International Journal of Recent Engineering Research and Development (IJRERD)
Volume No. 02 – Issue No. 05, ISSN: 2455-8761
www.ijrerd.com, PP. 17-25

Comparitive study of Stochastic and Security constrained Unit Commitment

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Abstract: Power system is an important field in Electrical Engineering. Power system involves the consideration of economy of operation and system security.

Main aim of this paper is to introduce the optimization techniques to Power system involves the consideration of economy of operation and system security. Minimize the total cost of generating power and generating power should meet the demand. Unit commitment is “committing the economically feasible units”. These methods are adopted in order to secure the system against contingencies and variable fluctuations in load.

My paper deals with the comparative study of stochastic unit commitment and security constrained unit commitment using Lagrangian relaxation and Benders decomposition. These algorithms and comparative scenarios help for easy study.

Introduction

The style of modern man follows habits and hence the present society also follows repeats cycles or pattern in daily life. So the consumption of electrical energy follows a daily, weekly and seasonal pattern. There are periods of high power consumption and low power consumption. It is therefore possible to commit the generating commitment schedules are thus required for economically committing the units in plants to service with the time at which individual units should be taken into the service.

The aim of my seminar is committing the cost effective units. Also seminar includes the optimization techniques and their solution methodologies.

Unit commitment (UC) is an optimization problem used to determine the operation schedule of the generating units at every hour interval with varying loads under different constraints and environments. Many algorithms have been invented in the past five decades for optimization of the UC problem, but still researchers are working in this field to find new hybrid algorithms to make the problem more realistic. The importance of UC is increasing with the constantly varying demands. Therefore, there is an urgent need in the power sector to keep track of the latest methodologies to further optimize the working criterions of the generating units. This paper focuses on providing a clear review of the latest techniques employed in optimizing UC problems for both stochastic and deterministic loads, which has been acquired from many peer reviewed published papers. It has been divided into many sections which include various constraints based on profit, security, emission and time. It emphasizes not only on deregulated and regulated environments but also on renewable energy and distributed generating systems.

UNIT COMMITMENT PROBLEM

The unit commitment problem (UC) in electrical power production is a large family of mathematical optimization problems where the production of a set of electrical generators is coordinated in order to achieve some common target, usually either match the energy demand at minimum cost or maximize revenues from energy production. This is necessary because it is difficult to store electrical energy on a scale comparable with normal consumption; hence, each (substantial) variation in the consumption must be matched by a corresponding variation of the production.

Coordinating generation units is a difficult task for a number of reasons:

- The number of units can be large (hundreds or thousands).
- There are several types of units, with significantly different energy production costs and constraints about how power can be produced.
- Generation is distributed across a vast geographical area (e.g., a country), and therefore the response of the electrical grid, itself a highly complex system, has to be taken into account: even if the production levels of all units are known, checking whether the load can be sustained and what the losses are requires highly complex power flow computations.

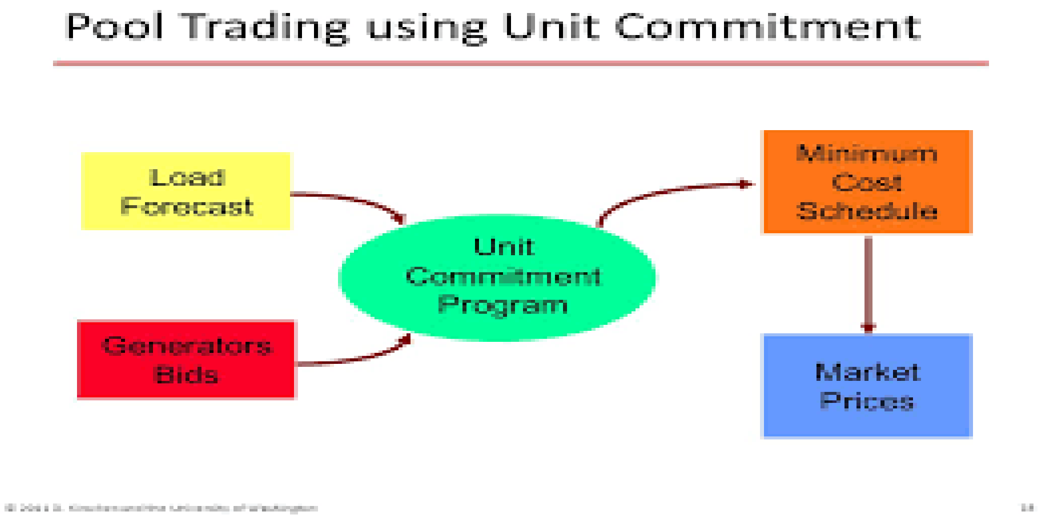


Fig 1 Unit commitment problem

Because the relevant details of the electrical system greatly vary worldwide, there are many variants of the UC problem, which are often very difficult to solve. This is also so because, since some units require quite a long time (many hours) to start up or shut down, the decisions need be taken well in advance (usually, the day before), which implies that these problems have to be solved within tight time limits (several minutes to a few hours). UC is therefore one of the fundamental problems in power system management and simulation. It has been studied for many years, and still is one of the most significant energy optimization problems. Recent surveys on the subject count many hundreds of scientific articles devoted to the problem. Furthermore, several commercial products comprise specific modules for solving UC.Problems where the production of a set of electrical generators is coordinated in order to achieve some common target, usually either match the energy demand at minimum cost or maximize revenues from energy production. This is necessary because it is difficult to The unit commitment problem (UC) in electrical power production is a large family of mathematical optimization problems where the production of a set of electrical generators is coordinated in order to achieve some common target, usually either match the energy demand at minimum cost or maximize revenues from energy production. This is necessary because it is difficult to store electrical energy on a scale comparable with normal consumption; hence, each (substantial) variation in the consumption must be matched by a corresponding variation of the production.

Elements of unit commitment problems

There are many different UC problems, as the electrical system is structured and governed differently across the world. Common elements are:

- A time horizon along which the decisions have to be made, sampled at a finite number of time instants. This is usually one or two days, up to a week, where instants are usually hours or half-hours; less frequently, 15 or 5 minutes. Hence, time instants are typically between 24 and around 2000.
- A set of generating units with the corresponding energy production cost and/or emission curves, and (complex) technical constraints.
- A representation of the significant part of the grid network.
- A (forecasted) load profile to be satisfied, i.e., the net amount of energy to be delivered to each node of the grid network at each time instant.
- Possibly, a set of reliability constraints ensuring that demand will be satisfied even if some unforeseen events occur.
- Possibly, financial and/or regulatory conditions (energy revenues, market operation constraints, financial instruments, etc).

The objectives of UC depend on the aims of the actor for which it is solved. This is basically to minimize energy production costs while satisfying the demand; reliability and emissions are usually treated as constraints. In a free-market regime, the aim is rather to maximize energy production profits, i.e., the difference between revenues (due to selling energy) and costs (due to producing it). This means bidding its production at high cost so as to raise market prices, losing market share but retaining some because, essentially, there is not enough generation capacity. For some regions this may be due to the fact that there is not enough grid network capacity to import energy from nearby regions with available generation capacity. While the electrical markets are highly regulated in order to, among other things, rule out such behavior, large producers can still benefit from simultaneously optimizing the bids of all their units to take into account their combined effect on market prices. On the contrary, price takers can simply optimize each generator independently, as, not having a significant impact on prices, the corresponding decisions are not correlated.

UNCERTAINITY IN UNIT COMMITMENT PROBLEM

A troubling consequence of the fact that UC needs be solved well in advance to the actual operations is that the future state of the system is not known exactly, and therefore needs be estimated. This used to be a relatively minor problem when the uncertainty in the system was only due to variation of users' demand, which on aggregate can be forecasted quite effectively, and occurrence of lines or generators faults, which can be dealt with by well-established rules (spinning reserve). However, in recent years the production from intermittent renewable production sources has significantly increased. This has, in turn, very significantly increased the impact of uncertainty in the system, so that ignoring it (as traditionally done by taking average point estimates) risks significant cost increases. This had made it necessary to resort to appropriate mathematical modeling techniques to properly take uncertainty into account. Also certain optimization techniques are introduced to reduce the uncertainties in unit commitment problem.

OPTIMIZATION TECHNIQUES

Some of the optimization techniques are:

- Stochastic optimization approaches.
- Robust Scenario optimization approaches.
- Security constrained optimization approaches.

The combination of the (already, many) traditional forms of UC problems with the several (old and) new forms of uncertainty gives rise to the even larger family of Uncertain Unit Commitment (UUC) problems.

The challenge of committing reserves lies in optimizing the tradeoff between system security and economic operation of the system. Any level of security can be achieved in the system given a sufficient amount of reserves. The challenge rests in choosing the level of reserves that satisfies certain operational criteria in an uncertain environment at least cost.

STOCHASTIC OPTIMIZATION

The stochastic unit commitment modeling as a group of many deterministic models. Each of the models is related to a production scenario of the non-conventional Renewable energy unit . Also, every model has attached the probability of the generation scenario. Many researchers have studied stochastic modeling for the unit commitment problem. Takritistudied the stochastic unit commitment considering the stochastic of the load in the year 1996. Mainly, these studies has been made considering high amounts of wind power integrations to conventional electric systems which can be reviewed in propose the WILMAR MODEL that uses rolling planning. This means that it has the capability to modify the dispatch during te same day. This model has two main components. First is the Scenario Tree Tool that calculates the probability of wind forecasts and load. Second, they devolped a stochastic model that includes reserves and the load and wind forecasts.

MODEL DESCRIPTION

The problem that this paper is focusing on is the day ahead scheduling of generators subject to real-time renewable power supply uncertainty and outages of transmission lines and generators. The problem is cast as a two-stage optimization, where the first stage represents day-ahead decisions and the second stage represents the real-time recourse to the revealed system conditions.

u represents a binary variable indicating the on-off status of a generator.

v is a binary startup variable and p is the production level of each generator.

The minimum load cost of a generator is denoted as Kg

The startup cost as Sg and

The constant marginal cost as Cg.

The model that we present in this paper accounts for transmission constraints, with power flows over transmission lines denoted as e.

The demand for each hour t at each bus of the network n is denoted as Dnt.

$$(UC) : \min \sum_{g\in G} \sum_{t\in T} (K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$$

$$s.t. \sum_{g\in G_n} p_{gt} = D_{nt}$$

$$P_g^- u_{gt} \leq p_{gt} \leq P_g^+ u_{gt}$$

STOCHASTIC UNIT COMMITMENT WITH UNCERTAINITY

The stochastic formulation follows the model of Ruiz and involves a two-stage process, where the set of uncertain outcomes is represented as S. First-stage unit commitment and startup decisions are represented respectively as w and z and apply for those generators Gs for which commitment decisions need to be made in advance, in the day-ahead time frame.

$$(SUC) :$$

$$\min \sum_{g\in G} \sum_{s\in S} \sum_{t\in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$

$$s.t. \sum_{g\in G_n} p_{gst} = D_{nst},$$

$$P_{gs}^- u_{gst} \leq p_{gst} \leq P_{gs}^+ u_{gst}$$

SCENARIO BASED SECURITY CONSTRAINED UNIT COMMITMENT

Load shedding is permitted in the stochastic unit commitment model with lost load incurring a high penalty in the objective function. Loads L are therefore represented as a dummy generator with second-stage production decisions plst and a marginal cost equal to the value of lost load. As a result, the feasible region of each scenario, Ds, is non-empty for any choice of first-stage decision variables wgt; zgt. In a security-constrained model discrete disturbances are accounted for by requiring that the system be capable of withstanding any element failure. This implies that each scenario s now consists of at most a single contingency. Following the model of Wu et al. We account for continuous disturbances (net demand forecast errors) by associating a renewable supply outcome with each scenarios rather than imposing exogenous reserve requirements. Scenarios that involve no contingency are weighed with a positive probability in the objective functions whereas scenarios that involve contingencies are only included in the constraint set. The feasible region is equal to Ds with the additional constraint that plst = 0 for load shedding, and in contrast to (SUC) there may be choices of first-stage decisions for which the model is infeasible.

$$(SCUC) :$$

$$\min \sum_{g\in G} \sum_{s\in S} \sum_{t\in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$

$$s.t. \sum_{g\in G_n} p_{gst} = D_{nst},$$

$$P_{gs}^- u_{gst} \leq p_{gst} \leq P_{gs}^+ u_{gst}$$

$$e_{lst} = B_{ls}(\theta_{nst} - \theta_{mst})$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}_s$$

$$p_{lst} = 0, l \in L$$

$$u_{gst} = w_{gt}, v_{gst} = z_{gt},$$

SCENARIO SELECTION

The selection of scenarios in the stochastic unit commitment model is based on an idea inspired by importance sampling . A large number of candidate scenarios are evaluated in terms of their cost impact to the system, where this cost impact is evaluated against an easily computable deterministic unit commitment model. Candidate scenarios are then selected to enter the set of selected scenarios S by sampling according to a probability which is proportional to their cost impact. These scenarios are assigned a weights in the objective function of (SUC) which Sis inversely proportional to their cost impact CD in order to un-bias their selection.

In the case of the scenario-based security-constrained model, the set S is generated by the Cartesian product of a set of renewable supply outcomes with the no-contingency outcome and the most severe single-element contingencies in the system. The set of scenarios that involve the no-contingency outcome are assigned an equal positive probability in the objective function, whereas the scenarios involving single element contingencies have no direct impact on the objective function through their weight, s = 0, but only through their presence in the constraint set.

SOLUTION METHODOLOGY

In the following section we present two decomposition methods for solving (SUC) and (SCUC), as well as distributed implementations of the decomposition algorithms.

- **Lagrangian Relaxation**
- **Benders Decomposition**

LAGRANGIAN RELAXATION

It is a technique well suited for problems where the constraints can be divided into two sets:

- “good” constraints, with which the problem is solvable very easily.
- “bad” constraints that make it very hard to solve.

The main idea is to relax the problem by removing the “bad” constraints and putting them into the objective function, assigned with weights (the Lagrangian multiplier). Each weight represents a penalty which is added to a solution that does not satisfy the particular constraint.

The Lagrangian relaxation algorithm relies on the observation that the relaxation of the non-anticipatively constraints in (SUC) results in unit commitment sub problems that are independent across scenarios. The Lagrangian dual function

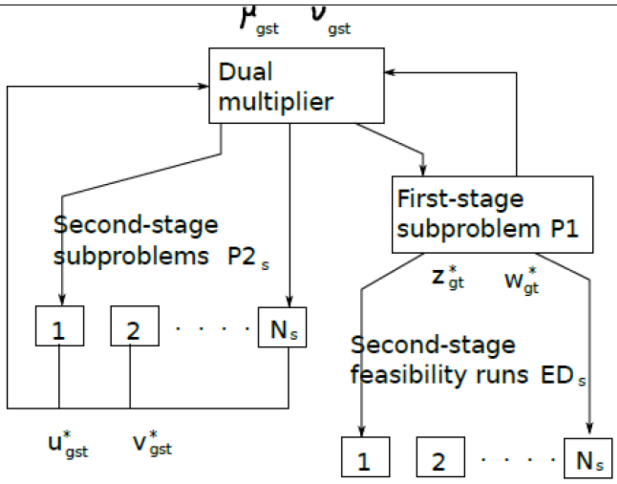
$$\mathcal{L} = \sum_{s \in S} \pi_s \Big(\sum_{g \in G} \sum_{t \in T} (K_g u_{gst} + S_g v_{gst} + C_g p_{gst}) + \sum_{g \in G_s} \sum_{t \in T} \big(\mu_{gst}(u_{gst} - w_{gt}) + \nu_{gst}(v_{gst} - z_{gt})\big) \quad (4)$$

The problem is solved by maximizing the Lagrangian dual function using the sub-gradient algorithm. The solution of the Lagrangian involves one second-stage unit commitment problem for each scenario (P2s), and one first-stage optimization (P1). The first-stage optimization is formulated as:

$$(P1) : \max \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst} w_{gt} + \nu_{gst} z_{gt})$$

$$s.t. \mathcal{D}_1,$$

By introducing redundant second stage decision variables on startup decisions, we are able to enforce minimum up and down times on slow units. Given these unit commitment schedules, we can solve an economic dispatch model (EDs), which is (P2s) with ugst; vgst fixed for g 2 Gs.

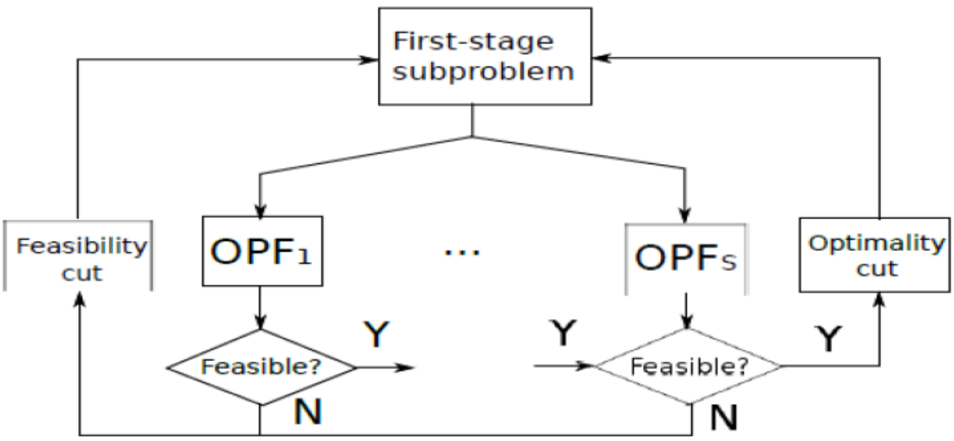


. The parallel implementation of the Lagrangian relaxation algorithm.

BENDERS DECOMPOSITION

Security constraints are enforced in power system operations in order to protect the system against the failure of any given transmission or generation element. The security constrains reduces the loss of any single component in the system while fully satisfying demand. Security-constrained unit commitment can be approximated as a special case of the (SUC) model

Presented when _s > 0 for the no-contingency scenarios, and _s = 0 for scenarios involving contingencies. This implies that the constraints associated with each contingency scenario are enforced in the constraint set, but are not weighed in the objective function. This remains an approximation of (SCUC) since the constraint plst, l 2 L, is not enforced in (SUC).In principle, this approximation of the security-constrained unit commitment problem can be solved by using the solution algorithm of Section III-A. In practice this approach presents convergence problems when solved by Lagrangian relaxation. The dual function is not increasing even when the step size is reduced to a very small amount, and the unit commitment schedule of slow generators is inverted after each iteration. This numerical instability is due to the fact that the dual function is very steep, which results from the fact that the operating cost terms vanish since s = 0 for the scenarios associated with contingencies. This motivates a Benders decomposition scheme for solving the problem. This can be justified by the fact that all feasibility constraints can be satisfied with only a few feasibility cuts associated with the most severe contingencies in the system. Optimality cuts can be defined by solving only those few scenarios associated with the no-contingency outcome. The advantage of using a Benders decomposition scheme is that the generation of feasibility cuts and optimality cuts can be parallelized, which implies that the second stage of the model is no more the computational bottleneck.



Benders decomposition algorithm

The algorithm that we propose in this paper requires two assumptions:

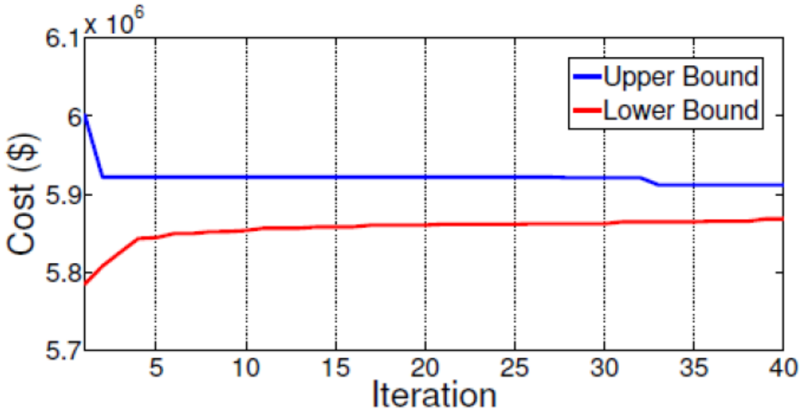
Assumption 1: In order to maintain the convexity of the second-stage value function, it is necessary to assume that second-stage problems are continuous. Therefore, we impose the assumption that unit commitment decisions have to be fixed for all generators in the network from the first stage. This is contrasted to the Lagrangian relaxation algorithm that can involve integer decisions in the second stage for fast generators g 2 Gf = G Gs.

Assumption 2: The generation of feasibility cuts according to Van-Slyke and Wets [23] removes one candidate integer solution at each iteration, however this process can easily stall when there is a large number of candidate integer solution combinations that need to be tested before a feasible solution can be obtained, as is the case in the stochastic unit commitment problem. By assuming away ramping constraints in (SCUC), we obtain a feasible region (Dst) that is decomposable both by time period as well as scenario. Rather than using the feasibility cuts of Van-Slyke and Wets [23], we then impose the constraints represented by Dst in the first-stage problem for the scenario and time period that represents the most severe contingency given the current candidate integer solution. The motivation is that accounting for the most severe contingency in the first stage of the problem is capable of satisfying most operating constraints associated with less severe contingencies.

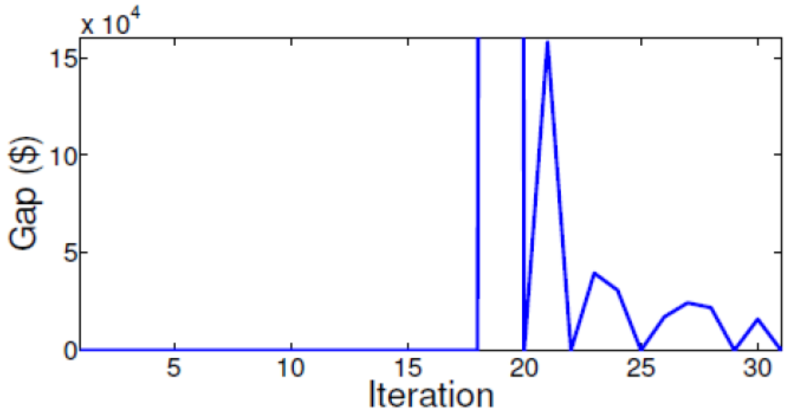
The model captures temporal correlations of wind speed, the nonlinear conversion of wind speed to wind power, the locational correlations of the wind sites under consideration, as well as systematic seasonal and diurnal characteristics of the data set. The wind power production time series model was used both in order to generate scenarios for the unit commitment optimization models, as well as for generating outcomes. The Benders decomposition algorithm required 31 iterations to converge. During these iterations, either feasibility cuts were added to the first-stage program, or a new approximation of the value function was generated, along with an estimate of the gap in the current candidate unit commitment solution.

RESULTS AND RELATIVE PERFORMANCE

The hourly day-ahead capacity committed by each model in each hour of the day. We note that the (SCUC) model is committing significantly more capacity than the (SUC) model. This can be attributed to Assumption 2 of Section III-B. Due to the fact that the Benders decomposition algorithm requires that all units be committed in the day-ahead time frame.

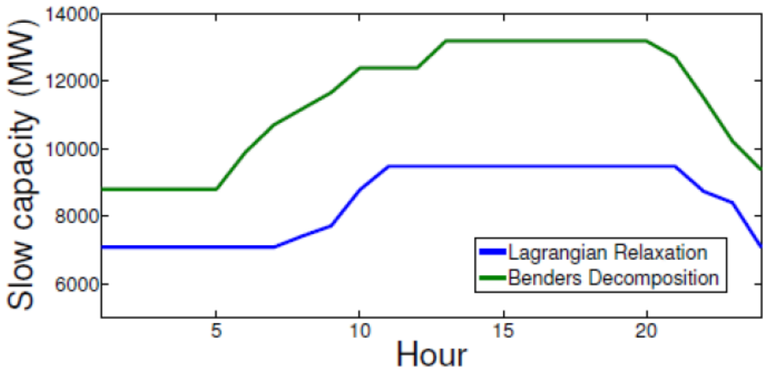


Lagrangian algorithm



Benders decomposition gap

The speedup of the algorithm is due to the parallelization of the continuous DC optimal power flow problems that are required for generating feasibility and optimality cuts. The marginal benefits vanish beyond 15 processors. The entire model requires 26.6 minutes to solve in a fully serial implementation, versus 14.8. The running time of the Benders decomposition algorithm as a function of processor number minutes in a fully parallel implementation. We note that the benefits of parallelism are expected to increase as we increase the number of contingencies or wind scenarios considered in the model. However, as an excessive number of second stage problems is added to the (SCUC) model, additional feasibility cuts are required in order to generate feasible unit commitment schedules. This may result in a non –decomposable first-stage problem that is excessively large, and for which distributed computation can offer no speedup benefits. In that case, the first-stage problem will dominate the total running time of the problem. The motivation of using Benders decomposition in unit commitment problems is that the most severe contingencies in the system often suffice for withstanding most minor contingencies. However, the possibility that the Benders decomposition algorithm may not suffice to solve the problem if an excessive number of feasibility cuts are required. We have encountered this behavior in an instance of the (SCUC) problem with 100 contingencies (which results in 1,000 scenarios when the contingencies are interleaved with 10 wind scenarios), and in future research we intend to explore alternative approaches for solving larger instances of the problem. The marginal benefits of parallelization vanish beyond 15 processors. The solution time of the Lagrangian relaxation algorithm ranges between 15.8 hours for the fully serial implementation to 47.7 minutes in the fully parallel implementation. The benefits of parallelization are evident in this example, as they enable us to reduce the solving time of the original problem to a time horizon that is acceptable for operational purposes. In contrast to the (SCUC) model, the proposed Lagrangian relaxation can scale to a very large number of scenarios provided that a sufficient number of processors is available.



Comparison of Lagrangian and benders decomposition algorithm

ADVANTAGES

- The method helps in committing local reserves in order to system against contingencies and variable fluctuations.
- Optimizes the system security.
- Helps in economic operation of the system.
- Helps to avoid the uncertainty in the system operation.

DISADVANTAGES

- SUC requires large number of uncertainties and weighted scenarios.
- Selection of scenarios and weighing them is non-obvious and has a significant impact on commitment.
- Computation in Lagrangian Relaxation and Benders decomposition is very complex.

CONCLUSION

We present two approaches for solving the unit commitment problem in order to mitigate the uncertainty stemming from continuous sources of uncertainty (renewable energy or demand forecast error) as well as discrete disturbances (generator and transmission line failures). The stochastic unit commitment model optimizes the expected cost of operation of the system, while the scenario-based security constrained unit commitment model minimizes the cost of system operations while guaranteeing that the system can withstand major contingencies without shedding load. We present a Lagrangian relaxation algorithm for solving the stochastic unit commitment model and a Benders decomposition algorithm for solving the security-constrained unit commitment model and we implement both algorithms in a high performance computing environment. The Benders decomposition algorithm is implemented by passing power flow constraints associated to the most severe contingencies in the system to the first-stage problem.

We observe that the security constrained model commits significantly greater quantities of day-ahead capacity and outperforms the stochastic unit commitment model in terms of load shedding. Instead, the stochastic unit commitment model outperforms the security constrained model in terms of expected cost by reducing minimum load, startup and fuel costs. We also find that the parallel implementation of the stochastic unit commitment problem reduces the running time of the model to a level that is acceptable for operational purposes. The Benders algorithm also benefits from parallelization, although running time in the Benders algorithm is dictated by the first-stage sub problem. In contrast to the Lagrangian relaxation algorithm which can scale to a very large number of scenarios provided a sufficient number of processors is available, further research is required in order to solve larger instances of the security-constrained model.