added carbon emissions from providing these reserves make it infeasible to stay below the CO_2 limit while complying with the RPS and providing reserves.

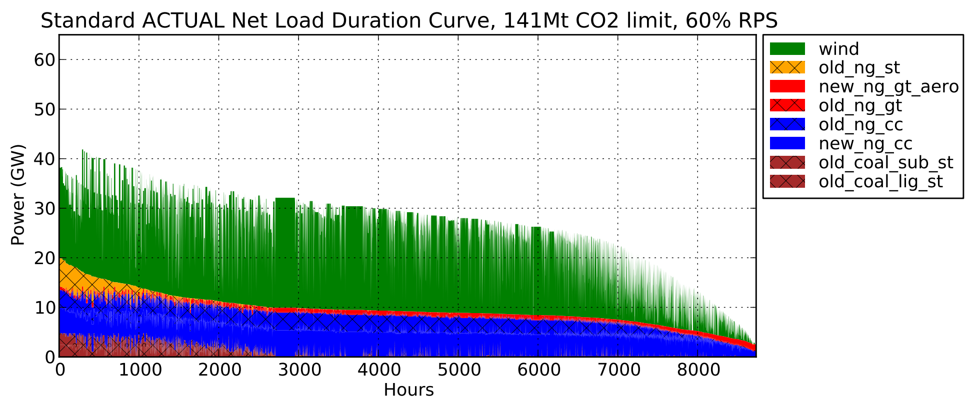
In contrast, as seen in Figure 4.13(c), the Advanced model alleviates these problems in two ways: 1) the overbuilt wind capacity is able to provide sufficient renewable energy to meet both demand and the RPS, and 2) the highly flexible NG-GT plants in the Advanced mix can provide sufficient operating reserves while running at lower output levels, thereby requiring less wind shedding and easing the need to overbuild wind.

In the 80% RPS scenarios, the Advanced model counterintuitively builds less wind capacity than the Standard model because even the highly flexible NG-GT can no longer provide sufficient reserves without shedding demand. Instead, as seen in Figure 4.14 the system operates almost exclusively as a combination of wind with NG-GT for reserves. In these scenarios, the Standard model builds more wind, with the expectation that it can all be used toward the load; however, with only a small addition of flexible NG-GT, the resulting system proves infeasible in operations, as seen in Figure 4.12.

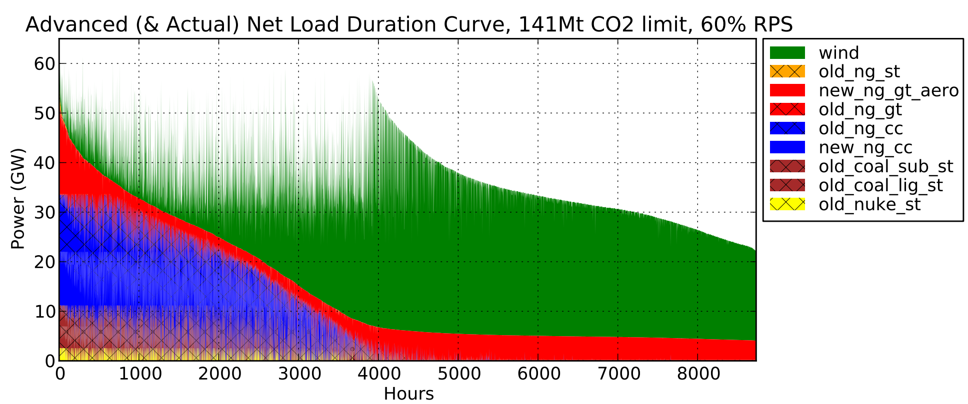
At 80% RPS, operating the system without loss of load requires additional options for flexibility beyond the set of thermal generation considered here. This could include non-thermal options such as highly operationally flexible hydro, storage, or demand response. Alternatively, the additional flexibility could come from an expanded set of



(a)



(b)



(c)

Figure 4.13: Comparison of (a) Standard model predicted net load duration curve vs (b) simulated actual operations of the Standard model's mix for 141Mt CO_2 limit and 60% RPS. "Actual" operations of (c) the Advanced model mix included for comparison.

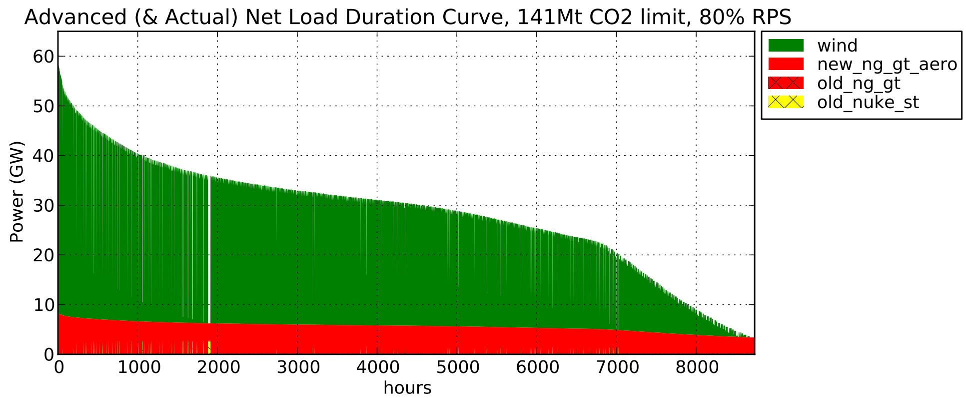


Figure 4.14: Net load duration curve for "Actual" operations of the Advanced model at 80% RPS. The 141Mt case shown is identical to that for all tested CO_2 limits from no limit down to 47Mt.

	Actual (Advanced) - Carbon Emissions (Mt CO2e)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	47	47	47	47	25
94	94	94	94	63	25
141	141	127	97	63	25
None	163	127	97	63	25

Table 4.5: "Actual" CO_2 emissions for Advanced model. Scenarios where the RPS alone drives CO_2 emissions below that required by the carbon policy are highlighted in green.

thermal generators that includes more operationally flexible but higher cost versions of the fundamental generation types. Such flexibility enhancement would otherwise seem prohibitively expensive and hence would not be built when flexibility is not captured by the capacity planning model. Exploring these alternative sources of flexibility is left for future research.

4.6.3 *RPS and Carbon Emissions*

Another interesting observation about the 80% RPS cases is that, as seen in Figure 4.11, the different generation mixes by the Standard and Advanced model are identical across all CO_2 limits. Table 4.5, shows how this similarity is simply because the carbon limits are never binding under the 80% RPS. In all cases, the 80% RPS requirement alone is enough to force the CO_2 emissions level to 25Mt. This is expected since if 80% of generation is supplied by carbon-free renewables, carbon-emitting generation will only provide 20% of the energy. Even if this 20% of non-renewable energy had the same carbon intensity as the baseline system, the 80% RPS would represent an 80% reduction in total emissions. But, since sufficient operational flexibility is required to provide reserves, this remaining non-renewable generation will be biased toward the most flexible NG-GT units, which have a lower carbon intensity than the baseline system, resulting in further emissions reductions.

The ability of the RPS to lower emissions creates a diagonal in Table 4.5 below which imposing the RPS requirement alone meets or exceeds the policy imposed carbon limit. As seen in Figure 4.11 and Figure 4.12 respectively, this effect also implies that the generation and energy mixes below the diagonal will be dictated by RPS alone, independent of the carbon limit imposed.

4.6.4 *Utility Perspective*

The operational differences described above clearly indicated the importance of capturing operational flexibility within the utility planning process in order to prevent lost load (or policy non-compliance) for high RPS levels or strict carbon policies; however, it would also be useful to know if and when the standard merit order based planning model is sufficient, even if the generation mixes are slightly different than those from the Advanced model. Table 4.6 shows that the standard, merit order based capacity planning model provides good results for the No limit and 141Mt CO_2 limit policies at and below a 20% RPS as well as the 94Mt-20% case. In these situations, which include the current states of nearly all operating power systems, capturing only merit order operations with a standard capacity planning model may be sufficient and only results in small cost increases. For all other cases with this test system, capturing operational flexibility, such as using an advanced UC-based model, is essential to avoiding infeasible operations and the non-served energy that drives the observed excessive price increases.

	Standard - Cost Increase over Advanced ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	1362	2720	Infeasible	Infeasible	Infeasible
94	97	0.0	1256	4850	Infeasible
141	0.0	0.0	847	4833	Infeasible
None	0.0	0.0	848	4844	Infeasible

(a)

	Advanced - Total Annual System Cost ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	32	35	41	71	3188
94	28	31	38	69	3188
141	26	30	38	69	3188
None	26	30	38	69	3188

(b) Advanced Baseline

Table 4.6: (a) Increase in total annual cost — including capital and operations — for the Standard generation mix compared to that built considering operational flexibility with the Advanced model. Scenarios costs differ substantially are highlighted in red. The corresponding costs for the Advanced mix are shown in (b).

In practice, the second simulation stage of the modern planning process described in Section 1.6.2, would likely catch the Standard model's shortcomings before physical hardware is actually built; however, since the initial capacity mix for consideration is produced by a flexibility-ignorant Standard operations model, planners would be left with ad hoc adjustments to correct the problem. As a result the detailed analysis phase, and later construction, could very likely be based on a sub-optimal generation mix. If a flexibility aware, advanced UC-based model was used instead for the initial screening stage, an optimized, lower cost and/or higher reliability system can be carefully analyzed and built.

4.6.5 *Policy Analyst Perspective*

The potential to (over)analyze the wrong generation mix as a result of ignoring operational flexibility could easily afflict policy analysts and renewable integration researchers. In the later case, the most advanced researchers follow a multi-step planning process similar to the utility, such that a standard merit order based screening phase could result in a sub-optimal generation mix for further analysis, unless ad-hoc adjustments are made. However, other researchers and most policy analysts, use only a single phase approach to capacity planning, such that the initial capacity expansion model is the only chance to capture the impacts of operational flexibility.

To illustrate the potential shortcomings of the standard, flexibility-ignorant capacity planning models for the policy analyst, Table 4.8 compares the error in energy mix predictions for the Advanced and Standard planning models. The energy mix is used, rather than the emissions errors used previously for the policy analyst perspective because the emission limits are dictated by carbon policies under test. These differences are computed using the normalized RMS energy error from Equation (4.1). As before, the "actual" emissions are assumed to result from the utility building and operating a generation mix suggested by theAdvanced model.

These mappings show how the Standard model has significant forecast errors for higher RPS levels and/or strict CO_2 policies. The most significant Standard model differences (>20% for the E-mix metric) correspond to similar pattern as the cost increases seen from the utility perspective. In these cases, operational flexibility needs to be cap-

	Standard - Policy: Energy Forecast Error (Normalized RMS)				
CO2 Limit (Mt)	**0% RPS**	**20% RPS**	**40% RPS**	**60% RPS**	**80% RPS**
47	92%	68%	97%	44%	101%
94	32%	15%	25%	50%	101%
141	4%	16%	20%	54%	101%
None	90%	14%	22%	56%	101%

Table 4.7

Table 4.8: Energy mix prediction errors from the policy maker perspective for the Standard planning model. Errors are relative to a baseline of operations simulations from the Advanced model. Increasing error levels are highlighted with a spectrum changing from white (no error) to yellow to red (very poor estimates).

tured to accurately estimate the energy mix. Additionally, the Standard model also has significant forecast errors for the baseline case of 0% RPS and no carbon policy. Again, this results from not considering operational flexibility. As seen in Figure 4.11, the Standard model suggests a larger capital investment in relatively inflexible coal, rather than natural gas. For the utility, this mix can be built and operated with minimal added cost, but for the policy analyst interested in the energy mix and associated carbon emissions, the increased coal capacity and hence increased predicted coal emissions can be important.

In this No Limit-0%RPS case, the standard merit order based planning model over estimates the carbon emissions by 5%. While this discrepancy would be conservative in terms of future emissions impacts, it could produce unintended effects if used as the basis for policy. For example, overestimates of carbon emissions could produce windfall profits if used for allocating emissions permits or result in the collapse of an emissions trading market prices if used as a basis for a cap and trade system[19].

19 For this and other reasons, most proposals for both policy schemes rely on historic emissions rather than projections to avoid this particular issue.

	Standard - Capacity Difference (Normalized RMS relative to UC)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	110%	54%	68%	65%	57%
94	36%	6%	32%	68%	57%
141	10%	19%	26%	68%	58%
None	69%	16%	28%	68%	58%

Table 4.9: New capacity mix prediction errors for the merit order based planning model (Standard) relative to the baseline Advanced generation mix. Increasing error levels are highlighted with a spectrum changing from white (little difference) to yellow to red (large differences).

4.6.6 *Capacity Revisited*

The color highlighted table format seen in the last subsection provides a concise way to summarize the differences between the Advanced and Standard model results. Looking forward to the next section which adds additional model types to this already high dimensional comparison, its helpful to consider a similar mapping for the capacity differences to see if can capture the key results from Figure 4.11.

Table 4.9 maps out the normalized, RMS capacity difference for the Standard model. The fill patterns do correspond to capacity mix differences described above and further highlight how the Standard planning model diverges from the Advanced model's full-UC optimum for 3 distinct regions as described in detail earlier: 1) high RPS for all CO_2, 2) low-mod RPS/mid-strict CO_2 limits, and to a lesser extent 3) low RPS/Unlimited CO_2.

4.6.7 *System Dependence*

It is important to remember, that these mappings of when operational flexibility, as captured by the Advanced model, impact planning are highly system specific. A system with more flexible existing generation, such as extensive hydro, might be able to use standard merit order operations for a larger subset of cases. In contrast, systems with more inflexible legacy generators, including retirement rates lower than the 50% considered here, could require capturing operational flexibility for more, if not all scenarios. Moreover, if technologies that derive significant value from providing operational flexibility — including storage, demand response, or flexibility-augmented thermal generation — are considered as expansion candidates, operational flexibility should be considered earlier in order to properly compare these technologies value streams.

4.6.8 *Summary*

This section demonstrates how the impact of operational flexibility depends on the carbon policy and RPS scenario. When operational flexibility is not challenged, merit-order operations based models can produce good expansion plans for utilities and good impact estimates for policy analysts. However when carbon policy encourage investment in less flexible generation or large quantities of renewables require increased operational flexibility, the use of simplified models can produce bad expansion plans for utilities or poor estimates of policy impacts for analysts.

Additional figures and tables can be found in Appendix C.

4.7 APPROACHES FOR CAPTURING OPERATIONAL FLEXIBILITY IN PLANNING

4.7.1 *Operational Flexibility Approaches Compared*

With the motivation that operational flexibility is important to capture during the planning process, this section explores a few alternative methods of modeling flexibility during planning model optimization. If successful, these simpler methods could provide faster, simpler ways to capture operational flexibility without resorting to the full clustered integer UC approach used by the full Advanced model. In order of increasing complexity the complete set of operations types compared are:

MERIT ORDER OPERATIONS (STANDARD): As seen before, this approach ignores operational flexibility and will dispatch generation in order of increasing variable cost to meet the demand;

MERIT ORDER WITH "FLEXIBILITY" RESERVES (MTOFLEX): This approach is similar to that used by de Jonghe, et al. [18] and the

NETPLAN[20] model [214]. MtoFlex recognizes the importance of operating reserves for operational flexibility by adding two classes of combined operating reserves (as described in Section 2.5.2) to the Standard formulation: 1) "Flexibility up" to capture the need to maintain some generation below its maximum output such that it can be increased if needed to account for forecast errors or contingencies, and 2) "Flexibility down" which analogously requires sufficient generation to be on-line such that it can be reduced if needed to account for forecast errors. To compute reserve needs and generator capabilities, the separate reserve classes used in the full Advanced model are divided between "up" and "down" and summed. Without information about which units are running, the mtoFlex formulation assumes that all operating generation can be used for reserve down while upward reserves are restricted the the difference between installed capacity and current output. Furthermore, since reserve constraints are also strongly limited by ramping rates, additional restrictions are placed on reserve capabilities; however, without information about which units are currently on-line, these ramp-based reserve limits are based on the total installed capacity rather than only committed units. This can overestimate available reserves – and hence underestimate flexibility challenges and corresponding costs. To partially account for this, I use de Jonghe, et al.'s heuristic that reduces reserve capability of "off-line" generators to 60%[21]. Since there are no commitment variables, this off-line capacity is estimated as the difference in total capacity and current output production [18].

UNIT COMMITMENT WITH RELAXED INTEGERS (UCLP): This approach uses all of the same relations as the full clustered unit commitment operations sub-model, but relaxes the integer constraint for unit commitment state, startup, and shutdown variables. Instead, these variables can take on any value over the continuous interval from zero to the maximum number of generators, $n_{\hat{g}}^{max}$.

20 NETPLAN maintains separate reserve classes but the other assumptions are comparable.

21 For reference, NETPLAN assumes 100% of offline generation can provide reserves, which would result in even larger differences compared to unit commitment based reserves.

FULL CLUSTERED UNIT COMMITMENT (ADVANCED): This is the complete, integer based unit commitment model for operations described in Chapter 2 and used in the previous analyses of this chapter.

For all of the approaches the overall model is still classified as a MILP since investment decisions are always modeled as discrete. The operations portion of theAdvanced model is also a MILP; however, the operations portions of the Standard, mtoFlex and UcLp are captured as LPs. With the Standard and mtoFlex approaches, maintenance is not explicitly optimized during planning, rather the maximum output for each unit is derated by the fraction of the year spent on scheduled maintenance. For UcLp and Advanced, the maintenance constraints are modeled with discrete variables.

4.7.2 *Results*

Capacity and Energy

The two intermediate approaches for capturing operational flexibility, mtoFlex and UcLp, produce improvements over the Standard model in most cases, but UcLp provides substantially better results and nearly matches the full Advanced model for almost all cases including higher RPS levels (>= 60%) and strict carbon policies (47Mt CO_2 limit). Table 4.10 shows the patterns for the capacity difference metric for the Standard, mtoFlex, and UcLp models relative to the full Advanced model. Full bar charts and tables the capacity and energy mixes can be found in Appendix C.

Compared to the Standard model, the mtoFlex capacity mixes are noticeably closer to the full Advanced optimal, with improvements of 10% to nearly 40% for the capacity metric, except for the No Limit-0% and 141Mt-0% cases where mtoFlex does poorly. However, the mtoFlex model does worse than the UcLp model in all but two cases.

The relaxed integer unit commitment model (UcLp) provides nearly identical results to the full Advanced model in all but a few cases. The few exception occur with the 47Mt cap and 0-40% RPS, where the UcLp model fails to recognize the need fully adapt capacity to compensate for baseload (in)flexibility. For example, the UcLp model may underbuild wind capacity since it doesn't capture the full inflexibility of the nuclear baseload, or may fail to invest sufficiently in highly flexible NG-GT units. As explored more thoroughly in the next section,

CO2 Limit (Mt)	Standard - Capacity Difference (Normalized RMS relative to UC)				
	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	110%	54%	68%	65%	57%
94	36%	6%	32%	68%	57%
141	10%	19%	26%	68%	58%
None	69%	16%	28%	68%	58%

(a)

CO2 Limit (Mt)	mtoFlex - Capacity Difference (Normalized RMS relative to UC)				
	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	77%	33%	47%	51%	44%
94	6%	11%	7%	52%	44%
141	2%	10%	7%	52%	43%
None	69%	12%	7%	52%	43%

(b)

CO2 Limit (Mt)	UcLp - Capacity Difference (Normalized RMS relative to UC)				
	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	41%	10%	22%	9%	1%
94	9%	3%	2%	3%	0%
141	10%	5%	1%	1%	1%
None	11%	3%	3%	1%	1%

(c)

Table 4.10: New capacity mix differences for the (a) Standard merit order operations-based, (b) merit order with flexibility reserves (mtoFlex), and (c) unit commitment with relaxed integer commitment (UcLp) planning models relative to the baseline Advanced, UC-based generation mix. Increasing error levels are highlighted with a spectrum changing from white (little difference) to yellow to red (large differences).

the challenge comes from UcLp's failure to fully consider minimum output and minimum up and down time constraints, since it's relaxed formulation allows fractional commitment states. Section 4.7.3 explains the drivers behind these differences in more detail.

Policy analyst perspective

From the policy analyst perspective, Table 4.11 shows how the predicted energy mix follows a similar pattern, but further emphasizes how mtoFlex provides only a minor improvement over the Standard operations based model for energy estimates. In contrast, the UcLp model provides energy mix estimation errors near or below the approximately 20% accuracy threshold for this metric for all cases except 47Mt-0% and 47Mt-60%. Section 4.7.3 explains the drivers behind these differences in more detail.

Utility perspective

From the utility perspective, the total annual cost, Table 4.12 shows how the mtoFlex approach expands the region of minimal[22] cost increases beyond that of the Standard model to include most of the 40% RPS cases, except 47Mt-40%, and suggests a reasonable mix for the 94Mt-0% cases. However, the mtoFlex model still produces infeasible mixes for all 80% cases and loss of load still causes very high operating costs for all other strict carbon policy (47Mt) cases.

Here the UcLp simplification does extremely well, producing generation mixes that cost essentially[23] the same as those from the full Advanced model for all cases, including those that had some larger variations in energy and capacity. The next section explains the drivers behind these differences in more detail.

22 Though an increase of 0.2 still corresponds to $200Million, so the improvements from the UcLp and full Advanced model would still important in practice.

23 The slightly lower costs observed for the UcLp model are likely due to small discrepancies in MILP convergence during the initial planning phase. In most cases these are simply rounding differences, but in some they may correspond to places where the simpler UcLp model was actually able to achieve a small improvement over the full Advanced model before reaching the run time limit. Further study of this possibility is left for future research.

	Standard - Policy: Energy Forecast Error (Normalized RMS)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	92%	68%	97%	44%	101%
94	32%	15%	25%	50%	101%
141	4%	16%	20%	54%	101%
None	90%	14%	22%	56%	101%

(a)

	mtoFlex - Policy: Energy Forecast Error (Normalized RMS)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	73%	60%	89%	41%	97%
94	10%	15%	16%	50%	97%
141	2%	10%	17%	55%	97%
None	90%	8%	19%	56%	97%

(b)

	UcLp - Policy: Energy Forecast Error (Normalized RMS)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	41%	14%	40%	23%	0%
94	10%	1%	2%	7%	0%
141	3%	5%	2%	2%	0%
None	10%	2%	2%	2%	0%

(c)

Table 4.11: Energy mix prediction errors from the policy maker perspective for the (a) Standard, (b) mtoFlex, and (c) UcLp planning models relative to a baseline of operations-only simulations for the Advanced generation mix. Increasing error levels are highlighted with a spectrum changing from white (no error) to yellow to red (very poor estimates).

	Standard - Cost Increase over Advanced ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	1362	2720	Infeasible	Infeasible	Infeasible
94	97	0.0	1256	4850	Infeasible
141	0.0	0.0	847	4833	Infeasible
None	0.0	0.0	848	4844	Infeasible

(a)

	mtoFlex - Cost Increase over Advanced ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	101	89	233	954	Infeasible
94	-0.1	0.2	0.2	946	Infeasible
141	0.0	0.2	0.2	946	Infeasible
None	0.0	0.2	0.2	946	Infeasible

(b)

	UcLp - Cost Increase over Advanced ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	-0.1	-0.1	-0.2	-0.1	0.1
94	0.0	0.0	0.0	0.0	0.0
141	0.0	0.0	0.0	0.0	0.1
None	0.0	0.0	0.0	-0.1	-0.2

(c)

	Advanced - Total Annual System Cost ($Billions)				
CO2 Limit (Mt)	0% RPS	20% RPS	40% RPS	60% RPS	80% RPS
47	32	35	41	71	3188
94	28	31	38	69	3188
141	26	30	38	69	3188
None	26	30	38	69	3188

(d) Advanced Baseline

Table 4.12: Increase in total annual cost — including capital and operations — for the (a) Standard, (b) mtoFlex, and (c) UcLp planned generation mixes compared to that built considering operational flexibility with the Advanced model. Scenarios costs differ substantially are highlighted in red. The corresponding costs for the Advanced mix are shown in (d).

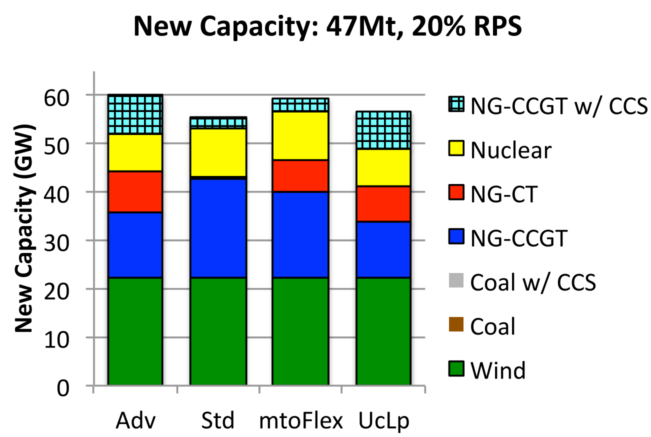


Figure 4.15: Comparison of capacity additions for each of the capacity planning model types for a 47Mt CO_2 limit and 20% RPS.

4.7.3 *A closer look*

To better understand how the different operating models impact the planning results, this section explores the 47Mt-20% case in greater detail. As seen in Table 4.10, this is the one case where all of the model approaches do a poor job of approximating the full Advanced results. In other scenarios, one or more approximate models do a good job of estimating the full Advanced results, making comparisons difficult.

Capacity and Energy

Figure 4.15 compares the new capacity mix across the models. All of the approximate model types underinvest in wind capacity, leaving minimal margin for any possible wind shedding. In addition, Standard and mtoFlex both build more inflexible nuclear. As seen in Figure 4.16 this combination causes the generation mix from Standard and mtoFlex to have substantial non-served energy in order to simultaneously meet the RPS, CO_2 limit, provide reserves, and comply with operating constraints. The UcLp model, despite under building wind, has sufficient operational flexibility from the very low carbon NG-CC with CCS, enabling actual operations without loss of load.

Net Load Duration Curve

The predicted net load duration curves, shown in Figure 4.17 , high-

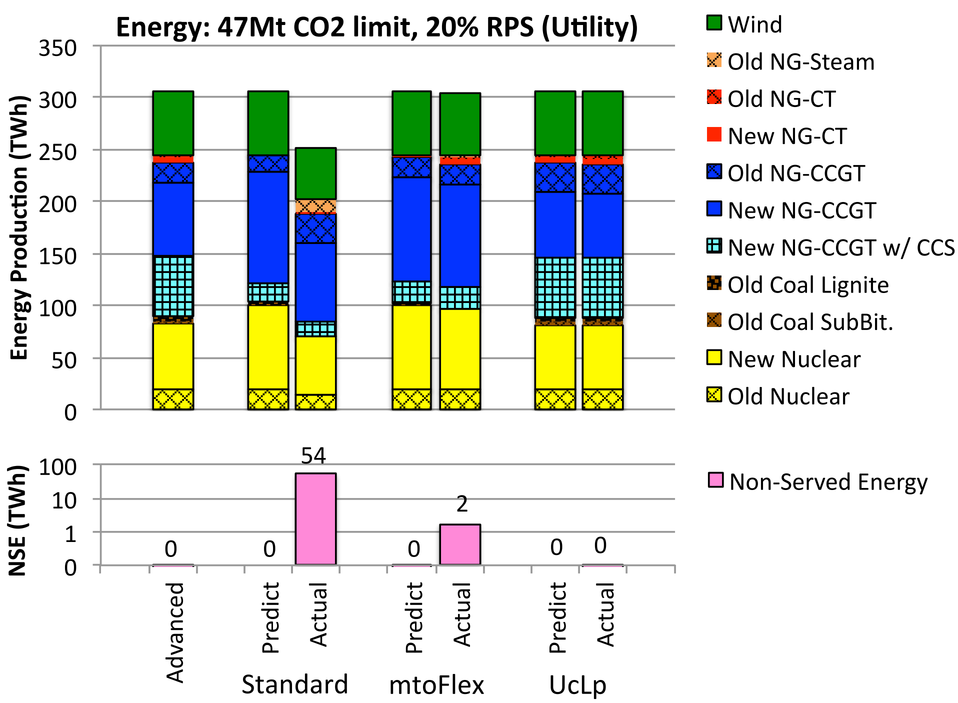


Figure 4.16: Comparison of capacity additions for each of the capacity planning model types for a 47Mt CO_2 limit and 20% RPS.

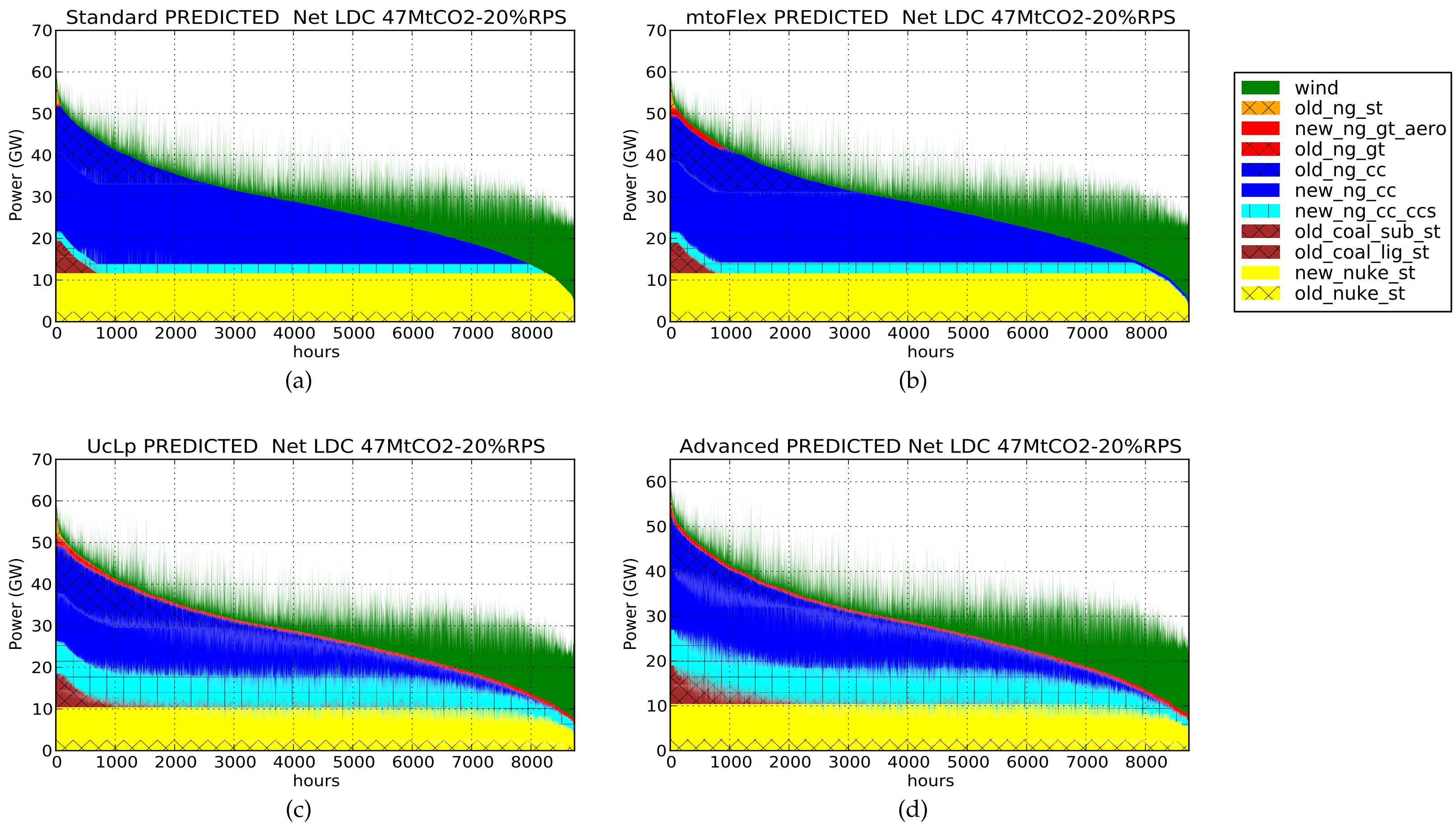


Figure 4.17: Predicted net load duration curves and associated power production for the (a) Standard, merit order, (b) merit order with flexibility reserves (mtoFlex), (c) unit commitment with relaxed integer commitment (UcLp), and (d) Advanced, full unit commitment based capacity planning models. Differences in generation mix explain the differences in maximum power for nuclear, NG-CC with CCS, and NG-CC without CCS, but other variations are due to operations constraints associated with flexibility.

light how differences in the planning models' approaches to capturing operating reserves drive these results. WIthout any operating reserves, the Standard model produces the simple banded structure from merit order economic dispatch seen in Section 4.3.3. The mtoFlex model recognizes the need for operating reserves as evident by the thin strip of NG-GT operation extending out nearly 1000 hours beyond the peak. Similarly, during the lower demand hours, mtoFlex operates a small quantity of NG-CC with and without CCS to provide reserves for the less flexible nuclear generation. The UcLp and Advanced models use even more out-of-merit operation to provide operating reserves. Both UC models (UcLp and Advanced) operate a small quantity of highly flexible NG-GT at all times and use significantly more NG-CC with CCS to augment nuclear during the low demand periods. This need for additional reserves is what drives the mtoFlex, UcLp and Advanced models to invest in the highly flexible NG-GT units.

The smaller reserve-driven operations for mtoFlex, seen by comparing Figure 4.17(b) and (d),result directly from the approximation that all non-running capacity[24] can still provide reserves at a reduced level[25]. As a result the added mtoFlex operation of NG-GT and NG-CC units is only enough to provide the much smaller *downward* reserve requirements that by definition require some output power that can be reduced if required. As a result the mtoFlex model considerably underestimates the operation of these flexible natural gas units required to provide reserves. Furthermore, the mtoFlex model does not capture unit minimum output constraints and therefore underestimates even the required downward reserves. It assumes that the entire operating power, limited only by ramp rate, can be turned off if needed to reduce system generation if needed. In actuality, real thermal units can only provide reserves down to their minimum stable output, requiring additional output such that operation for downward reserves is in addition to the required minimum output. As a result, the mtoFlex model builds more nuclear and fewer flexible NG-GT and NG-CC with CCS units than the UcLp and full Advanced models.

24 Recall that since mtoFlex ignores commitment constraints, non-running capacity is approximated as the installed capacity minus the current power output.

25 Note that if this assumption is removed and only running capacity is allowed to provide reserves, the mtoFlex results are much further off. In unreported trial runs conducted as part of model testing, allowing reserves based on power output greatly overestimated flexibility challenges resulting in very poor results.

The more subtle differences between the UcLp and Advanced models is also evident by comparing the very lowest demand hours of Figure 4.17(c) and (d) where the thermal output for the UcLp model falls under 7GW, producing a rounded end, while the Advanced model always keeps thermal output above about 10GW, making a more blunt end. This is due to the UcLp's model acceptance of fractional, rather than purely integer, commitment states. Though it is physically impossible to run, for example, a nuclear plant halfway on, this assumption by the UcLp model partially avoids the impact of minimum output levels, and thereby enables the UcLp model to assume that most of the wind production can actually be used, rather than shed. Additional regions of greater wind shedding with full UC operations are evident in the altered shape of the net load duration curve for 5000 to 8000 hours. As a result, the UcLp model builds less new wind capacity, even though the rest of its generation mix effectively matches the full Advanced model.

The mtoFlex, like the Standard model, also does not capture minimum up and downtime constraints, resulting in unrealistic under operation of the operationally inflexible legacy coal units, as described before in Section 4.3.3. This is evident by the abrupt end in coal operations before 1000 hours in contrast to the scattered operation of coal out beyond 7000 hours as suggested by the jagged border between nuclear and NG-CC with CCS. To better understand this effect it is helpful to look at a single week of operations as seen in the next section.

One week time series

Figure 4.18 shows the impact of flexibility driven operations constraints during the week beginning just after midnight August 14. The lack of minimum up and down time constraints in the mtoFlex and Standard models is evident by the operationally impossible isolated blocks of coal operation during the peaks of the first four days. In contrast, both the UcLp and Advanced models capture the need to keep these units running during nighttime lows to avoid coal startup costs and comply with the combination of minimum output and minimum up/down time constraints. As seen in 4.16, this difference explains the larger share of coal energy production predicted by the UcLp and Advanced models, which in turn motivates a UcLp and Advanced to increase the portion of NG-CC investment that has CCS as seen in 4.15.

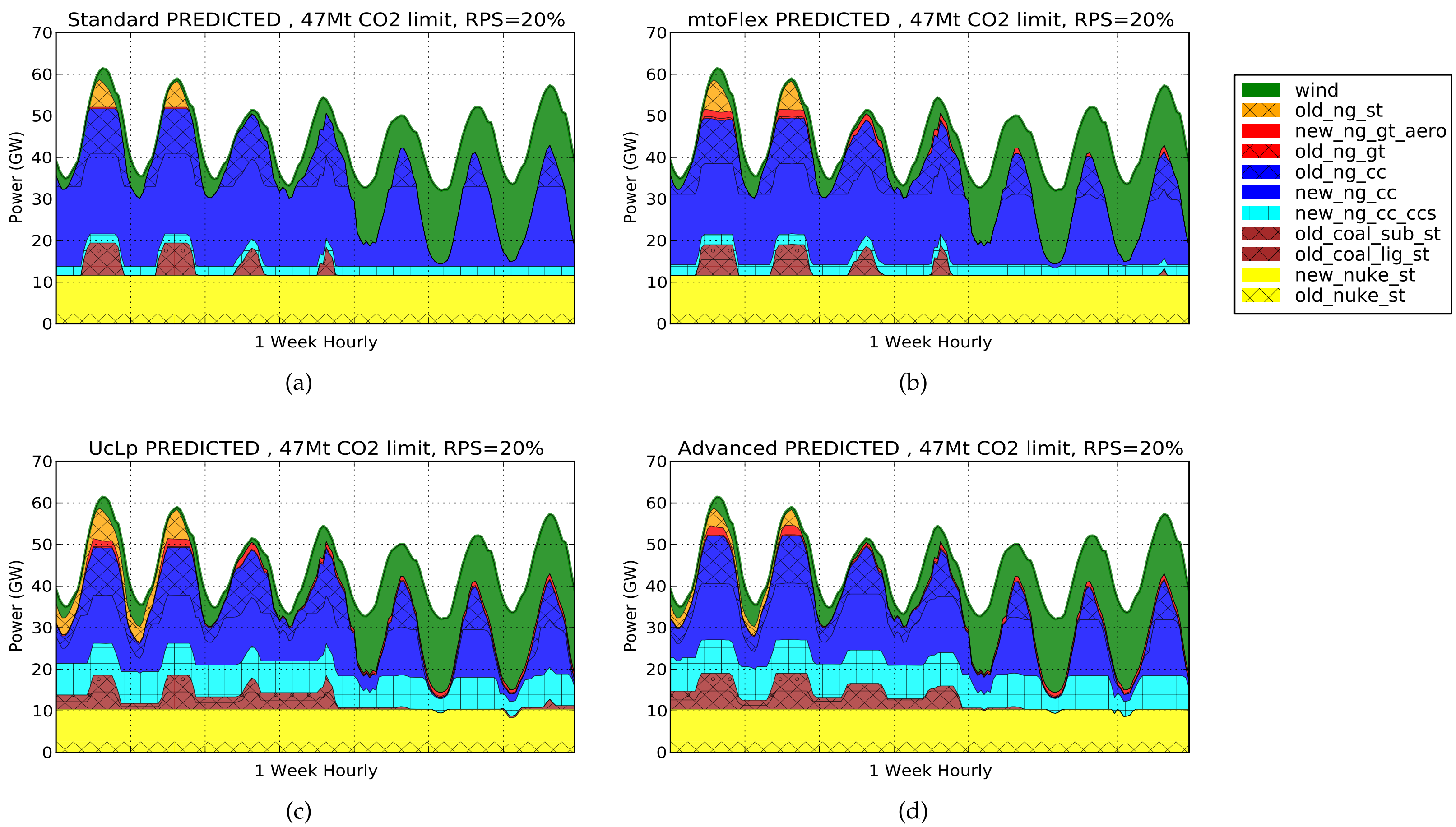


Figure 4.18: Comparison of one week of operations in August as predicted using (a) Standard merit order operations, (b) merit order with flexibility reserves (mtoFlex), (c) unit commitment with relaxed integer commitment (UcLp), and (d) full clustered unit commitment (Advanced) capacity planning models.

The additional operation of flexible generation to provide reserves is best seen during the sixth nighttime low. During this period, the Standard model does not deviate from its simple merit order, the mtoFlex maintains a small amount of additional NG-CC, while both the UcLp and Advanced models maintain a sizable quantity of NG-GT and NG-CC with CCS for reserves, even though it requires reducing nuclear output. As described above, these difference motivate the investment in flexible NG-GT for the mtoFlex, UcLp, and Advanced models and the increased investment in NG-CC with CCS for the UcLp and Advanced models.

4.7.4 *Summary*

This section shows that relaxing the integer constraints in unit commitment (UcLp) provides a significantly more accurate simplification for capturing operational flexibility during planning than the reserve-only approximation found in the literature (mtoFlex). The UcLp simplification produces capacity mixes that very nearly match the full Advanced model in all cases except those with strict CO_2 limits (47Mt with 0%-60% RPS). In these cases UcLp still provides a significantly improvement over other simplifications for all accuracy metrics including capacity difference, energy mix difference, energy forecast accuracy, and increase in total operating costs. Moreover, even where UcLp capacity mixes differ from the full Advanced optimal, from the utility perspective, the total costs match those from the more complex full Advanced model.

The mtoFlex approximation, which is similar to that used in [18] and [214], does provide noticeable improvement over the ignoring operational flexibility in the Standard, merit order model. In particular, from both the policy analyst and utility perspective, mtoFlex provides more accurate emissions predictions and lower cost generation mixes than the Standard approach in almost all situations.

Complete results and additional figures and tables can be found in Appendix C.

5 CONCLUSIONS

5.1 SUMMARY

This dissertation has shown the important role that operational flexibility—the ability of a power system to respond to changes in generation requirements due to predictable and unexpected variations in demand and supply—plays in planning and analyzing future power systems, particularly those with substantial variable renewable energy production (e.g. wind and solar) or strict carbon policies. Including operational flexibility is shown to lower system costs, improve policy impact estimates, and enable system designs capable of meeting strict regulatory targets. Moreover, this work explains some general principles as to when and how operational flexibility is of particular concern for planning. These can guide future power system designs and inform associated regulations. All of this analysis relies on, and thereby showcases, a new clustered combined unit commitment/maintenance/capacity planning formulation that tractably combines these problem types while also capturing the operating constraints that drive flexibility.

5.1.1 *How flexibility is a driver*

Fundamentally, operational flexibility balances the system's technical operating constraints with its need to respond to both predictable and unexpected variations in supply and demand. As a result, operational flexibility is most influential in scenarios with high flexibility need, such as the increased uncertainty from extensive variable renewables, and/or scenarios with low flexibility available, such as with technically constrained baseload technologies including coal steam, geothermal, and traditional nuclear. The precise scenarios where operational flexibility impacts planning and the extent of these impacts are system-specific; however, some general observations are possible, at least for thermally dominated power systems, as described below.

With moderate to large quantities of variable renewables (>20% on an energy basis) inherently imprecise forecasting requires additional reserves. This in turn encourages increased investment in and operation of highly flexible resources such as open-cycle natural gas combustion turbines, storage, or demand response. As renewable increase, these flexible assets may be allocated (nearly) all the time to provide the necessary reserves.

On the other side of this balance, strict carbon policies and low to moderate Renewable Portfolio Standard (RPS) levels make low-carbon, but operationally inflexible, baseload technologies, such as geothermal, traditional nuclear, or coal steam with carbon capture, attractive for reducing carbon emissions. However, the combined flexibility challenges of these technologies as currently built make such generation mixes impractical, even without any flexibility demands from variable renewables. This is because inflexible baseload units have high minimum output levels, long minimum up/down time constraints, and high startup-costs that can make it difficult or impossible to provide sufficient reserves or to cycle off during low thermal output periods. In these situations, including flexibility shifts investment toward more operationally flexible alternatives, including potentially more carbon intensive natural gas combined-cycle units with and without carbon capture and sequestration.

Strict carbon policies also create difficult operating environments for legacy coal steam units. Without carbon limits these units operate as (nearly) always-on baseload. But strict carbon polices drive effective variable costs high enough that economics alone would push coal generators to act as peaking units by running only during the highest (net) demand periods. However, technical operating constraints such as minimum up and down times alter this behavior, forcing the units to run between peaks, thereby increasing carbon emissions, altering the operations of other units, or encountering the same issues described for low-carbon baseload above.

At high RPS levels, ignoring operational flexibility can also incorrectly reduce investment in renewable capacity and/or require additional renewable shedding due to reserve-driven operational challenges. In these cases, when operational flexibility is ignored during planning, meeting a strictly enforced RPS could require shedding significant load. In extreme cases, generation mixes built without considering operational flexibility are simply infeasible to operate in compliance with regulations.

5.1.2 *Results Summary*

Example results from an Electric Reliability Council of Texas (ERCOT)-based test system, over a range of carbon policies and RPS levels, validate these trends. These results also demonstrate that capturing operational flexibility during expansion planning can ensure sufficiently flexible generation mixes and prevent negative consequences. Specifically capturing operational flexibility during planning:

- Reduces errors in projected impacts of carbon emissions policies,
- Decreases total costs of the generation built and operated by a utility,
- Decreases wind shedding,
- Enables the system to meet RPS and carbon policy requirements without shedding demand, and,
- In the most difficult cases, enables the system to be operated at all.

At lower RPS levels (<=20%) and looser carbon policies (<=$45/ton carbon dioxide ($CO_2$) or <25% CO_2 reductions in this test system) the impact of operational flexibility was small but noticeable. Including flexibility resulted in generally 0-20% improvements for a range of metrics that cover generation mix, energy mix, costs, and corresponding prediction errors. However, at higher RPS levels and stricter carbon policies, including operational flexibility provided substantial improvements, generally 30-100% improvement for the same metrics.

5.1.3 *Modeling flexibility*

Another major component of this work was identifying a new model formulation that overcomes the large computational burden of accurately including operational flexibility within the capacity planning problem. This formulation uses clustering to tractably combine unit commitment, maintenance, and investment planning into a single Mixed Integer Linear Program (MILP). Clustering is a procedure that groups similar but non-identical units into clusters that are assigned integer rather than binary variables to maintain individual unit decisions and constraints.

Side-by-side comparisons show significant improvements in solution quality for operational flexibility constrained scenarios, using this clustering approach, compared to the leading alternative for flexibility-aware planning in the literature. This alternative, economic dispatch with "flexibility" reserves, did provide improvements over ignoring flexibility, slightly expanding the range where faster non-unit-commitment-based methods result in only moderate loss of fidelity. However, the clustered unit commitment approach still provided the largest improvements in all cases and was the only method to produce satisfactory results with higher RPS and/or stricter carbon policies. These more realistic clustered unit commitment operations do require increased computation time due to larger problem size and additional discrete variables; however, relaxing the integer commitment constraints in the clustered formulation is shown to decrease run times considerably while maintaining most of the accuracy advantages.

Moreover, the clustering approach makes it *possible* to capture the true unit-level commitment and other constraints that drive operational flexibility within planning optimization. Without clustering, capturing accurate reserve capabilities, minimum up/down time constraints, and minimum output constraints would require a much larger traditional binary unit commitment model which would be computationally prohibitive to include within planning optimization. In direct operations-only comparisons, the clustering technique kept errors for a range of metrics that cover total cost, CO_2, commitment, power and energy to generally less than 1% while decreasing run times by orders of magnitude (e.g. 5000x) relative to the traditional approach. Errors could be further reduced, at the expense of somewhat increased computation time, by adjusting the clustering aggregation method. These same trials also explored alternative speedup strategies for unit commitment and found that while none are as effective as clustering alone, some can be used in combination with clustering for even faster computations.

5.1.4 *Implications*

Awareness of the need to consider operational flexibility and availability of tools to do so can enable power systems to achieve carbon reduction targets and/or operate successfully with large fractions of renewable energy. For utility planners and renewable integration researchers, the methods of this thesis allow capturing flexibility during the initial screening phase, rather than discovering problems later during detailed analysis. This provides operationally optimized generation mixes directly, even with carbon constraints and renewables, and eliminates the need for ad hoc adjustments later. Flexibility-aware planning also enables policy analysts to make more realistic impact forecasts and design improved policies capable of achieving targets. Taken together, these results encourage and offer a new flexibility-aware approach to capacity planning that can enable a cleaner, less expensive electric power system in the future.

Specific recommendations for decision makers can be found in Section 5.4.

5.2 CONTRIBUTIONS

This research enhances our understanding of how constraints at the hourly operations timescale can impact long-term planning decisions at the scale of years. It also extends state of the art for electric power system generation expansion planning to tractably embed operational flexibility into planning optimization models. Specifically, the primary contributions of this work are:

1. Demonstrating that operational flexibility can have an important impact on power system planning, and providing insights as to *when* endogenous operating flexibility impacts investment decisions, and *how* generator technical constraints drive these impacts;

2. Demonstrating that a failure to account for operational flexibility can result in undesirable outcomes for both utility planners and policy analysts. These include significantly increased system costs, reduced system reliability, inability to comply with RPS and carbon requirements, underestimating emissions reductions, suboptimal generation mixes, and unrealistic energy mix predictions; and

3. Presenting a new combined unit commitment and capacity planning model formulation that makes capturing operational flexibility within planning optimization computationally tractable. This research further demonstrates the use of this formulation for

a large test system (hundreds of generators) at hourly time resolutions (8760 hours) using modern solvers on a personal computer. A similar approach for production costing incorporates simplified maintenance scheduling into the same mixed-integer linear optimization model without decomposition.

Additionally, this dissertation further contributes to the electric power systems literature by comparing among this new formulation and alternative operations and planning simplifications from the literature. These comparisons demonstrate the accuracy and efficiency of the clustered formulation and show trade-offs between accuracy and run-time for various approaches to generator clustering. These results can also guide future selection of power system models and appropriate simplifications while the analysis metrics used can be applied to future power system model comparisons.

5.3 LIMITATIONS AND FUTURE RESEARCH

Overall, this research will serve as a base for future planning exercises and as a foundation for future studies of operational flexibility. The current work also has a number of important limitations, each of which motivates further research. Furthermore, the methods presented here can enable new lines of inquiry including appropriate valuation of technologies that derive value from operational flexibility and capturing realistic operations within other complex energy models. This section highlights these potentials along with other other specific areas for further exploration.

Most of this dissertation focussed on a single ERCOT-based test system, and though ERCOT is generally representative of large, thermally dominated power systems, it has very limited hydro resources and minimal power exchange with surrounding areas. Further research is needed to explore how results vary in other power systems and with such alternative sources of operational flexibility. Specifically, differences in existing generation mixes, seasonal and daily wind and demand patterns, interchange with other systems, and other system-specific attributes could make including operational flexibility more or less important and/or alter the patterns of when it has significant impact.

Furthermore, due to data limitations, this research relied on a simplified representation of the ERCOT system and used the same operations model for both optimization and "actual" simulation. It would be interesting to cross-check these results using a commercial operations simulation model and/or simulating operations with more complete unit data.

Additionally, the current approach treats operations deterministically and only *requires* sufficient reserves, but stops short of *deploying* these reserves to estimate the impacts of forecasts errors or unplanned outages. Some of these impacts may average out over long time periods when the same unit types provide both upward and downward reserves thereby allowing up & down fluctuations, such as wind forecast errors, to partially cancel. But, since upward reserves tend to be larger than downward and reserves may be provided by different types of unit across time, reserve deployment may also shift some energy production to those units that provide reserves and away from variable renewables and thermal units with high forced outage rates. This suggests further research into stochastic simulation or statistical estimates for reserve deployment and corresponding impacts. Of particular interest is the incorporation of recent developments in stochastic unit commitment for both dynamic reserve allocation and probabilistic simulation. For such analysis, the clustering approach could help by reducing the combinatorial set of outcomes to consider thereby easing sampling requirements or possibly enabling a multinomial-like analytic approach.

Another notable limitation with this research results from ignoring transmission constraints and implicitly assuming an optimized transmission system. Congestion can alter the dispatch order of generation and limit the extent to which reserves can be shared across a large geographic region, thereby impacting operational flexibility. Furthermore, the transmission system limits the number of units that can be successfully grouped using the clustering formulation. This research has shown that clustering into more groups with fewer units each can still provide significant performance benefit. Additionally, it is well known that only a small number of transmission constraints are typically binding. Together these facts suggest multiple research directions including exploring how transmission further impacts planning with operational flexibility, developing methods for clustering with transmission constraints, and incorporating operational flexibility into integreated generation and transmission expansion planning.

This research also only considers the operational flexibility available from thermal power plants and only considers renewable energy from wind, making the addition of other technologies a ripe area for further research. Some emerging technologies, such as responsive demand and grid-scale storage, could help the system flexibility balance by providing additional sources of operational flexibility; while others, such as electric vehicles and solar power could help or hurt flexibility depending on the power system and deployment strategy. Furthermore, additional thermal generation technologies including flexibility-enhanced, but more expensive, versions of those considered here could be explored. Evaluating these technologies and the corresponding extensions to the methods presented here represent promising future research areas.

Also, although the significant speed improvements of clustering enable capturing operational flexibility within planning optimization, the combined models still remain computationally demanding. Further research could explore additional approaches for faster performance. A starting point would be to use the well established approach of reducing the number of simulation weeks to only a carefully selected representative subset, perhaps using one week per month plus peak demand and wind weeks. Research remains in this area on the best methods for selecting this subset, particularly because of the need to capture demand and wind variations along with their correlation. In some ways the complete 52 (or more) week record implicitly sample from multiple wind and weather regimes, requiring care to duplicate with less data. Furthermore, the success of relaxing integer commitment constraints hints at the potential of further speed improvements by carefully analyzing which operating constraints are most important to accurately model operational flexibility. It is likely that the relevance of different constraints will be a function of the system and the scenario, such that additional characterization of which constraints to consider and when could offer a large area for future research. Such work could also lead to an improved understanding of the relevant dimensions to include in flexibility metrics, or even a generalized closed-form theory of which, when, and how operating constraints impact planning.

Additional areas for future research include exploring the impact of operational flexibility within multi-period, multi-sector, multi-agent—including market based,and/or stochastic problems. For such work, general speed improvements would be welcome, but more importantly each new model attribute might afford an additional, problem specific methodology advance. For example, work carried out by the author in parallel with this dissertation suggests that the modeling framework of Approximate Dynamic Programming (ADP) represents a promising foundation for the case of stochastic, multi-period capacity planning. ADP uses function approximation, careful Monte Carlo sampling, and machine learning to overcome the "curse-of-dimensionality" inherent in traditional Dynamic Programming (DP). However, existing ADP approaches still require large numbers of sub-model runs—a full year of unit commitment modeling in this case—making practical sized problems difficult to solve even with clustered unit commitment. This difficulty has prompted the development of promising new techniques to further reduce the time spent in the sub-model including reducing the need for sub-model runs using contribution function approximation and multi-fidelity operations modeling that uses ever richer models as the ADP algorithm narrows in on the most promising options. Additional details of this work-in-progress can be found in [215].

5.4 recommendations for decision makers

This dissertation has demonstrated the important role that operational flexibility plays in future power systems; and hence, the importance of including it when making capacity investment decisions and analyzing policy outcomes for the electric power system. Specific recommendations for decision makers include:

design for operational flexibility Operational flexibility has always been required to provide reliable electric power, but historically was not a explicit design goal. In the past, flexibility inherent in generation has been sufficient; however, increased use of variable renewables and of low-carbon baseload technologies can exceed the inherent flexibility of the rest of system. Furthermore, regulations, such as carbon policies, can prevent the full use of any inherent flexibility. In such cases, sufficient flexibility must be designed-in. Additional flexibility could be provided by a combination of natural gas technologies, storage, fuel cells, flywheels, hydro where available, and demand response systems. Alternatively, flexibility requirements could be reduced through improved renewable forecasting, more flexible thermal plant designs, and flexibility-aware market procedures.

include operational flexibility in analysis Ignoring operational flexibility during system planning or policy analysis can lead to underperforming or infeasible generation mixes and/or potentially large errors in estimated energy mix and carbon emissions, particularly with large quantities of variable renewables (e.g. wind) or under strict carbon regulations. Moreover, given the long lifetimes of power sector assets it is important to consider not just current operational flexibility needs, but also those of potentially very different futures. In particular, new generation built today will still be operating in 2050 and hence may be subject to ambitious low-carbon and renewable targets.

CONSIDER MARKETS AND FLEXIBILITY This research demonstrated how flexibility challenges can be avoided through careful design. In modern, market-based systems, there is an additional challenge to ensure that the market mechanisms sufficiently incentivize operational flexibility so that the required investments will actually occur.

DEVELOP HOLISTIC REGULATIONS Challenges with operational flexibility expose the potential for piece-meal regulation of the power system to result in very poor dynamics and undesirable outcomes. For example, combinations of renewable standards, carbon policies, and inflexible power systems can create a downward spiral of operations constraints that results in significant renewable shedding or non-served energy. To avoid such challenges, regulations and associated market designs need to be developed and refined synergistically.

USE CLUSTERED UNIT COMMITMENT For flexibility constrained systems, accurate assessments of flexibility—and hence optimal generation plans and accurate estimates of policy outcomes—require capturing unit commitment based constraints, which can greatly increase the computational burden. Clustering generators by type and using the formulation introduced by this dissertation, can speed up unit commitment based modeling by orders of magnitude while still maintaining small errors. Furthermore, the leading alternative for capturing flexibility by including heuristic reserves within standard merit order economic dispatch is shown in many cases to only provide a small improvement over ignoring flexibility and in other cases can be completely inadequate.

LEARN WHEN FLEXIBILITY IS NOT A DRIVER In some low RPS and loose carbon policy cases, operational flexibility does not have a large impact on planning, and hence standard merit order based operations with or without heuristic reserves will provide good results with less computational effort. However, the relevance of flexibility is system specific, so some exploration, similar to that performed here, of when flexibility is and is not a decision driver is necessary for each power system.

APPENDIXES

A

TEST SYSTEM DATA

This appendix includes additional test system data used in Chapter 3 and Chapter 4.

A.1 IEEE RELIABILITY TEST SYSTEM (ADDITIONAL DATA)

Complete system data for the IEEE Reliability Test System (RTS) is contained in [204, 205, 206]; however, only point information is provided for heat rates. The corresponding piecewise linear approximation used in Chapter 3 is included in Table A.1.

Table A.1: Piecewise linear fit of IEEE RTS (1996) fuel use based on data in [206]

	Segment 1		Segment 2		Segment 3	
Plant Type	Slope MMBTU/MWh	Intercept MMBTU	Slope MMBTU/MWh	Intercept MMBTU	Slope MMBTU/MWh	Intercept MMBTU
Oil_St_12MW	10.155	14.068	10.900	9.600	12.400	-4.800
Oil_CT_20MW	10.023	79.632	12.395	41.684	14.400	1.980
Coal_St_76MW	9.657	113.240	10.672	74.683	12.400	-30.400
Oil_St_100MW	8.401	114.950	9.065	81.733	9.652	34.800
Coal_St_155MW	8.386	155.068	8.713	124.620	9.128	73.160
Oil_St_197MW	8.590	148.932	9.026	97.397	9.424	34.672
Coal_St_350MW	8.640	218.400	9.067	121.333	9.500	0
Nuke_400MW	8.899	385.200	9.078	349.333	9.320	272.000

A.2 ERCOT-BASED TEST SYSTEM

A.2.1 *Generator Technical Parameters*

Generator technical data was taken from a combination of sources. The Energy Information Administration (EIA)'s Annual Energy Outlook (AEO) 2011 is used for cost assumptions. Specifically, generator cost and performance parameters are used from [213], while fuel costs are based on electricity sector fuel prices for 2007 (in 2008 dollars) for the south central west region (which includes Texas) reported in [209]. EIA does not report fuel cost for uranium, so data from the Royal Academy of Engineering [216] is used to derive estimated uranium costs. Fuel specific carbon dioxide (CO_2) emission rates are based on EIA Voluntary Greenhouse Gas Reporting Program data from [217]. Generator technical data for unit commitment operating constraints are adapted from The Sixth Northwest Power Plan, Appendix I [208].

Additional data is provided for some generator types not used in this dissertation to aid future analyses.

Table A.2: Unit Type name cross-reference by source

Unit Type	EIA AEO2011 (NEMS) Name	NW Power Plan (for non-cost data)
Coal_ST	Dual Unit Advanced PC	Supercritical pulverized coal
Coal IGCC	Dual Unit Coal IGCC	Coal-fired Gasification Combined-cycle
NG_CC	Advanced NGCC	Combined Cycle NG
NG_GT	Advanced CT (F-class)	Heavy Duty Frame Gas Turbine
NG_GT_AERO	Advanced CT (F-class)	Aeroderivative Gas Turbine
NG_ST	Average of Coal & NGCT	Average of Coal & NGCT
U235_ST	Dual Unit Nuclear	Gen III+ (Advanced) LWR
Wind	On-shore Wind	Wind
PV_Util	Photovoltaic (150MW plant)	Utility-scale Photovoltaic (Si-flat plate, single axis track)
Coal_ST w/ CCS	Dual Unit Advanced PC with CCS	Super critical pulverized coal with 90% CCS
NG_CC w/ CCS	Advanced NGCC with CCS	Use ratios from coal w/ and w/o CCS applied to CCGT baseline
Coal IGCC w/CCS	Single Unit Coal IGCC	Coal-fired Gasification Combined-cycle with CCS
Wind_off	Off-shore Wind	N/A
PV_Dist	Photovoltaic (7MW plant)	N/A

Table A.3: Generation unit cost, size and related parameters. Adapted from **(author?)** [213].

type code	c_var_om [$/MWh]	c_fix_om [M$/GW-yr]	c_cap [M$/GW]	life [yr]	heatrate [MMBTU/MWh]	lead_time [yr]	co2_embed [Mt/GW]	co2_ccs [p.u.]	cap_credit [p.u.]	gen_size [GW]
coal_lig_st	4.25	29.67	2844	30	8.80	7	0	0	0.93	0.650
coal_sub_st	4.25	29.67	2844	30	8.80	7	0	0	0.93	0.650
coal_igcc	6.87	48.9	3221	30	8.70	7	0	0	0.9	0.600
ng_cc	3.11	14.62	1003	30	6.43	4.5	0	0	1	0.400
ng_gt	9.87	6.7	665	30	9.75	2.75	0	0	0.95	0.210
ng_gt_aero	9.87	6.7	665	30	9.75	2.75	0	0	0.95	0.210
ng_st	3.68	22.145	1923.5	30	8.80	5.75	0	0	0.965	0.310
u235_st	2.04	88.75	5335	30	10.4	10	0	0	0.96	1.118
wind	0	28.07	2438	20	1	4.5	0	0	0.105	0.100
pv_util	0	16.7	4755	25	1	3	0	0	0.6	0.150
coal_sub_st_ccs	9.05	63.21	4579	30	12.00	9	0	0.9	0.93	0.650
ng_cc_ccs	6.45	30.25	2060	30	7.525	5.79	0	0.9	1	0.385
coal_igcc_ccs	8.04	69.3	5348	30	10.70	9	0	0.88	0.9	0.520
wind_off	0	53.33	5975	20	1	6	0	0	0.105	0.400
pv_dist	0	26.04	6050	25	1	3	0	0	0.6	0.007

Table A.4: Generation unit unit commitment parameters. Adapted from **(author?)** [208]

type code	ramp_max [p.u./hr]	unit_min_pu [p.u.]	fuel_start [BTUe9/start]	c_start_fix [K$/start]	max_start [start/yr]	quick_start [p.u.]	reg_up [p.u.]	reg_down [p.u.]	spin_rsv [p.u.]	max_cap_fact [p.u.]	derate [p.u.]	min_up [hr]	min_down [hr]	efor [hr]	maint_wks [wk/yr]	repair_hr [hr]
coal_lig_st	0.3	0.5	2.60236	3.58095	104	0	0.025	0.025	0.05	0.85	0.85	24	12	0.07	5	40
coal_sub_st	0.3	0.5	2.60236	3.58095	104	0	0.025	0.025	0.05	0.85	0.85	24	12	0.07	5	40
coal_igcc	0.1	0.7	2.60236	3.58095	52	0	0.008	0.008	0.02	0.81	0.81	48	24	0.1	4	100
ng_cc	1	0.3	0.58947	9.25091	365	0	0.083	0.083	0.17	0.89	0.89	6	12	0.06	3	32
ng_gt	6	0.25	0.18772	7.81123	Inf	0	0.500	0.500	1.00	0.91	0.91	0	0	0.05	2	88
ng_gt_aero	6	0.25	0	1	Inf	1	0.500	0.500	1.00	0.91	0.91	0	0	0.05	2	88
ng_st	0.3	0.5	2.60236	3.58095	52	0	0.025	0.025	0.05	0.85	0.85	24	12	0.07	5	40
u235_st	0.1	0.8	0	100	1	0	0.000	0.000	0.00	0.9	0.9	48	24	0.042	4	112
wind	1	0	0	0	Inf	0	0.000	0.000	0.00	1	1	0	0	0	0	0
pv_util	1	0	0	0	Inf	0	0.000	0.000	0.00	1	1	0	0	0	0	0
coal_sub_st_ccs	0.3	0.5	2.60236	3.58095	52	0	0.025	0.025	0.05	0.85	0.85	24	12	0.07	5	40
ng_cc_ccs	1	0.3	0.58947	9.25091	365	0	0.083	0.083	0.17	0.89	0.89	6	12	0.06	3	32
coal_igcc_ccs	0.1	0.7	2.60236	3.58095	52	0	0.008	0.008	0.02	0.81	0.81	48	24	0.1	4	100
wind_off	1	0	0	0	Inf	0	0	0	0	1	1	0	0	0	0	0
pv_dist	1	0	0	0	Inf	0	0	0	0	1	1	0	0	0	0	0

Table A.5: Fuel cost and emission assumptions

Fuel	code	cost $/MMBTU	CO_2 t/MMBTU
Enriched Uranium	u235	0.766	0
(Generic) Coal	coal	1.956	0.0965
Coal Bituminous	coal_bit	1.956	0.0933
Coal-Sub-bituminous	coal_sub	1.956	0.0965
Coal-Lignite	coal_lig	1.956	0.0977
Natural Gas	ng	6.840	0.0531
Wind	wind	0	0
Water	water	0	0

A.2.2 *ERCOT 2007 (simplified) Clustering Information*

Cluster Parameters

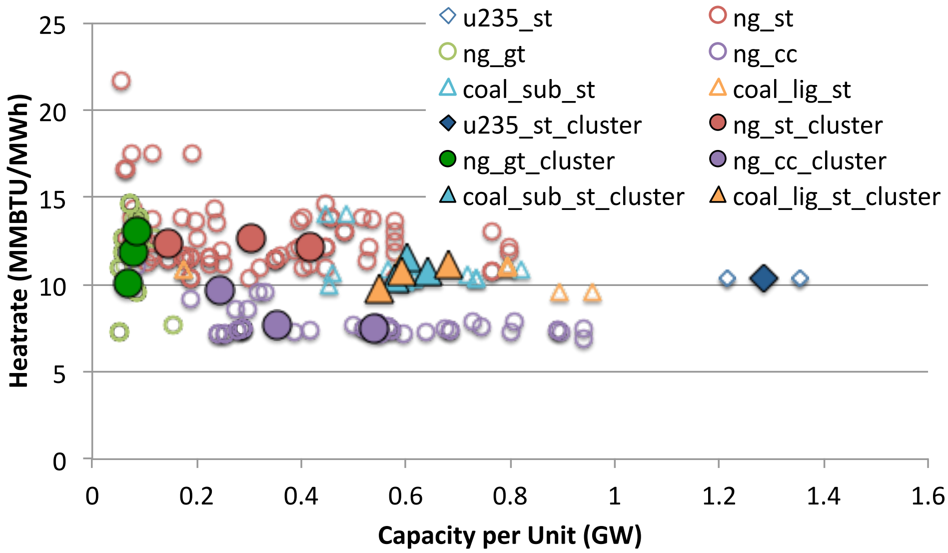
Table A.6: ERCOT 2007 Clustering Parameters

			Age (year in service)			Size (Cap >= X MW)			Efficiency (HR >= X MMBTU/MWh)		
Type	Fuel	Use Clusters	old	midAge	new	small	med	large	hiEff	avgEff	loEff
coal_lig_st	coal_lig	TRUE	0	1975	1985	0	500	650	0	10.5	12
coal_sub_st	coal_sub	TRUE	0	1980	1985	0	500	650	0	10.2	12
ng_cc	ng	TRUE	0	2000	2005	0	300	600	0	7.5	9
ng_gt	ng	TRUE	0	1980	2000	0	75	100	0	10	13
ng_st	ng	TRUE	0	1960	1970	0	150	300	0	11.5	13
u235_st	u235	FALSE									
wind	wind	FALSE									

Cluster by Type Only (Full Clustering)

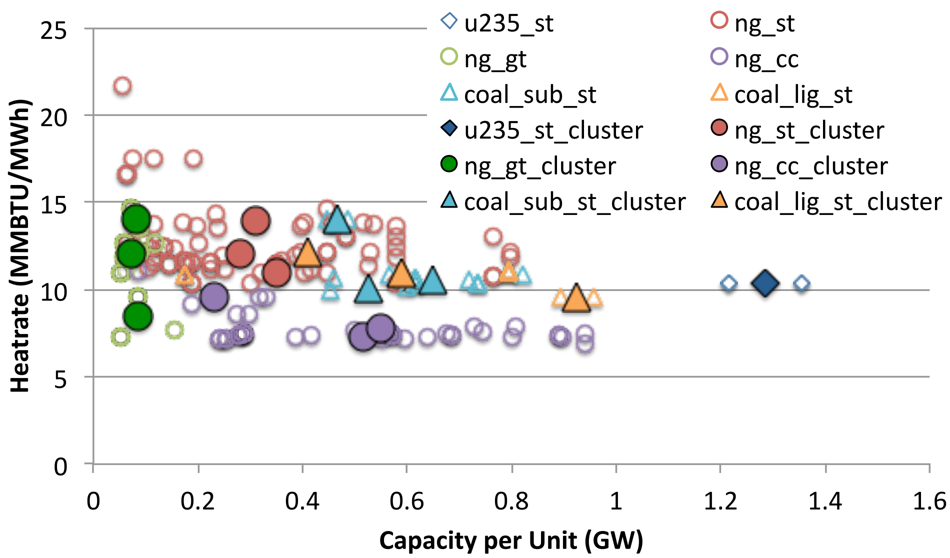
Cluster Name Code	# units	Weighted Average Heat Rate (MMBTU/MWh)	Average Capacity (GW)	Total Capacity (GW)
coal_lig_st	14	10.730	0.62471	8.74594
coal_sub_st	14	10.897	0.60566	8.47924
ng_cc	46	7.551	0.50089	23.04094
ng_gt	52	11.969	0.07893	4.10436
ng_st	74	12.340	0.30934	22.89116
u235_st	4	10.400	1.28465	5.13860
wind	1	1.000	3.71050	3.71050

Cluster by Type and Age



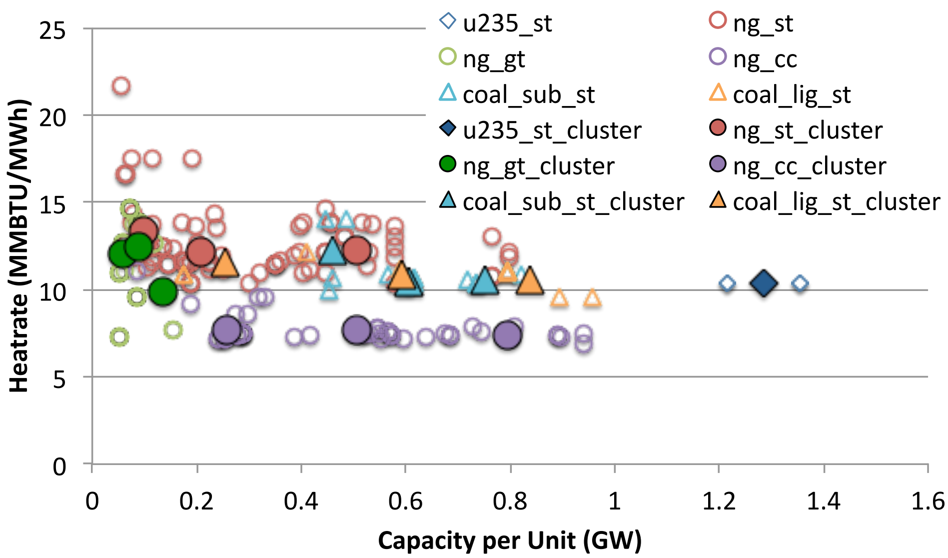
Cluster Name Code	# units	Weighted Average Heat Rate (MMBTU/MWh)	Average Capacity (GW)	Total Capacity (GW)
coal_lig_st_old	3	10.770	0.59340	1.78020
coal_lig_st_midAge	7	11.139	0.68097	4.76679
coal_lig_st_new	4	9.810	0.54975	2.19900
coal_sub_st_old	5	11.584	0.60304	3.01520
coal_sub_st_midAge	5	10.330	0.57962	2.89810
coal_sub_st_new	4	10.729	0.64150	2.56600
ng_cc_old	3	9.711	0.24447	0.73341
ng_cc_midAge	38	7.459	0.54048	20.53824
ng_cc_new	5	7.723	0.35384	1.76920
ng_gt_old	12	11.891	0.07850	0.94200
ng_gt_midAge	24	13.071	0.08499	2.03976
ng_gt_new	16	10.031	0.07018	1.12288
ng_st_old	18	12.347	0.14534	2.61612
ng_st_midAge	27	12.624	0.30353	8.19531
ng_st_new	29	12.146	0.41655	12.07995
u235_st	4	10.400	1.28465	5.13860
wind	1	1.000	3.71050	3.71050

Cluster by Type and Efficiency



Cluster Name Code	# units	Weighted Average Heat Rate (MMBTU/MWh)	Average Capacity (GW)	Total Capacity (GW)
coal_lig_st_hiEff	2	9.612	0.92490	1.84980
coal_lig_st_avgEff	11	10.959	0.58965	6.48615
coal_lig_st_loEff	1	12.148	0.41000	0.41000
coal_sub_st_hiEff	2	10.066	0.52695	1.05390
coal_sub_st_avgEff	10	10.575	0.64934	6.49340
coal_sub_st_loEff	2	14.073	0.46600	0.93200
ng_cc_hiEff	29	7.331	0.51626	14.97154
ng_cc_avgEff	13	7.746	0.54972	7.14636
ng_cc_loEff	4	9.595	0.23075	0.92300
ng_gt_hiEff	12	8.518	0.08530	1.02360
ng_gt_avgEff	20	12.069	0.07053	1.41060
ng_gt_loEff	20	13.998	0.08353	1.67060
ng_st_hiEff	20	10.976	0.35009	7.00180
ng_st_avgEff	29	12.028	0.27965	8.10985
ng_st_loEff	25	13.892	0.31120	7.78000
u235_st	4	10.400	1.28465	5.13860
wind	1	1.000	3.71050	3.71050

Cluster by Type and Size



Cluster Name Code	# units	Weighted Average Heat Rate (MMBTU/MWh)	Average Capacity (GW)	Total Capacity (GW)
coal_lig_st_small	3	11.556	0.25307	0.75921
coal_lig_st_med	5	10.878	0.59284	2.96420
coal_lig_st_large	6	10.518	0.83710	5.02260
coal_sub_st_small	4	12.221	0.46138	1.84552
coal_sub_st_med	6	10.510	0.60427	3.62562
coal_sub_st_large	4	10.550	0.75205	3.00820
ng_cc_small	16	7.681	0.25799	4.12784
ng_cc_med	17	7.651	0.50482	8.58194
ng_cc_large	13	7.415	0.79472	10.33136
ng_gt_small	23	12.042	0.05957	1.37011
ng_gt_med	25	12.456	0.08755	2.18875
ng_gt_large	4	9.828	0.13640	0.54560
ng_st_small	21	13.323	0.09697	2.03637
ng_st_med	20	12.171	0.20713	4.14260
ng_st_large	33	12.262	0.50644	16.71252
u235_st	4	10.400	1.28465	5.13860
wind	1	1.000	3.71050	3.71050

A.2.3 *Individual ERCOT 2007 (simplified) Unit Data*

Table A.7: Individual Unit data for (simplified) ERCOT test system adapted from 2007 data in eGrid 2010 v1.1 [207]

Unit Name	Unit Type	Capacity (MW)	Fuel	Heatrate (MBTU/MWh)
Arthur_Von_Rosenberg_Combined	ng_cc	550	ng	7.499
Barney_M_Davis_1	ng_st	352	ng	11.415
Barney_M_Davis_2	ng_st	351	ng	11.415
Bastrop_Combined	ng_cc	727.8	ng	7.845
Big_Brown_1	coal_lig_st	593.4	coal_lig	10.698
Big_Brown_2	coal_lig_st	593.4	coal_lig	10.698
Bosque_County_Peaking_GT_1	ng_gt	154	ng	7.639
Bosque_County_Peaking_GT_2	ng_gt	154	ng	7.639
Bosque_County_Peaking_Units3to5_Combined	ng_cc	499	ng	7.639
Brazoz_Valley_Generating_Facility_Combined	ng_cc	675.6	ng	7.462
Bryan_6	ng_st	54	ng	21.683
Cedar_Bayou_1	ng_st	765	ng	10.729
Cedar_Bayou_2	ng_st	765	ng	10.729
Coleto_Creek_1	coal_sub_st	600.4	coal_sub	10.133
Colorado_Bend_Energy_Center_Combined_1	ng_cc	278.1	ng	7.386
Colorado_Bend_Energy_Center_Combined_2	ng_cc	278.1	ng	7.386
Comanche_Peak_1	u235_st	1215	u235	10.400
Comanche_Peak_2	u235_st	1215	u235	10.400
Dansby_1	ng_st	105	ng	11.288
Decker_Creek_1	ng_st	321	ng	11.002
Decker_Creek_2	ng_st	405	ng	11.002
Decker_Creek_GT1	ng_gt	51.5	ng	11.002
Decker_Creek_GT2	ng_gt	51.5	ng	11.002
Decker_Creek_GT3	ng_gt	51.5	ng	11.002
Decker_Creek_GT4	ng_gt	51.5	ng	11.002
DeCordova_Steam_Electric_Station_1	ng_st	799.2	ng	12.147
DeCordova_Steam_Electric_Station_CT1	ng_gt	89.4	ng	12.147
DeCordova_Steam_Electric_Station_CT2	ng_gt	89.4	ng	12.147
DeCordova_Steam_Electric_Station_CT3	ng_gt	89.4	ng	12.147
DeCordova_Steam_Electric_Station_CT4	ng_gt	89.4	ng	12.147
Ennis_Power_Company_Combined	ng_cc	418	ng	7.361
Exelon_LaPorte_Generating_Station_GT1	ng_gt	59	ng	12.676
Exelon_LaPorte_Generating_Station_GT2	ng_gt	59	ng	12.676
Exelon_LaPorte_Generating_Station_GT3	ng_gt	59	ng	12.676
Exelon_LaPorte_Generating_Station_GT4	ng_gt	59	ng	12.676
Fayette_Power_Project_1	coal_sub_st	615	coal_sub	10.679
Fayette_Power_Project_2	coal_sub_st	615	coal_sub	10.679
Fayette_Power_Project_3	coal_sub_st	460	coal_sub	10.679

Simplified ERCOT 2007 individual unit data (continued)

Unit Name	Unit Type	Capacity (MW)	Fuel	Heatrate (MBTU/MWh)
Forney_Energy_Center_Combined_1	ng_cc	891.9	ng	7.351
Forney_Energy_Center_Combined_2	ng_cc	891.9	ng	7.351
Freestone_Power_Generation_LP_Combined_1	ng_cc	518	ng	7.522
Freestone_Power_Generation_LP_Combined_2	ng_cc	518	ng	7.522
Frontera_Energy_Center_Combined	ng_cc	529	ng	7.535
Gibbons_Creek_1	coal_sub_st	453.5	coal_sub	9.977
Graham_1	ng_st	247.7	ng	11.947
Graham_2	ng_st	387	ng	11.947
Greens_Bayou_5	ng_st	446.4	ng	14.681
Greens_Bayou_73	ng_gt	72	ng	14.681
Greens_Bayou_74	ng_gt	72	ng	14.681
Greens_Bayou_81	ng_gt	72	ng	14.681
Greens_Bayou_82	ng_gt	72	ng	14.681
Greens_Bayou_83	ng_gt	72	ng	14.681
Greens_Bayou_84	ng_gt	72	ng	14.681
Guadalupe_Generating_Station_Combined_1	ng_cc	571.1	ng	7.423
Guadalupe_Generating_Station_Combined_2	ng_cc	571.1	ng	7.423
Handley_2	ng_st	74.8	ng	13.823
Handley_3	ng_st	404.8	ng	13.823
Handley_4	ng_st	455	ng	13.823
Handley_5	ng_st	455	ng	13.823
Hays_Energy_Project_U1	ng_cc	241.7	ng	7.158
Hays_Energy_Project_U2	ng_cc	241.7	ng	7.158
Hays_Energy_Project_U3	ng_cc	252.8	ng	7.158
Hays_Energy_Project_U4	ng_cc	252.8	ng	7.158
Hidalgo_Energy_Center_Combined	ng_cc	551.3	ng	7.219
J_K_Spruce_1	coal_sub_st	566	coal_sub	10.822
J_K_Spruce_2	coal_sub_st	820	coal_sub	10.822
J_T_Deely_1	coal_sub_st	486	coal_sub	14.073
J_T_Deely_2	coal_sub_st	446	coal_sub	14.073
Jack_County_Combined	ng_cc	640	ng	7.284
Kiamichi_Energy_Facility_Combined_1	ng_cc	685	ng	7.397
Kiamichi_Energy_Facility_Combined_2	ng_cc	685	ng	7.397
Lake_Creek_ST1	ng_st	79.6	ng	14.369
Lake_Creek_ST2	ng_st	236	ng	14.369
Lake_Hubbard_1	ng_st	396.5	ng	12.159
Lake_Hubbard_2	ng_st	531	ng	12.159
Lamar_Power_Project_Combined_1	ng_cc	545.4	ng	7.768
Lamar_Power_Project_Combined_2	ng_cc	545.4	ng	7.768
Laredo_3	ng_st	115.2	ng	11.592
Leon_Creek_3	ng_st	75	ng	11.834
Leon_Creek_4	ng_st	113.7	ng	11.834

Simplified ERCOT 2007 individual unit data (continued)

Unit Name	Unit Type	Capacity (MW)	Fuel	Heatrate (MBTU/MWh)
Leon_Creek_CGT1	ng_gt	57.4	ng	11.834
Leon_Creek_CGT2	ng_gt	57.4	ng	11.834
Leon_Creek_CGT3	ng_gt	57.4	ng	11.834
Leon_Creek_CGT4	ng_gt	57.4	ng	11.834
Limestone_1	coal_lig_st	893	coal_lig	9.612
Limestone_2	coal_lig_st	956.8	coal_lig	9.612
Lost_Pines_1_Power_Project_Combined	ng_cc	595	ng	7.217
Magic_Valley_Generating_Station_Combined	ng_cc	801	ng	7.275
Martin_Lake_1	coal_lig_st	793.2	coal_lig	11.090
Martin_Lake_2	coal_lig_st	793.2	coal_lig	11.090
Martin_Lake_3	coal_lig_st	793.2	coal_lig	11.090
Midlothian_Energy_Facility_STK1	ng_cc	289	ng	7.460
Midlothian_Energy_Facility_STK2	ng_cc	289	ng	7.460
Midlothian_Energy_Facility_STK3	ng_cc	289	ng	7.460
Midlothian_Energy_Facility_STK4	ng_cc	289	ng	7.460
Midlothian_Energy_Facility_STK5	ng_cc	289	ng	7.460
Midlothian_Energy_Facility_STK6	ng_cc	289	ng	7.460
Monticello_1	coal_lig_st	593.4	coal_lig	10.916
Monticello_2	coal_lig_st	593.4	coal_lig	10.916
Monticello_3	coal_lig_st	793.2	coal_lig	10.916
Morgan_Creek_5	ng_st	170.4	ng	13.844
Morgan_Creek_6	ng_st	517.5	ng	13.844
Morgan_Creek_CT1	ng_gt	89.4	ng	13.844
Morgan_Creek_CT2	ng_gt	89.4	ng	13.844
Morgan_Creek_CT3	ng_gt	89.4	ng	13.844
Morgan_Creek_CT4	ng_gt	89.4	ng	13.844
Morgan_Creek_CT5	ng_gt	89.4	ng	13.844
Morgan_Creek_CT6	ng_gt	89.4	ng	13.844
Mountain_Creek_3	ng_st	74.9	ng	12.481
Mountain_Creek_6	ng_st	135.7	ng	12.481
Mountain_Creek_7	ng_st	136	ng	12.481
Mountain_Creek_8	ng_st	580.5	ng	12.481
Newgulf_Cogen_GEN1	ng_gt	78.7	ng	13.784
North_Lake_1	ng_st	176.8	ng	11.651
North_Lake_2	ng_st	170.4	ng	11.651
North_Lake_3	ng_st	361.3	ng	11.651
O_W_Sommers_1	ng_st	446	ng	12.109
O_W_Sommers_2	ng_st	446	ng	12.109
Odessa_Ector_Generating_Station_Combined_1	ng_cc	567.6	ng	7.604
Odessa_Ector_Generating_Station_Combined_2	ng_cc	567.6	ng	7.604
Oklaunion_1	coal_sub_st	720	coal_sub	10.582
P_H_Robinson_1	ng_st	484.5	ng	13.008

Simplified ERCOT 2007 individual unit data (continued)

Unit Name	Unit Type	Capacity (MW)	Fuel	Heatrate (MBTU/MWh)
P_H_Robinson_2	ng_st	484.5	ng	13.008
P_H_Robinson_3	ng_st	580.5	ng	13.008
P_H_Robinson_4	ng_st	765	ng	13.008
Permian_Basin_5	ng_st	114.9	ng	13.750
Permian_Basin_6	ng_st	535.5	ng	13.750
Permian_Basin_CT1	ng_gt	89.4	ng	13.750
Permian_Basin_CT2	ng_gt	89.4	ng	13.750
Permian_Basin_CT3	ng_gt	89.4	ng	13.750
Permian_Basin_CT4	ng_gt	89.4	ng	13.750
Permian_Basin_CT5	ng_gt	89.4	ng	13.750
Quail_Run_Energy_Center_Combined_1	ng_cc	298	ng	8.540
Quail_Run_Energy_Center_Combined_2	ng_cc	275	ng	8.540
R_W_Miller_1	ng_st	66	ng	12.666
R_W_Miller_2	ng_st	100	ng	12.666
R_W_Miller_3	ng_st	200	ng	12.666
R_W_Miller_4	ng_gt	118.8	ng	12.666
R_W_Miller_5	ng_gt	118.8	ng	12.666
Ray_Olinger_1	ng_st	75	ng	12.326
Ray_Olinger_2	ng_st	113.4	ng	12.326
Ray_Olinger_3	ng_st	156.6	ng	12.326
Ray_Olinger_4	ng_gt	82.7	ng	12.326
Rio_Nogales_Power_Project_Combined	ng_cc	898.2	ng	7.298
Sam_Bertron_3	ng_st	225.3	ng	11.572
Sam_Bertron_4	ng_st	225.3	ng	11.572
Sam_Bertron_ST1	ng_st	187.8	ng	11.572
Sam_Bertron_ST2	ng_st	187.8	ng	11.572
Sam_Rayburn_Units7to10_Combined	ng_cc	189.6	ng	9.147
San_Jacinto_Steam_Electric_Station_1	ng_gt	88.2	ng	13.516
San_Jacinto_Steam_Electric_Station_2	ng_gt	88.2	ng	13.516
San_Miguel_1	coal_lig_st	410	coal_lig	12.148
Sand_Hill_5Combined	ng_cc	388	ng	7.328
Sand_Hill_SH1	ng_gt	51.4	ng	7.328
Sand_Hill_SH2	ng_gt	51.4	ng	7.328
Sand_Hill_SH3	ng_gt	51.4	ng	7.328
Sand_Hill_SH4	ng_gt	51.4	ng	7.328
Sandow_No_4_4	coal_lig_st	590.6	coal_lig	11.163
Silas_Ray_10	ng_gt	61	ng	11.083
Silas_Ray_Units6and9_Combined	ng_cc	86	ng	11.083
Sim_Gideon_1	ng_st	144	ng	11.456
Sim_Gideon_2	ng_st	144	ng	11.456
Sim_Gideon_3	ng_st	351	ng	11.456
South_Texas_Project_1	u235_st	1354.3	u235	10.400

Simplified ERCOT 2007 individual unit data (continued)

Unit Name	Unit Type	Capacity (MW)	Fuel	Heatrate (MBTU/MWh)
South_Texas_Project_2	u235_st	1354.3	u235	10.400
Spencer_4	ng_st	61.1	ng	16.622
Spencer_5	ng_st	65.4	ng	16.622
Stryker_Creek_ST1	ng_st	176.8	ng	11.375
Stryker_Creek_ST2	ng_st	526.6	ng	11.375
T_H_Wharton_3Combined	ng_cc	318.3	ng	9.529
T_H_Wharton_4Combined	ng_cc	329.1	ng	9.529
T_H_Wharton_51	ng_gt	85	ng	9.529
T_H_Wharton_52	ng_gt	85	ng	9.529
T_H_Wharton_53	ng_gt	85	ng	9.529
T_H_Wharton_54	ng_gt	85	ng	9.529
T_H_Wharton_55	ng_gt	85	ng	9.529
T_H_Wharton_56	ng_gt	85	ng	9.529
Tenaska_Frontier_Generation_Station_Combined	ng_cc	939.7	ng	6.901
Tenaska_Gateway_Generation_Station_Combined	ng_cc	939.6	ng	7.475
Thomas_C_Ferguson_1	ng_st	446	ng	10.994
Tradinghouse_1	ng_st	580.5	ng	11.838
Tradinghouse_2	ng_st	799.2	ng	11.838
Trinidad_6	ng_st	239.3	ng	13.508
Twin_Oaks_Power_One_1	coal_lig_st	174.6	coal_lig	10.860
Twin_Oaks_Power_One_2	coal_lig_st	174.6	coal_lig	10.860
V_H_Braunig_1	ng_st	225	ng	11.161
V_H_Braunig_2	ng_st	252	ng	11.161
V_H_Braunig_3	ng_st	417	ng	11.161
Valley_1	ng_st	198.9	ng	13.664
Valley_2	ng_st	580.5	ng	13.664
Valley_3	ng_st	396	ng	13.664
W_A_Parish_1	ng_st	187.8	ng	10.382
W_A_Parish_2	ng_st	187.8	ng	10.382
W_A_Parish_3	ng_st	299.2	ng	10.382
W_A_Parish_4	ng_st	580.5	ng	10.382
W_A_Parish_5	coal_sub_st	734.1	coal_sub	10.382
W_A_Parish_6	coal_sub_st	734.1	coal_sub	10.382
W_A_Parish_7	coal_sub_st	614.6	coal_sub	10.382
W_A_Parish_8	coal_sub_st	614.6	coal_sub	10.382
W_B_Tuttle_1	ng_st	75	ng	17.474
W_B_Tuttle_3	ng_st	113.6	ng	17.474
W_B_Tuttle_4	ng_st	191.7	ng	17.474
Wind	wind	3710.5	wind	1.000
Wise_County_Power_LP_Combined	ng_cc	746	ng	7.609
Wolf_Hollow_I_LP_Combined	ng_cc	809.6	ng	7.882

B

COMPLETE UNIT COMMITMENT OPERATIONS RESULTS

This appendix contains complete result tables from Chapter 3. These large tables start on the next page.

Table B.1: Complete IEEE RTS MIP Heuristics Results

						mip gap		Total Cost		CO2		energy mix	commitment		power		Time	
System	# gens	# clust	# hrs	units	cheat	target	actual	$M	% diff	Mt	% diff	avg diff	# diff	avg |diff|	# diff	avg |diff|	sec	speed-up
1 day, 1x scaling, Baseline=Optimal																		
IEEE RTS96	26	26	24	separate	0	0	0	0.72	NA	0.0	0.000%			Baseline			12.1	1
IEEE RTS96	26	26	24	perturbed	0	0	0	0.72	0.000%	0.0	0.000%	0.000%	0	0.000%	0	0.000%	7.0	1.7
IEEE RTS96	26	8	24	clustered	0	0	0	0.72	0.000%	0.0	0.000%	0.000%	0	0.000%	2	0.000%	0.2	63
IEEE RTS96	26	26	24	separate	0	0.10%	0.09%	0.72	0.000%	0.0	0.000%	0.000%	0	0.000%	0	0.000%	3.2	4
IEEE RTS96	26	26	24	perturbed	0	0.10%	0.10%	0.72	0.000%	0.0	0.000%	0.000%	0	0.000%	0	0.000%	2.1	6
IEEE RTS96	26	8	24	clustered	0	0.10%	0.10%	0.72	0.000%	0.0	0.000%	0.000%	0	0.000%	2	0.000%	0.2	69
1 day, 10x scaling, Baseline=Optimal																		
IEEE RTS96	260	260	24	separate	0	0	0.018%	6.74	NA	0.3	0.000%			Baseline			36000.7	1
IEEE RTS96	260	260	24	perturbed	0	0	0.016%	6.74	0.000%	0.3	-0.114%	0.022%	9	0.182%	18	0.030%	36000.7	1
IEEE RTS96	260	8	24	clustered	0	0	0	6.73	-0.233%	0.3	-0.458%	0.675%	49	1.136%	80	0.612%	5.6	6416
IEEE RTS96	260	260	24	separate	0.001	0	0	6.74	0.031%	0.3	0.012%	0.106%	37	0.215%	64	0.099%	517.4	70
IEEE RTS96	260	260	24	perturbed	0.001	0	0.105%	6.75	0.088%	0.3	-0.245%	0.852%	46	1.508%	80	0.750%	36000.7	1
IEEE RTS96	260	8	24	clustered	0.001	0	0	6.73	-0.208%	0.3	-0.459%	0.678%	45	1.137%	79	0.615%	0.2	167445
IEEE RTS96	260	260	24	separate	0	0.10%	0.09%	6.74	0.031%	0.3	0.012%	0.106%	37	0.215%	64	0.099%	254.2	142
IEEE RTS96	260	260	24	perturbed	0	0.10%	0.08%	6.74	0.037%	0.3	-0.223%	0.717%	39	1.042%	60	0.628%	338.2	106
IEEE RTS96	260	8	24	clustered	0	0.10%	0.05%	6.73	-0.208%	0.3	-0.459%	0.678%	45	1.137%	79	0.615%	0.2	174761
IEEE RTS96	260	260	24	separate	0.001	0.10%	0.00%	6.74	0.031%	0.3	0.012%	0.106%	37	0.215%	64	0.099%	546.1	66
IEEE RTS96	260	260	24	perturbed	0.001	0.10%	0.10%	6.75	0.088%	0.3	-0.245%	0.852%	46	1.508%	80	0.750%	36000.6	1
IEEE RTS96	260	8	24	clustered	0.001	0.10%	0.00%	6.73	-0.208%	0.3	-0.459%	0.678%	45	1.137%	79	0.615%	0.2	169017
1 day, 10x scaling, Baseline=0.1% MIP gap																		
IEEE RTS96	260	260	24	separate	0	0.10%	0.09%	6.74	NA	0.3	0.000%			Baseline			254.2	1
IEEE RTS96	260	260	24	perturbed	0	0.10%	0.08%	6.74	0.006%	0.3	-0.235%	0.616%	44	0.933%	71	0.542%	338.2	1
IEEE RTS96	260	8	24	clustered	0	0.10%	0.05%	6.73	-0.240%	0.3	-0.471%	0.579%	44	1.057%	77	0.531%	0.2	1234
IEEE RTS96	260	260	24	separate	0.001	0.10%	0.00%	6.74	0.000%	0.3	0.000%	0.000%	0	0.000%	0	0.000%	546.1	0.5
IEEE RTS96	260	260	24	perturbed	0.001	0.10%	0.10%	6.75	0.057%	0.3	-0.257%	0.749%	35	1.327%	60	0.651%	36000.6	0
IEEE RTS96	260	8	24	clustered	0.001	0.10%	0.00%	6.73	-0.240%	0.3	-0.471%	0.579%	44	1.057%	77	0.531%	0.2	1193
7 day, 1x scaling, Baseline=Optimal																		
IEEE RTS96	26	26	168	separate	0	0	0.044%	4.29	NA	0.2	0.000%			Baseline			36004.4	1
IEEE RTS96	26	26	168	perturbed	0	0	0.075%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	0	0.000%	36030.8	1
IEEE RTS96	26	26	168	priority list	0	0	0.000579	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	36001.3	1
IEEE RTS96	26	8	168	clustered	0	0	0	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	41.7	864
IEEE RTS96	26	26	168	separate	0.001	0	0.000%	4.30	0.055%	0.2	0.001%	0.022%	56	0.286%	124	0.035%	23589.9	2
IEEE RTS96	26	26	168	perturbed	0.001	0	0.001034	4.29	0.030%	0.2	0.046%	0.014%	18	0.082%	46	0.026%	36003.1	1
IEEE RTS96	26	26	168	priority list	0.001	0	0.00%	4.29	0.034%	0.2	0.017%	0.005%	9	0.035%	21	0.008%	1859.9	19
IEEE RTS96	26	8	168	clustered	0.001	0	0.00%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	27.6	1306
IEEE RTS96	26	26	168	separate	0	0.10%	0.10%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	0	0.000%	2543.7	14
IEEE RTS96	26	26	168	perturbed	0	0.10%	0.10%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	0	0.000%	11029.7	3
IEEE RTS96	26	26	168	priority list	0	0.10%	0.10%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	4892.5	7
IEEE RTS96	26	8	168	clustered	0	0.10%	0.10%	4.29	0.023%	0.2	0.015%	0.014%	7	0.024%	17	0.016%	9.3	3891
IEEE RTS96	26	26	168	separate	0.001	0.10%	0.00%	4.30	0.055%	0.2	0.001%	0.022%	56	0.286%	124	0.035%	19717.8	2
IEEE RTS96	26	26	168	perturbed	0.001	0.10%	0.00%	4.29	0.030%	0.2	0.046%	0.014%	18	0.082%	46	0.026%	33672.2	1
IEEE RTS96	26	26	168	priority list	0.001	0.10%	0.00%	4.29	0.034%	0.2	0.017%	0.005%	9	0.035%	21	0.008%	1918.2	19
IEEE RTS96	26	8	168	clustered	0.001	0.10%	0.00%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	23.7	1519
7 day, 1x scaling, Baseline=0.1% MIP gap																		
IEEE RTS96	26	260	168	separate	0	0.10%	0.10%	4.29	NA	0.2	0.000%			Baseline			2543.7	1
IEEE RTS96	26	260	168	perturbed	0	0.10%	0.10%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	0	0.000%	11029.7	0
IEEE RTS96	26	8	168	priority list	0	0.10%	0.10%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	4892.5	1
IEEE RTS96	26	260	168	clustered	0	0.10%	0.10%	4.29	0.023%	0.2	0.015%	0.014%	7	0.024%	17	0.016%	9.3	274.9
IEEE RTS96	26	8	168	separate	0.001	0.10%	0.00%	4.30	0.055%	0.2	0.001%	0.022%	56	0.286%	124	0.035%	19717.8	0
IEEE RTS96	26	260	168	perturbed	0.001	0.10%	0.00%	4.29	0.030%	0.2	0.046%	0.014%	18	0.082%	46	0.026%	33672.2	0.1
IEEE RTS96	26	260	168	priority list	0.001	0.10%	0.00%	4.29	0.034%	0.2	0.017%	0.005%	9	0.035%	21	0.008%	1918.2	1
IEEE RTS96	26	8	168	clustered	0.001	0.10%	0.00%	4.29	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	23.7	107
7 day, 3x scaling, Baseline=Optimal																		
IEEE RTS96	78	78	168	separate	0	0	0.085%	12.16	NA	0.6	0.000%			Baseline			36032.8	1
IEEE RTS96	78	78	168	perturbed	0	0	0.086%	12.16	0.002%	0.6	0.064%	0.035%	123	0.334%	247	0.082%	36028.4	1
IEEE RTS96	78	78	168	priority list	0	0	0.002924	12.19	0.208%	0.6	-0.021%	0.060%	211	0.605%	396	0.155%	36012.4	1
IEEE RTS96	78	8	168	clustered	0	0	0.000195	12.16	-0.028%	0.6	0.045%	0.026%	141	0.416%	318	0.075%	36001.1	1
IEEE RTS96	78	78	168	separate	0.001	0	0.176%	12.17	0.091%	0.6	0.125%	0.080%	129	0.736%	278	0.166%	36002.2	1
IEEE RTS96	78	78	168	perturbed	0.001	0	0.001737	12.17	0.088%	0.6	0.133%	0.091%	172	0.516%	323	0.156%	36035.0	1
IEEE RTS96	78	78	168	priority list	0.001	0.00%	0.25%	12.18	0.166%	0.6	0.041%	0.067%	218	0.643%	410	0.138%	36012.4	1
IEEE RTS96	78	8	168	clustered	0.001	0.00%	0.00%	12.16	-0.027%	0.6	0.017%	0.022%	98	0.279%	238	0.063%	6426.4	6
IEEE RTS96	78	78	168	separate	0	0.10%	0.10%	12.16	0.010%	0.6	0.053%	0.018%	102	0.329%	228	0.052%	5980.8	6
IEEE RTS96	78	78	168	perturbed	0	0.10%	0.09%	12.16	0.007%	0.6	0.030%	0.008%	85	0.327%	197	0.038%	23367.1	2
IEEE RTS96	78	78	168	priority list	0	0.10%	0.29%	12.19	0.208%	0.6	-0.021%	0.060%	211	0.605%	396	0.155%	36012.4	1
IEEE RTS96	78	8	168	clustered	0	0.10%	0.10%	12.17	0.039%	0.6	-0.036%	0.053%	172	0.462%	341	0.129%	42.0	857
IEEE RTS96	78	78	168	separate	0.001	0.10%	0.18%	12.17	0.091%	0.6	0.125%	0.080%	129	0.736%	278	0.166%	36001.8	1
IEEE RTS96	78	78	168	perturbed	0.001	0.10%	0.17%	12.17	0.088%	0.6	0.133%	0.091%	172	0.516%	323	0.156%	36011.7	1
IEEE RTS96	78	78	168	priority list	0.001	0.10%	0.25%	12.18	0.166%	0.6	0.041%	0.067%	218	0.643%	410	0.138%	36012.4	1
IEEE RTS96	78	8	168	clustered	0.001	0.10%	0.00%	12.16	-0.027%	0.6	0.017%	0.022%	98	0.279%	238	0.063%	4912.1	7
7 day, 3x scaling, Baseline=0.1% MIP gap																		
IEEE RTS96	78	260	168	separate	0	0.10%	0.10%	12.16	NA	0.6	0.000%			Baseline			5980.8	1
IEEE RTS96	78	260	168	perturbed	0	0.10%	0.09%	12.16	-0.002%	0.6	-0.023%	0.011%	93	0.397%	188	0.048%	23367.1	0
IEEE RTS96	78	8	168	priority list	0	0.10%	0.29%	12.19	0.199%	0.6	-0.074%	0.065%	192	0.602%	358	0.148%	36012.4	0
IEEE RTS96	78	260	168	clustered	0	0.10%	0.10%	12.17	0.029%	0.6	-0.089%	0.060%	173	0.516%	319	0.130%	42.0	142.3
IEEE RTS96	78	8	168	separate	0.001	0.10%	0.18%	12.17	0.082%	0.6	0.072%	0.074%	135	0.735%	275	0.175%	36001.8	0
IEEE RTS96	78	260	168	perturbed	0.001	0.10%	0.17%	12.17	0.079%	0.6	0.080%	0.074%	168	0.509%	316	0.143%	36011.7	0.2
IEEE RTS96	78	260	168	priority list	0.001	0.10%	0.25%	12.18	0.156%	0.6	-0.012%	0.084%	197	0.609%	367	0.119%	36012.4	0
IEEE RTS96	78	8	168	clustered	0.001	0.10%	0.00%	12.16	-0.037%	0.6	-0.035%	0.034%	95	0.280%	202	0.055%	4912.1	1

Table B.2: Complete IEEE RTS Unit Commitment Simplifications Results

					Simplifications						mip gap		Total Cost		CO2		energy mix	commitment		power		Time		
System	# gens	# clust	# hrs	units	ignore min up & down times	max_start	UC integer threshold (MW)	combine rsrv	afine fuel use	cheat	target	actual	$M	% diff	Mt	% diff	avg diff	# diff	avg |diff|	# diff	avg |diff|	sec	speed-up from baseline	additional speedup for clustering
7 day, 1x scaling, Baseline=0.1% MIP gap, No Cheat																								
IEEE RTS96	26	26	168	separate	-	-	NaN	-	-	0	0.10%	0.10%	4	NA	0.2	0.000%	Baseline					2543.7	1.0	
IEEE RTS96	26	8	168	clustered	-	-	NaN	-	-	0	0.10%	0.10%	4	0.023%	0.2	0.015%	0.014%	7	0.024%	17	0.016%	9.3	274.9	275
IEEE RTS96	26	26	168	separate	-	-	5	-	-	0	0.10%	0.10%	4	-0.052%	0.2	-0.049%	0.015%	75	0.328%	185	0.045%	362.1	7.0	
IEEE RTS96	26	8	168	clustered	-	-	5	-	-	0	0.10%	0.10%	4	-0.036%	0.2	0.002%	0.035%	60	0.243%	161	0.043%	7.8	324.1	46
IEEE RTS96	26	26	168	separate	-	-	20	-	-	0	0.10%	0.10%	4	-0.127%	0.2	-0.087%	0.029%	69	0.274%	271	0.073%	153.6	16.6	
IEEE RTS96	26	8	168	clustered	-	-	20	-	-	0	0.10%	0.09%	4	-0.105%	0.2	-0.208%	0.025%	80	0.315%	290	0.083%	1.4	1875.9	113
IEEE RTS96	26	26	168	separate	-	-	0	-	Y	0	0.10%	0.09%	4	-0.212%	0.2	-0.154%	0.084%	0	0.000%	55	0.105%	532.2	4.8	
IEEE RTS96	26	8	168	clustered	-	-	0	-	Y	0	0.10%	0.04%	4	-0.195%	0.2	-0.140%	0.089%	5	0.018%	69	0.118%	27.6	92.0	19
IEEE RTS96	26	26	168	separate	-	-	0	Y	-	0	0.10%	0.10%	4	-0.194%	0.2	-0.035%	0.061%	126	1.458%	407	0.155%	560.3	4.5	
IEEE RTS96	26	8	168	clustered	-	-	0	Y	-	0	0.10%	0.08%	4	-0.153%	0.2	-0.083%	0.054%	120	1.279%	397	0.152%	27.0	94.3	21
IEEE RTS96	26	26	168	separate	Y	-	0	-	-	0	0.10%	0.10%	4	-0.652%	0.2	0.043%	0.170%	89	0.754%	176	0.231%	1191.0	2.1	
IEEE RTS96	26	8	168	clustered	Y	-	0	-	-	0	0.10%	0.06%	4	-0.630%	0.2	0.046%	0.166%	95	0.775%	189	0.245%	4.6	558.7	262
IEEE RTS96	26	26	168	separate	Y	-	0	-	-	0	0.10%	0.10%	4	-0.645%	0.2	0.055%	0.172%	93	0.776%	188	0.236%	236.0	10.8	
IEEE RTS96	26	8	168	clustered	Y	-	0	-	-	0	0.10%	0.09%	4	-0.599%	0.2	0.066%	0.164%	96	0.791%	190	0.249%	8.4	303.7	28
IEEE RTS96	26	26	168	separate	-	Y	0	-	-	0	0.10%	0.10%	4	0.000%	0.2	0.000%	0.000%	0	0.000%	1	0.000%	3916.3	0.6	
IEEE RTS96	26	8	168	clustered	-	Y	0	-	-	0	0.10%	0.10%	4	0.062%	0.2	-0.073%	0.015%	44	0.283%	77	0.033%	19.9	128.0	197
7 day, 3x scaling, Baseline=0.1% MIP gap, No Cheat																								
IEEE RTS96	78	78	168	separate	-	-	0	-	-	0	0.10%	0.10%	12	NA	0.6	0.000%	Baseline					5980.8	1.0	
IEEE RTS96	78	8	168	clustered	-	-	0	-	-	0	0.10%	0.10%	12	0.029%	0.6	-0.089%	0.060%	173	0.516%	319	0.130%	42.0	142.3	142
IEEE RTS96	78	78	168	separate	-	-	5	-	-	0	0.10%	0.08%	12	-0.015%	0.6	-0.044%	0.030%	141	0.584%	353	0.061%	105.9	56.5	
IEEE RTS96	78	8	168	clustered	-	-	5	-	-	0	0.10%	0.09%	12	0.006%	0.6	-0.017%	0.025%	109	0.337%	304	0.056%	1.3	4562.0	81
IEEE RTS96	78	78	168	separate	-	-	20	-	-	0	0.10%	0.08%	12	-0.013%	0.6	-0.046%	0.028%	158	0.639%	419	0.077%	113.7	52.6	
IEEE RTS96	78	8	168	clustered	-	-	20	-	-	0	0.10%	0.08%	12	-0.014%	0.6	-0.038%	0.035%	109	0.391%	348	0.056%	1.4	4375.1	83
IEEE RTS96	78	78	168	separate	-	-	0	-	Y	0	0.10%	0.08%	12	-0.143%	0.6	-0.144%	0.386%	216	0.801%	456	0.435%	1619.0	3.7	
IEEE RTS96	78	8	168	clustered	-	-	0	-	Y	0	0.10%	0.10%	12	-0.107%	0.6	-0.174%	0.360%	199	0.597%	456	0.411%	22.9	260.8	71
IEEE RTS96	78	78	168	separate	-	-	0	Y	-	0	0.10%	0.10%	12	-0.052%	0.6	0.004%	0.065%	171	0.488%	405	0.143%	5197.3	1.2	
IEEE RTS96	78	8	168	clustered	-	-	0	Y	-	0	0.10%	0.07%	12	-0.071%	0.6	0.050%	0.054%	160	0.515%	404	0.116%	2.9	2097.1	1822
IEEE RTS96	78	78	168	separate	Y	-	0	-	-	0	0.10%	0.16%	12	-0.044%	0.6	-0.148%	0.150%	223	0.831%	418	0.225%	36064.5	0.2	
IEEE RTS96	78	8	168	clustered	Y	-	0	-	-	0	0.10%	0.08%	12	-0.108%	0.6	-0.092%	0.201%	189	0.678%	372	0.212%	12.0	498.1	3003
IEEE RTS96	78	78	168	separate	Y	-	0	-	-	0	0.10%	0.08%	12	-0.133%	0.6	-0.086%	0.185%	219	0.732%	413	0.238%	27739.8	0.2	
IEEE RTS96	78	8	168	clustered	Y	-	0	-	-	0	0.10%	0.10%	12	-0.103%	0.6	-0.058%	0.171%	175	0.621%	333	0.173%	2.7	2247.6	10425
IEEE RTS96	78	78	168	separate	-	Y	0	-	-	0	0.10%	0.08%	12	-0.015%	0.6	-0.043%	0.030%	182	0.645%	327	0.120%	2962.9	2.0	
IEEE RTS96	78	8	168	clustered	-	Y	0	-	-	0	0.10%	0.09%	12	0.003%	0.6	-0.055%	0.040%	141	0.394%	296	0.085%	7.9	759.3	376

Table B.3: Complete ERCOT 2007 Unit Commitment Simplifications Results

					Simplifications					mip gap		Total Cost		CO2		energy mix	commitment		power		Time		
System	# gens	# clust	# hrs	units	ignore min up & down times	max_start	UC integer threshold (MW)	combine rsrv	afine fuel use	target	actual	$M	% diff	Mt	% diff	avg diff	# diff	avg |diff|	# diff	avg |diff|	sec	speed-up from baseline	additional speedup for clustering
1 week,No Cheat, Baseline=Full Problem																							
ERCOT2007	205	205	168	separate	-	-	0	-	Y	0.10%	0.06%	349	NA	3.27	0.000%	Baseline					4517.2	1.0	
ERCOT2007	205	7	168	clustered	-	-	0	-	Y	0.10%	0.10%	352	0.785%	3.31	1.253%	0.377%	336	1.150%	625	0.533%	2.2	2073.1	2073
ERCOT2007	205	205	168	separate	-	-	5	-	Y	0.10%	0.06%	349	0.000%	3.27	0.000%	0.000%	0	0.000%	0	0.000%	3693.8	1.2	
ERCOT2007	205	7	168	clustered	-	-	5	-	Y	0.10%	0.10%	352	0.785%	3.31	1.253%	0.377%	336	1.150%	625	0.533%	1.9	2409.2	1970
ERCOT2007	205	205	168	separate	-	-	20	-	Y	0.10%	0.03%	349	-0.033%	3.28	0.103%	0.051%	298	1.071%	508	0.076%	951.7	4.7	
ERCOT2007	205	7	168	clustered	-	-	20	-	Y	0.10%	0.01%	352	0.696%	3.31	1.174%	0.330%	233	0.971%	598	0.504%	0.5	9798.7	2064
ERCOT2007	205	205	168	separate	-	-	0	Y	Y	0.10%	0.01%	349	-0.026%	3.28	0.194%	0.141%	296	2.293%	546	0.187%	376.6	12.0	
ERCOT2007	205	7	168	clustered	-	-	0	Y	Y	0.10%	0.03%	351	0.555%	3.31	1.293%	0.340%	140	0.665%	598	0.524%	0.3	16486.1	1374
ERCOT2007	205	205	168	separate	Y	Y	0	-	Y	0.10%	0.03%	349	-0.138%	3.28	0.316%	0.090%	146	0.449%	492	0.141%	508.0	8.9	
ERCOT2007	205	7	168	clustered	Y	Y	0	-	Y	0.10%	0.04%	352	0.728%	3.31	1.203%	0.334%	318	1.169%	601	0.504%	1.5	3005.5	338
ERCOT2007	205	205	168	separate	-	-	0	-	Y	0.10%	0.05%	349	-0.009%	3.27	0.039%	0.013%	266	0.418%	532	0.057%	1681.9	2.7	
ERCOT2007	205	7	168	clustered	-	-	0	-	Y	0.10%	0.05%	352	0.739%	3.31	1.210%	0.346%	307	1.114%	613	0.510%	1.5	2993.5	1115
13 weeks, Combined Reserves, No Cheat, Baseline=Full Problem, Timeout Extended to 60hrs. Run using faster machine, compare with care																							
ERCOT2007	205	205	2184	separate	-	-	0	Y	Y	0.10%	0.06%	6147	NA	55.62	0.000%	Baseline					37633.5	1.0	
ERCOT2007	205	7	2184	clustered	-	-	0	Y	Y	0.10%	0.00%	6203	0.907%	56.04	0.744%	0.243%	5064	2.627%	7354	0.412%	7.2	5234.1	1115
ERCOT2007	205	205	2184	separate	-	-	5	Y	Y	0.10%	0.06%	6147	0.000%	55.62	0.000%	0.000%	0	0.000%	0	0.000%	35203.2	1.1	
ERCOT2007	205	7	2184	clustered	-	-	5	Y	Y	0.10%	0.00%	6203	0.907%	56.04	0.744%	0.243%	5064	2.627%	7354	0.412%	6.6	5704.6	1116
ERCOT2007	205	205	2184	separate	-	-	20	Y	Y	0.10%	0.00%	6142	-0.082%	55.60	-0.039%	0.015%	3506	0.675%	4921	0.083%	10630.6	3.5	
ERCOT2007	205	7	2184	clustered	-	-	20	Y	Y	0.10%	0.00%	6203	0.902%	56.03	0.738%	0.246%	5046	2.600%	7330	0.413%	6.1	6211.2	1117
ERCOT2007	205	205	2184	separate	Y	Y	0	Y	Y	0.10%	0.41%	6166	0.300%	55.76	0.248%	0.055%	5008	0.812%	5957	0.489%	216044.2	0.2	
ERCOT2007	205	7	2184	clustered	Y	Y	0	Y	Y	0.10%	0.00%	6186	0.623%	55.91	0.512%	0.474%	5071	2.693%	7320	0.587%	18.0	2087.4	1118
ERCOT2007	205	205	2184	separate	-	-	0	Y	Y	0.10%	0.02%	6158	0.170%	55.73	0.191%	0.116%	4283	1.257%	5164	0.302%	72667.3	0.5	
ERCOT2007	205	7	2184	clustered	-	-	0	Y	Y	0.10%	0.00%	6203	0.907%	56.04	0.744%	0.242%	5069	2.632%	7357	0.418%	7.4	5076.7	1119

Table B.4: Complete ERCOT 2007 Cluster Comparison Results

					mip gap		Total Cost		CO2		energy mix	commitment		power		Time	
System	# gens	# clust	# hrs	units	target	actual	$M	% diff	Mt	% diff	avg diff	# diff	avg |diff|	# diff	avg |diff|	sec	speed-up
13 weeks, Combined Reserves, Afine Fuel Use, No Cheat, Baseline=Full Problem, Timeout Extended to 60hrs.																	
ERCOT2007	205	205	2184	separate	0.10%	0.06%	6147	NA	55.6	0.000%	Baseline					37633.5	1
ERCOT2007	205	90	2184	clust_plant	0.10%	0.07%	6133	-0.232%	55.6	0.008%	0.082%	3869	0.842%	7311	0.117%	7701.8	5
ERCOT2007	205	17	2184	clust_age	0.10%	0.02%	6468	5.211%	56.0	0.601%	1.753%	9601	2.633%	12041	1.970%	33.1	1135
ERCOT2007	205	17	2184	clust_size	0.10%	0.03%	6192	0.727%	56.0	0.667%	0.222%	5072	2.454%	5222	0.319%	33.4	1128
ERCOT2007	205	17	2184	clust_efficiency	0.10%	0.01%	6153	0.100%	55.7	0.062%	0.136%	4436	0.898%	5213	0.208%	41.9	898
ERCOT2007	205	7	2184	clustered	0.10%	0.00%	6203	0.907%	56.0	0.744%	0.243%	5064	2.627%	7354	0.412%	7.2	5234
1 year, Combined Reserves, Afine Fuel, No Cheat, Baseline=Full Problem, Run on standard machine with standard 10hr timelimit																	
ERCOT2007	205	205	8760	separate	0.10%	No Solution				No solution for Comparison						10hr Timeout	
ERCOT2007	205	90	8760	clust_plant	0.10%	No Solution										10hr Timeout	
ERCOT2007	205	17	8760	clust_age	0.10%	0.10%	22759	-	200.0							34230.6	-
ERCOT2007	205	17	8760	clust_size	0.10%	0.07%	21881	-	201.3							10722.1	-
ERCOT2007	205	17	8760	clust_efficiency	0.10%	0.13%	21781	-	200.2							10hr Timeout	
ERCOT2007	205	7	8760	clustered	0.10%	0.01%	21933	-	201.7							129.5	-

Table B.5: Complete ERCOT 2007 Problem Size and Solution Time Results.

					mip gap		Problem size (Before CPLEX pre-solve)				Time	
System	# gens	# clust	# hrs	units	target	actual	# equations	# variables	# discretes	# non-zeros	sec	speed-up
No Cheat, 0.1% MIP Gap, Separate Reserves, All runs on standard machines with 10hour timeout												
ERCOT2007	205	205	24	separate	0.10%	0.00%	63,786	50,008	4,896	293,093	6	1.0
ERCOT2007	205	90	24	clust_plant	0.10%	0.01%	28,290	21,592	2,136	133,589	4	1.6
ERCOT2007	205	17	24	clust_size	0.10%	0.02%	5,394	3,928	384	25,997	0	37.5
ERCOT2007	205	7	24	clustered	0.10%	0.00%	2,130	1,480	144	10,109	0	71.7
ERCOT2007	205	205	48	separate	0.10%	0.03%	132,162	97,504	9,792	654,317	30	1.0
ERCOT2007	205	90	48	clust_plant	0.10%	0.10%	59,058	42,592	4,272	298,445	7	4.0
ERCOT2007	205	17	48	clust_size	0.10%	0.04%	10,914	7,696	768	55,565	0	67.1
ERCOT2007	205	7	48	clustered	0.10%	0.018%	4,290	2,896	288	22,157	0	314.2
ERCOT2007	205	205	72	separate	0.10%	0.06%	198,234	146,248	14,688	981,461	104	1.0
ERCOT2007	205	90	72	clust_plant	0.10%	0.07%	88,578	63,880	6,408	447,653	42	2.5
ERCOT2007	205	17	72	clust_size	0.10%	0.02%	16,362	11,536	1,152	83,333	1	157.2
ERCOT2007	205	7	72	clustered	0.10%	0.024%	6,426	4,336	432	33,221	0	695.0
ERCOT2007	205	205	96	separate	0.10%	0.03%	264,306	194,992	19,584	1,308,605	140	1.0
ERCOT2007	205	90	96	clust_plant	0.10%	0.08%	118,098	85,168	8,544	596,861	22	6.3
ERCOT2007	205	17	96	clust_size	0.10%	0.03%	21,810	15,376	1,536	111,101	1	99.2
ERCOT2007	205	7	96	clustered	0.10%	0.020%	8,562	5,776	576	44,285	0	758.9
ERCOT2007	205	205	168	separate	0.10%	0.06%	446,394	349,960	34,272	2,068,949	4,517	1.0
ERCOT2007	205	90	168	clust_plant	0.10%	0.06%	197,922	151,048	14,952	943,685	435	10.4
ERCOT2007	205	17	168	clust_size	0.10%	0.04%	37,650	27,400	2,688	186,173	10	442.7
ERCOT2007	205	7	168	clustered	0.10%	0.096%	14,802	10,264	1,008	74,957	2	2073.1
ERCOT2007	205	205	2184	separate	0.10%	NA	5,802,906	4,549,288	445,536	26,895,989	Timeout	
ERCOT2007	205	90	2184	clust_plant	0.10%	0.102%[A]	2,572,770	1,963,432	194,376	12,267,557	36030.6[A]	1.0
ERCOT2007	205	17	2184	clust_size	0.10%	0.099%	489,234	356,008	34,944	2,419,901	897	3.4
ERCOT2007	205	7	2184	clustered	0.10%	0.01%	192,210	133,240	13,104	974,093	48	278.0
ERCOT2007	205	205	8760	separate	0.10%	NA	23,275,338	18,247,096	1,787,040	107,879,430	Timeout	
ERCOT2007	205	90	8760	clust_plant	0.10%	NA	10,319,298	7,875,256	779,640	49,204,949	Timeout	
ERCOT2007	205	17	8760	clust_size	0.10%	0.07%	1,962,258	1,427,896	140,160	9,706,109	10,722	1.0
ERCOT2007	205	7	8760	clustered	0.10%	0.01%	770,898	534,376	52,560	3,906,989	129	82.8

[A] 13wk (2184 hr) cluster by plant results included despite time out at 10hrs, because MIP gap was only 0.002% greater than target

C

ADDITIONAL INTEGRATED UNIT COMMITMENT AND PLANNING RESULTS

This appendix contains complete result tables and additional figures from Chapter 4.

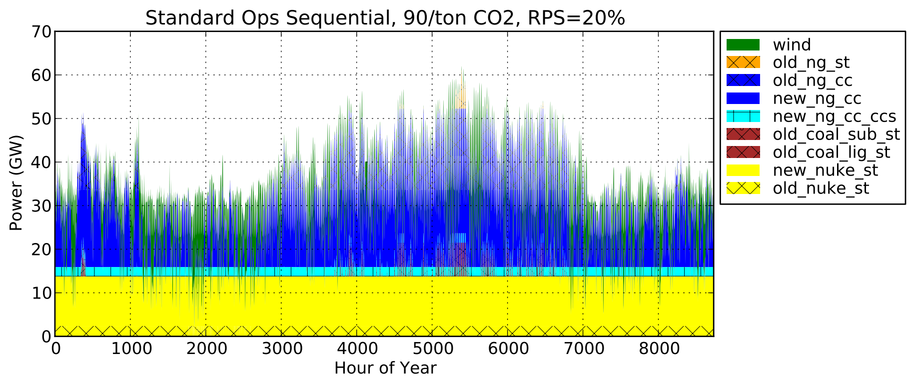
C.1 COMPLETE CARBON PRICE RESULTS TABLES

Table C.1: New Capacity for Carbon Costs from \$0 to \$120/ton CO_2 for Standard and Advanced planning models.

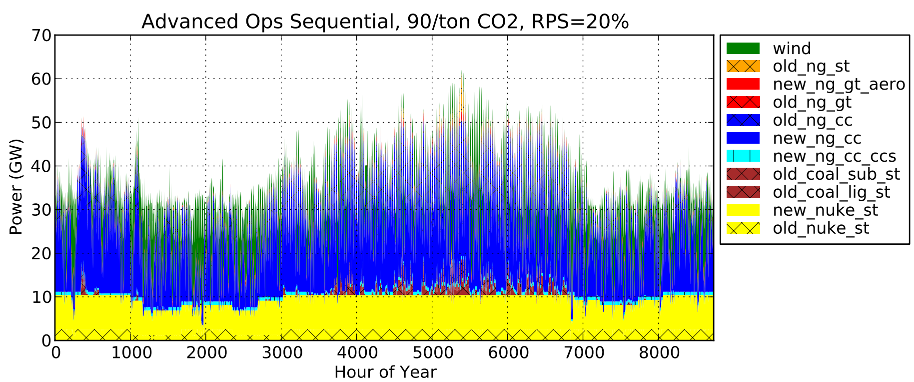
				New Installed Capacity (GW)							
Run Type	RPS	Carbon Cost (\$/ton CO2)	Carbon Emissions Mt CO2e	Wind	NG-CT	NG-CCGT	NG-CCGT w/ CCS	Coal	Coal w/ CCS	Nuclear	Effective Planning Margin
Advanced (& Actual)	20%	0	126.8	22.26	12.18	21.20	0.00	0.00	0.00	0.00	13.9%
Standard Predicted	20%	0	125.9	22.26	9.87	23.60	0.00	0.00	0.00	0.00	14.2%
Advanced (& Actual)	20%	15	126	22.26	11.13	22.40	0.00	0.00	0.00	0.00	14.2%
Standard Predicted	20%	15	125.7	22.26	9.03	24.40	0.00	0.00	0.00	0.00	14.2%
Advanced (& Actual)	20%	30	120.9	22.26	9.66	23.60	0.00	0.00	0.00	0.00	13.9%
Standard Predicted	20%	30	125.5	22.26	8.19	25.20	0.00	0.00	0.00	0.00	14.2%
Advanced (& Actual)	20%	45	87.05	22.26	6.30	28.00	0.00	0.00	0.00	0.00	15.8%
Standard Predicted	20%	45	85.66	22.26	2.73	30.40	0.00	0.00	0.00	0.00	14.2%
Advanced (& Actual)	20%	60	82.39	22.26	4.20	32.80	0.00	0.00	0.00	0.00	20.4%
Standard Predicted	20%	60	79.58	22.26	0.63	32.40	0.00	0.00	0.00	0.00	14.2%
Advanced (& Actual)	20%	75	76.14	22.26	6.09	29.60	0.00	0.00	0.00	2.24	21.6%
Standard Predicted	20%	75	64.09	22.26	0.21	27.20	0.00	0.00	0.00	5.59	13.9%
Advanced (& Actual)	20%	90	62.3	22.26	7.35	19.60	0.77	0.00	0.00	7.83	17.3%
Standard Predicted	20%	90	41.06	22.26	0.00	18.80	2.31	0.00	0.00	12.30	14.1%
Advanced (& Actual)	20%	105	39.26	22.26	8.61	10.80	10.78	0.00	0.00	7.83	21.1%
Standard Predicted	20%	105	27.56	22.26	0.21	11.60	9.24	0.00	0.00	12.30	14.0%
Advanced (& Actual)	20%	120	19.71	22.26	7.56	4.80	23.10	0.00	0.00	6.71	28.0%
Standard Predicted	20%	120	21.26	22.26	0.00	8.00	11.94	0.00	0.00	13.42	14.0%

C.2 ADDITIONAL $90/TON, 20% RPS OPERATIONS FIGURES

C.2.1 *Annual Time series*



(a)



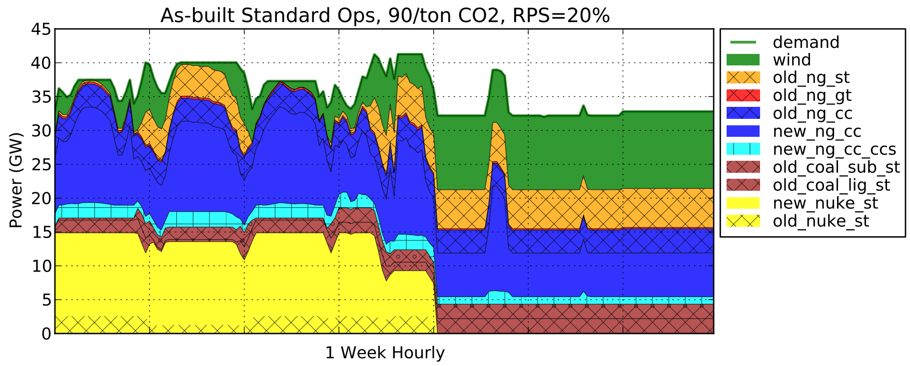
(b)

Figure C.1: Comparison of sequential hourly power production by generator type for (a) Standard, merit order operations and (b) Advanced UC-based operations. Baseload maintenance (coal & nuclear) can be seen as multi-week-long reductions in otherwise nearly flat output.

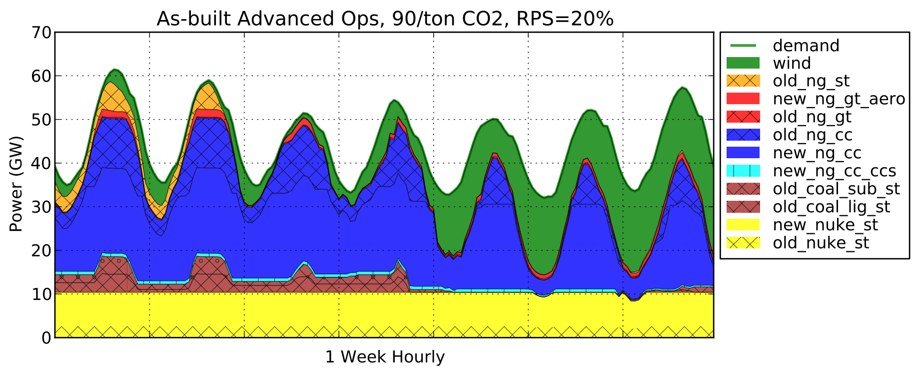
Table C.2: Energy for carbon costs from $0 to $120/ton CO2 price for Standard and Advanced Capacity Planning

				Energy (TWh)														
Run Type	RPS	Carbon Cost ($/ton CO2)	Carbon Emissions Mt CO2e	Wind	Old NG-Steam	Old NG-CT	New NG-CT	Old NG-CCGT	New NG-CCGT	New NG-CCGT w/ CCS	Old Coal SubBit.	Old Coal Lignite	New Coal (SubBit.)	New Coal w/ CCS	New Nuclear	Old Nuclear	Non-Served Energy (GWh)	Wind Shedding (GWh)
Advanced (& Actual)	0.2	0	126.8	61.6	1.3	2.3	4.8	24.0	126.4	0.0	32.2	33.6	0.0	0.0	0.0	20.6	0	298
Standard Predicted	0.2	0	125.9	61.9	0.2	0.0	3.3	17.6	135.8	0.0	32.8	34.5	0.0	0.0	0.0	20.7	-	-
Standard Actual	0.2	0	126.1	61.58	1.28	2.30	3.50	17.39	134.36	0.00	32.14	33.56	0.00	0.00	0.00	20.61	0	291
Advanced (& Actual)	0.2	15	126	61.6	1.3	2.3	4.0	20.6	131.2	0.0	31.8	33.4	0.0	0.0	0.0	20.6	0	283
Standard Predicted	0.2	15	125.7	61.9	0.2	0.0	2.7	16.2	137.8	0.0	32.8	34.5	0.0	0.0	0.0	20.7	-	-
Standard Actual	0.2	15	125.5	61.58	1.31	2.26	3.10	15.44	137.33	0.00	31.78	33.30	0.00	0.00	0.00	20.62	0	283
Advanced (& Actual)	0.2	30	120.9	61.7	1.4	2.2	3.1	18.0	141.4	0.0	27.7	30.6	0.0	0.0	0.0	20.6	0	156
Standard Predicted	0.2	30	125.5	61.9	0.2	0.0	2.2	14.8	139.7	0.0	32.8	34.5	0.0	0.0	0.0	20.7	-	-
Standard Actual	0.2	30	119.8	61.72	1.32	2.18	2.46	14.12	147.04	0.00	27.20	30.06	0.00	0.00	0.00	20.65	0	152
Advanced (& Actual)	0.2	45	87.05	61.7	1.2	1.9	1.6	26.0	183.3	0.0	3.4	7.0	0.0	0.0	0.0	20.6	0	216
Standard Predicted	0.2	45	85.66	61.9	0.2	0.0	0.3	13.0	199.0	0.0	1.3	10.4	0.0	0.0	0.0	20.7	-	-
Standard Actual	0.2	45	88.19	61.35	1.64	2.02	0.44	23.78	187.30	0.00	4.17	7.05	0.00	0.00	0.00	18.98	2	521
Advanced (& Actual)	0.2	60	82.39	61.4	1.1	2.0	0.6	15.4	200.7	0.0	2.1	2.7	0.0	0.0	0.0	20.6	0	427
Standard Predicted	0.2	60	79.58	61.9	0.2	0.0	0.0	16.6	204.5	0.0	0.8	2.0	0.0	0.0	0.0	20.7	-	-
Standard Actual	0.2	60	87.94	60.40	0.02	1.82	0.18	32.09	181.95	0.00	3.98	6.89	0.00	0.00	0.00	14.65	4,750	1,470
Advanced (& Actual)	0.2	75	76.14	61.5	1.0	2.2	1.7	16.3	181.1	0.0	1.5	2.8	0.0	0.0	17.9	20.6	0	336
Standard Predicted	0.2	75	64.09	61.9	0.2	0.0	0.0	16.1	160.2	0.0	0.7	1.9	0.0	0.0	45.0	20.6	-	-
Standard Actual	0.2	75	88.18	58.36	7.99	1.98	0.09	35.46	142.02	0.00	7.66	9.81	0.00	0.00	19.09	9.33	14,946	3,509
Advanced (& Actual)	0.2	90	62.3	61.3	1.2	2.4	4.3	26.8	117.4	5.4	2.6	3.4	0.0	0.0	61.8	20.1	-	520
Standard Predicted	0.2	90	41.06	61.9	0.2	0.0	0.0	15.3	92.6	17.0	0.6	1.8	0.0	0.0	96.8	20.5	-	-
Standard Actual	0.2	90	85.31	48.05	27.09	1.78	0.00	29.08	82.69	13.60	11.32	12.48	0.00	0.00	10.78	3.40	66,461	13,813
Advanced (& Actual)	0.2	105	39.26	61.3	0.7	2.5	5.0	21.4	52.7	76.9	1.9	2.5	0.0	0.0	61.8	20.0	0	520
Standard Predicted	0.2	105	27.56	61.9	0.2	0.0	0.1	15.8	47.0	62.0	0.6	1.8	0.0	0.0	96.8	20.5	-	-
Standard Actual	0.2	105	74.98	50.50	25.07	1.87	0.01	35.78	48.22	50.12	10.66	11.75	0.00	0.00	14.40	4.12	54,232	11,367
Advanced (& Actual)	0.2	120	19.71	61.3	0.1	2.5	3.6	10.1	12.8	141.1	0.6	1.2	0.0	0.0	53.3	20.1	0	520
Standard Predicted	0.2	120	21.26	61.9	0.2	0.0	0.0	15.4	27.7	73.6	0.6	1.8	0.0	0.0	105.0	20.5	-	-
Standard Actual	0.2	120	70.83	44.98	29.11	1.73	0.00	29.12	26.66	57.82	12.25	13.09	0.00	0.00	7.56	2.58	81,841	16,889

C.2.2 *As built Weekly Operations*



(a)



(b)

Figure C.2: Comparing 1-week of sequential hourly power production if generation mix proposed by the (a) Standard or (b) Advanced models were actually built.

C.3 CO2 LIMIT, RPS, AND FLEXIBILITY FORMULATION RESULT TABLES

Table C.3: New Installed Capacity for No CO_2 limit and 141Mt CO_2 limit across 0-80% RPS with all flexibility formulations.

				New Installed Capacity (GW)								
Run Type	RPS	Carbon Limit ($/ton CO2e)	Carbon Emissions Mt CO2e	Wind	NG-CT	NG-CCGT	NG-CCGT w/ CCS	Coal	Coal w/ CCS	Nuclear	Required Planning Margin	Effective Planning Margin
Adv	0%	Inf	162.8	0.00	9.45	22.00	0.00	4.55	0.00	0.00	13.75%	14.04%
Std	0%	Inf	190.6	0.00	8.82	16.00	0.00	11.70	0.00	0.00	13.75%	14.13%
mtoFlex	0%	Inf	190.7	0.00	8.82	16.00	0.00	11.70	0.00	0.00	13.75%	14.13%
UcLp	0%	Inf	160	0.00	8.82	23.20	0.00	3.90	0.00	0.00	13.75%	14.04%
Adv	20%	Inf	126.8	22.26	12.18	21.20	0.00	0.00	0.00	0.00	5.00%	13.88%
Std	20%	Inf	125.9	22.26	9.87	23.60	0.00	0.00	0.00	0.00	13.75%	14.21%
mtoFlex	20%	Inf	126.2	22.26	14.49	22.00	0.00	0.00	0.00	0.00	5.00%	18.71%
UcLp	20%	Inf	126.7	22.26	11.76	21.60	0.00	0.00	0.00	0.00	5.00%	13.88%
Adv	40%	Inf	97.06	55.66	18.48	16.80	0.00	0.00	0.00	0.00	5.00%	22.09%
Std	40%	Inf	96.31	51.95	10.08	20.00	0.00	0.00	0.00	0.00	13.75%	13.76%
mtoFlex	40%	Inf	93.75	55.66	19.53	18.80	0.00	0.00	0.00	0.00	5.00%	26.93%
UcLp	40%	Inf	96.95	55.66	17.64	17.20	0.00	0.00	0.00	0.00	5.00%	21.45%
Adv	60%	Inf	63.51	163.26	35.28	10.80	0.00	0.00	0.00	0.00	5.00%	56.39%
Std	60%	Inf	65.06	115.03	11.97	14.00	0.00	0.00	0.00	0.00	13.75%	17.66%
mtoFlex	60%	Inf	64.96	122.45	28.14	13.60	0.00	0.00	0.00	0.00	5.00%	43.05%
UcLp	60%	Inf	63.64	163.26	35.07	10.40	0.00	0.00	0.00	0.00	5.00%	55.42%
Adv	80%	Inf	25.38	237.47	40.74	0.00	0.00	0.00	0.00	0.00	5.00%	59.90%
Std	80%	Inf	33.98	282.00	0.00	5.60	0.00	0.00	0.00	0.00	13.75%	14.04%
mtoFlex	80%	Inf	34.61	282.00	49.77	0.00	0.00	0.00	0.00	0.00	5.00%	81.28%
UcLp	80%	Inf	25.38	237.47	39.27	0.00	0.00	0.00	0.00	0.00	5.00%	57.65%
Adv	0%	141	141	0.00	8.19	27.60	0.00	0.00	0.00	0.00	13.75%	14.32%
Std	0%	141	141	0.00	7.14	28.40	0.00	0.00	0.00	0.00	13.75%	14.00%
mtoFlex	0%	141	141	0.00	8.40	27.60	0.00	0.00	0.00	0.00	5.00%	14.64%
UcLp	0%	141	141	0.00	7.14	28.40	0.00	0.00	0.00	0.00	13.75%	14.00%
Adv	20%	141	126.9	22.26	12.81	20.80	0.00	0.00	0.00	0.00	5.00%	14.20%
Std	20%	141	125.9	22.26	9.87	23.60	0.00	0.00	0.00	0.00	13.75%	14.21%
mtoFlex	20%	141	126.2	22.26	14.49	22.00	0.00	0.00	0.00	0.00	5.00%	18.71%
UcLp	20%	141	126.6	22.26	11.97	21.60	0.00	0.00	0.00	0.00	5.00%	14.20%
Adv	40%	141	95.62	55.66	17.64	17.20	0.00	0.00	0.00	0.00	5.00%	21.45%
Std	40%	141	96.31	51.95	10.08	20.00	0.00	0.00	0.00	0.00	13.75%	13.76%
mtoFlex	40%	141	93.75	55.66	19.53	18.80	0.00	0.00	0.00	0.00	5.00%	26.93%
UcLp	40%	141	97.09	55.66	17.64	16.80	0.00	0.00	0.00	0.00	5.00%	20.81%
Adv	60%	141	63.48	163.26	35.07	10.80	0.00	0.00	0.00	0.00	5.00%	56.07%
Std	60%	141	65.06	115.03	11.97	14.00	0.00	0.00	0.00	0.00	13.75%	17.66%
mtoFlex	60%	141	64.96	122.45	28.14	13.60	0.00	0.00	0.00	0.00	5.00%	43.05%
UcLp	60%	141	63.67	163.26	35.07	10.40	0.00	0.00	0.00	0.00	5.00%	55.42%
Adv	80%	141	25.38	237.47	42.00	0.00	0.00	0.00	0.00	0.00	5.00%	61.83%
Std	80%	141	33.98	282.00	0.00	5.60	0.00	0.00	0.00	0.00	13.75%	14.04%
mtoFlex	80%	141	34.61	282.00	49.77	0.00	0.00	0.00	0.00	0.00	5.00%	81.28%
UcLp	80%	141	25.38	237.47	40.74	0.00	0.00	0.00	0.00	0.00	5.00%	59.90%

Table C.4: New Installed Capacity for 94Mt and 47Mt CO_2 limits across 0-80% RPS with all flexibility formulations.

				New Installed Capacity (GW)								
Run Type	RPS	Carbon Limit ($/ton CO2e)	Carbon Emissions Mt CO2e	Wind	NG-CT	NG-CCGT	NG-CCGT w/ CCS	Coal	Coal w/ CCS	Nuclear	Required Planning Margin	Effective Planning Margin
Adv	0%	94	94	0.00	3.15	30.40	0.00	0.00	0.65	2.24	13.75%	15.55%
Std	0%	94	94	0.00	0.00	34.00	0.00	0.00	0.00	1.12	13.75%	13.82%
mtoFlex	0%	94	94	0.00	3.57	30.00	0.00	0.00	0.00	2.24	5.00%	14.57%
UcLp	0%	94	94	0.00	2.52	31.20	0.00	0.00	0.00	2.24	13.75%	14.90%
Adv	20%	94	94	22.26	7.14	26.80	0.00	0.00	0.00	0.00	5.00%	15.19%
Std	20%	94	94	22.26	5.88	27.20	0.00	0.00	0.00	0.00	13.75%	13.91%
mtoFlex	20%	94	94	22.26	9.45	27.20	0.00	0.00	0.00	0.00	5.00%	19.38%
UcLp	20%	94	94	22.26	6.51	26.80	0.00	0.00	0.00	0.00	5.00%	14.23%
Adv	40%	94	94	55.66	17.43	17.60	0.00	0.00	0.00	0.00	5.00%	21.78%
Std	40%	94	94	51.95	8.19	22.00	0.00	0.00	0.00	0.00	13.75%	14.08%
mtoFlex	40%	94	93.75	55.66	19.53	18.80	0.00	0.00	0.00	0.00	5.00%	26.93%
UcLp	40%	94	94	55.66	16.80	18.00	0.00	0.00	0.00	0.00	5.00%	21.46%
Adv	60%	94	61.56	163.26	36.54	12.00	0.00	0.00	0.00	0.00	5.00%	60.25%
Std	60%	94	65.06	115.03	11.97	14.00	0.00	0.00	0.00	0.00	13.75%	17.66%
mtoFlex	60%	94	64.96	122.45	28.14	13.60	0.00	0.00	0.00	0.00	5.00%	43.05%
UcLp	60%	94	63.65	163.26	35.07	10.40	0.00	0.00	0.00	0.00	5.00%	55.42%
Adv	80%	94	25.38	237.47	39.27	0.00	0.00	0.00	0.00	0.00	5.00%	57.65%
Std	80%	94	33.98	282.00	0.00	5.60	0.00	0.00	0.00	0.00	13.75%	14.04%
mtoFlex	80%	94	34.61	282.00	49.77	0.00	0.00	0.00	0.00	0.00	5.00%	81.28%
UcLp	80%	94	25.38	237.47	39.27	0.00	0.00	0.00	0.00	0.00	5.00%	57.65%
Adv	0%	47	47	0.00	6.51	5.60	0.00	0.00	0.00	22.36	5.00%	10.88%
Std	0%	47	47	0.00	0.00	17.60	0.39	0.00	0.00	17.89	13.75%	13.96%
mtoFlex	0%	47	47	0.00	2.94	14.40	0.00	0.00	0.00	19.01	5.00%	14.41%
UcLp	0%	47	47	0.00	5.67	10.40	0.00	0.00	0.00	20.12	5.00%	13.88%
Adv	20%	47	47	22.26	8.40	13.60	8.09	0.00	0.00	7.83	5.00%	20.99%
Std	20%	47	47	22.26	0.42	20.40	2.31	0.00	0.00	10.06	13.75%	13.88%
mtoFlex	20%	47	47	22.26	6.51	18.00	2.70	0.00	0.00	10.06	5.00%	19.96%
UcLp	20%	47	47	22.26	7.35	11.60	7.70	0.00	0.00	7.83	5.00%	15.53%
Adv	40%	47	47	55.66	15.54	7.60	13.09	0.00	0.00	0.00	5.00%	23.86%
Std	40%	47	47	51.95	0.00	23.60	6.16	0.00	0.00	0.00	13.75%	14.05%
mtoFlex	40%	47	47	55.66	11.34	21.60	6.16	0.00	0.00	0.00	5.00%	28.83%
UcLp	40%	47	47	55.66	14.70	14.40	9.63	0.00	0.00	0.00	5.00%	27.96%
Adv	60%	47	47	163.26	29.19	24.00	1.16	0.00	0.00	0.00	5.00%	70.21%
Std	60%	47	47	115.03	5.67	20.40	0.00	0.00	0.00	0.00	13.75%	18.33%
mtoFlex	60%	47	47	122.45	24.57	17.20	0.00	0.00	0.00	0.00	5.00%	43.39%
UcLp	60%	47	47	163.26	30.45	16.80	2.70	0.00	0.00	0.00	5.00%	63.01%
Adv	80%	47	25.38	237.47	39.27	0.00	0.00	0.00	0.00	0.00	5.00%	57.65%
Std	80%	47	33.98	282.00	0.00	5.60	0.00	0.00	0.00	0.00	13.75%	14.04%
mtoFlex	80%	47	34.61	282.00	49.77	0.00	0.00	0.00	0.00	0.00	5.00%	81.28%
UcLp	80%	47	25.38	237.47	38.43	0.00	0.00	0.00	0.00	0.00	5.00%	56.36%

c.4 flexibility formulation comparison figures

These large tables begin on the next page.

Table C.5: Energy (Predicted and Actual) for no CO_2 limit across 0-80% RPS with all flexibility formulations.

								Energy (TWh)														
Run Type	Model Type	RPS	Carbon Limit (Mt CO2)	Carbon Emissions Mt CO2e	MIP Gap	Run Time (min)	Parallel Threads	Wind	Old NG-Steam	Old NG-CT	New NG-CT	Old NG-CCGT	New NG-CCGT	New NG-CCGT w/ CCS	Old Coal SubBit.	Old Coal Lignite	New Coal (SubBit.)	New Coal w/ CCS	New Nuclear	Old Nuclear	Non-Served Energy (TWh)	Wind Shedding (TWh)
Advanced Predict	Plan	0%	Inf	162.8	0.07%	752.5	1	10.81	0.57	2.10	2.81	20.78	145.24	0.00	33.39	34.45	35.86	0.00	0.00	20.72	-	-
Standard Predict	Plan	0%	Inf	190.6	0.07%	0.2	1	10.81	0.15	0.00	2.77	17.96	93.98	0.00	33.43	34.53	92.38	0.00	0.00	20.72	-	-
mtoFlex Predict	Plan	0%	Inf	190.7	0.07%	0.9	1	10.81	0.49	0.10	2.33	17.96	93.98	0.00	33.43	34.53	92.38	0.00	0.00	20.72	-	-
UcLp Predict	Plan	0%	Inf	160	0.09%	168.8	1	10.81	0.55	2.06	2.53	19.07	152.40	0.00	33.40	34.46	30.73	0.00	0.00	20.72	-	-
Advanced (Actual)	Ops.	0%	Inf	162.6	0.10%	44.2	1	10.81	0.58	2.10	2.88	20.57	145.70	0.00	33.28	34.45	35.64	0.00	0.00	20.72	0	-
Standard Actual	Ops.	0%	Inf	190.6	0.07%	45.3	1	10.81	0.47	2.51	3.53	14.93	94.76	0.00	32.59	34.28	92.14	0.00	0.00	20.72	0	-
mtoFlex Actual	Ops.	0%	Inf	190.6	0.07%	35.2	1	10.81	0.47	2.51	3.53	14.93	94.76	0.00	32.59	34.28	92.14	0.00	0.00	20.72	0	-
UcLp Actual	Ops.	0%	Inf	160	0.07%	42.2	1	10.81	0.57	2.05	2.57	18.91	152.51	0.00	33.40	34.46	30.73	0.00	0.00	20.72	0	-
Advanced Predict	Plan	20%	Inf	126.8	0.05%	1414.6	1	61.57	1.32	2.27	4.78	24.00	126.40	0.00	32.18	33.60	0.00	0.00	0.00	20.61	0	0
Standard Predict	Plan	20%	Inf	125.9	0.05%	0.7	1	61.87	0.16	0.00	3.27	17.64	135.80	0.00	32.81	34.47	0.00	0.00	0.00	20.72	-	-
mtoFlex Predict	Plan	20%	Inf	126.2	0.02%	4.9	1	61.87	0.32	0.07	4.33	20.87	131.51	0.00	32.64	34.42	0.00	0.00	0.00	20.72	0	-
UcLp Predict	Plan	20%	Inf	126.7	0.03%	383.6	1	61.54	1.29	2.27	4.55	22.91	127.80	0.00	32.17	33.59	0.00	0.00	0.00	20.60	0	0
Advanced (Actual)	Ops.	20%	Inf	126.8	0.03%	85.6	1	61.57	1.35	2.28	4.76	24.02	126.35	0.00	32.18	33.61	0.00	0.00	0.00	20.61	0	0
Standard Actual	Ops.	20%	Inf	126.1	0.08%	38.1	1	61.58	1.28	2.30	3.50	17.39	134.36	0.00	32.14	33.56	0.00	0.00	0.00	20.61	0	0
mtoFlex Actual	Ops.	20%	Inf	126.3	0.08%	30.4	1	61.57	0.42	2.26	4.71	21.92	129.46	0.00	32.18	33.60	0.00	0.00	0.00	20.61	0	0
UcLp Actual	Ops.	20%	Inf	126.7	0.09%	38.6	1	61.55	1.34	2.28	4.51	22.77	127.91	0.00	32.18	33.60	0.00	0.00	0.00	20.61	0	0
Advanced Predict	Plan	40%	Inf	97.06	0.07%	10001.1	12	122.69	0.97	2.01	15.20	26.53	77.65	0.00	22.79	24.36	0.00	0.00	0.00	14.53	0	16
Standard Predict	Plan	40%	Inf	96.31	0.00%	0.8	1	123.59	0.28	0.00	4.06	18.18	89.13	0.00	25.36	28.27	0.00	0.00	0.00	17.87	-	6
mtoFlex Predict	Plan	40%	Inf	93.75	0.01%	8.4	1	127.78	0.23	0.04	4.87	19.80	85.75	0.00	24.28	26.99	0.00	0.00	0.00	16.98	0	11
UcLp Predict	Plan	40%	Inf	96.95	0.02%	2498.8	1	122.69	1.02	2.02	14.66	25.58	79.18	0.00	22.70	24.44	0.00	0.00	0.00	14.43	0	16
Advanced (Actual)	Ops.	40%	Inf	97.09	0.09%	244.2	8	122.69	0.92	2.01	15.16	26.47	77.71	0.00	22.80	24.43	0.00	0.00	0.00	14.52	0	16
Standard Actual	Ops.	40%	Inf	85.81	0.91%	1381.1	16	115.94	0.02	2.20	5.96	17.63	102.37	0.00	17.90	19.07	0.00	0.00	0.00	8.76	17	14
mtoFlex Actual	Ops.	40%	Inf	96.46	0.06%	400.9	1	122.69	0.33	2.02	13.82	22.05	83.87	0.00	22.93	24.40	0.00	0.00	0.00	14.60	0	16
UcLp Actual	Ops.	40%	Inf	96.99	0.10%	411.2	1	122.69	1.06	2.02	14.70	25.59	78.95	0.00	22.85	24.35	0.00	0.00	0.00	14.53	0	16
Advanced Predict	Plan	60%	Inf	63.51	0.14%	3600.5	1	184.04	0.26	1.70	46.19	24.39	30.62	0.00	7.68	9.12	0.00	0.00	0.00	2.74	0	201
Standard Predict	Plan	60%	Inf	65.06	0.01%	0.5	1	185.69	0.51	0.01	6.21	20.26	46.16	0.00	16.92	18.92	0.00	0.00	0.00	12.06	0	89
mtoFlex Predict	Plan	60%	Inf	64.96	0.01%	7.0	1	184.74	0.22	0.04	6.56	20.19	48.72	0.00	16.56	18.37	0.00	0.00	0.00	11.34	0	107
UcLp Predict	Plan	60%	Inf	63.64	0.02%	2528.2	1	184.04	0.35	1.70	47.11	24.82	29.43	0.00	7.55	9.08	0.00	0.00	0.00	2.65	-	201
Advanced (Actual)	Ops.	60%	Inf	62.83	1.10%	1382.6	1	184.04	0.45	1.70	47.18	24.78	30.39	0.00	7.29	8.18	0.00	0.00	0.00	2.73	0	201
Standard Actual	Ops.	60%	Inf	38.9	0.54%	3601.3	1	125.69	4.60	1.72	6.09	23.93	39.79	0.00	3.53	4.13	0.00	0.00	0.00	0.00	97	149
mtoFlex Actual	Ops.	60%	Inf	56.63	0.05%	20.9	1	172.53	0.00	1.70	27.21	25.54	42.54	0.00	7.35	8.10	0.00	0.00	0.00	2.58	19	119
UcLp Actual	Ops.	60%	Inf	63.45	0.35%	1380.6	1	184.04	0.47	1.70	47.49	24.97	29.28	0.00	7.78	8.40	0.00	0.00	0.00	2.61	0	201
Advanced Predict	Plan	80%	Inf	25.38	0.01%	1209.2	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Predict	Plan	80%	Inf	33.98	0.00%	0.2	1	237.42	0.49	0.00	0.00	18.65	12.16	0.00	9.92	11.05	0.00	0.00	0.00	7.07	10	420
mtoFlex Predict	Plan	80%	Inf	34.61	0.00%	1.7	1	229.15	0.00	0.00	0.45	27.88	0.00	0.00	10.51	11.59	0.00	0.00	0.00	6.86	20	428
UcLp Predict	Plan	80%	Inf	25.38	0.00%	1121.6	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Advanced (Actual)	Ops.	80%	Inf	25.38	0.00%	7.2	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Actual	Ops.	80%	Inf	0	'UNDF'	0.2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
mtoFlex Actual	Ops.	80%	Inf	0	'UNDF'	12.5	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
UcLp Actual	Ops.	80%	Inf	25.38	0.00%	6.0	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360

Note: Undefined MIP gaps correspond to infeasible solutions

Table C.6: Energy (Predicted and Actual) for 141Mt CO_2 limit across 0-80% RPS with all flexibility formulations.

								Energy (TWh)														
Run Type	Model Type	RPS	Carbon Limit (Mt CO2)	Carbon Emissions Mt CO2e	MIP Gap	Run Time (min)	Parallel Threads	Wind	Old NG-Steam	Old NG-CT	New NG-CT	Old NG-CCGT	New NG-CCGT	New NG-CCGT w/ CCS	Old Coal SubBit.	Old Coal Lignite	New Coal (SubBit.)	New Coal w/ CCS	New Nuclear	Old Nuclear	Non-Served Energy (TWh)	Wind Shedding (TWh)
Advanced Predict	Plan	0%	141	141	0.09%	1073.1	1	10.81	0.62	1.48	2.52	16.89	190.28	0.00	28.95	34.46	0.00	0.00	0.00	20.72	0	-
Standard Predict	Plan	0%	141	141	0.05%	0.3	1	10.81	0.19	0.00	1.99	15.67	192.84	0.00	29.98	34.53	0.00	0.00	0.00	20.72	-	-
mtoFlex Predict	Plan	0%	141	141	0.07%	1.8	1	10.81	0.49	0.10	2.07	17.20	191.15	0.00	29.65	34.53	0.00	0.00	0.00	20.72	-	-
UcLp Predict	Plan	0%	141	141	0.01%	139.0	1	10.81	0.64	1.48	2.20	14.88	192.36	0.00	29.19	34.46	0.00	0.00	0.00	20.72	-	-
Advanced (Actual)	Ops.	0%	141	141	0.07%	41.1	1	10.81	0.60	1.48	2.53	16.93	190.25	0.00	28.95	34.46	0.00	0.00	0.00	20.72	0	-
Standard Actual	Ops.	0%	141	141	0.05%	42.4	1	10.81	0.67	1.48	2.22	14.81	192.40	0.00	29.18	34.46	0.00	0.00	0.00	20.72	0	-
mtoFlex Actual	Ops.	0%	141	141	0.05%	28.9	1	10.81	0.57	1.47	2.58	16.93	190.23	0.00	29.17	34.25	0.00	0.00	0.00	20.72	0	-
UcLp Actual	Ops.	0%	141	141	0.05%	39.0	1	10.81	0.67	1.48	2.22	14.81	192.40	0.00	29.18	34.46	0.00	0.00	0.00	20.72	0	-
Advanced Predict	Plan	20%	141	126.9	0.09%	459.1	1	61.54	1.25	2.27	5.09	25.26	124.91	0.00	32.19	33.62	0.00	0.00	0.00	20.60	0	0
Standard Predict	Plan	20%	141	125.9	0.05%	0.9	1	61.87	0.16	0.00	3.27	17.64	135.80	0.00	32.81	34.47	0.00	0.00	0.00	20.72	-	-
mtoFlex Predict	Plan	20%	141	126.2	0.02%	5.3	1	61.87	0.32	0.07	4.33	20.87	131.51	0.00	32.64	34.42	0.00	0.00	0.00	20.72	0	-
UcLp Predict	Plan	20%	141	126.6	0.05%	490.0	1	61.58	1.23	2.28	4.60	22.72	127.95	0.00	32.18	33.60	0.00	0.00	0.00	20.61	-	0
Advanced (Actual)	Ops.	20%	141	126.9	0.10%	105.8	1	61.57	1.21	2.27	5.10	25.21	124.95	0.00	32.19	33.61	0.00	0.00	0.00	20.61	0	0
Standard Actual	Ops.	20%	141	126.1	0.10%	35.1	1	61.58	1.28	2.30	3.51	17.30	134.45	0.00	32.15	33.56	0.00	0.00	0.00	20.61	0	0
mtoFlex Actual	Ops.	20%	141	126.3	0.03%	27.8	1	61.57	0.43	2.26	4.72	21.81	129.56	0.00	32.17	33.60	0.00	0.00	0.00	20.61	0	0
UcLp Actual	Ops.	20%	141	126.6	0.05%	88.6	1	61.57	1.23	2.27	4.59	22.75	127.93	0.00	32.17	33.60	0.00	0.00	0.00	20.61	0	0
Advanced Predict	Plan	40%	141	95.62	1.31%	3600.6	6	123.15	1.07	2.00	15.51	27.37	79.05	0.00	21.69	23.09	0.00	0.00	0.00	13.80	0	15
Standard Predict	Plan	40%	141	96.31	0.00%	1.0	1	123.59	0.28	0.00	4.06	18.18	89.13	0.00	25.36	28.27	0.00	0.00	0.00	17.87	-	6
mtoFlex Predict	Plan	40%	141	93.75	0.01%	8.5	1	127.78	0.23	0.04	4.87	19.80	85.75	0.00	24.28	26.99	0.00	0.00	0.00	16.98	0	11
UcLp Predict	Plan	40%	141	97.09	0.03%	2402.3	1	122.69	1.17	2.02	14.98	26.40	77.76	0.00	22.76	24.42	0.00	0.00	0.00	14.55	0	16
Advanced (Actual)	Ops.	40%	141	97.03	0.07%	238.1	8	122.69	1.06	2.02	14.63	25.53	79.18	0.00	22.81	24.42	0.00	0.00	0.00	14.40	0	16
Standard Actual	Ops.	40%	141	85.87	1.43%	3608.6	1	115.90	0.00	2.20	6.00	15.82	103.80	0.00	18.01	19.25	0.00	0.00	0.00	8.77	17	14
mtoFlex Actual	Ops.	40%	141	96.42	0.07%	213.9	1	122.69	0.34	2.03	13.87	22.07	83.74	0.00	22.87	24.44	0.00	0.00	0.00	14.69	0	16
UcLp Actual	Ops.	40%	141	97.16	0.13%	1383.4	1	122.69	1.20	2.01	15.02	26.56	77.74	0.00	22.84	24.31	0.00	0.00	0.00	14.37	0	16
Advanced Predict	Plan	60%	141	63.48	0.17%	3600.7	1	184.04	0.31	1.70	46.35	24.44	30.56	0.00	7.55	9.10	0.00	0.00	0.00	2.68	0	201
Standard Predict	Plan	60%	141	65.06	0.01%	1.0	1	185.69	0.51	0.01	6.21	20.26	46.16	0.00	16.92	18.92	0.00	0.00	0.00	12.06	0	89
mtoFlex Predict	Plan	60%	141	64.96	0.01%	7.2	1	184.74	0.22	0.04	6.56	20.19	48.72	0.00	16.56	18.37	0.00	0.00	0.00	11.34	0	107
UcLp Predict	Plan	60%	141	63.67	0.02%	3324.2	1	184.04	0.37	1.70	47.10	24.80	29.47	0.00	7.56	9.09	0.00	0.00	0.00	2.61	-	201
Advanced (Actual)	Ops.	60%	141	63.49	0.26%	1382.6	1	184.04	0.29	1.70	46.21	24.39	30.57	0.00	7.83	8.92	0.00	0.00	0.00	2.77	0	201
Standard Actual	Ops.	60%	141	38.98	0.32%	1381.5	1	125.82	4.56	1.72	6.10	23.93	39.81	0.00	3.43	4.33	0.00	0.00	0.00	0.00	97	149
mtoFlex Actual	Ops.	60%	141	56.63	0.05%	16.7	1	172.53	0.00	1.70	27.21	25.54	42.54	0.00	7.35	8.10	0.00	0.00	0.00	2.58	19	119
UcLp Actual	Ops.	60%	141	63.62	0.20%	1384.1	1	184.04	0.42	1.70	47.28	24.92	29.38	0.00	7.66	8.80	0.00	0.00	0.00	2.53	0	201
Advanced Predict	Plan	80%	141	25.38	0.01%	1215.0	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Predict	Plan	80%	141	33.98	0.00%	0.4	1	237.42	0.49	0.00	0.00	18.65	12.16	0.00	9.92	11.05	0.00	0.00	0.00	7.07	10	420
mtoFlex Predict	Plan	80%	141	34.61	0.00%	1.0	1	229.15	0.00	0.00	0.45	27.88	0.00	0.00	10.51	11.59	0.00	0.00	0.00	6.86	20	428
UcLp Predict	Plan	80%	141	25.38	0.01%	1486.2	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Advanced (Actual)	Ops.	80%	141	25.38	0.00%	8.7	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Actual	Ops.	80%	141	0	'UNDF'	0.2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
mtoFlex Actual	Ops.	80%	141	0	'UNDF'	9.4	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
UcLp Actual	Ops.	80%	141	25.38	0.01%	6.3	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360

Note: Undefined MIP gaps correspond to infeasible solutions

Table C.7: Energy (Predicted and Actual) for 94Mt CO_2 limit across 0-80% RPS with all flexibility formulations.

Run Type	Model Type	RPS	Carbon Limit (Mt CO2)	Carbon Emissions Mt CO2e	MIP Gap	Run Time (min)	Parallel Threads	Energy (TWh): Wind	Old NG-Steam	Old NG-CT	New NG-CT	Old NG-CCGT	New NG-CCGT	New NG-CCGT w/ CCS	Old Coal SubBit.	Old Coal Lignite	New Coal (SubBit.)	New Coal w/ CCS	New Nuclear	Old Nuclear	Non-Served Energy (TWh)	Wind Shedding (TWh)
Advanced Predict	Plan	0%	94	94	1.05%	10001.1	1	10.81	0.68	1.91	0.57	22.51	219.48	0.00	2.82	4.10	0.00	5.11	18.00	20.72	0	-
Standard Predict	Plan	0%	94	94	0.02%	1.7	1	10.81	0.66	0.00	0.00	18.76	244.23	0.00	0.38	2.16	0.00	0.00	9.02	20.72	-	-
mtoFlex Predict	Plan	0%	94	94	0.03%	12.3	1	10.81	0.56	0.11	0.25	24.33	225.58	0.00	1.88	4.47	0.00	0.00	18.03	20.72	0	-
UcLp Predict	Plan	0%	94	94	0.09%	1397.5	1	10.81	0.82	1.93	0.35	21.75	227.03	0.00	1.78	3.52	0.00	0.00	18.03	20.72	-	-
Advanced (Actual)	Ops.	0%	94	94	0.31%	1381.0	1	10.81	0.56	1.92	0.56	22.07	219.90	0.00	2.43	4.61	0.00	5.12	18.03	20.72	0	-
Standard Actual	Ops.	0%	94	94	0.31%	1380.9	1	10.81	5.32	1.61	0.00	21.70	235.62	0.00	0.00	0.00	0.00	0.00	9.02	20.72	2	-
mtoFlex Actual	Ops.	0%	94	94	0.69%	1381.3	1	10.81	2.16	1.98	0.66	23.92	224.08	0.00	1.52	2.85	0.00	0.00	18.03	20.72	0	-
UcLp Actual	Ops.	0%	94	94	1.07%	1381.9	1	10.81	1.29	1.95	0.35	21.32	227.17	0.00	2.09	2.99	0.00	0.00	18.03	20.72	0	-
Advanced Predict	Plan	20%	94	94	1.35%	3620.3	1	61.72	1.05	1.96	2.01	20.30	178.43	0.00	7.26	13.34	0.00	0.00	0.00	20.66	0	0
Standard Predict	Plan	20%	94	94	0.00%	2.5	1	61.87	0.19	0.00	1.23	11.79	187.66	0.00	9.11	14.17	0.00	0.00	0.00	20.72	-	-
mtoFlex Predict	Plan	20%	94	94	0.01%	8.0	1	61.87	0.31	0.07	1.04	11.82	187.66	0.00	9.08	14.17	0.00	0.00	0.00	20.72	0	-
UcLp Predict	Plan	20%	94	94	0.02%	1994.7	1	61.69	1.31	2.01	1.80	20.68	178.14	0.00	7.15	13.30	0.00	0.00	0.00	20.66	0	0
Advanced (Actual)	Ops.	20%	94	94	0.09%	506.1	1	61.72	1.12	1.96	2.00	20.37	178.36	0.00	7.27	13.28	0.00	0.00	0.00	20.66	0	0
Standard Actual	Ops.	20%	94	94	0.09%	1106.8	1	61.67	1.50	2.08	1.55	19.27	179.54	0.00	7.52	12.94	0.00	0.00	0.00	20.65	0	0
mtoFlex Actual	Ops.	20%	94	94	0.07%	323.9	1	61.73	0.40	1.86	2.42	18.35	180.30	0.00	7.60	13.42	0.00	0.00	0.00	20.66	0	0
UcLp Actual	Ops.	20%	94	94	0.08%	975.2	1	61.69	1.38	2.00	1.80	20.68	178.12	0.00	7.36	13.05	0.00	0.00	0.00	20.66	0	0
Advanced Predict	Plan	40%	94	94	0.04%	10001.6	12	122.69	1.00	2.02	13.90	25.09	82.83	0.00	20.89	22.82	0.00	0.00	0.00	15.49	0	16
Standard Predict	Plan	40%	94	94	0.04%	1.1	1	123.59	0.27	0.00	2.67	14.78	96.54	0.00	22.74	28.27	0.00	0.00	0.00	17.87	-	6
mtoFlex Predict	Plan	40%	94	93.75	0.01%	15.8	1	127.78	0.23	0.04	4.87	19.80	85.75	0.00	24.28	26.99	0.00	0.00	0.00	16.98	0	11
UcLp Predict	Plan	40%	94	94	0.01%	2565.9	1	122.69	1.04	2.03	13.49	24.22	83.91	0.00	20.98	22.88	0.00	0.00	0.00	15.50	0	16
Advanced (Actual)	Ops.	40%	94	94	0.09%	331.0	8	122.69	0.99	2.02	13.85	25.03	82.94	0.00	20.95	22.77	0.00	0.00	0.00	15.48	0	16
Standard Actual	Ops.	40%	94	81.84	1.20%	1382.2	1	112.63	0.10	2.40	3.04	7.51	113.32	0.00	16.71	18.14	0.00	0.00	0.00	7.74	25	17
mtoFlex Actual	Ops.	40%	94	94	0.08%	460.9	1	122.69	0.34	2.03	13.39	22.38	86.06	0.00	21.31	23.06	0.00	0.00	0.00	15.47	0	16
UcLp Actual	Ops.	40%	94	94	0.25%	1381.4	1	122.69	1.08	2.03	13.53	24.34	83.88	0.00	21.01	22.76	0.00	0.00	0.00	15.42	0	16
Advanced Predict	Plan	60%	94	61.56	1.49%	3600.6	1	184.37	0.13	1.69	47.05	24.14	33.49	0.00	6.18	7.60	0.00	0.00	0.00	2.08	0	201
Standard Predict	Plan	60%	94	65.06	0.01%	0.7	1	185.69	0.51	0.01	6.21	20.26	46.16	0.00	16.92	18.92	0.00	0.00	0.00	12.06	0	89
mtoFlex Predict	Plan	60%	94	64.96	0.01%	6.7	1	184.74	0.22	0.04	6.56	20.19	48.72	0.00	16.56	18.37	0.00	0.00	0.00	11.34	0	107
UcLp Predict	Plan	60%	94	63.65	0.02%	2338.9	1	184.04	0.35	1.70	47.13	24.83	29.43	0.00	7.54	9.09	0.00	0.00	0.00	2.63	-	201
Advanced (Actual)	Ops.	60%	94	63.13	0.09%	515.7	1	184.04	0.09	1.69	43.64	22.81	33.42	0.00	8.17	9.30	0.00	0.00	0.00	3.57	0	201
Standard Actual	Ops.	60%	94	38.92	0.66%	1381.3	1	125.62	4.50	1.72	6.10	23.71	39.93	0.00	3.53	4.24	0.00	0.00	0.00	0.00	97	149
mtoFlex Actual	Ops.	60%	94	56.63	0.04%	18.4	1	172.53	0.00	1.70	27.21	25.54	42.54	0.00	7.35	8.10	0.00	0.00	0.00	2.58	19	119
UcLp Actual	Ops.	60%	94	63.63	0.97%	1382.5	1	184.04	0.45	1.70	47.15	24.85	29.42	0.00	7.72	8.81	0.00	0.00	0.00	2.60	0	201
Advanced Predict	Plan	80%	94	25.38	0.01%	1303.7	1	195.76	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Predict	Plan	80%	94	33.98	0.00%	0.3	1	237.42	0.49	0.00	0.00	18.65	12.16	0.00	9.92	11.05	0.00	0.00	0.00	7.07	10	420
mtoFlex Predict	Plan	80%	94	34.61	0.00%	1.7	1	229.15	0.00	0.00	0.45	27.88	0.00	0.00	10.51	11.59	0.00	0.00	0.00	6.86	20	428
UcLp Predict	Plan	80%	94	25.38	0.00%	747.9	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Advanced (Actual)	Ops.	80%	94	25.38	0.00%	7.1	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Actual	Ops.	80%	94	0	'UNDF'	0.2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
mtoFlex Actual	Ops.	80%	94	0	'UNDF'	10.7	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
UcLp Actual	Ops.	80%	94	25.38	0.00%	6.6	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360

Note: Undefined MIP gaps correspond to infeasible solutions

Table C.8: Energy (Predicted and Actual) for 47Mt CO_2 limit across 0-80% RPS with all flexibility formulations.

Run Type	Model Type	RPS	Carbon Limit (Mt CO2)	Carbon Emissions Mt CO2e	MIP Gap	Run Time (min)	Parallel Threads	Energy (TWh) Wind	Old NG-Steam	Old NG-CT	New NG-CT	Old NG-CCGT	New NG-CCGT	New NG-CCGT w/ CCS	Old Coal SubBit.	Old Coal Lignite	New Coal (SubBit.)	New Coal w/ CCS	New Nuclear	Old Nuclear	Non-Served Energy (TWh)	Wind Shedding (TWh)
Advanced Predict	Plan	0%	47	47	0.63%	10015.3	12	10.79	1.11	2.55	8.79	33.70	39.04	0.00	3.78	8.50	0.00	0.00	177.88	20.59	0	0
Standard Predict	Plan	0%	47	47	0.03%	3.0	1	10.81	0.20	0.00	0.00	17.60	106.97	3.17	0.71	2.31	0.00	0.00	144.25	20.72	-	-
mtoFlex Predict	Plan	0%	47	47	0.02%	15.0	1	10.81	0.52	0.10	0.19	22.38	93.46	0.00	1.74	3.61	0.00	0.00	153.20	20.72	-	-
UcLp Predict	Plan	0%	47	47	0.03%	1269.9	1	10.81	0.53	2.54	7.23	28.79	69.32	0.00	1.80	3.73	0.00	0.00	161.40	20.59	-	0
Advanced (Actual)	Ops.	0%	47	47	0.06%	898.5	8	10.79	1.00	2.55	8.80	33.77	39.08	0.00	3.79	8.52	0.00	0.00	177.90	20.53	0	0
Standard Actual	Ops.	0%	47	47	2.11%	3600.4	1	9.54	20.42	2.24	0.00	28.50	59.11	2.47	0.00	0.00	0.00	0.00	138.27	18.93	27	1
mtoFlex Actual	Ops.	0%	47	47	0.79%	3602.1	1	10.67	7.63	2.56	5.56	17.53	87.25	0.00	0.08	0.17	0.00	0.00	152.79	20.47	2	0
UcLp Actual	Ops.	0%	47	47	0.71%	1380.4	1	10.81	0.76	2.53	7.38	28.52	69.34	0.00	2.29	3.12	0.00	0.00	161.51	20.49	0	0
Advanced Predict	Plan	20%	47	47	0.77%	10000.8	1	61.35	0.29	2.47	4.23	19.42	70.23	58.18	2.50	5.75	0.00	0.00	62.11	20.19	-	1
Standard Predict	Plan	20%	47	47	0.03%	4.4	1	61.87	0.20	0.00	0.03	16.18	107.34	17.68	0.74	2.13	0.00	0.00	79.96	20.61	-	-
mtoFlex Predict	Plan	20%	47	47	0.01%	12.5	1	61.87	0.28	0.06	1.38	20.11	99.60	20.45	0.90	2.13	0.00	0.00	79.29	20.67	0	-
UcLp Predict	Plan	20%	47	47	0.04%	1002.6	1	61.35	0.87	2.46	4.82	28.47	62.84	57.48	2.35	4.16	0.00	0.00	61.91	20.02	-	1
Advanced (Actual)	Ops.	20%	47	47	0.18%	1380.9	1	61.35	0.27	2.47	4.29	19.52	70.20	57.95	2.37	5.84	0.00	0.00	62.15	20.32	0	1
Standard Actual	Ops.	20%	47	47	1.25%	1381.4	1	50.46	11.90	1.93	0.00	28.28	75.20	14.19	0.00	0.08	0.00	0.00	56.35	13.90	54	11
mtoFlex Actual	Ops.	20%	47	47	2.64%	1380.7	16	61.00	0.72	2.55	4.74	18.98	98.81	20.56	0.00	0.00	0.00	0.00	78.08	19.56	2	1
UcLp Actual	Ops.	20%	47	47	1.56%	3601.8	1	61.35	1.40	2.46	4.86	28.37	62.72	57.56	2.56	3.66	0.00	0.00	61.68	20.12	0	1
Advanced Predict	Plan	40%	47	47	0.64%	10001.0	12	122.69	0.88	1.92	12.97	34.06	33.85	75.66	3.59	5.79	0.00	0.00	0.00	15.32	0	16
Standard Predict	Plan	40%	47	47	0.02%	2.5	1	123.59	0.93	0.00	0.00	15.58	105.63	40.80	0.26	2.08	0.00	0.00	0.00	17.87	-	6
mtoFlex Predict	Plan	40%	47	47	0.01%	24.7	1	127.53	0.19	0.04	1.33	18.51	98.40	40.16	1.06	2.30	0.00	0.00	0.00	17.20	-	11
UcLp Predict	Plan	40%	47	47	0.02%	1968.0	8	122.69	0.30	1.90	12.66	27.24	63.31	59.87	0.95	2.60	0.00	0.00	0.00	15.21	-	16
Advanced (Actual)	Ops.	40%	47	47	0.10%	2290.6	8	122.69	0.73	1.93	12.62	33.33	34.19	75.64	3.82	5.99	0.00	0.00	0.00	15.79	0	16
Standard Actual	Ops.	40%	47	0	'UNDF'	113.7	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	130
mtoFlex Actual	Ops.	40%	47	47	1.67%	1381.1	16	120.84	0.00	2.01	6.66	18.21	96.19	43.28	0.00	0.00	0.00	0.00	0.00	14.91	5	18
UcLp Actual	Ops.	40%	47	47	0.26%	2821.5	8	122.69	0.56	1.90	12.73	27.15	63.22	59.99	1.10	2.29	0.00	0.00	0.00	15.09	0	16
Advanced Predict	Plan	60%	47	47	0.28%	3600.9	1	184.04	0.00	1.70	33.92	14.11	63.40	4.19	0.06	0.35	0.00	0.00	0.00	4.96	0	201
Standard Predict	Plan	60%	47	47	0.01%	0.9	1	185.69	0.51	0.01	1.67	18.05	77.08	0.00	2.46	9.21	0.00	0.00	0.00	12.06	0	89
mtoFlex Predict	Plan	60%	47	47	0.00%	29.7	1	184.45	0.22	0.04	3.71	26.19	70.75	0.00	3.49	6.28	0.00	0.00	0.00	11.60	0	107
UcLp Predict	Plan	60%	47	47	0.01%	981.9	8	184.04	0.09	1.70	38.97	20.05	46.35	9.51	0.20	0.80	0.00	0.00	0.00	5.03	-	201
Advanced (Actual)	Ops.	60%	47	47	0.08%	569.4	8	184.04	0.00	1.70	33.80	14.03	63.16	4.16	0.11	0.48	0.00	0.00	0.00	5.26	0	201
Standard Actual	Ops.	60%	47	0	'UNDF'	374.7	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	275
mtoFlex Actual	Ops.	60%	47	47	0.10%	456.9	1	172.42	0.00	1.70	26.22	25.18	56.87	0.00	0.59	1.73	0.00	0.00	0.00	2.66	19	119
UcLp Actual	Ops.	60%	47	47	0.24%	2824.7	8	184.04	0.27	1.70	38.98	20.17	46.27	9.50	0.25	0.61	0.00	0.00	0.00	4.95	0	201
Advanced Predict	Plan	80%	47	25.38	0.00%	1418.0	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Predict	Plan	80%	47	33.98	0.00%	0.4	1	237.42	0.49	0.00	0.00	18.65	12.16	0.00	9.92	11.05	0.00	0.00	0.00	7.07	10	420
mtoFlex Predict	Plan	80%	47	34.61	0.00%	1.3	1	229.15	0.00	0.00	0.45	27.88	0.00	0.00	10.51	11.59	0.00	0.00	0.00	6.86	20	428
UcLp Predict	Plan	80%	47	25.38	0.00%	1131.2	1	195.76	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Advanced (Actual)	Ops.	80%	47	25.38	0.00%	9.4	1	195.77	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360
Standard Actual	Ops.	80%	47	0	'UNDF'	0.2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
mtoFlex Actual	Ops.	80%	47	0	'UNDF'	8.2	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	657
UcLp Actual	Ops.	80%	47	25.38	0.00%	10.1	1	195.76	0.00	1.70	46.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	62	360

Note: Undefined MIP gaps correspond to infeasible solutions

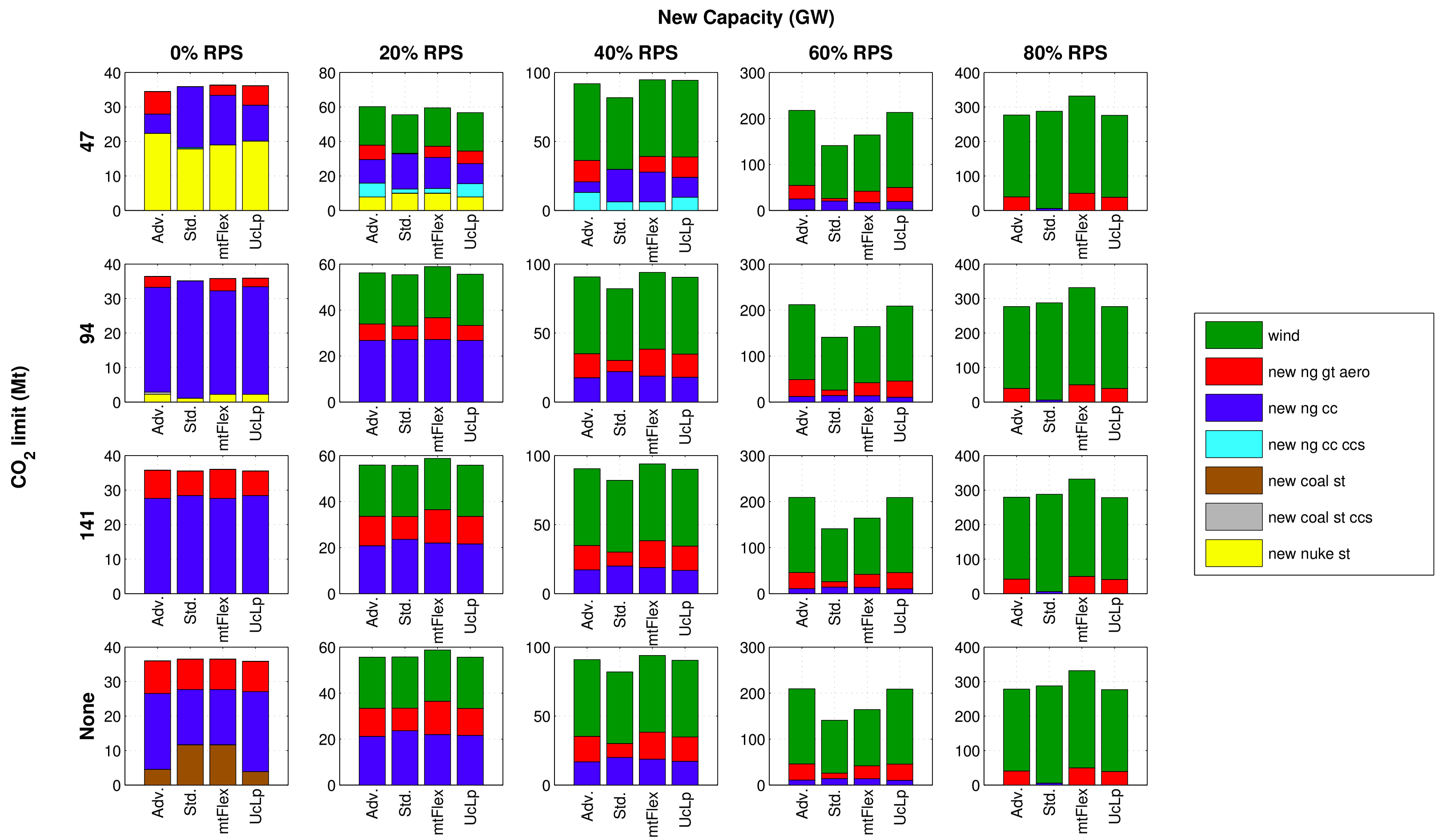


Figure C.3: Comparison of new capacity differences between four methods of capturing operational flexibility with planning. Each sub-figure shows the differences between (1) Full: the complete integer unit commitment based operations, (2) Simp: simple merit order dispatch, (3) edRsv: a modified economic dispatch that considers reserves in a way similar to that in [18] and [214] and (4) UClp: the full unit commitment operations model but with the integer operating constraints relaxed.

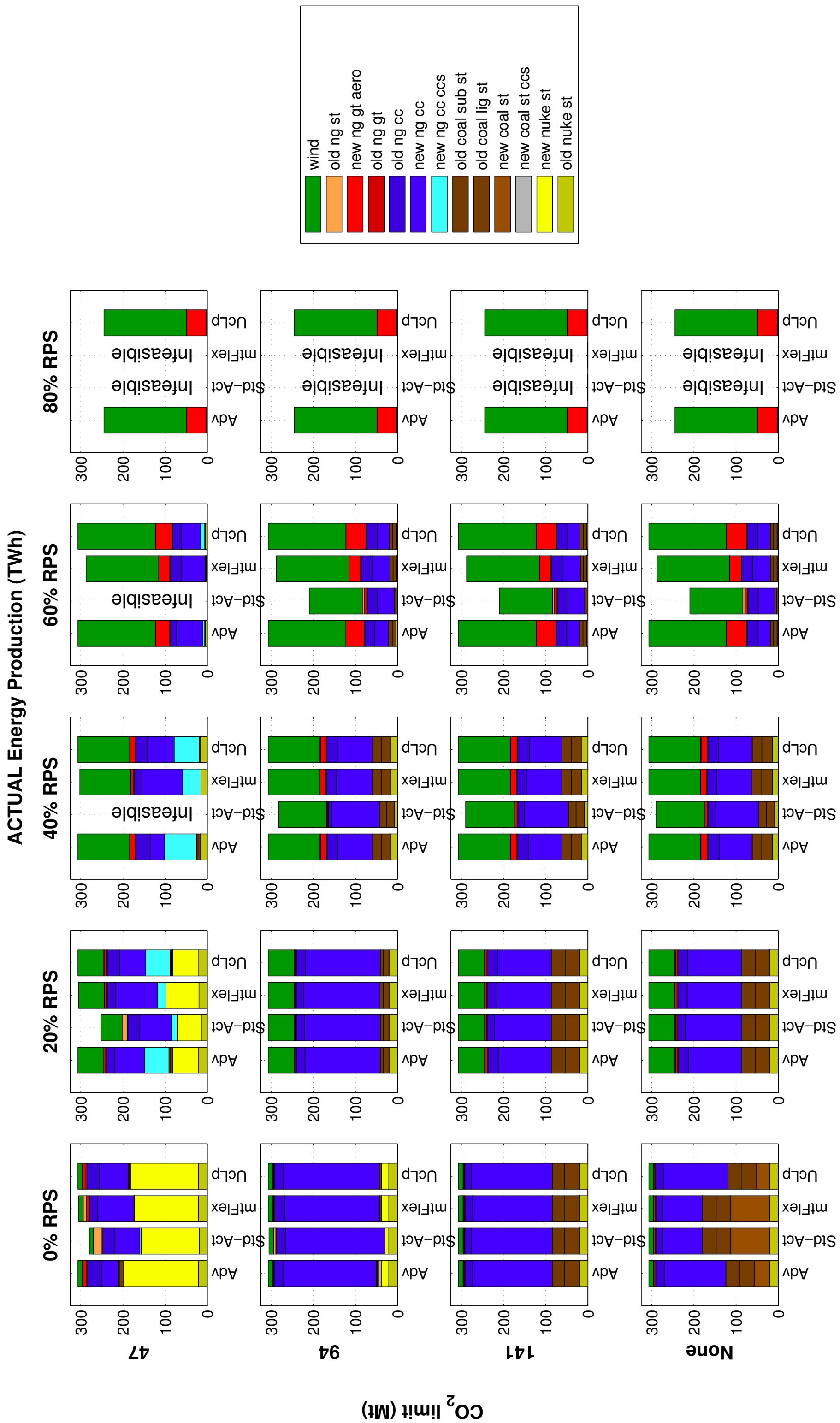


Figure C.4: Actual Energy Mix comparison

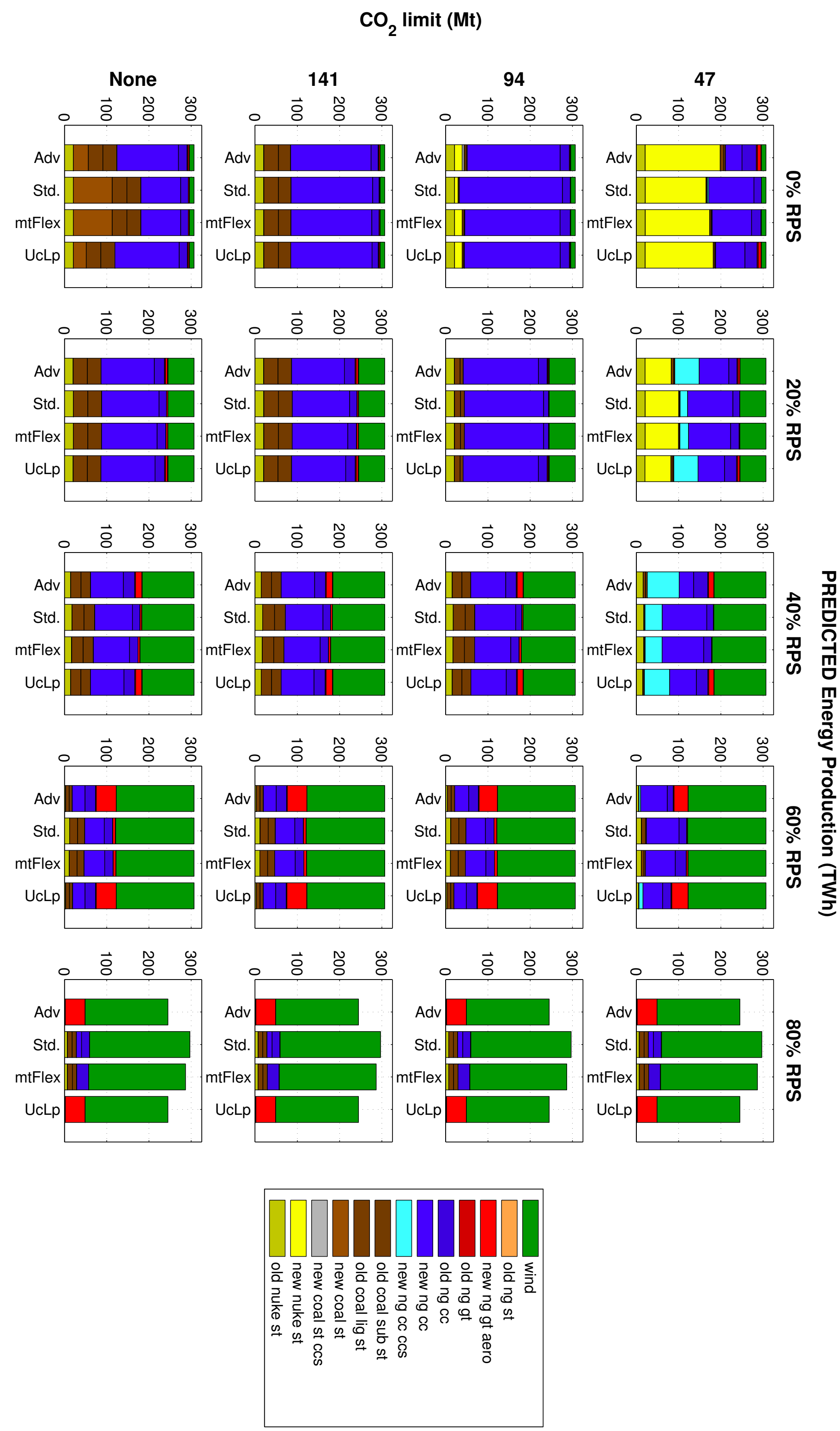


Figure C.5: Predicted Energy Mix comparison

Table C.9: Summary of model run times and problem sizes. Only the twenty runs of each type reported in summary tables are used for these statistics

Run Type	Reruns Required	Average MIP Gap[A]	Average Solver Time (min)[B]	Problem Size: Equations	Problem Size: Variables	Problem Size: Discrete Variables	Problem Size: Non-Zeros
Standard	0	0.02%	1	349,518	235,947	7	1,009,932
mtoFlex	0	0.02%	9	594,126	463,083	7	2,075,724
UcLp	2	0.03%	1710	1,478,348	1,050,321	1,879	8,373,668
Advanced	8	0.29%	2603	1,740,428	1,312,401	263,959	8,897,828

[A] Does not include cases when re-runs required

[B] Max time of 3600 min (60hr) used if re-run required

D

SELECTED MODEL CODE

This appendix contains listings for the core model files used in this analysis. As described in Section 2.11, the Advanced Power family of models, including StaticCapPlan and UnitCommit, are implemented in GAMS and solved using CPLEX. The models are designed to be modular and very configurable. For example, the StaticCapPlan model only contains the planning specific code and relies on UnitCommit for all operations-related code. UnitCommit can also be run by itself for operations-only modeling. UnitCommit, in turn, relies on shared include files for specialized constraints such as reserves, minimum up and down time, etc. that are also shared by other models in the suite. The high level of configurability allows individually selecting the operating constraints to include, data file selection, and more. This enables the same models to be used for all of the levels of operational detail considered in this dissertation from relatively simple merit order dispatch up to full clustered unit commitment and everything in between. The dozens of command line configuration options for StaticCapPlan are itemized in its extended initial comments. UnitCommit shares all these options, except those specific to capacity planning. The initial comments for UnitCommit and the other include files are omitted for brevity. Also not shown are the extensive collection of shared output formatting include files.

Listing D.1: StaticCapPlan.gms: the top level capacity planning model, relies on UnitCommit for operations.

```
$ontext
----------------------------------------------------
 Static Capacity Planning model
----------------------------------------------------
  A deterministic static (aka single period) electricity generation capacity planning
  model with discrete or continuous build decisions.

 Command Line Options (defaults shown):
 ====================================
 Data
  Primary data setup file:
   --sys=test_sys.inc     System parameters include file. This file references all data for a model
                          run. Typically single value data such as: cost of carbon, WACC, etc. are
                          included directly, while larger tables are in separate sub-include files.
                          The standard sub-include files are:
                              fuel.inc      Fuel names, prices, and emissions
                              gens.inc      Generator set, operating parameters, and availability
                              demand.inc    Demand block set, duration, and power levels

  Files used to override values set or referenced in sys and sub-includes (assumed to to be
  located in data_dir, except as noted):
   --fuel=(from sys)     Fuel prices and emissions
   --gens=(from sys)     Generation set & tables of parameters & availability/renewable output.
   --gparams=(OPTIONAL from sys)    Default generator parameters to use for any missing values.
   --avail=(from sys)    Generation availability/renewable output
   --demand=(from sys)   Demand include file that defines demand blocks, levels, and duration
   --update=NONE         An optional final include file to override selected settings from other
                          include files. Does not override any explicit command-line values. The
                          path for update file is relative to the model (not data_dir).
                          IMPORTANT: the update file works in S space, so most parameters must
                          be indexed by S and you must use the scenario dependent
                          parameters: pFuel, pDemand, pGen, and pGenAvail. Changes to the
                          p*Data parameters (pGenData, pDemandData, etc) will NOT be used.
   --scen=NONE           For multiple scenario problems (multi-period or stochastic) specifies
                          the list of scenarios (populates the S set) and their associated
                          weight/probability table, pScenWeight(S).


  Specific Value Overrides (take precedence over all values defined in data files. Use for
  sensitivity analysis, etc.) IMPORTANT, these values are used for ALL scenarios, use an update
  for changing these on a by scenario basis.
   --co2cost=#            Cost of CO2 in $/t-co2e (default: use sys or update value)
   --demscale=#           Factor to uniformly scale demand (default: use sys or update value)
   --rps=#                Renewable Portfolio Standard     (default: use sys or update value)
   --co2cap=#             Carbon Emission Cap (Mt-co2e)         (default: use sys or update value)

  Model Setup Flags (by default these are not set. Set to any number, including zero, to enable)
   --startup=(off)        Compute startup costs (also enables unit_commit)   (default: ignore)
   --unit_commit=(off)    Compute unit commitment constraints   (default: ignore)
   --ramp=(off)           Flag to limit inter period ramp rates  (default: ignore)
   --ignore_integer=(off) Flag to ignore integer constraints in new capacity investments,
                           (eg allow 1MW nuclear plants) and in Unit Commitment if enabled (unit is
                           either committed or not) (default: use integer constraints)
   --avg_avail=(off)      Flag to use the average rather than time dependent availabilities. Using
                           averages is OK for thermal units, but highly simplifies time varying
                           renewables. This simplification is made in the analytic version of the
                           model, but not generally a good idea for numeric estimates. (default: use
                           complete time varying information.)
   --ignore_cap_credit=(off) Flag to ignore the distinction between capacity credit and availability
                           When set, the capacity credit parameter is set equal to the time weighted
                           average of availability. (default: use cap_credit value from GenParams)
   --uc_ignore_unit_min=(0)   Threshold for unit_min to ignore integer commitment decisions in unit
                           commitment. Gens with unit_min less than or equal to this value will be
                           treated as continuous to speed performance
   --uc_int_unit_min=(0)   Threshold for unit_min to ignore INTEGER commitment
                            decisions & constraints. Gens with unit_min less than or equal to
                            this value will still have commitment variables, but their valid
                            range is relaxed to be continous. The same equations are used
                            as for those units with integer constraints.
    --uc_lp=(0)            Ignore integer constraints on all UC variables (& startup/shutdown)
   --adj_rsrv_for_nse=(off)  Adjust reserves for non-served energy. This uses actual power
                  production rather than total desired demand for setting reserve requirements.
                  This distinction is only significant if there is non-served energy. When
                  enabled (old default for SVN=479-480), then non-served energy provides a way
                  to reduce reserve requirements. [Default= use total non-adjusted demand]
   --rsrv=(none)  Specify Type of reserve calculation. Options are:
        =separate  Enforce separate reserve requirements based on "classic" ancillary
                    services plus additions for renewable uncertainty. This includes Reg Up,
                    Reg Down, Spin Up, & Quick Start
        =flex      Use combined "flexibility" reserves grouped simply into flex up and flex down
        =both      Compute both separate and flexibility reserves
        =(none)    If not set, no reserve limits are computed
  --non_uc_rsrv_up_offline=0   For non-unit commitment generators, the fraction of non-running
                    generation capacity to use toward UP reserves. This parameter has no
                    effect on UC generators. deJonge assumes 0.6, NETPLAN assumes 1.0,
                    (default=0).
  --non_uc_rsrv_down_offline=0 For non-unit commitment generators, the fraction of non-running
                    generation capacity to use toward DOWN reserves. This parameter has no
                    effect on UC generators. deJonge assumes 0.6, NETPLAN assumes 1.0,
                    (default=0).
  --no_quick_st=(off)     Flag to zero out quickstart reserve contribution to spinning/flex up
                           reserves. Useful when non_uc_rsrv... > 0
   --no_nse=(off)        Don't allow non-served energy
   --force_renewables=(off) Force all renewable output to be used. This is only feasible until
                           the point where load and op_reserves dictate a max. (until we add storage).
                           When used with cap_fix, it is a bit more widely useful b/c we can limit
                           output to the level of demand. (this is NLP when capacity is a decision)
   --fix_cap=(off)        Fix capacity to cap_cur by not allowing additions or retirements
   --max_start=(off)      Enforce maximum number of startups   (default: ignore)
   --force_gen_size=(off)  Force all plant sizes to equal the specified value (in GW)
   --min_gen_size=(off)   Force small plant sizes to be larger than specified value (in GW)
   --derate=(off)         Use simple derating of power output, typically for non-reserves
   --from_scratch=(off)   Zero out existing capacity and build new system from scratch
   --no_cap_limit=(off)   Allow unlimited expansion of all generators (useful with from_scratch)
   --basic_pmin=(off)     Enforce non-UC based minimum output levels for each generator type.
                          This can be useful for baseload plants with simple (non-UC) operations.
   --no_capital=(off)     Ignore capital costs, used for operations models to only compute non
                           capital costs. Not recommended for planning models. [default: include
                           capital costs]
   --renew_lim=(avg)     Technique for limiting renewable expansion:
         =avg   Limit Avg to demand peak:
                 average power < peak*(1+renew_overbuild) [default]
         =firm  Limit base on firm capacity (typically way to high):
                 cap_credit < peak*(1+plan_margin)*(1+renew_overbuild)
         =rps   Limit expansion to that required to meet the RPS (maybe too low for high rps):
                 rps*(1+renew_overbuild)
         =norm  Treat As Normal Gen (uses general overbuild, not renew_specific):
```

```
             (1+overbuild)*max(avg < peak*(1+plan), cap_credit < peak(1+plan))
 --overbuild=0.2        Amount (a fraction) over the planning margin to limit the maximum
                         number of plants for each type. Also used with the heuristic capacity
                         limit described below.
 --renew_overbuild=0.2  Amount (a fraction) over the peak/rps energy requirements for
                         renewables.
 --skip_cap_limit=(off) Do not enforce the heuristic capacity limit equation that can greatly
                         speed MIP tree searches by ignoring capacity combinations, such as
                         maxing out all gens, that exceed the tougher of the planning margin
                         or operating reserve requirements by more than the overbuild factor.
                         In rare cases, with few generator types, strange availability patterns,
                         etc. this heuristic may be overly restrictive.
 --no_loop=(off)       Do not loop around demand periods for inter-period constraints
                        such as ramping, min_up_down. (default= assume looping)
 --maint=(off)         Compute Maintenance schedule (default = use avail data, typically
                        assumes full availability for thermal plants)
 --maint_lp=(off) Relax integer constraints on maintenance decisions (default: use integers)
 --maint_om_fract=0.5   If maintenance planning enabled, the default fraction of total fixed
                         O&M costs to divide among the required weeks of maintenance.
 --plan_margin=(off)    Enforce the planning margin. Set to 1 to enable and use the problem
                         defined pPlanReserve (typically in sys.inc). Alternatively can set
                         to a value < 1 that then is used for pPlanReserve overriding other
                         definitions.
 --plan_margin_penalty=(off) Allow planning margin to be not met and define associated penalty
                         [$/MW-firm] (default= must meet planning margin)
 --rps_penalty=(off)    Allow planning margin to be not met and define associated penalty
                         [$/MWh] (default= must meet rps)
 --retire=(0)           Fraction of current capacity to retire. Max capacity is also adjusted
                         down accordingly (value 0 to 1)
  --derate_to_maint=(off) Override gen datafile derating value and derate based on
                          the maintenance value only.

Additional Model Components & Related
 --calc_water=(off)     Compute water use and limits
       Related options (see shared_dir/WaterEquations for complete details)
         --h2o_limit=(Inf)     System wide maximum water use [Tgal]. Only computed for gens
                                with specified water usage (h2o_withdraw_var)
         --h2o_cost=(0)        System wide water cost [$/kgal]. Only computed for gens
                                with specified water usage (h2o_withdraw_var)


Solver Options
  --debug=(off)           Print out extra material in the *.lst file (timing, variables, equations,
        etc)
  --max_solve_time=10800  Maximum number of seconds to let the solver run. (Default = 3hrs)
  --mip_gap=0.001        max MIP gap to treat as valid solution
  --par_threads=1         Number of parallel threads to use. Specify 0 to use one thread per core
                           (Default = use only 1 thread)
  --par_mode=1            CPLEX parallel mode 1=deterministic & repeatable, 0=automatic,
                           -1=Opportunistic, but not repeatable (Default = determinstic)
  --lp_method=4           CPLEX code for lp_method to use for pure root node, LP, RMIP, and
                           final MIP solve.  Options: 0=automatic, 2=Dual Simplex, 4=barrier,
                           6=concurrent (a race between dual simplex and barrier in parallel)
                           (Default = 4, barrier) Use 6 if running in parallel
  --cheat=(off)           use epsilon-optimal branch & bound by removing solutions that are
                           not "cheat" better than the current best. This can speed up the
                           MIP search, but may miss the true optimal solution. Note that this
                           value is specified in absolute terms of the objective function.
  --rel_cheat=(off)       Similar to cheat, but specified in relative percentage of objective
                           this works in CPLEX only
  --probe=0               CPLEX code for probing, a technique to more fully examine a MIP
                           problem before starting branch-and-cut. Can sometimes dramatically
                           reduce run times. Options: 0=automatic, 1=limited, 2=more, 3=full,
                           -1=off. (default = 0, automatic). Probe time also limited to 5min.
  --priority=off          Use branching priorities for Branch & Bound tree, set to anything
                           other than off to enable.

File Locations (Note, on Windows & DOS, \'s are used for defaults)
 --data_dir=../data/     Relative path to data file includes
 --out_dir=out/          Relative path to output csv files
 --util_dir=../util/     Relative path to csv printing and other utilities
 --shared_dir=../shared/ Relative path to shared model components
 --out_prefix=SCP_       Prefix for all our our output data files

Output Control Flags (by default these are not set. Set to any number, including zero, to enable)
 --debug=(off)           Print out extra material in the *.lst file (timing, variables,
                          equations, etc)
 --debug_avail=(off)    Display full availability table in *.lst file for debugging
 --no_csv=(off)         Flag to suppress creation of csv output files (default: create csv output)
 --summary_only=(off)   Only create output summary data (default: create additional tables)
 --summary_and_power_only=(off)   Create only summary & power table outputs (Default: all files)
 --out_gen_params=(off) Create output file listing generator parameter input data (Default: skip)
 --out_gen_avail=(off)  Create output file listing generator availability input data (Default: skip)
 --memo=(none)          Free-form text field added to the summary table NO COMMAS (Default: none)
 --gdx=(off)            Export the entire solved model to a gdx file in the out_dir (Default: no gdx
       file)
 --debug_off_maint=(off) Create table of capacity off maintenance


Supports:
  - multiple operations model modes:
      + simple economic dispatch
      + ramp (up & down) constrained economic dispatch
      + integer unit commitment:
         - minimum output for committed generators
         - startup costs (optional)
         - ramp (up & down) constraints (optional)
  - arbitrary number of generation technologies/units with
      + availability factors (separate from capacity credit, see below)
      + maximum installed capacity by unit
      + minimum power for baseload units
      + existing installed capacity, with ability to not fully use
      + discrete plant sizes (can ignore)
      + technology specific operating reserve capabilities
  - features designed explicitly for proper wind support:
      + RPS (minimum wind energy penetration %)
      + Non-unity capacity credits (how much does each generator help the peak?)
      + time varying wind availability/output
  - (optional) endogenous operating reserves during each time block (hourly for 8760) including:
      + Spinning Reserves
      + Quick Start Reserves (effectively non-spin)
      + Regulation Up & Down
  - planning reserves (during peak block only)
  - arbitrary number of demand blocks of varying duration
  - heat rates + separate fuel costs for easy scenario analysis
  - carbon intensity
     + imbedded carbon from construction
     + carbon content of fuels
  - carbon constraint (carbon cap)
  - carbon tax
  - non-served energy
  - ability to mothball plants to save fixed O&M costs (still pay capital costs)

Outputs
  - Summary, Power, Commitment, New capacity, #startups, emissions, wind shedding, cost breakdown.
```

```
Additional Features:
    - loading of data from include files to allow an unchanging core model.
        - These file names can be optionally specified at the command line.
    - A final, optional "update" file to allow for adjusting parameters for easy sensitivity
      analysis or to change the values for a model run without changing the default values
    - internal annualizing of capital costs (requires definition of WACC)
    - ability to scale demand
    - ability to ignore integer constraints
    - automatically estimates max integer # of plants based on gen_size
    - Force wind mode to require using all wind production with no shedding (only valid for small %wind)

Performance enhancements:
    - ignores unit commitment for plants with no/low unit minimum output such as renewables and
      peakers. This threshold is tunable with --unit_min

Assumptions:
    - Ramping and Startup "loop" such that the state at the endo of the year must match the
      beginning of year. This prevents turning off baseload in anticipation of the "end of the world"


ToDo:
    * Decouple ops into blocks for faster UC?
    * Add hydro
    ? compute fixed and var cost by gen
    - compute required market based incentives to achieve same results
    - automatic scaling of demand blocks based on year, baseline, & growth rate

  Originally Coded in GAMS by:
   Bryan Palmintier, MIT
   March 2010

 Version History
Ver   Date       Time  Who            What
---  ---------- ----- -------------- ---------------------------------
  1  2010-05-20  23:30  bpalmintier   Original version merged: ToyCapPlan v7 + DemoCapPlanWind v4
  2  2010-05-21  04:00  bpalmintier   Expanded & Improved features for MATLAB integration
  3  2010-05-21  10:30  bpalmintier   Added support for lumpy (integer plant) investments
  4  2010-05-21  10:50  bpalmintier   Made existing capacity also pay capital costs (no change to
                                      solution by "grandma's theorem")
  5  2010-07-31  08:40  bpalmintier   Added flag (no_csv) to suppress output of csv files.
  6  2010-08-02  00:40  bpalmintier   Fixed MAJOR bug: derate power output by availability
  7  2010-09-06  22:00  bpalmintier   Added total energy to summary output
  8  2010-09-06  23:45  bpalmintier   - Made include paths platform independent
                                      - Moved data includes to ../data directory
                                      - Fix no_csv default
                                      - explicitly compute total capacity
  9  2010-09-07  20:23  bpalmintier   Separated pGenAvail for time varying availability
 10  2010-09-07  23:00  bpalmintier   Added flag to use averages for availability
 11  2010-09-07  18:30  bpalmintier   Converted to single sys.inc with subincludes. Updated comments
 12  2010-09-08  23:55  bpalmintier   Added ramp_limits (optional) for ramp constrained dispatch
 13  2010-09-09  17:35  bpalmintier   Adjusted solve parameters for more realistic runtimes
 14  2010-09-09  19:35  bpalmintier   Made key solution parameters available on the command line
 15  2010-09-11  20:00  bpalmintier   Minor tweaks and bug fixes:
                                       - loop around for ramp constraints to prevent start from 0
                                       - use RMIP for ignore_integer (also fix related $if bugs)
                                       - renamed --limit_ramps to --ramp
                                       - renamed --mip_tol to --mip_gap
 16  2010-09-17  12:15  bpalmintier   Added option to use avg avail for cap_credit (traditional approach
       )
 17  2010-10-24  01:00  bpalmintier   Added calculation of energy production mix
 18  2010-10-26  13:00  bpalmintier   Major rework to ignore integer unit commitment for unit_min=0
                                      Result is 10-300x speed up for MIP (startup) solutions!!!
                                      Also:
                                        - improved comments
                                        - Expanded RPS to include a subset based on fuel type (not name)
 19  2010-11-xx         bpalmintier   made unit_min a tunable parameter (default = 0)
 20  2010-11-13  23:00  bpalmintier   Key Update to include both up & down ramping
 21  2010-11-14  10:30  bpalmintier   Additional features:
                                        - debug mode to print more complete *.lst file
                                        - More realistic ramping for unit commitment that considers
                                          the on-line generator fleet rather than the total fleet
 22  2010-11-14  18:30  bpalmintier   Added hourly reserves (finally!) including Spin, QuickStart,
                                       RegUp, and RegDown.
 23  2010-11-14  22:30  bpalmintier   Added non-served energy & some solution helpers
 24  2010-11-15  02:30  bpalmintier   New features:
                                        - Ability to restart from a saved solution (should help initial
                                              LP only)
                                        - Command line switches for non-served, op_reserves, etc.
                                        - Reworked equations so unit_commit dictated by $G_UC(G)
 25  2010-11-16  09:00  bpalmintier   BUG FIX: corrected ramp limits for UC
 26  2010-11-16  09:00  bpalmintier   Tweaks:
                                        - Only compute ramp for units with ramp_max < 1
                                        - Consider availability in ramp for non-UC
                                        - Shortened command line options to no_nse & no_op_rsrv
 27  2010-11-16  23:59  bpalmintier   Report Startup Data
 30  2010-11-18  03:00  bpalmintier   Added max_start
 31  2010-11-19         bpalmintier   FIXED major bug in op reserve: loophole for spin_rsv, etc = 0
 32  2010-11-20  11:00  bpalmintier   FIXED major bug where startup did not actually turn on UC
 33  2010-11-22  10:30  bpalmintier   Added fix_cap mode
 34  2010-11-23  20:50  bpalmintier   Added & renamed output for use with StaticCapPlanScripter.m
 35  2010-11-24  11:15  bpalmintier   Added carbon price and marginal emissions
 36  2011-01-11  20:00  bpalmintier   Added command-line parameter checks
 37  2011-05-26  20:00  bpalmintier   Added startup cost to summary
 38  2011-06-18  03:15  bpalmintier   Added --avail option to fix bug with inconsitant gen availability
       files
 39  2011-06-20  12:15  bpalmintier   change update file path to relative to the model (not data_dir)
 40  2011-07-08  02:15  bpalmintier   Added ability to force plant (bin) sizes to a specified value
 41  2011-07-15  10:15  bpalmintier   move output summary to shared include file
 42  2011-07-20  03:00  bpalmintier   re-arrange data includes for sys definition of avail file
 43  2011-07-20  15:00  bpalmintier   Added support for parallel processing with par_threads
 44  2011-07-21  03:00  bpalmintier   Added --memo, set cap_max=0 integer limit to zero
 45  2011-07-21  03:30  bpalmintier   Added --co2cap
 46  2011-07-22  14:55  bpalmintier   Added combined Flexibility reserves (from OpsLp v5)
 47  2011-07-24  01:00  bpalmintier   Added max_cap_factor and derate, cleaned up flex vs separate
       reserves
 48  2011-07-24  01:15  bpalmintier   Remove down req't for wind when shedding OK, Added --from_scratch
 49  2011-07-24  08:30  bpalmintier   Replace availability CSV with GAMS table format
 50  2011-07-24  11:30  bpalmintier   Corrected (again) double counting for separate & flex reserves
 51  2011-07-24  19:30  bpalmintier   User configurable --out_prefix
 52  2011-07-26  16:30  bpalmintier   Made support of p_min optional with --basic_pmin
 53  2011-08-02  17:00  bpalmintier   Made planning margin optional with --plan_margin
 54  2011-08-02  17:30  bpalmintier   More flexible force_renewables with min of demand and renew output
        (borrow from OpsLp)
 55  2011-08-02  21:30  bpalmintier   Corrections based on OpsLp:
                                        - only G_WIND used for reserves since req't are tech specific
                                        - cleaned up ramping limit equations
 56  2011-08-03  00:10  bpalmintier   BUG FIX: pPlanRserve use for non fix_cap settings
 57  2011-08-03  00:40  bpalmintier   Added support for water limits via include file
 58  2011-08-05  01:40  bpalmintier   TWEAKED solver option file to use barrier algorithm
 59  2011-08-05  11:30  bpalmintier   Increased output precision to 5 after decimal
 60  2011-08-06  16:15  bpalmintier   Further refinement of solver to use concurrent optimization
 61  2011-08-17  15:55  bpalmintier   Added water cost
 62  2011-08-19  10:35  bpalmintier   Force renewables on system-wide, rather than per gen, basis
 63  2011-09-21  17:00  bpalmintier   Comments & other updates from UnitCommit extraction
 64  2011-10-11  14:15  bpalmintier   Renamed plant_size to gen_size (also related flags)
```

```
 65  2011-10-14  09:55  bpalmintier   BUGFIX: corrected scaling for co2_cap passed from command line
 66  2011-11-06  13:15  bpalmintier   Updated to use AdvPwrSetup and AdvPwrDataRead
 67  2011-11-07  15:25  bpalmintier   Corrected comments re: sys.inc
 68  2011-11-10  12:15  bpalmintier   Added no_capital option
  69 2012-01-26  11:05  bpalmintier   Search and replace to partially match UnitCommit scenario overhaul
        (v26)
  70 2012-01-28  02:45  bpalmintier   Modularize to call UnitCommit for operations
  71 2012-01-29  00:10  bpalmintier   Removed "helper" lower bound on new cap b/c causing errors
  72 2012-02-03  15:15  bpalmintier   MAJOR
                                        -- scaling: MW to GW, Capital costs to M$/GW
                                        -- Default to using barrier for LP solver (typically faster,
                                               especially for LPs)
                                        -- Cleaned-up Capacity limit equations
  73 2012-02-21  15:15  bpalmintier   Stricter capacity limits for renewables. Added renew_overbuild and
        renew_to_rps
  74 2012-03-07  11:35  bpalmintier   Added support for partial period simulation through B_SIM
  75 2012-05-02  12:40  bpalmintier   Separate demand (D) into blocks (B) and time sub-periods (T)
  76 2012-06-14  05:10  bpalmintier   Added no_cap_limit option
  77 2012-06-14  15:05  bpalmintier   Added rps & planning margin penalties (via UnitCommit)
  78 2012-08-21  16:05  bpalmintier   Updated comments, prevent negative max for rps gens with low rps &
        renew_to_rps
  79 2012-08-22  00:15  bpalmintier   Shortened file names, no more "out_"
  80 2012-08-22  15:05  bpalmintier   Added priority (B&B tree) option
  81 2012-08-23  14:05  bpalmintier   BUGFIX: ignore integers for startup/shutdown when ignoring uc
       integers, publish uc_lp option
  82 2012-08-25  09:05  bpalmintier   BUGFIX: correct renew_to_rps logic (previously reversed).
  83 2012-08-25  11:10  bpalmintier   Replace renew_to_rps with more flexible renew_lim
  84 2012-08-29  17:45  bpalmintier   Update to set integer bounds for all except uclp
  85 2012-08-31  00:35  bpalmintier   Allow non-served energy to reduce reserve needs (old behavior with
        --rsrv_use_tot_demand=1)
  86 2012-08-31  07:15  bpalmintier   UPDATE: default to rsrv to demand (without nse). Flag renamed to
       adj_rsrv_for_nse
  87 2012-09-02  17:05  bpalmintier   BUGFIX: Correct maintenance by preventing mismatch between local &
        global values of capacity_G, Ergh!
  88 2012-09-02  17:08  bpalmintier   Replace all $set with $setglobal (to prevent other possible
       troubles)
  89 2012-09-03  07:08  bpalmintier   Add derate_to_maint & debug_off_maint
-----------------------------------------------------
$offtext

*================================*
*            Setup             *
*================================*

* First define the shared directory

* ======  Platform Specific Adjustments
* Setup the file separator to use for relative pathnames
$iftheni %system.filesys% == DOS $setglobal filesep "\"
$elseifi %system.filesys% == MS95 $setglobal filesep "\"
$elseifi %system.filesys% == MSNT $setglobal filesep "\"
$else $setglobal filesep "/"
$endif

* By default look for shared components in sibling directory "shared"
$if not set shared_dir $setglobal shared_dir ..%filesep%shared%filesep%

* Enable $ variables from include file to propagate back to this master file
$onglobal

* Include common setup definitions including:
*  -- Platform specific path adjustments
*  -- GAMS options
```

```
*  -- debug settings
*  -- standardized AdvPower directories
$include %shared_dir%AdvPwrSetup

* Disable influence of $ settings from include files
$offglobal


* ======  Additional setup

* == Identify if we are the master calling model
$ifthen.we_are_main NOT set model_name
*Establish the title
$Title "Static Capacity Planning model"

*If so set it
$setglobal model_name StaticCapPlan

* == And we want to idenfify whether or not we are using a mixed integer solution
$ifthen.mip set ignore_integer
$setglobal use_mip no
$else.mip
$setglobal use_mip yes
$endif.mip

$endif.we_are_main

* == Default to UnitCommit based operations
$if not set ops_model $setglobal ops_model UnitCommit

* Setup output prefix
$if NOT set out_prefix $setglobal out_prefix SCP_

* ======  Handle some initial command line parameters
*Additional factor for capacity/unit commitment upper limits
$if not set overbuild $setglobal overbuild .2
$if not set renew_overbuild $setglobal renew_overbuild .2
$if not set renew_lim $setglobal renew_lim avg

*================================*
*        Declarations          *
*================================*

* ====== Bypass Declarations & Model if doing a restart
$if defined StaticCapPlan $goto skip_redef


* ======  Declare all sets so can use in equations
* Note: be sure to quote descriptions otherwise "/" can not be used in a description.

sets
* Sets for table parameters

    DEM_PARAMS  "demand block table parameters from load duration curve"
        /dur        "duration of block                 [hrs]"
         power      "average power demand during block [GW]"
        /

    GEN_PARAMS  "generation table parameters"
       /
        cap_credit  "Capacity Credit during peak block           [p.u.]"
        c_cap       "total capital cost                          [$/GW]"
        life        "economic lifetime for unit                  [yr]"
```

```
        cap_cur     "Current installed capacity for generation   [GW]"
        cap_max     "Maximum installed capacity for generation   [GW]"
        lead_time   "Delay from construction to operation        [yr]"
        gen_size    "typical discrete plant size                 [GW]"
        derate       "Derating factor for simple (non-reserves) cap planning [p.u.]"
       /

* Sets for data, actual definitions can be found in include files
    G           "generation types (or generator list)"
    S           "scenarios for multi-period and stochastic problems"
    B           "Demand blocks (e.g. weeks or ldc)"
      T                 "Demand time sub-periods (e.g. hours or ldc sub-blocks)"
    B_SIM(B)    "demand blocks used in simulation"

* Subsets for special purposes

* ======  Declare the data parameters. Actual data imported from include files
parameters
* Data Tables
    pGen   (G, GEN_PARAMS, S)       "table of generator data"
* Post Processing Results Parameters
    pGenAvgAvail (G, S)             "average availability (max capacity factor)"
* Additional Parameters
    pScenWeight(S)     "Scenario weighting for cost calcs. Use for probability or time discounting"
    pCRF       (G)               "capital recovery factors      [/yr]"
    pDemandMax (S)               "Maximum demand level          [GW]"

scalars
    pWACC             "weighted average cost of capital (utility investment discount rate) [p.u.]"

*Include operating reserves in total capacity limits only if they are used
$ifthen.skip_lim not set skip_cap_limit
$ifthen.fix_cap not set fix_cap
$ifthen.plan_marg set plan_margin
$ifthen.rsrv set rsrv
    pSpinReserveLoadFract       "addition Fraction of load for spin reserves               [p.u.]"
    pRegUpLoadFract             "additional Fraction of load for regulation up             [p.u.]"
    pRegDownLoadFract           "Fraction of load over unit minimums for regulation down    [p.u.]"
    pSpinReserveMinGW           "Additional spinning reserve for max contingency           [GW]"
    pReplaceReserveGW           "Offline replacement reserve to replace deployed spinning   [GW]"
$endif.rsrv
$endif.plan_marg
$endif.fix_cap
$endif.skip_lim

$ifthen set plan_margin
    pPlanReserve                "planning reserve                                          [p.u.]"
$endif

* ======  Declare Variables
variables
   vObjective  "Objective: scenario weighted average (EV or discounted ops cost)  [M$]"
   vTotalCost      (S)          "total system cost for scenario              [M$]"
   vOpsCost        (S)          "system operations cost in target year       [M$]"
   vCapitalCost    (S)          "annualized capital costs of new capacity     [M$]"

* Specify integer variables. If ignore_integer flag is specified these are treated as continous by
* GAMS by using the RMIP solution type.
integer variables
    vNumNewPlants(G, S)   "number of discrete new plants to construct         [integer]"


positive variables
   vCapInUse (   G, S)   "total installed capacity that is used [GW]"

   vNewCapacity( G, S)   "new capacity constructed              [GW]"
* ======  Declare Equations
equations
$ifthen %model_name% == StaticCapPlan
   eObjective  "Objective function: scenario weighted average (EV or discounted ops cost)  [M$]"
   eTotalCost  (S)     "total cost = ops + capital cos            [M$]"
$endif
   eCapitalCost (S)    "annualized capital cost of new capacity      [M$]"

$ifthen not set fix_cap
   ePositiveNew(G, S)   "prevent negative net new capacities w slack variable."
   eInstCap  (   G, S)  "installed capacity                    [GW]"
$endif

$ifthen.skip_lim not set skip_cap_limit
$ifthen.fix_cap not set fix_cap
$ifthen set plan_margin
   eLimitTotalCap (S)     "Set a rough upper bound on total capacity to aid MIP solver"
$endif
$endif.fix_cap
$endif.skip_lim

$ifthen not set fix_cap
   eNewPlants (G, S)      "integer constraints on new capacity investment"
$endif
   ;

*================================*
*  Additional Model Formulation  *
*================================*
* Note: this must be included between declarations & equations so that the included file
* has access to our declarations, and any objective function additions can be used.

* Enable $ variables from included model(s) to propagate back to this master file
$onglobal

* Include operations model, which greatly expands the parameter, variable, and equation set
$include ../ops/%ops_model%

* Include Planning Margin if required
$if set plan_margin $include %shared_dir%PlanMarginEquations

* Water equations included in operations model

* Disable influence of $ settings from include files
$offglobal

*================================*
*       The Actual Model         *
*================================*
*====== objective function and components
* == Objective (eObjective)
*
* The standard objective is total cost (see below for alternative objective options). We use
* our definition of this equation whenever we are the main model. Otherwise we expect our caller
* to define a similar objective function.
*
$ifthen.we_are_main   %model_name% == StaticCapPlan
$if not set obj_var $setglobal obj_var vTotalCost

eObjective  ..  vObjective =e= sum[(S), pScenWeight(S) * %obj_var%(S)];
```

```
* Allows uniform use of total cost for both operations and planning models
eTotalCost (S)  ..  vTotalCost (S) =e= vOpsCost (S) + vCapitalCost (S);

$endif.we_are_main

* == Total Capital Costs (eCapitalCost)
*capital cost = existing+new capacity*annualized cost of capital using capital recovery factor
*
*Note: We can't use %capacity_G% here because we still want to pay the capital costs on old
* capacity even if it is not used.
* Scaling:
*  1x       pGen(c_cap)     M$/GW
*  1x       vCapCost        M$
eCapitalCost(S)  .. vCapitalCost(S) =e= sum[(G), pCRF(G)*(
$ifthen not set fix_cap
                                            vNewCapacity(G, S)+
$endif
                                            pGen(G,'cap_cur', S))*pGen(G,'c_cap', S)]
                                        * pFractionOfYear(S);

*====== Intermediate Calculations
$ifthen not set fix_cap
*introduce a slack variable so we don't get a credit for unused plants which will have negative net
*capacities because vCapInUse < current capacity
    ePositiveNew(G, S)  .. vNewCapacity(G, S) =e= vCapInUse(G, S)-pGen(G,'cap_cur',S)
*    + vCapSlack(G,S)
    ;

*Constrain new capacity to integer numbers of plants
    eNewPlants(G,S) .. vNewCapacity(G,S) =e= vNumNewPlants(G,S) * pGen(G, 'gen_size',S);
$endif

$ifthen not set fix_cap
    eInstCap(G,S)    .. vCapInUse(G,S) =l= pGen(G,'cap_max',S);
$endif

*======  Additional Constraints

*======  Integer Solution helpers (to speed up MIP searching)
$ifthen.skip_lim not set skip_cap_limit
$ifthen.fix_cap not set fix_cap
$ifthen.plan_marg set plan_margin
    eLimitTotalCap (S)  .. sum[(G), vCapInUse(G,S)*pGen(G,'cap_credit',S)] =l=
                         (1+%overbuild%)*
$ifthen.rsrv set rsrv
                         max(
* Existing capacity if overbuilt
                                sum[(G), pGen(G,'cap_cur',S)*pGen(G,'cap_credit',S)]
                                ,
* Operating reserve based limits
                                (1+ pSpinReserveLoadFract + pRegUpLoadFract)* pDemandMax(S)
                                    + pSpinReserveMinGW + pReplaceReserveGW
                                ,
$else.rsrv
                            (
$endif.rsrv
* Traditional Planning Reserve limits
                                (1 + pPlanReserve) * pDemandMax(S)
                            );
$endif.plan_marg
$endif.fix_cap
$endif.skip_lim
```

```
*Skip ahead to here on restart
$label skip_redef
*================================*
*        Handle The Data         *
*================================*

* Data read in by operations model

* ====== Additional Calculations...

*Clear out existing capacity when building from scratch
$ifthen set from_scratch
    pGen(G, 'cap_cur', S) = 0;
$endif
$ifthen set no_cap_limit
    pGen(G, 'cap_max', S) = Inf;
$endif

* ====== Compute max integer number of plants & unit_commitment states
*Note: by default GAMS restricts to the range 0 to 100 so this provides two features:
*  1) allowing for higher integer numbers for small plant types as required for a valid solution
*  2) Restricting the integer search space for larger plants
parameter
  pMaxNumPlants(G,S)
  ;

* Only compute pMax for non-zero cap_max.
  pMaxNumPlants(G,S)$(pGen(G, 'cap_max', S)) =
        round((1+%overbuild%)
            *min(
*bound by max capacity
                floor( pGen(G, 'cap_max',S)/pGen(G, 'gen_size',S) ),
*and use looser of
                max(
*peak period cap credit
                    ceil(   (pDemandMax(S)
$ifthen set plan_margin
                             * (1 + pPlanReserve)
$endif
                                )/ (pGen(G, 'gen_size',S) * pGen(G, 'cap_credit',S) )
                        ),
*and average availability vs peak demand
                    ceil(   pDemandMax(S)/ (pGen(G, 'gen_size',S) * min(pGenAvgAvail(G,S), pGen(G, '
                          derate',S) ) )
                        )
                    )
                )
            );

* Adjust max number of plants for variable renewables (assumed to apply to all renewables)
* By default, assume renewables may compete on their own and supply power for economic reasons
$ifthen.re_lim set renew_lim
$ifthen.lim_type %renew_lim%==avg
* In this case, we limit new capacity to that capable of supplying the peak demand based on the greater
      of
* capacity factor and average availability
    pMaxNumPlants(G,S)$G_RPS(G) =
                round((1+%renew_overbuild%)
                    * ceil(   pDemandMax(S)
                                / ( pGen(G, 'gen_size',S) * max(pGen(G, 'cap_credit',S), pGenAvgAvail(G,
                                      S)) )
                          )
```

```
                );
$elseif.lim_type %renew_lim%==rps
* But if indicated, instead limit renewable expansion to the RPS level (plus renew_overbuild)
    pMaxNumPlants(G,S)$G_RPS(G) =
        max[0,
                round((1+%renew_overbuild%)
                    * ceil(   pDemandAvg(S)*pRPS(S)
                                / ( pGen(G, 'gen_size',S) * pGenAvgAvail(G,S) )
                          )
                 )
            ];
$elseif.lim_type %renew_lim%==firm
* But if indicated, instead limit renewable expansion to the RPS level (plus renew_overbuild)
    pMaxNumPlants(G,S)$G_RPS(G) =
        max[0,
                round((1+%renew_overbuild%)
                    * ceil(   (pDemandMax(S)
$ifthen set plan_margin
                             * (1 + pPlanReserve)
$endif
                                )/ (pGen(G, 'gen_size',S) * pGen(G, 'cap_credit',S) )
                          )
                 )
            ];
$endif.lim_type
$endif.re_lim

*list max plant numbers in *.lst file
display pMaxNumPlants;

*Compute Max new plants by subtracting off existing capacity
 vNumNewPlants.up(G,S)$(pGen(G, 'cap_max',S)) = max[0, pMaxNumPlants(G,S) - floor(pGen(G, 'cap_cur',S)/
       pGen(G, 'gen_size',S))];
*For units that the current capacity is greater than max, no new plants (prevent negatives)
 vNumNewPlants.fx(G,S)$(pGen(G, 'cap_cur',S)-pGen(G, 'cap_max',S)>=0) = 0;

$ifthen set unit_commit
    vUcInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
$endif

$ifthen not set uc_lp
    vStartInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
    vShutInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
$endif

$ifthen set maint
    vOnMaint.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
    vMaintBegin.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
    vMaintEnd.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
*Fix maintenance at zero if maintenance not required
      vOnMaint.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
    vMaintBegin.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
    vMaintEnd.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
$endif

* ===== Take some initial guesses =====
if (sum(G_RPS,1) > 0) then
    vNewCapacity.l('wind',S) = sum[(B_SIM, T), pDemand(B_SIM, T, 'power',S)*pDemand(B_SIM, T, 'dur',S)]*
          pRPS(S) - pGen('wind','cap_cur',S);
endif;
* ===== Fix any values we can
$ifthen set fix_cap
    vCapInUse.fx(G,S) = pGen(G,'cap_cur',S);
    vNumNewPlants.fx(G,S) = 0;
    vNewCapacity.fx(G,S) = 0;
$endif

*=================================*
*   Additional Data Processing   *
*=================================*

* Enable $ variables from included model(s) to propagate back to this master file
$onglobal

* Include water limiting equations and associated parameters and variables
$if set calc_water $include %shared_dir%WaterDataSetup

* Disable influence of $ settings from sub-models
$offglobal

*=================================*
*       Solve & Related          *
*=================================*
*Only run the rest of this file if we are the main function.
$ifthen.we_are_main %model_name% == StaticCapPlan

* ======  Setup the model
* Skip this definition if we are doing a restart
$ifthen.scp_model not defined StaticCapPlan
    model StaticCapPlan  /all/;

* ======  Adjust Solver parameters
* Enable/Disable Parallel processing
*By default, use only one thread, since this is often faster for small problems
$if not set par_threads $setglobal par_threads 1
*Default to barrier b/c typically faster
$if not set lp_method $setglobal lp_method 4
*Use default probing
$if not set probe $setglobal probe 0

*Create a solver option file
$onecho > cplex.opt
* Note: the number of threads can either be specified explicitly or using "0" for use all cores
threads %par_threads%

*Parallel mode. Options:
* 1=deterministic & repeatable, 0=automatic, -1=opportunistic & non-repeatable
parallelmode %par_mode%

* Conserve memory when possible... hopefully avoid crashes b/c of memory
memoryemphasis 1

* Declare solution method for pure LP, RMIP, and final MIP solve.
*   Options: 0=automatic, 2=Dual Simplex, 4=barrier, 6=concurrent (a race between
* dual simplex and barrier in parallel)
*
* Sometimes barrier is notably faster for operations problems, but more often dual simplex wins
* Barrier is often better for planning problems
LPmethod %lp_method%
* Solution method for solving the root MIP node. See description and options for LPmethod above
startalg %lp_method%
* Solution method for solving sub MIP nodes. See description and options for LPmethod above
* For some reason, the default (usually dual simplex) is typically better here.
*subalg %lp_method%

* Tighten LP tolerance (default 1e-6). For problems with objective values close to 1, this
```

```
* may be necessary to find the true optimal. In particular, with MILP, using the default can
* cause the final LP solve to stop short of finding the best node from the MILP branch-and-cut
* Surprisingly, a tighter tolerance can also achieve FASTER run times for MILP, presumably
* because the nodes can be compared more carefully.
epopt 1e-9

* Stay with barrier until the optimal solution is found rather than crossing over to simplex
* This can run much faster for these problems, because the final simplex iterations can be
* slow and b/c the cross-over itself takes a good bit of time. However, the approach is not
* robust and can fail or be slower than the default behavior. Not recommended with barrier
* alone (LPmethod = 4) b/c may not converge. Consider for concurrent optimization.
*barcrossalg -1

* Ignore small (dual) infeasibilities in the final LP solve. Without this setting, occasionally
* CPLEX will get unhappy with an infeasibility on the order of 1e-6
relaxfixedinfeas 1

* Probing: a technique to more fully examine a MIP problem before starting branch-and-cut. Can
* sometimes dramatically reduce run times. Options: 0=automatic, 1=limited, 2=more, 3=full,
* -1=off.
probe %probe%
* Limit the probe time to 5min, experience shows the default is typically <=1 sec, so this
* Will seldom be a big driver
probetime 300

*enable relative epsilon optimal (cheat) parameter
*This value is not used if cheat is defined
relobjdif %rel_cheat%

$offecho

*Tell GAMS to use this option file
StaticCapPlan.optfile = 1;

* ======  Tune performance with some initial guesses and settings to speed up the solution
$ifthen.prior_set set priority
$ifthen.prior_on not %priority%==off
*Setup branching priorities to prioritize capacity decisions
    StaticCapPlan.prioropt = 1 ;

    vNumNewPlants.prior(G,S) = 1 ;

* And then maintenance decisions
$if set maint          vOnMaint.prior(B, G, S) = 2 ;
$if set maint          vMaintBegin.prior(B, G, S) = 2 ;
$if set maint          vMaintEnd.prior(B, G, S) = 2 ;

$endif.prior_on
$endif.prior_set

*Note: the following endif is for the $ifthen not the $if
$endif.scp_model
```

```
* ====== Check command line options
* Check spelling of command line -- options
* Notes:
*  - all command line options have to have either been used already or be listed
* here to avoid an error. We place it here right before the solve statment such that
* if there is an error, we don't wait till post solution to report the problem
$setddlist ignore_integer summary_only summary_and_power_only memo gdx out_gen_params out_gen_avail
       out_gen_simple debug_off_maint

* ======  Actually solve the model
$ifthen set ignore_integer
     solve %model_name% using RMIP minimizing vObjective;
$else
     solve %model_name% using MIP minimizing vObjective;
$endif

*=================================*
*         Postprocessing          *
*=================================*

*-- Suppress CSV output if no_csv flag is set
$if "no_csv = 1" $ontext

* ======  Post processing computations
* Most of these calculations are standardized in ../shared/calcSummary.gms
$include %shared_dir%calcSummary.gms

* ======  Write Standard Results to CSV files
$include %shared_dir%writeResults.gms

$if set summary_and_power_only $goto skip_non_summary
*-- [3] Output List of Total installed generation by type
$batinclude %util_dir%put2csv "%out_dir%%out_prefix%tot_cap.csv" "table" pCapTotal(G,S) G S

*-- [4] Output List of New plants by type
$batinclude %util_dir%put2csv "%out_dir%%out_prefix%new_plants.csv" "table" vNumNewPlants.l(G,S) G S

*-- [5] Output List of New capacity by type
$batinclude %util_dir%put2csv "%out_dir%%out_prefix%new_cap.csv" "table" vNewCapacity.l(G,S) G S


$label skip_non_summary
*-- end of output suppression when no_csv flag is set
$if "no_csv = 1" $offtext

$if set gdx execute_unload '%out_dir%%out_prefix%solve.gdx'

* Write value of all control variables to the list file (search for Environment Report)
$show

$endif.we_are_main
```

ListingD.2: UnitCommit.gms: the core, highly configurable clustered unit commitment model. It can be used standalone or included into larger planning models model. It relies on shared include files for many model features. Note: the initial help text is removed since it is nearly identical to that from StaticCapPlan.gms

```
*================================*
*             Setup              *
*================================*

* First define the shared directory

* ======  Platform Specific Adjustments
* Setup the file separator to use for relative pathnames
$iftheni %system.filesys% == DOS $setglobal filesep "\"
$elseifi %system.filesys% == MS95 $setglobal filesep "\"
$elseifi %system.filesys% == MSNT $setglobal filesep "\"
$else $setglobal filesep "/"
$endif

* By default look for shared components in sibling directory "shared"
$if not set shared_dir $setglobal shared_dir ..%filesep%shared%filesep%

* Enable $ variables from include file to propagate back to this master file
$onglobal

* Include common setup definitions including:
*  -- Platform specific path adjustments
*  -- GAMS options
*  -- debug settings
*  -- standardized AdvPower directories
$include %shared_dir%AdvPwrSetup

* Disable influence of $ settings from include files
$offglobal


* ======  Additional setup
* == Identify if we are the master calling model
$ifthen.we_are_main NOT set model_name
*Establish the title
$Title "Flexible Unit Commitment Model"
*If so set it
$setglobal model_name UnitCommit
*In this case, we also know the capacity is fixed so skip all of the capacity expansion terms
$setglobal fix_cap
*And we want to default to using unit-commitment
$if not set unit_commit $setglobal unit_commit on

* == And we want to identify whether or not we are using a mixed integer solution
$ifthen.mip set ignore_integer
$setglobal use_mip no
$else.mip
$setglobal use_mip yes
$endif.mip

$endif.we_are_main

* == Setup short hand alias for total capacity to use as a control variable
$ifthen.fix_cap set fix_cap
$setglobal capacity_G pGen(G,'cap_cur', S)
$else.fix_cap
$setglobal capacity_G vCapInUse(G, S)
$endif.fix_cap

$setglobal cap_for_plan_margin %capacity_G%

$ifthen.maint set maint
$setglobal capacity_G vCapOffMaint(B, T, G, S)
$endif.maint

*Set Maximum Capacity for Fixed O&M costs & computing vCapOffMaint
$ifthen.fix_cap set fix_cap
$setglobal max_cap_G pGen(G,'cap_cur', S)
$else.fix_cap
$setglobal max_cap_G vCapInUse(G, S)
$endif.fix_cap

* Setup output prefix
$if NOT set out_prefix $setglobal out_prefix UC_

* Make sure unit_commit is set if startup is set
$if set startup $setglobal unit_commit 1

* Make sure we compute startup & shutdown variables if we need them
$if set startup     $setglobal compute_state 1
$if set max_start   $setglobal compute_state 1
$if set min_up_down $setglobal compute_state 1

* Assign the power point for p0_fuel recovery for non-uc generators
$if not set p0_recover $setglobal p0_recover 0.85

*================================*
*         Declarations           *
*================================*

* ======  Declare all sets so can use in equations
* Note: be sure to quote descriptions otherwise "/" can not be used in a description.

sets
* Sets for table parameters

    DEM_PARAMS  "demand block table parameters from load duration curve"
        /
         dur         "duration of block                 [hrs]"
         power       "average power demand during block [GW]"
        /

    GEN_PARAMS  "generation table parameters"
       /
        c_var_om    "variable O&M cost                           [$/MWh]"
        c_fix_om    "fixed O&M cost                              [M$/GW-yr]"
        heatrate    "heatrate for generator (inverse efficiency) [MMBTU/MWh = BTUe9/GWh]"
        p0_fuel     "fuel use at zero power out (heatrate intercept) [BTUe9/hr]"
        fuel        "name of fuel used                           [name]"
        cap_cur     "Current installed capacity for generation   [GW]"
```

```
        co2_ccs     "Fraction of carbon capture & sequestration  [p.u.]"
        co2_embed   "CO2_eq emissions from plant construction    [Mt/GW]"
        p_min       "minimum power output (for baseload)         [p.u.]"
        gen_size    "typical discrete plant size                   [GW]"
        ramp_max    "Maximum hourly ramp rate                    [fract/hr]"
        unit_min    "Minimum power output per committed unit     [GW]"
        c_start_fix "Fixed cost to start up a unit               [K$/start]"
        fuel_start  "Fuel usage to start up a unit               [BTUe9/start]"
        quick_start "Fraction of capacity avail for non-spin reserves [p.u.]"
        reg_up      "Fraction of capacity avail for regulation up reserves [p.u.]"
        reg_down    "Fraction of capacity avail for regulation down reserves [p.u.]"
        spin_rsv    "Fraction of capacity avail for spinning reserves [p.u.]"
        max_start   "Maximum number of startups per plant per year [starts/unit/yr]"
        max_cap_fact "Maximum capacity factor, use for maintanence [p.u.]"
        derate       "Derating factor for simple (non-reserves) cap planning [p.u.]"
       /

    FUEL_PARAMS "fuel table parameters"
        /
         name        "The name as a string (acronym) for comparison  [name]"
         cost        "Unit fuel cost                                 [$/MMBTU = $K/BTUe9]"
         co2         "Carbon Dioxide (eq) emitted                    [t/MMBTU = Kt/BTUe9]"
        /

* Sets for data, actual definitions can be found in include files
    G           "generation types (or generator list)"
        /
         wind
        /
    B           "Demand blocks (e.g. weeks or ldc)"
      T                 "Demand time sub-periods (e.g. hours or ldc sub-blocks)"
    B_SIM(B)    "demand blocks used in simulation"
    F           "fuel types"
    S           "scenarios for multi-period and stochastic problems"

* Sets associated with piecewise linear cost (fuel) functions
        HR_SEG       "piece-wise linear fuel use segments (slope=heatrate)"
*      (Note only define the first segment here, assume other segs defined in data files as needed
                /seg1/

        PWL_COEF    "Coefficients for piecewise linear representation"
                /
                 slope
                 intercept
                /


* Sets for mapping between other sets
    GEN_FUEL_MAP(G, F)     "map for generator fuel types"

* Subsets for special purposes
    G_UC(G)       "Generators to compute continuous or discrete unit commitment state and constraints"
    G_UC_INT(G)   "Generators with integer on/off values for unit commitment"
    G_RPS(G)      "Generators included in the Renewable Portfolio Standard"
    G_WIND(G)     "Wind generators (for reserve requirements)"
    G_RAMP(G)     "Generators for which to enforce ramping limits"
    G_PWL_COST(G) "Generators for which to use multi-segment piecewise linear fuel use"
    PWL_COST_SEG(G, HR_SEG) "Valid piece-wise linear segments"

* ======  Declare the data parameters. Actual data imported from include files
parameters
* Data Tables
    pDemand    (B, T, DEM_PARAMS, S)   "table of demand data"
```

```
    pGen       (G, GEN_PARAMS, S)   "table of generator data"
    pGenAvail  (B, T, G, S)            "table of time dependent generator availability"
    pFuel      (F, FUEL_PARAMS, S)  "table of fuel data"
$ifthen set pwl_cost
    pGenHrSegments(G, HR_SEG, PWL_COEF)    "Piecewise Linear Fuel use Table (slope=heatrate)"
$endif

* Additional Parameters
   pScenWeight(S)     "Scenario weighting for cost calcs. Use for probability or time discounting"

   pCostCO2     (S)     "cost of carbon (in terms of CO2 equivalent)                         [$/t-CO2eq
         = M$/Mt]"
   pRPS         (S)     "fraction of energy from wind                                        [p.u.]"
   pCarbonCap   (S)     "max annual CO2 emissions                                            [Mt CO2e]"
   pDemandScale (S)     "factor by which to scale demand"
   pFractionOfYear(S)   "fraction of year covered by the simulation"

   pMaxNumPlants(G, S)  "upper bound on number of plants for unit commitment"

scalars
   pWACC             "weighted average cost of capital (utility investment discount rate) [p.u.]"
   pPriceNonServed     "Cost of non-served energy                                        [$/MWh]"

* ======  Declare Variables
variables
   vObjective  "Objective: scenario weighted average (EV or discounted ops cost)  [M$]"
   vTotalCost      (S)         "total system cost for scenario              [M$]"
   vOpsCost        (S)         "system operations cost in target year       [M$]"
   vFixedOMCost    (S)         "fixed O&M costs in target year              [M$]"
   vVariableOMCost (S)         "variable O&M costs in target year           [M$]"
   vFuelCost       (S)         "total fuel costs in target year             [M$]"
   vCarbonCost     (S)         "cost of all carbon emissions                [M$]"
   vPenaltyCost    (S)         "rps and plan_margin penalty costs           [M$]"

$ifthen set startup
   vStartupCost    (S)         "total startup (fixed) costs, not including fuel & carbon [M$]"
$endif
$ifthen not set no_nse
    vNonServedCost (S)         "total cost of non-served energy             [M$]"
$endif
   vCarbonEmissions(G, S)          "carbon from operations + fraction embedded   [Mt-CO2e]"

* See below for integerization
positive variables
   vUnitCommit(B, T, G, S)  "number of units of each gen type on-line during period     [continuous]"
   vStartUp  (B, T, G, S)   "number of units of each type that starts up during each period  [continuous
         ]"
   vShutDown (B, T, G, S)   "number of units of each type that shuts down during each period  [
         continuous]"

* Specify integer variables. If ignore_integer flag is specified these are treated as continous by
* GAMS by using the RMIP solution type.
$ifthen not set uc_lp
integer variables
$endif
   vUCInt(B, T,G,S)         "integer match to vUnitCommit for members of G_INT_UC [integer]"

* Previously, we made vStartup and vShutDown continuous since the unit commitment constraint (eState)
* forces them to integers since vUnitCommit is an integer. This trick reduces the number
* integer variables, BUT in testing and as is described in [1] with modern solvers, this
* actually takes longer to run.
* [1] J. Ostrowski, M. F. Anjos, and A. Vannelli,
* "Tight Mixed Integer Linear Programming Formulations for the Unit Commitment Problem,"
```

```
* IEEE Transactions on Power Systems, vol. 27, no. 1, pp. 39-46, Feb. 2012.

   vStartInt  (B, T, G, S)   "integer match to vStartUp for members of G_INT_UC [integer]"
   vShutInt (B, T, G, S)   "integer match to vShutDown for members of G_INT_UC [integer]"
   ;

positive variables
   vInstantFuel(B, T, G, S) "instantaneous fuel use by gen per period [BTUe9/hr]"
   vFuelUse  (F, G, S)   "fuel usage by generator & type           [BTUe12]"
   vPwrOut   (B, T, G, S)   "production of the unit                   [GW]"
   vNonServed(B, T   , S)   "non-served demand                        [GW]"

$ifthen set plan_margin_penalty
    vUnderPlanReserve(S)        "Firm capacity below required planning reserve [GW]"
$endif
$ifthen set rps_penalty
    vUnderRPS(S)                "Energy below that required by the RPS  [GWh]"
$endif
   ;

* ======  Declare Equations
equations
$ifthen %model_name% == UnitCommit
   eObjective  "Objective function: scenario weighted average (EV or discounted ops cost)  [M$]"
   eTotalCost  (S)     "total cost = ops                             [M$]"
$endif
   eOpsCost    (S)     "system operations cost for one year of operation  [M$]"
   eFixedOMCost(S)     "system fixed O&Mcosts for one year           [M$]"
   eVarOMCost  (S)     "system variable O&M costs for one year       [M$]"
   eFuelCost   (S)     "system fuel costs for one year               [M$]"
   eCarbonCost (S)     "cost of all carbon emissions                 [M$]"
$ifthen set startup
   eStartupCost(S)      "compute syste-wide unit startup costs                        [M$]"
$endif
$ifthen not set no_nse
   eNonServedCost (S)          "total cost of non-served energy             [M$]"
$endif
   ePenaltyCost(S)      "rps and plan_margin penalty costs                  [M$]"

   eCarbonEmissions(G, S) "carbon from operations + fraction embedded   [Mt-CO2e]"
   eInstantFuelByGen (B, T, G, S) "fuel use by gen and demand period       [BTUe9/hr]"
$ifthen set pwl_cost
    ePiecewiseFuelByGen (B, T, G, HR_SEG, S) "fuel use for gens with piecewise fuel use [BTUe9/hr]"
$endif
   eFuelUse (F, G, S)      "fuel usage by type                          [quad = BTUe15]"

$ifthen NOT set rsrv
   ePwrMax   (B, T, G, S)  "output w/o reserves lower than available max       [GW]"
   ePwrMin   (B, T, G, S)  "output w/o reserves greater than installed min     [GW]"
   ePwrMaxUC (B, T, G, S)  "output w/o reserves lower than committed max       [GW]"
   ePwrMinUC (B, T, G, S)  "output w/o reserves greater than committed min     [GW]"
$endif

   eDemand   (B, T   , S)  "output must equal demand                           [GW]"

   eRPS      (S)        "RPS Standard: minimum energy percent from renewables     [p.u.]"
   eCarbonCap(S)        "Limit total emissions                                    [Mt-CO2e]"

$ifthen set force_renewables
$if set fix_cap   eForceRenewables (B, T, S) "force the use of all renewable output (up to 100% of load)
        [GW]"
$if not set fix_cap   eForceRenewables (B, T, G, S) "force the use of all renewable output (up to 100%
       of load) [GW]"
$endif

$ifthen set ramp
   eRampUpLimitUC  (B, T, G, S)     "Limit period to period ramp up rates for integer commited plants"
   eRampDownLimitUC(B, T, G, S)     "Limit period to period ramp down for integer commited plants"
   eRampUpLimit    (B, T, G, S)     "Limit period to period ramp up rates"
   eRampDownLimit  (B, T, G, S)     "Limit period to period ramp down rates"
$endif

   eUnitCommit(B, T, G, S)  "can only commit up to the installed number of units     [continous]"
$ifthen not set uc_lp
*(possibly) Mixed Integer Equations
   eUnitCommitInteger(B, T, G, S) "Integerization for unit commitment"
   eStartUpInteger(B, T, G, S)    "Integerization for unit startup"
   eShutDownInteger(B, T, G, S)   "Integerization for unit shutdown"
$endif

$ifthen set compute_state
   eState     (B, T, G, S)  "compute unit commitment startup and shutdowns          [integer]"
$endif

$ifthen set max_start
   eMaxStart(G, S)       "enforce maximum number of startups per year            [start/yr]"
$endif
   ;

*=================================*
*  Additional Model Formulation  *
*=================================*
* Note: this must be included between declarations & equations so that the included file
* has access to our declarations, and any objective function additions can be used.

* Enable $ variables from included model(s) to propagate back to this master file
$onglobal

* Include Reserve constraints if required
$if set maint $include %shared_dir%MaintenanceEquations

* Include Planning Margin if required & we are the main function (CapPlan models include
* these equations directly
$if %model_name%==UnitCommit $if set plan_margin $include %shared_dir%PlanMarginEquations

* Include Reserve constraints if required
$if set rsrv $include %shared_dir%ReserveEquations

* Include Minimum Up and Down time formulation if required
$if set min_up_down $include %shared_dir%MinUpDownEquations

* Include water limiting equations and associated parameters and variables
$if set calc_water $include %shared_dir%WaterEquations

* Disable influence of $ settings from sub-models
$offglobal

*=================================*
*       The Actual Model         *
*=================================*
*====== objective function and components

* == Objective (eObjective)
*
* The standard objective is total cost (see below for alternative objective options). We use
* our definition of this equation whenever we are the main model. Otherwise we expect our caller
```

```
* to define a similar objective function.
*
$ifthen.we_are_main   %model_name% == UnitCommit
$if not set obj_var $setglobal obj_var vOpsCost

eObjective  ..  vObjective =e= sum[(S), pScenWeight(S) * %obj_var%(S)];

* Allows uniform use of total cost for both operations and planning models
eTotalCost (S)  ..  vTotalCost (S) =e= vOpsCost (S);

$endif.we_are_main

* == Operations Cost (eOpsCost)
* In this equation, A number of terms are always included:
*     -- fixed O&M cost
*     -- variable O&M costs
*     -- Fuel Costs
*     -- Carbon Costs
* In addition, other terms are added if needed based on command-line settings:
*     -- Startup Costs
*     -- Non served energy costs
*     -- Water costs
*     -- Maintenance costs
*
* Units:
*  all M$ unless otherwise noted
eOpsCost(S)    .. vOpsCost(S) =e= vFixedOMCost(S)
                                + vVariableOMCost(S)
                                + vFuelCost(S)
                                + vCarbonCost(S)
                                + vPenaltyCost(S)
$ifthen set startup
                                + vStartupCost(S)
$endif
$ifthen not set no_nse
                                + vNonServedCost(S)
$endif
$ifthen set calc_water
* Note scaling from Mgal (vH2oWithdrawPerGen) to kgal (pH2oCost), and usd (pH20Cost) to Musd (totals)
                                + sum[ (G_H2O_LIMIT), vH2oWithdrawPerGen(G_H2O_LIMIT, S) * pH2oCost(S)
                                      /1e3 ]
$endif
$ifthen set maint
                                + vMaintCost(S)
$endif
                                ;


* == Fixed Operations and Maintenance Costs (eFixedOMCost)
*
* Units & Scaling:
*   1x      c_fix_om        M$/GW-yr
eFixedOMCost(S)  .. vFixedOMCost(S) =e= sum[(  G), pGen(G,'c_fix_om', S)*(%max_cap_G%)]
                                           * pFractionOfYear(S);

* == Variable Operations and Maintenance Costs (eVarOMCost)
*
* Units & Scaling:          external    this eq.
*   1000x   vVarOMCost      M$          k$
*   1x      c_var_om        $/MWh   to  k$/GWh
*   1x      vPwrOut         GW
*   1x      Demand(dur)     hr
eVarOMCost(S)    .. vVariableOMCost(S)*1e3 =e= sum[(B_SIM, T, G), pGen(G,'c_var_om', S)*vPwrOut(B_SIM, T
       , G, S)*pDemand(B_SIM, T, 'dur', S)];


* == Total Fuel Costs (eFuelCost)
*
* Units & Scaling:          external    this eq.
*   1x      vFuelCost       M$      to  M$
*   1x      Fuel(cost)      $/MMBTU to  M$/BTUe12
*   1x      vFuelUse        BTUe12
eFuelCost(S)     .. vFuelCost(S) =e= sum[(GEN_FUEL_MAP(G,F)), pFuel(F,'cost', S)*vFuelUse(F, G, S)];


* == Carbon Emision Costs (eCarbonCost)
*carbon cost =  carbon price * carbon emissions
* Units & Scaling:          external    this eq.
*   1x      vCarbonCost     M$
*   1x      pCostCO2        $/t     to  M$/MT
*   1x      vCarbonEmmit    kT
eCarbonCost(S)   .. vCarbonCost(S) =e= pCostCO2(S) * sum[(G), vCarbonEmissions(G,S)];


* == Startup Costs (eStartupCost)
* Includes only fixed costs for startup. Costs associated with startup fuel use is captured
* as part of the total fuel use by generator. Hence startup fuel and carbon costs are computed
* as part of fuel and carbon costs respectively
*
* Units & Scaling:              external            this eq.
*   1000x   vStartCost          Musd        to      Kusd
*   1x      c_start_fix         Kusd/start
$ifthen set startup
    eStartupCost(S)  .. vStartupCost(S)*1e3 =e=
                            sum[(B_SIM, T,G_UC),
                                vStartup(B_SIM, T, G_UC, S)
                                    * ( pGen(G_UC, 'c_start_fix', S) )
                               ];
*Note: fuel use included elsewhere
$endif

* == Total non-served energy costs (eNonServedCost)
* Units & Scaling:             external    this eq.
*   1x      vNonServedCost      M$
*   1/1000x pPriceNonServe      $/MWh   to  M$/GWh
*   1x      vNonServed          GWh
$ifthen not set no_nse
    eNonServedCost(S) .. vNonServedCost(S) =e=
                                sum[(B_SIM, T), vNonServed(B_SIM, T, S)*pPriceNonServed*pDemand(B_SIM, T
                                      , 'dur', S)]/1e3;
$endif

* == Penalty costs (ePenaltyCost)
* Units & Scaling:             external         this eq.
*   1x      vPenaltyCost        M$
*   1x      vUnderPlanReserve   GW-firm
*   1/1000x plan_margin_penalty   $/MW-firm   to  M$/GW-firm
*   1x      vUnderRPS           GWh
*   1/1000x vNonServed          $/MWh       to  M$/GWh
    ePenaltyCost(S) .. vPenaltyCost(S) =e= 0
$ifthen set plan_margin_penalty
                                + vUnderPlanReserve(S) * %plan_margin_penalty% / 1000
$endif
$ifthen set rps_penalty
                                + vUnderRPS(S) * %rps_penalty% / 1000
```

```
$endif
                                ;


*====== Intermediate Calculations

* == Carbon Emissions (eCarbonEmissions) by generator
* carbon emissions (Mt) = (fuel use - ccs) * carbon intensity + embedded carbon * new capacity
*
* Notes:
*  -- we assume that the CCS system is operational during startup and apply ccs rate to
*      all fuel usage
*
* Units & Scaling:      external        this eq.
*   1x      pFuel(co2)      t/MMBTU     to  Mt/BTUe12
*   1x      vCarbonEm       Mt
*   1x      vFuelUse        BTUe12
*   1x      vNewCapacity    GW
*   1x      co2_embed       Mt/GW
eCarbonEmissions(G, S)   .. vCarbonEmissions(G, S) =e=
                                sum[(GEN_FUEL_MAP(G,F)),
                                    vFuelUse(F,G,S) *pFuel(F,'co2', S)*(1-pGen(G,'co2_ccs', S))
                                   ]
$ifthen not set fix_cap
                                + vNewCapacity(G, S)*pGen(G,'co2_embed', S)
$endif
                            ;


* == Fuel Consumption by generator for each period (eInstantFuelByGen)
* This equation implements an afine approximation (linear + intercept) for fuel use as a
* function of power output. This equation is suppressed and replaced with multiple heatrate
* segments for generators with piece-wise linear fuel use.
*
* Units & Scaling:      external        this eq.
*   1x  vInstantFuel    BTUe9/hr    to  BTUe9/hr
*   1x  heatrate        MMBTU/MWh   to  BTUe9/GWh
*   1x  p0_fuel         BTUe9/hr
*   1x  vPwrOut         GW
*   1x  vUnitCommit     integer (no units)
eInstantFuelByGen(B, T, G, S)$( B_SIM(B)
                             and (pGen(G,'gen_size', S) > 0 and not G_PWL_COST(G)) ) ..
    vInstantFuel(B, T, G, S) =e= pGen(G,'heatrate', S)*vPwrOut(B, T,G,S)
                            + pGen(G, 'p0_fuel', S)*vUnitCommit(B, T,G,S)$G_UC(G)
* For units not under unit commitment, divide up the p0 fuel usage such that it is fully
* accounted for at the p0_recover output level (typically 85%).
                            + pGen(G, 'p0_fuel', S)/pGen(G,'gen_size', S)/%p0_recover%
                                *vPwrOut(B, T,G,S)$(not G_UC(G))
                            ;
$ifthen set pwl_cost
* Units & Scaling:      external        this eq.
*   1x  vInstantFuel    BTUe9/hr    to  BTUe9/hr
*   1x  slope           MMBTU/MWh   to  BTUe9/GWh
*   1x  intercept       BTUe9/hr
*   1x  vPwrOut         GW
*   1x  vUnitCommit     integer (no units)
ePiecewiseFuelByGen (B, T, G, HR_SEG, S)$( B_SIM(B)
                                       and ( PWL_COST_SEG(G, HR_SEG) and pGen(G,'gen_size', S) > 0) )
                                              ..
    vInstantFuel(B, T, G, S) =g= pGenHrSegments (G, HR_SEG, 'slope')*vPwrOut(B, T,G,S)
                            + pGenHrSegments (G, HR_SEG, 'intercept')*vUnitCommit(B, T,G,S)$G_UC(G)
* For units not under unit commitment, divide up the p0 fuel usage such that it is fully
* accounted for at the p0_recover output level (typically 85%).
                            + pGenHrSegments (G, HR_SEG, 'intercept')/pGen(G,'gen_size',S)/%p0_recover%
                                *vPwrOut(B, T,G,S)$(not G_UC(G))
                            ;
$endif

* == Total Fuel Consuption by Generator (eFuelUse)
* Includes both startup and instantaneous use
*
* Units & Scaling:          external        this eq.
*   1000x   vFuelUse        BTUe12      to  BTUe9
*   1x      vInstantFuel    BTUe9/hr
*   1x      Demand(dur)     hr
*   1x      fuel_start      BTUe9/start
eFuelUse(F,G,S)$(GEN_FUEL_MAP(G,F)) .. vFuelUse(F,G,S)*1000 =e= sum[(B_SIM, T),
                                                vInstantFuel(B_SIM, T, G, S)*pDemand(B_SIM, T, 'dur', S)
$ifthen set startup
                                                + vStartup(B_SIM, T, G, S)$(G_UC(G)) * pGen(G, '
                                                    fuel_start', S)
$endif
                                            ];



*====== Constraints

* == Supply/Demand Balance (eDemand)
* It is important to use equality here, since we are interested in effects of minimum output limits, etc
      .
*
* Note: reserves are enforced in separate equations below
*
* Units & Scaling:      external        this eq.
*   all in GW
eDemand (B, T,S)$B_SIM(B)    .. sum[(G), vPwrOut(B, T, G,S)]
$ifthen not set no_nse
                    + vNonServed(B, T,S)
$endif
                    =e= pDemand(B, T,'power',S);


$ifthen.no_rsrv NOT set rsrv
*====== Generation output less than upper limit(s)
* Here we only worry about non-reserve limits. With reserves these equations will be
* replaced with expanded versions from the shared file AdvPwrReserves. Still there are
* multiple cases of interest:
*
* 1) Simplest (ePwrMax) is power out < installed capacity, with adjustments described below
* 2) For generation subject to unit commitment, things change slightly since we now only output
*    power up to the number of units that are turned on (ePwrMaxUC)
* Furthermore,  we might choose to derate the power output of the plant separately from
* availability (typically for simple models), this can be done by taking the minimum of availability
* and the derate factor. Since both are parameters, this is a valid (MI)LP formulation. Note that
* this derating is already taken into account for in eUnitCommit for the UC equations.

* == Output must be below the generator upper limits (ePwrMax)
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
*Note: Availability is handled in eState for unit commitment constrained generators
*
* Units & Scaling:
*   vPwrOut & capacity      GW
*   derate & pGenAvail      p.u.
ePwrMax (B, T, G, S)$( B_SIM(B)
                    and (not G_UC(G)) ) ..
                vPwrOut(B, T, G, S)  =l=  %capacity_G% *
```

```
$ifthen set derate
                            min( pGen(G, 'derate', S),
$else
                            (
$endif
                              pGenAvail(B, T, G, S)
                            );


* == Output Upper Limit for UnitCommitment Gens (ePwrMaxUC)
*
* Units & Scaling:
*   vPwrOut & gen_size      GW
*   vUnitCommit             integer
ePwrMaxUC (B, T, G, S)$( B_SIM(B)
                      and G_UC(G)
                      and pGen(G, 'gen_size', S) ) ..
                vUnitCommit(B, T,G,S) * pGen(G, 'gen_size', S) =g= vPwrOut(B, T, G, S);


*====== Generation output greater than lower limit(s)
* Here we find a complementary situation to the PwrMax equations described above
* (Still only included if no reserves defined)

* == Power greater than lower limits (ePwrMin)
* For simple models we might use a "technology minimum output" as a proxy for
* baseload plants. This lower limit is applied to entire generator category and is ignored by
* using p_min=0 or not defining p_min (unspecified parameters default to zero).
*
* Units & Scaling:
*   vPwrOut & capacity      GW
*   p_min                   p.u.
ePwrMin (B, T, G, S)$B_SIM(B) ..   vPwrOut(B, T, G, S) =g= %capacity_G% * pGen(G,'p_min', S);


* == Power greater than lower limits for Unit Commitment (ePwrMinUC)
* Minimum power output for commitment generators under UC
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
*
* Units & Scaling:
*   vPwrOut & unit_min      GW
*   vUnitCOmmit             #units
ePwrMinUC (B, T, G, S)$( B_SIM(B)
                      and G_UC(G) )
                .. vPwrOut(B, T, G, S) =g= vUnitCommit(B, T,G,S) * pGen(G, 'unit_min',S);

$endif.no_rsrv


*======  Additional Constraints

* == Renewable Portfolio Standard (eRPS)
* renewable energy / total energy > RPS
*
* Units & Scaling:
*   vPwrOut         GW
*   Demand(dur)     hr
*   pRPS            p.u.
eRPS(S)        ..  sum[(B_SIM, T, G_RPS), vPwrOut(B_SIM, T, G_RPS,S)*pDemand(B_SIM, T, 'dur',S)]
$ifthen set rps_penalty
                    + vUnderRPS(S)
$endif
                   =g=
                    pRPS(S)*sum[(G, B_SIM, T), vPwrOut(B_SIM, T,G,S)*pDemand(B_SIM, T, 'dur', S)];


* == Carbon Limit (eCarbonCap)
* Units & Scaling:
*   all in Mt CO2(e)
eCarbonCap(S)  ..  sum[(G), vCarbonEmissions(G, S)] =l= pCarbonCap(S);


* == Force use of renewables if required (eForceRenewables)
*force the use of all renewable output (up to 100% of load)
$ifthen.force_re set force_renewables
$ifthen.fix_cap set fix_cap
* Units & Scaling:
*   vPwrOut, cap_cur, pDemand(power)        GW
*   pGenAvail                               p.u.
* If capacity if fixed, we can use minimum of available power and demand (both parameters)
   eForceRenewables(B, T, S)$(B_SIM(B)) .. sum[(G)$G_RPS(G), vPwrOut(B, T, G, S)] =e=
                   min(  sum[(G)$G_RPS(G), pGen(G,'cap_cur', S)*pGenAvail(B, T,G,S)], pDemand(B, T, '
                         power', S) );
$else.fix_cap
* But if capacity is a decision variable, it is non-linear to use in the min, so we simply
* take all power. This will break if we have instant renewable power out > demand.
*
* Units & Scaling:
*   vPwrOut, cap_cur, vNewCapacity        GW
*   pGenAvail                               p.u.
   eForceRenewables(B, T, G, S)$( B_SIM(B)
                               and G_RPS(G) )
                .. vPwrOut(B, T, G, S) =e=
                   (pGen(G,'cap_cur',S) + vNewCapacity(G,S)) * pGenAvail(B, T,G,S);
$endif.fix_cap
$endif.force_re


*======  Unit Commitment Constraints

* == Limit commitments to available capacity (eUnitCommit)
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
* Units & Scaling:
*   vUnitCommit             #units (# of gens)
*   gen_size                GW/unit
*   capacity_G              GW
*   pGenAvail, derate       p.u.
eUnitCommit(B, T,G,S)$( B_SIM(B)
                     and G_UC(G) )
                .. vUnitCommit(B, T,G,S)
                    =l=
                    %capacity_G% / pGen(G, 'gen_size',S) *
$ifthen set derate
                    min( pGen(G, 'derate',S),
$else
                    (
$endif
                    pGenAvail(B, T, G, S)
                    );

* == Integerization for required gens (eUnitCommitInteger)
* This simple equation works since vUcInt is defined as an integer variable, and hence the
* otherwise continuous vUnitCommit will take on integer values as well for all members of the
* G_UC_INT subset. The redundant continuous variable should be removed during (MI)LP pre-solve
$ifthen.not_uc_lp not set uc_lp
```

```
   eUnitCommitInteger(B, T,G,S)$(B_SIM(B) and G_UC_INT(G) ) .. vUnitCommit(B, T,G,S) =e= vUcInt(B, T,G,S
          );
   eStartUpInteger(B, T, G, S)$(B_SIM(B) and G_UC_INT(G) ) .. vStartUp(B,T,G,S) =e= vStartInt(B,T,G,S);
   eShutDownInteger(B, T, G, S)$(B_SIM(B) and G_UC_INT(G) ) .. vShutDown(B,T,G,S) =e= vShutInt(B,T,G,S);
$endif.not_uc_lp

* == If startup costs or restrictions in use, compute startup & shutdowns (eState)
$ifthen set compute_state
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
   eState  (B, T,G,S)$(B_SIM(B) and G_UC(G))  ..
            vUnitCommit(B, T,G,S)
            =e= vUnitCommit(B, mDemShift(T,1),G,S) + vStartUp(B, T,G,S) - vShutDown(B, T,G,S);
$endif

* == Limit the total number of startups per generator group (eMaxStart)
* Note: pGen(max_start) already scaled from starts/yr to starts/model_timeframe by AdvPwrDataRead
*
* Units & Scaling:
*   vStartUp        starts, summed over all demand periods.
*   gen_size        GW/unit
*   capacity_G      GW
*   max_start       starts/unit/model_duration
$ifthen set max_start
   eMaxStart(G,S)$( (pGen(G,'gen_size',S) > 0) and (pGen(G, 'max_start',S) < Inf) ) ..
      sum[(B_SIM, T), vStartUp(B_SIM, T,G,S)] =l= %capacity_G% / pGen(G,'gen_size',S) * pGen(G, '
            max_start',S);
$endif

*======  Ramping Constraints ======
$ifthen.ramp_eq set ramp

* ===== Ramping for Clusters
* In this case, we restrict ramping to the limits of plants that are on-line for both this period
* and last period + the unit minimums for any units that startup or shutdown. Using the unit
* minimums is logical for startup, but conservative for shutdown because it forces units to ramp
* down before shutting off. It is tempting to use gen_size of shutdowns for ramp down, but this
* is likely incorrect because the plant is probably not running at full output power.
*
* Note: this constraint is made trickier by our use of lumped integer commitment since we don't know
* output levels for individual units.

* == Upward Ramp Limits with Unit Commitment (eRampUpLimitUC)
* Use these integer based limits for technologies with integer unit_commitments
* For UC ramp-up = ramp rate for committed units + startups
*  with startups limited either by min_out or by ramp_rate for new units
*
* Note: We ignore demand block durations and impose this limit between blocks
*
* Units & Scaling:
*   vPwrOut, unit_min       GW
*   gen_size                GW/unit
*   ramp_max                p.u./hr
*   vUnitCommit, vStartup   #units

    eRampUpLimitUC(B, T,G,S)$( B_SIM(B)
                            and G_UC(G)
                            and G_RAMP(G) )
                    .. vPwrOut(B, T, G, S) - vPwrOut(B, mDemShift(T,1), G, S)
                        =l=
                        pGen(G, 'ramp_max', S)*pGen(G, 'gen_size', S)
                            * (vUnitCommit(B,T,G,S) - vStartup(B,T,G,S))
                        + min(pGen(G, 'gen_size', S),
                              max(pGen(G, 'unit_min', S),
                                  pGen(G, 'quick_start', S)*pGen(G, 'gen_size', S),
                                  pGen(G, 'ramp_max', S)*pGen(G, 'gen_size', S)
                                 )
                             )*vStartup(B,T,G,S)
                        - pGen(G, 'unit_min', S)*vShutdown(B,T,G,S);


* == Downward Ramp Limits with Unit Commitment (eRampDownLimitUC)
* For UC ramp-down = ramp rate for committed units + shutdowns
*  with shutdowns limited either by min_out or by ramp_rate for new units
*
* Note: We ignore demand block durations and impose this limit between blocks
*
* Units & Scaling:
*   vPwrOut, unit_min       GW
*   gen_size                GW/unit
*   ramp_max                p.u./hr
*   vUnitCommit, vShutDown  #units
    eRampDownLimitUC(B, T,G,S)$( B_SIM(B)
                            and G_UC(G)
                            and G_RAMP(G))
                    ..
                    vPwrOut(B, mDemShift(T,1), G, S) - vPwrOut(B, T, G, S)
                    =l=
                    pGen(G, 'ramp_max', S)*pGen(G, 'gen_size', S)
                        * (vUnitCommit(B,T,G,S) - vStartup(B,T,G,S))
                    - pGen(G, 'unit_min', S)*vStartup(B,T,G,S)
                    + min(pGen(G, 'gen_size', S),
                          max(pGen(G, 'unit_min', S),
                              pGen(G, 'ramp_max', S)*pGen(G, 'gen_size', S)
                             )
                         )*vShutDown(B,T,G,S);


* == Upward Ramp Limits for non-Unit-Commitment generators (eRampUpLimit)
* Use total capacity based limits for everything else
* Rather than using the De Jonghe, et al 2011 ramping formulation based on FlexUp and FlexDown
* we use explicit ramping limit relations. We do this b/c FlexUp and FlexDown try to capture
* flexibility _within_ the hour, rather than between hours as in ramping
*
* This equation replaces eq 14 in De Jonghe, et al 2011. Here we simply assume that
* all capacity can contribute to ramping, since a given power out level could be from units
* running under full capacity. This limit exactly matches the UC limit if we assume all non-UC
* units are always running. It can over & under estimate with startup/shutdown.
*
* Note: We ignore demand block durations and impose this limit between blocks
*
* Units & Scaling:
*   vPwrOut, capacity       GW
*   ramp_max, quick_start   p.u./hr
*   pGenAvail               p.u.

    eRampUpLimit(B, T,G,S)$( B_SIM(B)
                        and G_RAMP(G)
                        and not G_UC(G) ) ..
                    vPwrOut(B, mDemShift(T,1), G, S) - vPwrOut(B, T, G, S)
                    =l=
                    max(pGen(G, 'ramp_max', S), pGen(G, 'quick_start', S))
                      * ( %capacity_G% *pGenAvail(B, T, G, S));

* == Downward Ramp Limits for non-Unit-Commitment generators (eRampDownLimit)
* Likewise, this equation replaces eq 15 in De Jonghe, et al 2011. Here we simply assume that
* all capacity can contribute to ramping, since a given power out level could be from units
```

```
* running under full capacity. This limit exactly matches the UC limit if we assume all non-UC
* units are always running. It can over & under estimate with startup/shutdown.
*
* Units & Scaling:
*   vPwrOut, capacity       GW
*   ramp_max                p.u./hr
*   pGenAvail               p.u.

    eRampDownLimit(B, T,G,S)$( B_SIM(B)
                            and G_RAMP(G)
                            and not G_UC(G) ) ..
                    vPwrOut(B, mDemShift(T,1), G, S) - vPwrOut(B, T, G, S)
                    =l=
                    pGen(G, 'ramp_max', S) * (%capacity_G%*pGenAvail(B,T,G,S));
$endif.ramp_eq

*================================*
*        Handle The Data         *
*================================*

* Read in standard data file set & handle command-line overrides. Including
*  -- sys, gens, demand, fuel, & avail data
*  -- update file
*  -- command-line overrides including: demscale, rps, co2cost, co2cap
*  -- additional options including: force_gen_size, min_gen_size, basic_pmin,
*      uc_ignore_unit_min, avg_avail
* Also computes sub-sets for G_UC, G_RPS, G_WIND, G_RAMP
$include %shared_dir%AdvPwrDataRead


* ====== Additional Calculations...

* == Identify generators for piecewise linear approximations
* Start by excluding all generators, which also sets thing properly for the non-pwl_cost case
G_PWL_COST(G) = no;
* Then if pwl_cost is set, we include any generator's that have a non-zero slope or intercept
* for the first segment, and include any segments with non-zero slope or intercepts
$ifthen set pwl_cost
    G_PWL_COST(G)$( (pGenHrSegments (G, 'seg1', 'slope') <> 0)
                        or (pGenHrSegments (G, 'seg1', 'intercept')) ) = yes;
    PWL_COST_SEG(G, HR_SEG)$( (pGenHrSegments (G, HR_SEG, 'slope') <> 0)
                                or (pGenHrSegments (G, HR_SEG, 'intercept') <> 0) ) = yes;
$endif

* == Compute max integers for unit_commitment states
*Note: by default GAMS restricts to the range 0 to 100 so this provides two features:
*  1) allowing for higher integer numbers for small plant types as required for a valid solution
*  2) Restricting the integer search space for larger plants
*Important: For capacity expansion problems, this parameter MUST be changed to account for new plants

$ifthen.max_plants %model_name% == UnitCommit

*Here we simply use the current capacity divided by the plant size.
  pMaxNumPlants(G, S)$pGen(G, 'gen_size', S) = ceil(pGen(G, 'cap_cur', S)/pGen(G, 'gen_size', S));

$ifthen set unit_commit
    vUcInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
$endif

$ifthen not set uc_lp
    vStartInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
    vShutInt.up(B_SIM, T, G_UC, S) = pMaxNumPlants(G_UC, S);
$endif

$ifthen set maint
    vOnMaint.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
    vMaintBegin.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
    vMaintEnd.up(B, G, S)$(pGen(G, 'maint_wks', S) > 0) = ceil(%max_maint% * pMaxNumPlants(G, S));
*Fix maintenance at zero if maintenance not required
      vOnMaint.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
    vMaintBegin.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
    vMaintEnd.fx(B, G, S)$(pGen(G, 'maint_wks', S) = 0) = 0;
$endif

$endif.max_plants

* ===== Take some initial guesses =====
vNonServed.l(B_SIM, T, S) = 0;

*================================*
*   Additional Data Processing   *
*================================*

* Enable $ variables from included model(s) to propagate back to this master file
$onglobal

* Include water limiting equations and associated parameters and variables
$if set calc_water $include %shared_dir%WaterDataSetup

* Disable influence of $ settings from sub-models
$offglobal

*================================*
*       Solve & Related          *
*================================*
*Only run the rest of this file if we are the main function.
$ifthen.we_are_main %model_name% == UnitCommit


* ======  Setup the model
* Skip this definition if we are doing a restart
    model %model_name%  /all/;

* ======  Adjust Solver parameters
* Enable/Disable Parallel processing
$if not set par_threads $setglobal par_threads 1
$if not set lp_method $setglobal lp_method 4

*Create a solver option file
$onecho > cplex.opt
* Note: the number of threads can either be specified explicitly or using "0" for use all cores
threads %par_threads%

*Parallel mode. Options:
* 1=deterministic & repeatable, 0=automatic, -1=opportunistic & non-repeatable
parallelmode %par_mode%

* Conserve memory when possible... hopefully avoid crashes b/c of memory
memoryemphasis 1

* Declare solution method for pure LP, RMIP, and final MIP solve.
*   Options: 0=automatic, 2=Dual Simplex, 4=barrier, 6=concurrent (a race between
* dual simplex and barrier in parallel)
*
* Sometimes barrier is notably faster for operations problems, but more often dual simplex wins
* Barrier is often better for planning problems
```

```
LPmethod %lp_method%
* Solution method for solving the root MIP node. See description and options for LPmethod above
startalg %lp_method%
* Solution method for solving sub MIP nodes. See description and options for LPmethod above
* subalg %lp_method%

* Tighten LP tolerance (default 1e-6). For problems with objective values close to 1, this
* may be necessary to find the true optimal. In particular, with MILP, using the default can
* cause the final LP solve to stop short of finding the best node from the MILP branch-and-cut
* Surprisingly, a tighter tolerance can also achieve FASTER run times for MILP, presumably
* because the nodes can be compared more carefully.
epopt 1e-9

* Stay with barrier until the optimal solution is found rather than crossing over to simplex
* This can run much faster for these problems, because the final simplex iterations can be
* slow and b/c the cross-over itself takes a good bit of time. However, the approach is not
* robust and can fail or be slower than the default behavior. Not recommended with barrier
* alone (LPmethod = 4) b/c may not converge. Consider for concurrent optimization.
*barcrossalg -1

* Ignore small (dual) infeasibilities in the final LP solve. Without this setting, occasionally
* CPLEX will get unhappy with an infeasibility on the order of 1e-6
relaxfixedinfeas 1

*enable relative epsilon optimal (cheat) parameter
*This value is not used if cheat is defined
relobjdif %rel_cheat%

$offecho

*Tell GAMS to use this option file
%model_name%.optfile = 1;

* ======  Tune performance with some initial guesses and settings to speed up the solution
$if set cheat %model_name%.cheat = %cheat%;


* ====== Check command line options
* Check spelling of command line -- options
* Notes:
*  - all command line options have to have either been used already or be listed
* here to avoid an error. We place it here right before the solve statment such that
* if there is an error, we don't wait till post solution to report the problem
$setddlist ignore_integer summary_only summary_and_power_only memo gdx out_gen_params out_gen_avail
       out_gen_simple p2c_debug debug_off_maint

* ======  Actually solve the model
$ifthen set ignore_integer
     solve %model_name% using RMIP minimizing vObjective;
$else
     solve %model_name% using MIP minimizing vObjective;
$endif

*=================================*
*         Postprocessing         *
*=================================*

* ======  Post processing computations
* Most of these calculations are standardized in ../shared/calcSummary.gms
$include %shared_dir%calcSummary.gms

* ======  Write Standard Results to CSV files
*-- Suppress CSV output if no_csv flag is set
$if "no_csv = 1" $ontext
$include %shared_dir%writeResults.gms

*-- end of output suppression when no_csv flag is set
$if "no_csv = 1" $offtext


$if set gdx execute_unload '%out_dir%%out_prefix%solve.gdx'

* Write value of all control variables to the list file (search for Environment Report)
$show

$endif.we_are_main
```

ListingD.3: AdvPwrDataRead.gms: shared include file to read and pre-process data files.

```
*=================================*
*        Handle The Data         *
*=================================*

* ====== Include Data files
* ---- Big picture problem setup
* Read in the scenario list first, if defined, so that we can properly populate the S set
* during subsequent data file reads
$ifthen set scen
$include %data_dir%%scen%
* If no scenario list is defined, establish a baseline default with only one scenario
$else
  set
    S   "scenario for multi-period and stochastic problems"
        /onlyS/
    ;
    pScenWeight('onlyS') = 1;
$endif

* By default use test_sys.inc if not not passed at the command line
$if NOT set sys    $setglobal sys    test_sys.inc

* Actually do include the system data definition file
* Note: often includes defaults for fuel, demand, gens, gparams, and/or avail
$include %data_dir%%sys%

* ---- Read-in scenario independent data tables
* Initially read in complete, baseline data from data files (not scenario differentiated)
* using the p*Data set of parameters that are not indexed by S
$if set fuel   $include %data_dir%%fuel%
$if set demand $include %data_dir%%demand%
* Note: include demand before gens, so can use the demand levels for time varying availabiilty
```

```
$if set gens   $include %data_dir%%gens%

* Use default generator parameters when needed
$ifthen set gparams
* First read in the data
$include %data_dir%%gparams%
* Then for any generator parameter that has a zero value, fill in the missing data
* from the corresponding default value.
*
* We do this before reading in availability data since the availability data might rely on
* information provided by the Gparams table
*
* Note: in this case the smax function is used to pull out a single matching data item. It
* is expected that there is only one match in the pGenDefaults table.
    pGenData(G,GEN_PARAMS)$(not pGenData(G,GEN_PARAMS))
        = smax[(GEN_TYPE)$( pGenData(G,'type')=pGenDefaults(GEN_TYPE,'type') ),
                    pGenDefaults(GEN_TYPE, GEN_PARAMS)];

* Summary data expresses minimum output in per unit. So here we convert to a power output level.
    pGenData(G,'unit_min')$(not pGenData(G,'unit_min'))
        = pGenData(G,'unit_min_pu') * pGenData(G,'gen_size');
$endif

* Divide out maintenance cost per week from O&M for any entries with maint req'd & no
* specific maintenance cost set (a zero value for c_maint_wk implies no specific cost set)
$ifthen set maint
$if not set maint_om_fract $setglobal maint_om_fract 0.5
    set
        G_OM_Maint(G)   "Subset of gens to divide fixed O&M costs among maint_wks"
        ;

    G_OM_Maint(G)$(pGenData(G, 'maint_wks') > 0 and  pGenData(G, 'c_maint_wk') = 0) = yes;

    pGenData(G, 'c_maint_wk')$G_OM_Maint(G)
        = %maint_om_fract% * pGenData(G, 'c_fix_om') / (pGenData(G, 'maint_wks'));
    pGenData(G, 'c_fix_om')$G_OM_Maint(G)
        = (1-%maint_om_fract%) * pGenData(G, 'c_fix_om');
$endif

*Handle retirements
$ifthen set retire
*Setup a parameter so we can subtract from both cap_cur and cap_max
    parameter
        pCapToRetire(G) "Current capacity to retire GW"
    ;
    pCapToRetire(G) = %retire% * pGenData(G, 'cap_cur');
    pGenData(G, 'cap_cur') = pGenData(G, 'cap_cur') - pCapToRetire(G);
    pGenData(G, 'cap_max') = pGenData(G, 'cap_max') - pCapToRetire(G);
$endif

*Read in availability data. If not specified, assume 100% availability for all
$ifthen set avail
$include %data_dir%%avail%
$else
    pGenAvail(B, T,G,S) = 1;
$endif

* ---- Match our scenario independent p*Data with the corresponding scenario indexed parameter
pFuel(F, FUEL_PARAMS, S) = pFuelData(F, FUEL_PARAMS);
pDemand(B, T, DEM_PARAMS, S) = pDemandData(B, T, DEM_PARAMS);
pGen(G, GEN_PARAMS, S)  = pGenData(G, GEN_PARAMS);

*If we have an availability matching demand set (D_AVAIL)
$ifthen.d_avail defined D_AVAIL
*Pull out the subset of availability data that matches our in-use demand periods
* Note: the mapping takes a few seconds for large data sets, consider a dedicated pGenAvail
*  for commonly used large data sets
* The mapping set was ~4x faster than attempting to put the conditional directly in the smax[]
    set
        AVAIL_MAP(B, T, D_AVAIL)
    ;
    AVAIL_MAP(B,T,D_AVAIL)$(pDemandData(B,T,'avail_idx') = ord(D_AVAIL)) = yes;
$ifthen defined pGenAvailDataByScen
    pGenAvail(B, T, G, S) = smax[(D_AVAIL)$AVAIL_MAP(B, T, D_AVAIL), pGenAvailDataByScen(D_AVAIL, G, S)
            ];
$elseif defined pGenAvailData
    pGenAvail(B, T, G, S) = smax[(D_AVAIL)$AVAIL_MAP(B, T, D_AVAIL), pGenAvailData(D_AVAIL, G)];

$endif
$else.d_avail
*Otherwise, assume matching B, T set membership and copy to all scenarios
$ifthen defined pGenAvailDataByScen
    pGenAvail(B, T, G, S) = pGenAvailDataByScen(B, T, G, S);
$elseif defined pGenAvailData
    pGenAvail(B, T, G, S) = pGenAvailData(B, T, G);
$endif
$endif.d_avail


* ---- Process Scenario Value file
*
* Note this file works in S space, so most parameters must be indexed by S and the
* scenario dependent parameters: pFuel, pDemand, pGen, and pGenAvail should be used. Changes
* to the p*Data parameters (pGen, pDemand, etc) will NOT be used
$if set scen_val $include %data_dir%%scen_val%

* ---- Process update file.
* Now allow for updates to any of the parameters for easier interfacing to external programs
* by loading this file after all of the core data, we can update the actual values used in the
* optimization. (Note: only possible b/c $onmulti used)
*
* Note the update file works in S space, so most parameters must be indexed by S and the
* scenario dependent parameters: pFuel, pDemand, pGen, and pGenAvail should be used. Changes
* to the p*Data parameters (pGenData, pDemandData, etc) will NOT be used
$if set update $include %update%

*Return to listing in the output file
$if not set debug $onlisting

* ===== Additional Command Line Parameters
*override CO2 price with command line setting if provided
$if set co2cost pCostCO2(S)=%co2cost%;

*override Demand scaling with command line setting if provided
$if set demscale pDemandScale(S)=%demscale%;

*override RPS level with command line setting if provided
$if set rps pRPS(S)=%rps%;

*override Carbon Cap (Kt) with command line setting if provided
$if set co2cap pCarbonCap(S)=%co2cap%;

*override planning margin value if provided a fraction < 100% (no spaces allowed)
$if set plan_margin $if not "%plan_margin%"=="on" $if not "%plan_margin%"=="off" $ife %plan_margin%<1
      pPlanReserve=%plan_margin%;
```

```
*allow user to specify a uniform gen_size
$if set force_gen_size pGen(G,'gen_size', S) = %force_gen_size%;
*and minimum plant size
$if set min_gen_size pGen(G,'gen_size', S) = max(pGen(G,'gen_size', S), %min_gen_size%);

*remove p_min value if not used
$if not set basic_pmin pGen(G, 'p_min', S) = 0;

*Zero out capital costs if not used
$if set no_capital pGen(G, 'c_cap', S) = 0;

*Set derating for maintenance only if requested
$if set derate_to_maint pGen(G, 'derate', S) = 1-pGen(G, 'maint_wks', S)/52;

*Zero out quickstart fraction of spin/flex reserves when disabled
$if set no_quick_st pQuickStSpinSubFract = 0;


*================================*
*    Additional Calculations     *
*================================*
* ====== Calculate subsets
*only include elements where the generator fuel name parameter matches the fuel name parameter
GEN_FUEL_MAP(G, F)$(pGenData(G,'fuel') = pFuelData(F,'name')) = yes;

*only solve unit commitment for plants with non-zero minimum outputs
$if NOT set uc_ignore_unit_min    $setglobal uc_ignore_unit_min 0
$if NOT set uc_int_unit_min    $setglobal uc_int_unit_min 0

** Assign gens to unit commitment sets
*start by setting all to not included
G_UC(G) = no;
G_UC_INT(G) = no;

*then add in if needed, note duplicate code b/c $ifthen doesn't like or
$if set unit_commit $setglobal unit_commit %unit_commit%
$ifthen.uc_set set unit_commit
$ifthen.uc_on   "%unit_commit% test" == "on test"
    G_UC(G)$(pGenData(G,'unit_min') > %uc_ignore_unit_min%) = yes;
    G_UC_INT(G)$(G_UC(G) and (pGenData(G,'unit_min') > %uc_int_unit_min%)) = yes;
$elseif.uc_on     %unit_commit% == 1
    G_UC(G)$(pGenData(G,'unit_min') > %uc_ignore_unit_min%) = yes;
    G_UC_INT(G)$(G_UC(G) and (pGenData(G,'unit_min') > %uc_int_unit_min%)) = yes;
$endif.uc_on
$endif.uc_set

*include all wind, solar, and geotherm plants in the RPS standard
acronyms wind, solar, geotherm;
G_RPS(G)$(pGenData(G,'fuel') = wind) = yes;
G_RPS(G)$(pGenData(G,'fuel') = solar) = yes;
G_RPS(G)$(pGenData(G,'fuel') = geotherm) = yes;

*create set for wind generators (for increased reserve requirements)
G_WIND(G)$(pGenData(G,'fuel') = wind) = yes;

*Only worry about ramping for plants with ramp limits < 1
G_RAMP(G)$(pGenData(G,'ramp_max') < 1) = yes;

*Handle time/demand subsets
* Note: for simple demand subsets to work, three control variables must be defined:
*          d_subset: flag to use subsets, rather than all demand periods
*          d_start:  first demand block to include (an integer)
*          d_end:    last demand block to include (an integer)
```

```
$ifthen.d_subset set d_subset
$ifthen.d_start set d_start
$ifthen.d_end set d_end
    B_SIM(B)$( ord(B) >= %d_start% and ord(B) <= %d_end% ) = yes;
$endif.d_end
$endif.d_start
$else.d_subset
    B_SIM(B) = yes;
$endif.d_subset


* ====== Calculate parameters
*Scale demand
pDemand(B, T,'power', S) = pDemandScale(S) * pDemand(B, T,'power', S);

*compute capital recovery factor (annualized payment for capital investment)
$if declared pCRF
pCRF(G)$(pGenData(G, 'cap_max')) = pWACC/(1-1/( (1 + pWACC)**pGenData(G,'life') ));

*Remove Wind driven Flex Down constraints if we allow wind shedding. b/c rather than
*ramping thermal down, we could simply shed wind
$ifthen.rsrv set rsrv
$ifthen not set force_renewables
    pWindFlexDownForecast = 0;
    pWindFlexDownCapacity = 0;
$endif
$endif.rsrv

* -- Use piecewise linear data for affine parameters if requested
$ifthen set pwl2afine
* If the generator has a defined first segment, extract & use the segment with the highest
* slope which b/c we assume concave, will be the last segment
    pGen(G,'heatrate', S)$(pGenHrSegments(G,'seg1','slope'))
        = smax[(HR_SEG), pGenHrSegments(G,HR_SEG, 'slope')];

* If the generator has a defined first segment, extract & use the segment with the lowest
* intercept that also has a positive slope which b/c we assume concave, will be the last segment
    pGen(G,'p0_fuel', S)$(pGenHrSegments(G,'seg1','slope'))
        = smin[(HR_SEG)$(pGenHrSegments(G,HR_SEG, 'slope') > 0),
                pGenHrSegments(G,HR_SEG, 'intercept')];
$endif

*Assign +INF to the cost of non served energy if it is not allowed
$if set no_nse pPriceNonServed = +inf;

display "Generator Data Table after AdvPwrDataRead...";
display pGen;

$ifthen.debug_avail set debug_avail
$ifthen defined pGenAvailData
    display "Raw Availability Data";
    display pGenAvailData;
$endif
$ifthen defined pGenAvailDataByScen
    display "Raw Availability Data by Scenario";
    display pGenAvailDataByScen;
$endif
    display "Availability Table after demand period matching";
    display pGenAvail;
$endif.debug_avail

* ====== Demand period based parameters
parameters
```

```
* Additional Parameters that may not have been defined
    pGenAvgAvail (G, S)             "average availability (max capacity factor)"

    pTotalDurationHr(S)             "the total time for the demand data in hrs"
    pFractionOfYear (S)             "fraction of year covered by the simulation"
    pDemandMax(S)                   "maximum demand for scenario [GW]"
    pDemandAvg(S)                   "average demand for scenario [GW]"
    pBlockDurWk(B, S)               "duration for each block in weeks"
;

pTotalDurationHr(S) = sum[(B, T), pDemand(B, T, 'dur', S)];
pFractionOfYear(S) = pTotalDurationHr(S)/8760;
pBlockDurWk(B, S) = sum[(T), pDemand(B, T, 'dur', S)] / 168;

$ifthen set debug_block_dur
    display "Block durations in weeks";
    display pBlockDurWk;
$endif


*Find resulting max demand
pDemandMax(S) = smax[(B, T), pDemand(B, T, 'power', S)];
*And resulting average demand
pDemandAvg(S) = sum[(B, T), pDemand(B, T, 'power', S)*pDemand(B, T, 'dur', S)] / pTotalDurationHr(S);

*Compute average availability for each generator
pGenAvgAvail(G, S) = sum[(B, T), pGenAvail(B, T, G, S)*pDemand(B, T, 'dur', S)] / pTotalDurationHr(S);


*Convert time varying to average availabilities if desired
$ifthen set avg_avail
    pGenAvail(B, T,G,S) = pGenAvgAvail(G,S);
$endif

* -- Scale annual values based on total simulation time
* max_num of startups
$ifthen set max_start
    pGen(G, 'max_start', S) = round(pGen(G, 'max_start', S) * pFractionOfYear(S));
$endif

$setglobal data_has_been_read
$label label_skip_data_read
```

ListingD.4: AdvPwrSetup.gms: shared include file to setup GAMS options, directories, and macros.

```
*================================*
*            Setup               *
*================================*

* ======  GAMS Options
*display $dollar commands in lst file (for easier pre-compiler debugging)
$ondollar
* Allow declaration of empty sets & variables
$onempty
* Allow additions to set elements with multiple set definitions
$onmulti
* Include symbol list in LST file
$onsymlist
*Enable alternate loop syntax using end* rather than ()'s
$onend


*get a more precise MIP solution  (optcr is relative convergence). GAMS default is only 10%
$if not set mip_gap $setglobal mip_gap 0.001
option optcr=%mip_gap%

*Allow for extra execution time. units are seconds of execution (needed to extend the GAMS default
* of only 1000 to successfully solve larger problems)
$if not set max_solve_time $setglobal max_solve_time 10800
option reslim = %max_solve_time%;

*Default to not using a relative cheat parameter
$if NOT set rel_cheat $setglobal rel_cheat 0

*Default to deterministic parallel mode
$if NOT set par_mode $setglobal par_mode 1

* Reduce the size of the LST file
* Turn off equation listing, (unless debug on) see below
* Note: limrow specifies the number of cases for each equation type that are included in the output
option limrow = 0;

* Turn off variable listing, (unless debug on) see below
* Note: limrow specifies the number of cases for each equation type that are included in the output
option limcol = 0;

*=== Solution Output options
* Enable csv output by default
$if NOT set no_csv $setglobal no_csv 0

* Turn off solution printing unless csv output is disabled
$ifthen %no_csv% == 1
    option solprint = on ;
$else
    option Solprint = off ;
$endif

*=== Debug options
*enable additional debugging information
$ifthen set debug
* include 10 example equation of each type
    option limrow = 10;
* inlude 10 example variables of each type
    option limcol = 10;
* Include solver output information
    option sysout = on;
* Print the solution (seems to happen even if turned off 11/2010 -BSP)
    option solprint = on;
* Include symbol cross-reference in LST file
$onsymxref
* Include summary execution times to identify slow assignments, etc.
    option profile = 1;
```

```
* Limit profile statements to those that take longer than 10msec
    option profiletol = 0.01;
$endif

* ======  Setup directories
* By default look for data in the sibling directory "data"
$if NOT set data_dir    $setglobal data_dir ..%filesep%data%filesep%

* By default store output in the sub-directory "out"
$if NOT set out_dir    $setglobal out_dir out%filesep%

* By default look for utilities in sibling directory "util"
$if NOT set util_dir   $setglobal util_dir ..%filesep%util%filesep%

* ======  Define Macros
* mDemShift, this is a general replacement for the set - and -- operators that allows
* the user to control whether or inter-demand period constraints loop"
$ifthen not set no_loop
$macro mDemShift(d_set, shift) d_set -- shift
$else
$macro mDemShift(d_set, shift) d_set - shift
$endif

* mDelFile, Delete an operating system file (quietly)
* Choose appropriate system delete function using filesep as a proxy for Unix-like vs Windows
* Note that both forms, quietly ignore any missing files
$ifthen %filesep% == "/"
$macro mDelFile(fname) execute "=rm -f &&fname"
$else
$macro mDelFile(fname) execute "=if exist &&fname del &&fname"
$endif

$setglobal setup_complete
$label label_skip_setup
```

ListingD.5: MaintenanceEquations.gms: shared include file for clustered maintenance.

```
*=================================*
*        Declarations           *
*=================================*
* ======  Declare Control Variables
* Default to 15% of capacity maximum on maintenance (plus 1, so always feasible)
$if not set max_maint $setglobal max_maint 0.15

* ======  Declare Parameters
parameter
    pBlockDurWk(B, S)              "duration for each block in weeks"
    ;

* ======  Declare Sets
set
    GEN_PARAMS
       /
        maint_wks   "Annual weeks of maintenance                    [wk/yr]"
        c_maint_wk   "Cost per week of maintenance                  [M$/wk]"
       /
    ;

* ======  Declare Variables
positive variables
    vMaintCost(S)     "Total maintenance cost for scenario"
    vCapOffMaint(B, T, G, S)    "Quantity of capacity available off maintenance [GW]"
$ifthen not set maint_lp
integer variables
$endif
* Note taking a queue from Ostrowski (2012) the extra integers actually help with modern
* solvers. See UnitCommitment for more
    vOnMaint(B, G, S)       "Number of units on maintenance in a block"
    vMaintBegin(B, G, S)    "Number of units starting maintenance during the block [integer]"
    vMaintEnd(B, G, S)      "Number of units finishing maintenance during the block [integer]"
    ;

* ======  Declare Equations
equations
    eMaintCost(S)         "Compute total maintenance cost for scenario"
    eMaintState(B, G, S)        "Compute maintenance begin and end"
    eMaintTime (B, G, S)        "Sum total maintenance over the time horizon"
    eTotalMaint(G, S)           "Sum total maintenance over the time horizon"
    eCapOffMaint(B, T, G, S)    "Compute resulting capacity available for dispatch"
    eMaintMax(B, G, S)          "Limit quantity of each gen type on maintenance simultaneously"
    ;

*=================================*
*     The Actual Equations      *
*=================================*
* Important: we must be included into a larger model, so no objective function defined

* == Compute total maintenance cost (eMaintState)
* Note: this formulation is the same as the unit commitment state formulation
eMaintCost(S)  ..
    vMaintCost(S)
    =e= sum[(B, G)$(pGen(G, 'maint_wks', S) > 0), vOnMaint(B, G, S) * pGen(G, 'c_maint_wk', S) *
          pBlockDurWk(B, S)];

* == Compute maintenance begin and end (eMaintState)
* Note: this formulation is the same as the unit commitment state formulation
eMaintState  (B, G, S)$(pGen(G, 'maint_wks', S) > 0)  ..
    vOnMaint(B, G, S)
    =e= vOnMaint(B--1, G, S) + vMaintBegin(B, G, S) - vMaintEnd(B, G, S);

* == Need to have sufficient Maintenance (scaled by time horizon) (eTotalMaint)
eTotalMaint(G, S)$(pGen(G, 'maint_wks', S) > 0) ..
    sum[(B), vOnMaint(B, G, S) * pBlockDurWk(B, S)]
    =g= pGen(G, 'maint_wks', S) * %max_cap_G% / pGen(G, 'gen_size', S) * pFractionOfYear(S);

* == Compute resulting capacity available for dispatch (eCapOffMaint)
* Note: must include for all generators, even without maintenance to ensure there is a
* reasonable upper limit on their dispatch
eCapOffMaint(B, T, G, S) ..
    vCapOffMaint(B, T, G, S) =e= %max_cap_G% - vOnMaint(B, G, S) * pGen(G, 'gen_size', S);

* == Limit quantity of each gen type on maintenance simultaneously (MaintMax)
```

```
eMaintMax(B, G, S)$(pGen(G, 'maint_wks', S) > 0) ..
    vOnMaint(B, G, S) =l= 1 + %max_maint% * %max_cap_G% / pGen(G, 'gen_size', S);

* == Once started, must take full time for maintanence (eMaintTime)
* Note: this formulation is basically the same as the min up/down time formulation
* the primary difference is that we sum over block duration to allow reasonable maintenance
* plans for partial year time periods
eMaintTime(B, G, S)$(pGen(G, 'maint_wks', S) > 0) ..
    vOnMaint(B, G, S)
    =g=
    vMaintBegin(B, G, S)
    + vMaintBegin(B--1, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) )
    + vMaintBegin(B--2, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) )
    + vMaintBegin(B--3, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S) )
    + vMaintBegin(B--4, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) )
    + vMaintBegin(B--5, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) + pBlockDurWk(B--4, S) )
    + vMaintBegin(B--6, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) + pBlockDurWk(B--4, S)
                                    + pBlockDurWk(B--5, S) )
    + vMaintBegin(B--7, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) + pBlockDurWk(B--4, S)
                                    + pBlockDurWk(B--5, S) + pBlockDurWk(B--6, S) )
    + vMaintBegin(B--8, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) + pBlockDurWk(B--4, S)
                                    + pBlockDurWk(B--5, S) + pBlockDurWk(B--6, S)
                                    + pBlockDurWk(B--7, S) )
    + vMaintBegin(B--9, G, S)$(pGen(G, 'maint_wks', S)
                                > pBlockDurWk(B, S) + pBlockDurWk(B--1, S) + pBlockDurWk(B--2, S)
                                    + pBlockDurWk(B--3, S) + pBlockDurWk(B--4, S)
                                    + pBlockDurWk(B--5, S) + pBlockDurWk(B--6, S)
                                    + pBlockDurWk(B--7, S) + pBlockDurWk(B--8, S) )
;
```

Listing D.6: MinUpDownEquations.gms: shared include file for minimum up and down time constraints.

```
*================================*
*        Declarations            *
*================================*
set
GEN_PARAMS
   /
    min_up
    min_down
   /
;

* ======  Declare Variables

* ======  Declare Equations
equations
    eMinUpTime(B, T, G, S)
    eMinDownTime(B, T, G, S)
    ;

*================================*
*     The Actual Equations       *
*================================*
* Important: we must be included into a larger model, so no objective function defined

* == Once on, a generator must remain on for specified number of periods (eMinUpTime)
eMinUpTime(B, T, G, S)$( B_SIM(B)
                      and G_UC(G)
                      and pGen(G, 'min_up', S) > 1
                      and pGen(G,'gen_size', S) <> 0 ) ..
    vUnitCommit(B, T, G, S)
    =g=
    vStartup(B, T, G, S)
    + vStartup(B, mDemShift(T,1), G, S)$(pGen(G, 'min_up', S) > 1)
    + vStartup(B, mDemShift(T,2), G, S)$(pGen(G, 'min_up', S) > 2)
    + vStartup(B, mDemShift(T,3), G, S)$(pGen(G, 'min_up', S) > 3)
    + vStartup(B, mDemShift(T,4), G, S)$(pGen(G, 'min_up', S) > 4)
    + vStartup(B, mDemShift(T,5), G, S)$(pGen(G, 'min_up', S) > 5)
    + vStartup(B, mDemShift(T,6), G, S)$(pGen(G, 'min_up', S) > 6)
    + vStartup(B, mDemShift(T,7), G, S)$(pGen(G, 'min_up', S) > 7)
    + vStartup(B, mDemShift(T,8), G, S)$(pGen(G, 'min_up', S) > 8)
    + vStartup(B, mDemShift(T,9), G, S)$(pGen(G, 'min_up', S) > 9)
    + vStartup(B, mDemShift(T,10), G, S)$(pGen(G, 'min_up', S) > 10)
    + vStartup(B, mDemShift(T,11), G, S)$(pGen(G, 'min_up', S) > 11)
    + vStartup(B, mDemShift(T,12), G, S)$(pGen(G, 'min_up', S) > 12)
    + vStartup(B, mDemShift(T,13), G, S)$(pGen(G, 'min_up', S) > 13)
    + vStartup(B, mDemShift(T,14), G, S)$(pGen(G, 'min_up', S) > 14)
    + vStartup(B, mDemShift(T,15), G, S)$(pGen(G, 'min_up', S) > 15)
    + vStartup(B, mDemShift(T,16), G, S)$(pGen(G, 'min_up', S) > 16)
    + vStartup(B, mDemShift(T,17), G, S)$(pGen(G, 'min_up', S) > 17)
    + vStartup(B, mDemShift(T,18), G, S)$(pGen(G, 'min_up', S) > 18)
    + vStartup(B, mDemShift(T,19), G, S)$(pGen(G, 'min_up', S) > 19)
    + vStartup(B, mDemShift(T,20), G, S)$(pGen(G, 'min_up', S) > 20)
    + vStartup(B, mDemShift(T,21), G, S)$(pGen(G, 'min_up', S) > 21)
    + vStartup(B, mDemShift(T,22), G, S)$(pGen(G, 'min_up', S) > 22)
    + vStartup(B, mDemShift(T,23), G, S)$(pGen(G, 'min_up', S) > 23)
    + vStartup(B, mDemShift(T,24), G, S)$(pGen(G, 'min_up', S) > 24)
    + vStartup(B, mDemShift(T,25), G, S)$(pGen(G, 'min_up', S) > 25)
    + vStartup(B, mDemShift(T,26), G, S)$(pGen(G, 'min_up', S) > 26)
    + vStartup(B, mDemShift(T,27), G, S)$(pGen(G, 'min_up', S) > 27)
    + vStartup(B, mDemShift(T,28), G, S)$(pGen(G, 'min_up', S) > 28)
    + vStartup(B, mDemShift(T,29), G, S)$(pGen(G, 'min_up', S) > 29)
    + vStartup(B, mDemShift(T,30), G, S)$(pGen(G, 'min_up', S) > 30)
    + vStartup(B, mDemShift(T,31), G, S)$(pGen(G, 'min_up', S) > 31)
    + vStartup(B, mDemShift(T,32), G, S)$(pGen(G, 'min_up', S) > 32)
    + vStartup(B, mDemShift(T,33), G, S)$(pGen(G, 'min_up', S) > 33)
    + vStartup(B, mDemShift(T,34), G, S)$(pGen(G, 'min_up', S) > 34)
    + vStartup(B, mDemShift(T,35), G, S)$(pGen(G, 'min_up', S) > 35)
    + vStartup(B, mDemShift(T,36), G, S)$(pGen(G, 'min_up', S) > 36)
```

```
    + vStartup(B, mDemShift(T,37), G, S)$(pGen(G, ’min_up’, S) > 37)
    + vStartup(B, mDemShift(T,38), G, S)$(pGen(G, ’min_up’, S) > 38)
    + vStartup(B, mDemShift(T,39), G, S)$(pGen(G, ’min_up’, S) > 39)
    + vStartup(B, mDemShift(T,40), G, S)$(pGen(G, ’min_up’, S) > 40)
    + vStartup(B, mDemShift(T,41), G, S)$(pGen(G, ’min_up’, S) > 41)
    + vStartup(B, mDemShift(T,42), G, S)$(pGen(G, ’min_up’, S) > 42)
    + vStartup(B, mDemShift(T,43), G, S)$(pGen(G, ’min_up’, S) > 43)
    + vStartup(B, mDemShift(T,44), G, S)$(pGen(G, ’min_up’, S) > 44)
    + vStartup(B, mDemShift(T,45), G, S)$(pGen(G, ’min_up’, S) > 45)
    + vStartup(B, mDemShift(T,46), G, S)$(pGen(G, ’min_up’, S) > 46)
    + vStartup(B, mDemShift(T,47), G, S)$(pGen(G, ’min_up’, S) > 47)
    + vStartup(B, mDemShift(T,48), G, S)$(pGen(G, ’min_up’, S) > 48)
    + vStartup(B, mDemShift(T,49), G, S)$(pGen(G, ’min_up’, S) > 49)
    ;

eMinDownTime(B, T, G, S)$( B_SIM(B)
                        and G_UC(G)
                        and pGen(G, ’min_down’, S) > 1
                        and pGen(G,’gen_size’, S) <> 0 ) ..
    (%capacity_G% / pGen(G,’gen_size’, S) - vUnitCommit(B, T, G, S))
    =g=
    vShutdown(B, T, G, S)
    + vShutDown(B, mDemShift(T,1), G, S)$(pGen(G, ’min_down’, S) > 1)
    + vShutDown(B, mDemShift(T,2), G, S)$(pGen(G, ’min_down’, S) > 2)
    + vShutDown(B, mDemShift(T,3), G, S)$(pGen(G, ’min_down’, S) > 3)
    + vShutDown(B, mDemShift(T,4), G, S)$(pGen(G, ’min_down’, S) > 4)
    + vShutDown(B, mDemShift(T,5), G, S)$(pGen(G, ’min_down’, S) > 5)
    + vShutDown(B, mDemShift(T,6), G, S)$(pGen(G, ’min_down’, S) > 6)
    + vShutDown(B, mDemShift(T,7), G, S)$(pGen(G, ’min_down’, S) > 7)
    + vShutDown(B, mDemShift(T,8), G, S)$(pGen(G, ’min_down’, S) > 8)
    + vShutDown(B, mDemShift(T,9), G, S)$(pGen(G, ’min_down’, S) > 9)
    + vShutDown(B, mDemShift(T,10), G, S)$(pGen(G, ’min_down’, S) > 10)
    + vShutDown(B, mDemShift(T,11), G, S)$(pGen(G, ’min_down’, S) > 11)
    + vShutDown(B, mDemShift(T,12), G, S)$(pGen(G, ’min_down’, S) > 12)
    + vShutDown(B, mDemShift(T,13), G, S)$(pGen(G, ’min_down’, S) > 13)
    + vShutDown(B, mDemShift(T,14), G, S)$(pGen(G, ’min_down’, S) > 14)
    + vShutDown(B, mDemShift(T,15), G, S)$(pGen(G, ’min_down’, S) > 15)
    + vShutDown(B, mDemShift(T,16), G, S)$(pGen(G, ’min_down’, S) > 16)
    + vShutDown(B, mDemShift(T,17), G, S)$(pGen(G, ’min_down’, S) > 17)
    + vShutDown(B, mDemShift(T,18), G, S)$(pGen(G, ’min_down’, S) > 18)
    + vShutDown(B, mDemShift(T,19), G, S)$(pGen(G, ’min_down’, S) > 19)
    + vShutDown(B, mDemShift(T,20), G, S)$(pGen(G, ’min_down’, S) > 20)
    + vShutDown(B, mDemShift(T,21), G, S)$(pGen(G, ’min_down’, S) > 21)
    + vShutDown(B, mDemShift(T,22), G, S)$(pGen(G, ’min_down’, S) > 22)
    + vShutDown(B, mDemShift(T,23), G, S)$(pGen(G, ’min_down’, S) > 23)
    + vShutDown(B, mDemShift(T,24), G, S)$(pGen(G, ’min_down’, S) > 24)
    + vShutDown(B, mDemShift(T,25), G, S)$(pGen(G, ’min_down’, S) > 25)
    + vShutDown(B, mDemShift(T,26), G, S)$(pGen(G, ’min_down’, S) > 26)
    + vShutDown(B, mDemShift(T,27), G, S)$(pGen(G, ’min_down’, S) > 27)
    + vShutDown(B, mDemShift(T,28), G, S)$(pGen(G, ’min_down’, S) > 28)
    + vShutDown(B, mDemShift(T,29), G, S)$(pGen(G, ’min_down’, S) > 29)
    + vShutDown(B, mDemShift(T,30), G, S)$(pGen(G, ’min_down’, S) > 30)
    + vShutDown(B, mDemShift(T,31), G, S)$(pGen(G, ’min_down’, S) > 31)
    + vShutDown(B, mDemShift(T,32), G, S)$(pGen(G, ’min_down’, S) > 32)
    + vShutDown(B, mDemShift(T,33), G, S)$(pGen(G, ’min_down’, S) > 33)
    + vShutDown(B, mDemShift(T,34), G, S)$(pGen(G, ’min_down’, S) > 34)
    + vShutDown(B, mDemShift(T,35), G, S)$(pGen(G, ’min_down’, S) > 35)
    + vShutDown(B, mDemShift(T,36), G, S)$(pGen(G, ’min_down’, S) > 36)
    + vShutDown(B, mDemShift(T,37), G, S)$(pGen(G, ’min_down’, S) > 37)
    + vShutDown(B, mDemShift(T,38), G, S)$(pGen(G, ’min_down’, S) > 38)
    + vShutDown(B, mDemShift(T,39), G, S)$(pGen(G, ’min_down’, S) > 39)
    + vShutDown(B, mDemShift(T,40), G, S)$(pGen(G, ’min_down’, S) > 40)
    + vShutDown(B, mDemShift(T,41), G, S)$(pGen(G, ’min_down’, S) > 41)
    + vShutDown(B, mDemShift(T,42), G, S)$(pGen(G, ’min_down’, S) > 42)
    + vShutDown(B, mDemShift(T,43), G, S)$(pGen(G, ’min_down’, S) > 43)
    + vShutDown(B, mDemShift(T,44), G, S)$(pGen(G, ’min_down’, S) > 44)
    + vShutDown(B, mDemShift(T,45), G, S)$(pGen(G, ’min_down’, S) > 45)
    + vShutDown(B, mDemShift(T,46), G, S)$(pGen(G, ’min_down’, S) > 46)
    + vShutDown(B, mDemShift(T,47), G, S)$(pGen(G, ’min_down’, S) > 47)
    + vShutDown(B, mDemShift(T,48), G, S)$(pGen(G, ’min_down’, S) > 48)
    + vShutDown(B, mDemShift(T,49), G, S)$(pGen(G, ’min_down’, S) > 49)
    ;
```

ListingD.7: PlanMarginEquations.gms: shared include file for planning margin.

```
*================================*
*  Additional Control Variables  *
*================================*

$if NOT set capacity_G $setglobal capacity_G pGen(G,’cap_cur’,S)

*================================*
*         Declarations           *
*================================*

* ======  Declare the data parameters. Actual data imported from include files
sets
* Sets for table parameters

    GEN_PARAMS  "generation table parameters"
       /
        cap_credit  "Capacity Credit during peak block           [p.u.]"
       /

* Sets for data, actual definitions can be found in include files
    G           "generation types (or generator list)"
    S           "scenarios for multi-period and stochastic problems"

parameters
* Data Tables
    pGen   (G, GEN_PARAMS, S)       "table of generator data"
* Additional Parameters
    pDemandMax (S)              "Maximum demand level          [GW]"

scalars
    pPlanReserve                "planning reserve              [p.u.]"
    ;

$ifthen set plan_margin_penalty
positive variables
    vUnderPlanReserve(S)        "Firm capacity below required planning reserve [GW]"
$endif
```

```
* ======  Declare Equations
equations
    ePlanMargin(S)             "Planning margin to ensure adequate capacity during peak  [p.u.]"
    ;
*=================================*
*     The Actual Equations       *
*=================================*
* Important: we must be included into a larger model, so no objective function defined

*====== Planning Reserve Margin (peak period only)
ePlanMargin(S) ..  sum[(G), %cap_for_plan_margin%*pGen(G,'cap_credit',S)]
$ifthen set plan_margin_penalty
                    + vUnderPlanReserve(S)
$endif
                     =g=
                     (1 + pPlanReserve)*pDemandMax(S);
```

ListingD.8: ReserveEquations.gms: shared include file for all types of reserves. (shared/ReserveEquations.gms)

```
*=================================*
*  Additional Control Variables  *
*=================================*
$ifthen.any_rsrv set rsrv
$if %rsrv% == flex $setglobal flex_rsrv
$if %rsrv% == separate $setglobal separate_rsrv
$ifthen %rsrv% == both
$setglobal flex_rsrv
$setglobal separate_rsrv
$endif
$endif.any_rsrv

*Default to NOT adjusting reserves for non-served energy (faster?)
$if NOT set adj_rsrv_for_nse $setglobal adj_rsrv_for_nse off

$ifthen.ar4n NOT adj_rsrv_for_nse==off
$ifthen not set no_nse
$setglobal load_for_rsrv   (pDemand(B,T,'power', S) - vNonServed(B, T,S))
$else
$setglobal load_for_rsrv   pDemand(B,T,'power', S)
$endif
$else.ar4n
$setglobal load_for_rsrv   pDemand(B,T,'power', S)
$endif.ar4n

$if NOT set capacity_G $setglobal capacity_G pGen(G, 'cap_cur', S)

$if not set non_uc_rsrv_up_offline $setglobal non_uc_rsrv_up_offline 0
$if not set non_uc_rsrv_down_offline $setglobal non_uc_rsrv_down_offline 0

*=================================*
*        Declarations            *
*=================================*

* ======  Declare the data parameters. Actual data imported from include files
scalars

*   pWindForecastError "forecast error as a fraction of wind capacity for quick start reserves [p.u.]"
*    pSpinResponseTime           "Response time for Spinning Reserves                         [minutes]"
*    pQuickStartLoadFract        "addition Fraction of load for non-spin reserves            [p.u.]"
    pSpinReserveLoadFract       "addition Fraction of load for spin reserves                [p.u.]"
    pSpinReserveMinGW           "minimum spining reserve                                    [GW]"
    pReplaceReserveGW           "offline replacement reserves to fill-in if spinning reserves are called
            [GW]"
    pRegUpLoadFract             "additional Fraction of load for regulation up              [p.u.]"
    pRegDownLoadFract           "Fraction of load over unit minimums for regulation down    [p.u.]"
    pQuickStSpinSubFract        "Fraction of Spinning Reserves that can be supplied by off-line
          generators [p.u.]"

*Additional Reserves for Wind see (De Jonghe, et al 2011)
* pWindFlexUpForecast=A_POS, pWindFlexUpCapacity=B_POS, pWindFlexDownForecast=A_NEG,
       pWindFlexDownCapacity=B_NEG
    pWindFlexUpForecast     "Additional up reserves based on wind power output (forecast)  [fraction of
          PwrOur]"
    pWindFlexUpCapacity     "Additional up reserves based on installed wind capacity [fraction of Wind
          capacity]"
    pWindFlexDownForecast   "Additional down reserves based on wind power output (forecast)  [fraction
          of PwrOur]"
    pWindFlexDownCapacity   "Additional down reserves based on installed wind capacity [fraction of Wind
           capacity]"

* ======  Declare Variables
positive variables

$ifthen set separate_rsrv
   vSpinReserve    (B,T,G,S)     "Contingency Spinning reserves service provision by generator class [GW
         ]"
   vNetLoadFollowDown(B,T,G,S)     "Load follow down reserves service provision by generator class [GW]"
   vRegUp          (B,T,G,S)     "Regulation up reserves service provision by generator class [GW]"
   vRegDown        (B,T,G,S)     "Regulation down reserves service provision by generator class [GW]"
$ifthen.no_qs not set no_quick_st
  vQuickStart     (B,T,G,S)     "Non-spin reserves service provision by generator class [GW]"
$endif.no_qs
$endif

$ifthen set flex_rsrv
   vFlexUp    (B,T,G,S)  "Flexibility up   (Spinning + QuickStart + RegUp + Renewable Up) reserves [GW]"
   vFlexDown  (B,T,G,S)  "Flexibility down (RegDown + Renewable Down) reserves [GW]"
$endif
   ;

* ======  Declare Equations
equations
$ifthen set flex_rsrv
    ePwrMaxFlexRsrv   (B,T, G, S)  "output w/ reserves lower than available max       [GW]"
    ePwrMinFlexRsrv   (B,T, G, S)  "output w/ reserves greater than installed min     [GW]"
    ePwrMaxFlexRsrvUC (B,T, G, S)  "output w/ reserves lower than committed max       [GW]"
    ePwrMinFlexRsrvUC (B,T, G, S)  "output w/ reserves greater than committed min     [GW]"

    eFlexUp    (B,T, S)     "Provide required flexibility up reserves (aka Positive Balance) [GW]"
    eFlexDown  (B,T, S)     "Provide required flexibility down reserves (aka Negative Balance) [GW]"
```

```
    eFlexUpMaxOnLine    (B,T,G,S) "Ensure that only some of the flex reserves come from off-line (quick
           start) gens [GW]"
$ifthen.no_qs not set no_quick_st
    eFlexUpMax    (B,T,G,S)     "Stay below max spinning reserves on-line generators of each class can
           supply [GW]"
$endif.no_qs
    eFlexDownMax  (B,T,G,S)     "Stay below max regulation up reserves on-line generators of each class
           can supply [GW]"
$endif

$ifthen set separate_rsrv
   ePwrMaxSepRsrv   (B,T, G, S)  "output w/ reserves lower than available max       [GW]"
   ePwrMinSepRsrv   (B,T, G, S)  "output w/ reserves greater than installed min     [GW]"
   ePwrMaxSepRsrvUC (B,T, G, S)  "output w/ reserves lower than committed max       [GW]"
   ePwrMinSepRsrvUC (B,T, G, S)  "output w/ reserves greater than committed min     [GW]"

   eSpinReserve    (B,T, S)     "Provide required spinning reserves [GW]"
   eNetLoadFollowDown(B,T, S)     "Provide required load following down reserves [GW]"
   eRegUp          (B,T, S)     "Provide required regulation up reserves [GW]"
   eRegDown        (B,T, S)     "Provide required regulation down reserves [GW]"
$ifthen.no_qs not set no_quick_st
   eQuickStart     (B,T, S)     "Provide required non-spinning reserves [GW]"
$endif.no_qs

   eSpinReserveMax    (B,T,G,S)     "Stay below max spinning reserves on-line generators of each class
          can supply [GW]"
   eNetLoadFollowDownMax(B,T,G,S)     "Stay below max load following down on-line generators of each
          class can supply [GW]"
   eRegUpMax          (B,T,G,S)     "Stay below max regulation up reserves on-line generators of each
          class can supply [GW]"
   eRegDownMax        (B,T,G,S)     "Stay below max regulation down on-line generators of each class can
           supply [GW]"
$ifthen.no_qs not set no_quick_st
   eQuickStartMax     (B,T,G,S)     "Stay below max non-spin reserves off-line generators of each class
          can supply [GW]"
$endif.no_qs
$endif
   ;

*================================*
*     The Actual Equations       *
*================================*
* Important: we must be included into a larger model, so no objective function defined

*====== Generation output less than upper limit(s)
* There are multiple limits here for different circumstances
* 1) Simplest (ePwrMaxFlexRsrv) is power out < installed capacity. But here there are twists since we
*    allow time varing availability, and for some capacity to be moth-balled and hence not in
*    active use. In addition, we also need to ensure headroom for reserves up.
* 2) For generation subject to unit commitment, things change slightly since we now only output
*    power up to the number of units that are turned on (ePwrMaxFlexRsrvUC)
* 3) If separate reserves are computed, they should not be simply added to the flexibility
*    reserves, but rather we want to take max(FlexUp, sum(other up reserves). In LP we do this
*    by adding an additional equation for the sum(other up reserves) term. (ePwrMaxSepRsrv)
* Furthermore,  we might choose to derate the power output of the plant separately from
* availability (typically for simple models), this can be done by taking the minimum of availability
* and the derate factor. Since both arer parameters, this is a valid (MI)LP formulation. Note that
* this derating is already taken into account for in eUnitCommit for the UC equations.

*====================================*
*  Combined (Flexibility) Reserves   *
*====================================*
* == Output (& Flex Reserves) must be below the generator upper limits (ePwrMaxFlexRsrv)
```

```
* These equations are used for the no reserves case and for combined (Flexibility) reserves
* they are also active when separate reserves are used as described in #3 above.
*
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
*Note: Availability is handled in eState for unit commitment constrained generators
$ifthen.flex set flex_rsrv
ePwrMaxFlexRsrv (B,T, G, S)$( B_SIM(B)
                            and not G_UC(G) ) ..
                        vPwrOut(B,T, G, S) + vFlexUp(B,T,G, S) =l= %capacity_G% *
$ifthen set derate
                            min( pGen(G, 'derate', S),
$else
                            (
$endif
                            pGenAvail(B,T, G, S)
                            );

* == Output Upper Limit for UnitCommitment Gens (ePwrMaxFlexRsrvUC)
* Note: we only include the flexible up output if it can't be provided by quick start units.
ePwrMaxFlexRsrvUC (B,T, G, S)$( B_SIM(B)
                              and G_UC(G) ) ..
                            vPwrOut(B,T, G, S)
                            + vFlexUp(B,T,G,S)$(pGen(G, 'quick_start', S) = 0)
                            =l= vUnitCommit(B,T,G,S) * pGen(G, 'gen_size', S);

*====== Generation output greater than lower limit(s)
* Here we find a complementary situation to the PwrMax equations described above

* == Power greater than lower limits (ePwrMinFlexRsrv)
* For simple models we might use a "technology minimum output" as a proxy for
* baseload plants. This lower limit is applied to entire generator category and is ignored by
* using p_min=0 or not defining p_min (unspecified parameters default to zero).
*
* Note: we keep this active for G_UC to enforce p_min if required
ePwrMinFlexRsrv (B,T, G, S)$B_SIM(B) ..   vPwrOut(B,T, G, S) =g= %capacity_G% * pGen(G,'p_min', S)
                            + vFlexDown(B,T,G,S);


* == Power greater than lower limits for Unit Commitment (ePwrMinFlexRsrvUC)
* Minimum power output for commitment generators under UC
*Note: the $subset(setname) format only defines the equation for members of G that are also in G_UC
ePwrMinFlexRsrvUC (B,T, G, S)$( B_SIM(B)
                              and G_UC(G) ) .. vPwrOut(B,T, G, S)
                            =g=
                            vUnitCommit(B,T,G,S) * pGen(G, 'unit_min', S)
                            + vFlexDown(B,T,G,S);

*=== Combined Flexibility Reserves including additional reserves as a function of Renewables
* These reserves combine all upward reserve requirements (Spin, Load Follow Up, Regulation Up,
* Renewable Flexibility Up) into FlexUp and all downward reserve requirements (Load Follow Down,
* Regulation Down, Renewable Follow Up

*Equivalent to (De Jonghe, et al 2011) eq 16 & 18 with BP addition of baseline (non-wind)
*requirement to meet Spin Reserve + Reg Up
    eFlexUp    (B,T, S)$B_SIM(B) .. sum[(G), vFlexUp(B,T, G, S)] =g=
                            %load_for_rsrv% * (pSpinReserveLoadFract + pRegUpLoadFract)
                            + pSpinReserveMinGW
                            + pWindFlexUpForecast * sum[(G)$G_WIND(G), vPwrOut(B,T, G, S)]
                            + pWindFlexUpCapacity * sum[(G)$G_WIND(G), %capacity_G%];

    eFlexDown  (B,T, S)$B_SIM(B) .. sum[(G), vFlexDown(B,T, G, S)] =g=
                            %load_for_rsrv% * (pSpinReserveLoadFract + pRegDownLoadFract)
                            + pWindFlexDownForecast * sum[(G)$G_WIND(G), vPwrOut(B,T, G, S)]
```

```
                            + pWindFlexDownCapacity * sum[(G)$G_WIND(G), %capacity_G%];

* Compute the maximum reserves per generator as a function of capabilities.
* Note: ePwrMaxFlexRsrv and ePwrMinFlexRsrv ensure that we do not double count capacity

    eFlexUpMaxOnLine    (B,T,G,S)$B_SIM(B) .. (1 - pQuickStSpinSubFract) * vFlexUp(B,T,G,S) =l=
                                    (pGen(G, ’spin_rsv’, S) + pGen(G, ’reg_up’, S))
                                    *(
                                        (vUnitCommit(B,T, G, S)*pGen(G, ’gen_size’, S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_up_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );

$ifthen not set no_quick_st
    eFlexUpMax    (B,T,G,S)$B_SIM(B) .. vFlexUp(B,T,G,S) =l=
                                    (pGen(G, ’spin_rsv’, S) + pGen(G, ’reg_up’, S))
                                    *(
                                        (vUnitCommit(B,T, G, S)*pGen(G, ’gen_size’, S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S))$(not G_UC(G))
                                    )
                                    + pGen(G, ’quick_start’, S)*( %capacity_G%
                                        - (
                                            (vUnitCommit(B,T, G, S)*pGen(G, ’gen_size’, S))$G_UC(G) +
                                            (vPwrOut(B,T, G, S)
                                                + %non_uc_rsrv_up_offline%
                                                    * (%capacity_G% - vPwrOut(B,T, G, S))
                                            )$(not G_UC(G))
                                          )
                                    );
$endif
*Equivalent to (De Jonghe, et al 2011) eq 12 with the BP correction that off-line generators can’t
*be used to provide downward flexibility, using BP field names and assuming the spin_rsv and
*reg_up limits are additive
    eFlexDownMax    (B,T,G,S)$B_SIM(B) .. vFlexDown(B,T,G,S) =l=
                                    (pGen(G, ’spin_rsv’, S) + pGen(G, ’reg_down’, S))*(
                                        (vUnitCommit(B,T, G, S)*pGen(G, ’gen_size’, S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_down_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );
$endif.flex


*======================*
*  Separate Reserves   *
*======================*
* == Output + Individual Reserves must be below the generator upper limits (ePwrMaxSepRsrv)
* These equations are used for the separate reserves case
$ifthen.sep_rsrv set separate_rsrv
ePwrMaxSepRsrv (B,T, G, S)$( B_SIM(B)
                           and not G_UC(G) ) ..
                            %capacity_G% *
$ifthen set derate
                            min( pGen(G, ’derate’, S),
$else
                            (
$endif
                                pGenAvail(B,T, G, S)
                            ) =g=
                            vPwrOut(B,T, G, S)
                            + vSpinReserve(B,T, G, S)$(pGen(G, ’spin_rsv’, S))
                            + vRegUp(B,T, G, S)$(pGen(G, ’reg_up’, S))
                            ;

* == Output Upper Limit for UnitCommitment Gens with Separate Reserves (ePwrMaxSepRsrvUC)
ePwrMaxSepRsrvUC (B,T, G, S)$( B_SIM(B)
                            and G_UC(G) ) .. vUnitCommit(B,T,G,S) * pGen(G, ’gen_size’, S)
                            =g=
                            vPwrOut(B,T, G, S)
                            + vSpinReserve(B,T, G, S)$(pGen(G, ’spin_rsv’, S))
                            + vRegUp(B,T, G, S)$(pGen(G, ’reg_up’, S))
                            ;

* == Output + Individual Reserves must be above the generator lower limits (ePwrMinSepRsrv)
* These equations are used for the separate reserves case
ePwrMinSepRsrv (B,T, G, S)$B_SIM(B) ..   vPwrOut(B,T, G, S) =g= %capacity_G% * pGen(G,’p_min’, S)
                        + vRegDown(B,T,G,S)$(pGen(G, ’reg_down’, S))
                        + vNetLoadFollowDown(B,T, G, S);


* == Output + Individual Reserves above the lower limits for Unit Commitment(ePwrMinSepRsrvUC)
ePwrMinSepRsrvUC (B,T, G, S)$( B_SIM(B)
                            and G_UC(G) ) .. vPwrOut(B,T, G, S)
                            =g=
                            vUnitCommit(B,T,G,S) * pGen(G, ’unit_min’, S)
                            + vRegDown(B,T,G,S)$(pGen(G, ’reg_down’, S))
                            + vNetLoadFollowDown(B,T, G, S);

*=== Separate Ancillary Services

*=== Ensure we have enough reserves for each operating period
* == Spinning Reserves (eSpinReserve) aka secondary reserves
*  Focus on contingencies (ie outages or failures) only. Here we compute the required
*  level as the greater of the specified minimum (typically set to the largest on-line plant
*  or transmission tie)
    eSpinReserve    (B,T, S)$B_SIM(B) .. sum[(G)$(pGen(G, ’spin_rsv’, S)), vSpinReserve(B,T, G, S)]
                            =g= (1 - pQuickStSpinSubFract)
                             * (    pSpinReserveMinGW
                                    + %load_for_rsrv% * pSpinReserveLoadFract
                                    + pWindFlexUpForecast * sum[(G)$G_WIND(G), vPwrOut(B,T, G, S)]
                                    + pWindFlexUpCapacity * sum[(G)$G_WIND(G), %capacity_G%]
                                );

* == Quick Start Reserves (eQuickStart) aka tertiary reserves
*  Allow QuickStart units (off-line or demand) to substitute for a fraction of secondary reserves
$ifthen.no_qs not set no_quick_st
    eQuickStart     (B,T, S)$B_SIM(B) .. sum[(G)$(pGen(G, ’quick_start’, S)), vQuickStart(B,T, G, S)]
                            + sum[(G)$(pGen(G, ’spin_rsv’, S)), vSpinReserve(B,T, G, S)]
                           =g=
                            pReplaceReserveGW
                            + pSpinReserveMinGW
                            + %load_for_rsrv% * pSpinReserveLoadFract
                            + pWindFlexUpForecast * sum[(G)$G_WIND(G), vPwrOut(B,T, G, S)]
                            + pWindFlexUpCapacity * sum[(G)$G_WIND(G), %capacity_G%]
                            ;
$endif.no_qs
* == Load Follow Down (eNetLoadFollowDown) aka secondary reserves
*  Handles second to second variations. Computed as a specified fraction of the load.
    eNetLoadFollowDown (B,T, S)$B_SIM(B) .. sum[(G)$(pGen(G, ’spin_rsv’, S)), vNetLoadFollowDown(B,T, G,
           S)]
                                =g= %load_for_rsrv% * pSpinReserveLoadFract
                                    + pWindFlexDownForecast * sum[(G)$G_WIND(G), vPwrOut(B,T, G, S)]
                                    + pWindFlexDownCapacity * sum[(G)$G_WIND(G), %capacity_G%];
```

```
                                ;

* == Regulation Up (eRegUp) aka primary reserves
*  Handles second to second variations. Computed as a specified fraction of the load.
    eRegUp          (B,T, S)$B_SIM(B) .. sum[(G)$(pGen(G, 'reg_up', S)), vRegUp(B,T, G, S)] =g=
                            %load_for_rsrv% * pRegUpLoadFract;

* == Regulation Down (eRegDown) aka primary reserves
*  Handles second to second variations. Computed as a specified fraction of the load.
    eRegDown        (B,T, S)$B_SIM(B) .. sum[(G)$(pGen(G, 'reg_down', S)), vRegDown(B,T, G, S)] =g=
                            %load_for_rsrv% * pRegDownLoadFract;

*=== Reserve Capability by reserve class and unit
* Compute the maximum reserves per generator as a function of capabilities.
* Note: ePwrMaxFlexRsrv and ePwrMinFlexRsrv (above) ensure that we do not double count capacity
* These equations are only created for generators capable of supplying the specified service


* == Generator limits on Spinning Reserves (eSpinReserveMax) aka secondary reserves
* Based on commitment state if available. For non-UC plants, we use output power as a proxy
* for quantity/amount of committed generation
    eSpinReserveMax    (B,T,G,S)$( B_SIM(B)
                                 and pGen(G, 'spin_rsv', S) ) ..
                                    vSpinReserve(B,T,G,S)
                                    =l=
                                    pGen(G, 'spin_rsv', S)*(
                                        (vUnitCommit(B,T, G, S)*pGen(G, 'gen_size', S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_up_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );


* == Generator limits on Load Following Down (eNetLoadDownMax) aka primary reserves
* Based on commitment state if available. For non-UC plants, we use output power as a proxy
* for quantity/amount of committed generation
    eNetLoadFollowDownMax(B,T,G,S)$( B_SIM(B)
                                   and pGen(G, 'spin_rsv', S) ) ..
                                    vNetLoadFollowDown(B,T,G,S)
                                    =l=
                                    pGen(G, 'spin_rsv', S)*(
                                        (vUnitCommit(B,T, G, S)*pGen(G, 'gen_size', S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_down_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );

* == Generator limits on Regulation Up (eRegUpMax) aka primary reserves
* Based on commitment state if available. For non-UC plants, we use output power as a proxy
* for quantity/amount of committed generation
    eRegUpMax(B,T,G,S)$( B_SIM(B)
                       and pGen(G, 'reg_up', S) ) ..
                                    vRegUp(B,T,G,S)
                                    =l=
                                    pGen(G, 'reg_up', S)*(
                                        (vUnitCommit(B,T, G, S)*pGen(G, 'gen_size', S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_up_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );

* == Generator limits on Regulation Down (eRegDownMax) aka primary reserves
* Based on commitment state if available. For non-UC plants, we use output power as a proxy
* for quantity/amount of committed generation
    eRegDownMax(B,T,G,S)$( B_SIM(B)
                         and pGen(G, 'reg_down', S) ) ..
                                    vRegDown(B,T,G,S)
                                    =l=
                                    pGen(G, 'reg_down', S)*(
                                        (vUnitCommit(B,T, G, S)*pGen(G, 'gen_size', S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S)
                                            + %non_uc_rsrv_down_offline%
                                                * (%capacity_G% - vPwrOut(B,T, G, S))
                                        )$(not G_UC(G))
                                    );

* == Generator limits on Quick Start (eQuickStartMax) aka tertiary reserves
* Here we care about the number of units that are OFF (rather than on as for other reserves). So
* we base the limit on available capacity minus that which is on-line. On-line quantity is based
* on commitment state if available. For non-UC plants, we use output power as a proxy
* for quantity/amount of committed generation.
$ifthen.no_qs not set no_quick_st
    eQuickStartMax(B,T,G,S)$( B_SIM(B)
                            and pGen(G, 'quick_start', S) ) ..
                            vQuickStart(B,T,G,S)
                            =l=
* Quick start capability times
                            pGen(G, 'quick_start', S)
                                *(
* Total available capacity
                                    %capacity_G% *
$ifthen set derate
                                        min( pGen(G, 'derate', S),
$else
                                        (
$endif
                                           pGenAvail(B,T, G, S)
                                        )
* Minus capacity already in use
                                    - (
                                        (vUnitCommit(B,T, G, S)*pGen(G, 'gen_size', S))$G_UC(G) +
                                        (vPwrOut(B,T, G, S))$(not G_UC(G))
                                      )
                                );
$endif.no_qs
$endif.sep_rsrv
```

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COLOPHON

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