

Modelling and Simulation of Power Systems

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Abstract This chapter presents major modelling and simulation techniques applied in power systems research. As the smart grids will be a journey through the modern power system environment, it is vital to know how these models and techniques are applied in a traditional power grid environment and how they can make advances to realize smart grid objectives. The chapter describes optimization techniques applied in power systems research and then extended to incorporate stochastic elements. The chapter ends with a brief exploration into the Monte Carlo simulation based research.

Keywords Deterministic approach • Monte Carlo simulation • Probabilistic techniques • Stochastic optimization

1 Introduction

Power systems are complex and dynamic and they employ advanced mathematical techniques for planning, operation, control, and analysis. One of the biggest challenges of power systems is that the physical experimentation and observation is not practical and thus planning and operation decisions rely on accurate replication of experiments using mathematical modelling and simulations. It is thus critical that simulation techniques are robust and reliable. Power system simulations incorporate robust mathematical representations of real life systems by utilising advanced modelling techniques to assess the interactions of individual component models.

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In addition, most power system analysis methodologies require solving highly non-linear and non-convex problems which necessitates the use of a large amount of computational resources. While advances in numerical computing and processing speed have resulted in significant benefits, it is still necessary to make models as efficient as possible to minimise computation times and to capture realistic effects.

At the same time, power systems consist of a number of expensive assets which can be damaged if operated incorrectly. A number of industries rely on electrical power and outages would result in huge financial losses. Thus, the consequences of incorrectly planning or operating a power system can have severe consequences. Additionally, due to the modern power systems are becoming increasingly dynamic, and real time modelling, state estimation, real time decision making requirements are placing added demands on power system modelling and simulation techniques. Thus, modelling and simulation techniques must meet the contradictory objectives of being fast, computationally efficient yet robust, secure, and reliable.

While some of the modern requirements of power system modelling and simulation are covered in the relevant chapters, this chapter discusses some of the developments in basic methodologies that form the basis for all analysis. This includes various forms of analytical and heuristic optimisation techniques as well as the application of probabilistic techniques for analysis under uncertainty.

2 Optimisation Techniques

Optimisation techniques are widely used for power systems analysis. The objective of optimal power flow (OPF) is to determine a steady state operating point that optimises the use of system resources while maintaining operational constraints such as voltage regulation, generator limits and line flow limits. It is formulated as a nonconvex, nonlinear constrained optimisation problem and a variety of algorithms have been used to solve it.

Reviews published by Huneault and Galiana (1991) and by Zhifeng et al. (2009) describe the evolution of OPF from its development till the present day. While attempts at establishing the OPF problem can be traced back to the 1940s, the first official publication on the subject was by Carpentier in 1962, who formulated the optimality conditions from the Kuhn-Tucker conditions for optimality for a mathematical function. Much of the research in the area for the next couple of decades focussed on finding efficient algorithms to solve the OPF problem. One of the earliest proposed methods used linear approximation of the nonlinear objective function and constraints and applied linear programming techniques to solve the problem (Wells 1968). The drawbacks of this include the final solution is not necessarily being optimal and constraint overloading due to rounding error (Zhifeng et al. 2009). Nonlinear programming techniques were developed shortly after with Dommel and Tinney (1968) representing the first successful attempt at using a gradient based method combined with penalty functions for violation of constraints.

In the 1970s quadratic programming (Nabona and Freris 1973; Nicholson and Sterling 1973) was used for the solution of the OPF formulation which involved using quadratic functions to approximate the objective function and linear functions for the constraints. Compared to linear programming, it offered a more flexible algorithm and higher reliability in terms of convergence but the computation time was increased with larger system scale.

In parallel to the aforementioned techniques, the interior point method was also used for solving the OPF problem. It can solve both linear and nonlinear problems and has robust convergence characteristics. There was renewed interest in the interior point method after Karmarkar (1984) devised an efficient algorithm to solve interior point problems. The subsequent development of the predictor-corrector technique by Mehrotra (1992) further improved the utility of interior point methods. Even in present day OPF problems, the interior point method is a very common algorithm for solving the OPF problem either in purely analytical or hybrid techniques due to their robustness and convergence characteristics (Jabr et al. 2002; Jabr 2008; Jabr and Pal 2009; JunHua et al. 2012; Zhang et al. 2005). Jabr et al. (2002) proposed an enhancement of existing primal dual interior point methods for OPF which involves a filter technique to guide the choice of the step length and search direction in order to avoid convergence to a non-minimizing stationary point. The proposed method addressed the issues of global convergence of interior point methods resulting in robust convergence characteristics and reduced computational time.

Another significant enhancement to reduce the complexity of the OPF problem was made by Torres and Quintana (1998) who expressed the bus voltages in rectangular form which resulted in a quadratic objective function and quadratic constraints. The rectangular form allows for ease of matrix setup with incorporation of higher-order information which improves tractability by predictor corrector nonlinear interior point methods. The modified power balance equations are shown as follows where the voltage at the bus $V_i = e_i + jf_i$. e_i represent the real part and the f_i represent the imaginary part of the voltage at bus i . P_i and Q_i represent real and reactive power at bus i respectively and V represents voltage magnitude. G_{ij} and B_{ij} represent the conductance and susceptance between bus i and j respectively.

$$P_i = \sum_{j=1}^n G_{ij}(e_i e_j + f_i f_j) + B_{ij}(f_i e_j - e_i f_j) \quad (1)$$

$$Q_i = \sum_{j=1}^n G_{ij}(f_i e_j - e_i f_j) - B_{ij}(e_i e_j + f_i f_j) \quad (2)$$

Following on from the rectangular formulation of the OPF problem, a nonlinear interior-point OPF method which substitutes the bus power mismatch formulation with a current mismatch formulation in rectangular coordinates was proposed by Zhang et al. (2005). The advantage of the current mismatch formulation is that some constraints become linear which improves ease of implementation. Results indicate that the two methods are comparable in terms of CPU (central processing

unit) time with the current mismatch formulation method having less computational complexity per iteration.

Jabr (2006) proposed the formulation of the OPF problem as a second order cone program which transforms the optimisation problem for radial distribution systems into a convex optimization problem. This method is used in a separate study (Jabr and Pal 2007) to determine the load capability of the radial system, thus avoiding the need for running a sequence of load flow solutions. The conic objective function yields a voltage stability indicator which quantifies the maximum percentage by which the current load profile can be uniformly increased before a voltage collapse occurs. Conic programming was extended to meshed networks by Jabr (2007) by including a trigonometric functional constraint for the voltage angle spread on each line in the network. As a result, the load flow solution of a meshed network can be obtained from a sequence of conic programming solutions. A complete extended conic quadratic OPF (ECQ-OPF) formulation was developed by Jabr (2008) to solve the economic dispatch and active power loss minimization problems including control devices such as tap-changing transformers, phase-shifting transformers, and unified power flow controllers. Reported advantages of the ECQ-OPF approach include easy integration within optimization routines that require the evaluation of second-order derivatives, efficient solution using primal-dual interior-point methods, and use of linear programming scaling techniques for improving numerical conditioning.

The extended conic quadratic (ECQ) form using the transformations is defined in (3) (Jabr 2008; Jabr and Pal 2009).

$$\begin{aligned} R_{in} &= V_i V_n \cos(\delta_i - \delta_n) \\ T_{in} &= V_i V_n \sin(\delta_i - \delta_n) \\ u_i &= \frac{V_i^2}{\sqrt{2}} \end{aligned} \quad (3)$$

where δ and V represent the voltage angle and the voltage magnitude respectively. R_{in} , T_{in} , and u_i represent ECQ variable representing real component of flow between buses i and n , ECQ variable representing imaginary component of flow between buses i and n , ECQ variable representing voltage at bus i respectively. When these transformations are applied, the power balance constraints are expressed as follows.

$$P_{sch} = \sqrt{2} G_{ii} u_i + \sum_{\substack{j=1 \\ j \neq i}}^N [G_{ij} R_{ij} + B_{ij} B_{ij} T_{ij}] \quad (4)$$

$$Q_{sch} = -\sqrt{2} B_{ii} u_i - \sum_{\substack{j=1 \\ j \neq i}}^N [B_{ij} R_{ij} - G_{ij} T_{ij}] \quad (5)$$

where, P_{sh} and Q_{sh} give the scheduled real and the reactive power respectively. Thus, the power balance constraints are transformed into linear equality constraints. The transformed equations are constrained by the following relation

$$2u_i u_n = R_{in}^2 + T_{in}^2 \quad (6)$$

The above formulation is sufficient to describe the power flow equations for a radial network. For a meshed network, the arctangent equality constraints must also be included.

$$\delta_i - \delta_n = \tan^{-1} \left(\frac{T_{in}}{R_{in}} \right) \quad (7)$$

Adding the rotated conic quadratic in (6) and arctangent equality constraints in (7) captured the nonlinearity of the classical OPF problem (Jabr 2008; Jabr and Pal 2009). All other constraints are transformed into linear expressions making the ECQ-OPF problem easily tractable by primal-dual interior point methods.

While the Optimal Power flow (OPF) problem has been a challenge for many decades, recent evolution of the electricity grid has further increased the complexity of this problem. Additional challenges include issues such as transient stability constraints, large scale renewable energy penetration, dynamic line ratings and use of flexible AC transmission system (FACTS) devices. While traditional OPF has considered only the steady state performance of the system, the transient performance is equally important to ensure reliability and quality of supply. Dynamic transient stability constraints including rotor angle limits during contingencies must be included which require the use of algebraic as well as differential equations (Zhifeng et al. 2009). One of the first efforts to effectively approximate the dynamic nature of the TSCOPF (transient stability constrained optimal power flow) problem using numerically equivalent algebraic equations was by Gan et al. (2000). Yue et al. (2003) modelled transient stability constraint under multiple contingencies by using interior point methods (IPM). Instead of approximating dynamic characteristics by equivalent algebraic equations, Cai et al. (2008) used artificial intelligence techniques based on evolutionary programming to solve the TSCOPF problem thus demonstrating the effectiveness of artificial intelligence techniques for OPF incorporating dynamic characteristics.

Incorporation of FACTS devices present similar challenges to TSCOPF as new control variables must be incorporated which results in increased power transfer across lines and the need to consider system stability constraints (Zhifeng et al. 2009). Early work on FACTS devices (Ge and Chung 1999; Taranto et al. 1992) used methods that approximate the characteristics of the devices using simplified linearized models. In modern power systems, the increased complexities due to FACTS devices require a more versatile modelling method. Some attempts at improving the modelling of FACTS devices include use of the thyristor firing angle

as a state variable (Ambriz-Perez et al. 2000) or by real and reactive power injections due to FACTS devices as additional independent variables in the OPF problem (Ying et al. 2002). Modern power systems include devices such as static VAR compensators, solid state synchronous compensators, thyristor controlled compensators and unified power flow controllers. Jabr et al. (2008) proposed transforming the OPF problem into a second order cone program with constraints for FACTS devices such as the UPFC (unified power flow controller). While there are some efforts such as these to create better power flow models for FACTS devices, existing algorithms still need further development to be versatile or reliable enough to adequately deal with new constraints arising from FACTS devices.

More recently the use of artificial intelligence techniques and heuristic methods have overcome a number of challenges associate with convergence of classical optimisation methods, especially for transient stability constrained problems (Hayes et al. 2014; Qi et al. 2013; Rahul et al. 2012; Bhattacharya and Roy 2012). As a result, it is now possible to incorporate a number of factors such as demand management and electric vehicles which have dynamic characteristics that may result in high sensitivity to initial conditions when solving by traditional analytical methods. Hayes et al. (2014) incorporate the effect of demand side management (DSM) into the OPF formulation by quantifying benefits in terms of the ability of demand-responsive loads to relieve upstream network constraints and provide ancillary services, such as operating reserve. It uses a time-sequential OPF applied to typical radial and meshed U.K. distribution networks which suggest that including DSM in the OPF formulation can optimise the benefit. JunHua et al. (2012) develops a hybrid method involving particle swarm optimisation (PSO) and interior point methods to include the effect of plug in electric vehicles (PEHV) in the OPF problem. Qi et al. (2013) formulates the OPF problem incorporating controllable and uncontrollable distributed generators in a power network. Furthermore, they consider single and multiple generator failures and use a particle swarm optimization technique and group search optimizer to solve the problem.

Other artificial intelligence techniques were proposed by Rahul et al. (2012) by using a Genetic Algorithm based approach to demonstrate the improvement over the Particle Swarm Optimization Technique. Bhattacharya and Roy (2012) propose a gravitational search algorithm (GSA) for solutions of multi-objective optimal power flow (OPF) problems demonstrating superior convergence speed and global search ability compared with mixed integer particle swarm optimisation, evolutionary programming, genetic algorithm and biogeography-based optimisation. While artificial intelligence techniques such as the ones presented have a higher likelihood of convergence they cannot still guarantee the global optimisation and solutions from AI techniques may often provide only a local optimum or may not have any physical/practical meaning (Zhifeng et al. 2009). As a result, there is a strong motivation to develop modern analytical techniques such as those outlined in (Jabr 2008; Jabr and Pal 2009) or analytical and AI hybrid techniques such as those in JunHua et al. (2012).

3 Probabilistic Techniques

It should be evident that modern power systems operate under a high level of uncertainty. This uncertainty is introduced by the variations in load, renewable generation as well as unexpected changes in system operating conditions. It is also becoming less economically viable to operate under the large risk margins of past power systems thus risk needs to be quantified quantitatively and more closer to the reality. As a result, probabilistic techniques have seen applications in various aspects of power systems simulation and modelling. This section discusses the use of probabilistic techniques in optimisation and outlines the use of Monte Carlo simulation as it is one of the most widely used simulation technique in power systems.

To incorporate the uncertainty, stochastic optimisation techniques use the expected value of uncertain variables in the OPF problem and minimise the cost of recourse actions (Jabr and Pal 2009; Meibom et al. 2011). As an improvement from conventional day ahead unit commitment methods, Meibom et al. (2011) propose a stochastic model to study operational impacts of future high wind penetrations for Ireland. It considers uncertainty due to load, wind and forced outages using a stochastic mixed integer linear optimization scheduling model with regular updating of schedules as more data becomes available. Jabr and Pal (2009) determine the expected wind power output including the error in wind power forecasts from a probability distribution derived from historical data or estimated by a bimodal normal distribution. It then determines the wind power to schedule by balancing the expected penalty cost for not using all available wind power and the expected cost of calling up reserves because of wind power shortage.

The aforementioned stochastic optimisation techniques use variables with a known probability distribution in conjunction with deterministic constraints. An alternative method of modelling stochastic variables as well as uncertainties in constraints is the chance constrained optimisation where the probability of violating a constraint is limited to a predetermined value (Qianfan et al. 2012; Hui and Pu 2011). Hui et al. (2011) identifies the additional complexity of the chance constrained OPF problem due to nonlinear constraints with multiple uncertain variables as well as uncertain constraints. It uses a back-mapping approach and a linear approximation of the nonlinear model equations to incorporate the chance constrained programming (CCP) approach to OPF under uncertainty. Qianfan et al. (2012) uses a two-stage chance-constrained stochastic program to include uncertainties due to wind power in the unit commitment problem, while maximising wind power utilisation. It develops a combined sample average approximation (SAA) algorithm to solve large-scale power grid optimization problems. Chance constrained optimisation is one the few methods that can use analytical techniques to capture uncertainty in constraints. However, it is required to have standards and guidelines to specify how the predetermined maximum probability of constraint violation is selected. Traditional stochastic optimisation avoids this problem by using expected values and penalties for deviating from the expected value, but it cannot account for uncertainties in constraints. Dynamic line ratings lead to

uncertainties in constraints and more research could be directed towards modelling such uncertainty so that dynamic line ratings may be incorporating into dispatch decisions.

4 Stochastic Optimal Power Flow

Stochastic optimization is the process by which the optimization is undertaken when there is an uncertainty in one or more of the variables. The uncertain variables must have a known probability distribution. The optimisation can then be solved with the expected value of the uncertain variable. To ensure that the expected value of the variable is chosen appropriately by the algorithm, it is assumed that there is a cost of recourse action if the actual value of the variable is different to the expected value. The total cost of the recourse action is included in the objective function. Variations from the scheduled value have a penalty factor associated with them and this ensures the best value is chosen for the scheduled variables.

The method of stochastic optimisation is often referred to as two stage stochastic programming. The first stage refers to the values of the known variables and the second stage refers to variables that are not yet known but will be realised in future. However, the optimisation decision should only account for the information available at the time which is usually in the form of a probability distribution. The general problem definition for optimisation under uncertainty is

$$\min_{x \in X} \{g(x) := c^T x + E[Q(x, \xi)]\} \quad (8)$$

where $E[.]$ represents the expected value and $Q(x, \xi)$ is the optimum value of the second stage problem.

$$\min_y q^T y \quad \text{subject to} \quad Tx + Wy \leq h \quad (9)$$

The first stage decision vector is x and the set of constraints are in X . The second stage decision vector is y and the second stage data is contained in $\xi = (q, T, W, h)$. The value of ξ is uncertain and a decision must be made based on the expected value when solving the first stage problem. The optimisation of the second stage can be considered in terms of recourse action for when the actual realisation of the uncertain vector is different to the value used for optimisation. The solution of the first stage problem should be such that the expected cost of recourse action is minimised.

The possible realisations of ξ present a challenge especially when there are a large number of outcomes possible. Monte Carlo techniques based on Sample average approximation can be used to reduce the number of realisations to a manageable size.

Sample average approximation (SAA) can be used for optimisation when there is uncertainty in the objective function. In practical scenarios objective functions may not be known accurately and hence the parameters defining the function are modelled as random variables with known probability distributions. The objective function $f(x)$ is replaced by the expected value which is obtained by repeatedly sampling $f(x, \xi)$ for different values of the uncertain vector ξ and finding the average of those samples as $f_N(x)$ for N samples. This is shown in (10) and it is assumed that each sample is independent and identically distributed (i.i.d).

$$f_N(x) = \frac{1}{N} \sum_{i=1}^N f(x, \xi_i) \quad (10)$$

where ξ_i represents the vector that contains all the parameter with uncertainty. In this instance $\xi_i = [\text{cOLp}]$ such that it contains Dynamic Line rating (DLR) cost parameter for each line in the system. The objective function of optimization can be replaced by the SAA function in (10). Thus, if the original objective function is denoted $f(x, \xi_i)$ it can be replaced by the SAA approximation $f_N(x)$.

If $f_N(\cdot)$ converges uniformly to $f(\cdot)$ then it is well established that for a given sample size N , the optimal solution, x_N and the optimal value, $f_N(x_N)$ are random variables with normal distribution (multivariate normal distribution in the case of the optimal solution x_N). $f_N(x_N)$ is approximately Normal (v^* , $\sigma^2(x_N)/N$) and x_N is Normal (x^* , $H^{-1}\psi H_{-1}$). The true values of optimal solution and optimal value are given by x^* and v^* respectively. H represents the hessian matrix of the objective function $f(x)$. ψ is the asymptotic covariance matrix of $\sqrt{N}[\nabla f_N(x) - \nabla f(x)]$.

Thus, it should be possible to determine a $(1 - \alpha)$ confidence region for the optimal solution in terms of a tolerance q . We can then state with probability $(1 - \alpha)$ that any estimator of the optimal solution based on N samples, will be within a tolerance of q from the true solution. The value of q can be expressed as a percentage and be made smaller for a more accurate solution by choosing a larger value of N as long as uniform convergence characteristics are satisfied.

It should be noted that for a multivariate normal distribution the confidence region is an ellipsoid. Thus, the tolerance q is defined in terms of the boundaries of the ellipsoid. As the worst case scenario, we may only consider the largest axis of the ellipsoid which represents the furthest distance a possible solution can be from the true solution.

An example of OPF under uncertainty occurs when wind generation output is considered. The OPF problem can be represented as a stochastic optimisation problem since the output from a wind farm is a random variable with a known probability distribution. The expected wind power output is determined from the probability distribution at the scheduling stage. During the operational phase any deficit or excess in actual wind power output compared to scheduled output, must be balanced by additional reserve generation or by curtailing excess wind. Thus, reserves and wasted wind are the recourse actions which account for any differences between expected wind output and actual wind power output. The wind power

intermittency cost ($C_w(P_w)$) is modelled using stochastic optimization by discretizing the probability distribution of wind power and balancing probabilistic reserve cost with cost of wasted wind (Jabr and Pal 2009) as shown in (11).

$$C_w(P_w) = \sum_{j=1}^{N_w} \left[e_j P_{wj} + c_{wj} \sum_{k=1}^M f_{jk} s_{jk} + c_{Rj} \sum_{k=1}^M f_{jk} t_{jk} \right] \quad (11)$$

where the power output of wind generator j is P_{wj} and the unit feed in cost is e_j . The cost of wind in (11) is subject to the constraints in (12).

$$\begin{aligned} t_{jk} &\geq P_{wj} - w_{jk} \\ s_{jk} &\geq w_{jk} - P_{wj} \\ t_{jk} &\geq 0, s_{jk} \geq 0 \end{aligned} \quad (12)$$

where (f_{jk}, w_{jk}) is the k th ordered pair (out of a total of M) representing the discretised probability distribution of wind generator j . N_w is the number of wind generators in the system and c_{wj} and c_{Rj} are the unit cost of wasted wind and reserve generation respectively at wind generator j . Based on the constraints in (12), the probability distribution of reserve generation is represented by the set of ordered pairs (f_{jk}, t_{jk}) and the probability distribution of wasted wind is represented by the set of ordered pairs (f_{jk}, s_{jk}) . The cost of wasted wind represents the opportunity cost of not being able to sell the energy generated.

4.1 Monte Carlo Simulation

Monte Carlo Methods are commonly used for modelling inherent variability in systems of which a closed form analytical expression cannot be obtained or is complex. Monte Carlo simulation is based on simulating the value of uncertain parameters using random number generators to determine the sampled statuses and estimating the outputs. After a large number of simulations (trials) are performed, it is expected that the probability distribution of the outputs will be obtained with a degree of confidence to the confidence interval. In contrast, a deterministic method may use the mean value of uncertain parameters and hence obtain the mean value of the output. This method may provide an accurate representation of the mean value of the output but does not capture the variability or in other words it assumes that each event has a same level of probability. Alternatively, some methods may attempt to evaluate every possible combination of uncertain parameters to obtain an exhaustive range of outputs. Such a method is complex, resource intensive, and often unnecessary as some combination of parameters is highly unlikely to occur in a practical scenario. Monte Carlo simulation considers different combinations of inputs and corresponding outputs, based on the likelihoods of these conditions occurring in a practical scenario (Rubinstein and Kroese 2008).

In power systems, Monte Carlo simulation has been used in a wide range of applications when there has been an uncertainty. One of the traditional applications of Monte Carlo simulation has been in reliability and security evaluation (Billinton and Peng 1999; Rios et al. 2002). A typical example of distribution system reliability using Monte Carlo techniques is presented by Billinton and Peng (1999). It is argued that considering the mean value of system reliability indices does not reflect the reliability seen by the customer due to the inherent variability of these indices. A time sequential Monte Carlo method is then used to obtain both the mean value and probability distribution of a range of system reliability indices. Rios et al. (2002) examines similar techniques for transmission system security where deterministic criteria have traditionally been used. It is proposed that the cost of the security margin should be weighed against the benefit obtained by using probabilistic techniques. This method also accounts for time dependent phenomena such as cascade tripping due to overloads, unreliable operation of protection devices, and potential power system instabilities. The advantage of this type of approach is that it can prevent over-designing of a system to meet deterministic security criteria where the added benefit may be minor.

Unit commitment is closely related to reliability and security at the transmission level and Monte Carlo analysis can be applied in modelling uncertainties (Lei et al. 2007, 2008, 2010; Zhai et al. 1994). Earlier studies on stochastic unit commitment (Zhai et al. 1994) considered the uncertainty due to load while more recent studies (Lei et al. 2007, 2008, 2010) consider effects of wind and other renewable generation in addition to likelihood of outages. These studies clearly demonstrate that Monte Carlo simulation captures not only uncertainties due to outages and component failures in the system but also the variability of load and renewable power generation and hence present a more accurate and comprehensive evaluation of unit commitment risk.

Probabilistic load flow is another application of Monte Carlo simulation techniques (Allan et al. 1981a, b). Allan et al. (1981a, b), Chun-Lien (2005) developed an improved method for probabilistic load flow using the results of Monte Carlo simulation. More recent studies used Monte Carlo simulation for probabilistic load flow with integration of renewable power generation and distributed generation (Jorgensen et al. 1998; Ruiz-Rodriguez et al. 2012). When wind integration is considered, reserve allocation in the presence of wind can also be determined by Monte Carlo techniques (Ortega-Vazquez and Kirschen 2009; Zhai et al. 1994).

5 Conclusion

Modern power systems rely on advanced modelling and simulation techniques to facilitate decision making. Increasing complexity of power systems has resulted in developments in advanced and innovative modelling and simulation methodologies. Most power system decision making involves determining the optimal configuration for operating system resources under a wide spectrum of static and

dynamic constraints. Modern optimisation techniques include both analytical and heuristic and often a combination of both to improve the solution efficiency for such problems. Probabilistic modelling can account for the uncertainties and associated risks of decision making. Stakeholders in the power system can thus plan contingencies accordingly.

The area of power system modelling and simulation is an active and wider area of research. There are a number of key areas that could further increase the effectiveness of the existing methodologies. Analytical and artificial intelligence based techniques continue to improve and new developments in mathematics are often applied to power systems. Improved understanding of risk and uncertainty continue to influence decisions which will lead to less built in redundancies in systems thus resulting in lower overall costs. These developments coupled with improvements in computing technologies will ensure that the power systems of the future will be flexible, robust and reliable.

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