Global Control of Complex Power Systems

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Abstract. This chapter presents an overview of recent results on an approach to total control of power systems. It is upwards compatible from any conventional or prior advanced control and provides a framework for coordinated development of control to address all major dynamical problems. The approach appears applicable to complex systems generally where behaviour is influenced by nonlinearity, large-scale, uncertainty and hybrid nature. In particular, the presence of bifurcations of various kinds is allowed for while using ideas from switching and optimal control. The approach will be illustrated by consideration of coordinated control for transient stability, voltage regulation and emergency voltage control of power systems.

1 Introduction

This chapter describes progress towards a general methodology for control of complex systems, particularly those that have large scale, are strongly not linear and have substantial uncertainty in their modeling. The work is motivated by earlier work, on transient stabilisation and network control for voltage security of power systems [1–6], and some ideas for general control. In arriving at progressively more general and flexible approaches, various techniques from advanced modern control have been absorbed such as dynamic programming, model predictive control, nonlinear control, so-called fuzzy control (as a non-linear control formula), switching and hybrid control. The overall framework to devise controllers which deal with complexity is called global control.

Models are assumed to be of a heterogeneous hybrid kind, i.e., a mixture of differential, algebraic and switching equations with different versions in different spatial and state domains. The various control elements correspond to existing physical controls, typically designed independently and assumed to be tunable, and other modules to be designed. Control is implemented in several layers of continuous and discrete actions.

Global hybrid control is presented as natural way to harness all the control elements optimally to coordinate a control response to dynamical problems as they arise. The controlled response can be designed to achieve feasible secondary specifications such as for transient behavior, quality of supply, economy. Global control can be regarded as a concept which has evolved from techniques like gain scheduling and, more recently, multi-model control. A further idea of global control is to combine the qualitative and quantitative knowledge through some hierarchy. This connects to methods of systematic switching via membership type functions. One of the most practically successful approaches for utilizing the qualitative knowledge of a system to design a controller is fuzzy control. Results have been obtained in [9] where heterogeneous control provides combination of local control actions appropriate to different operating regions. A common feature of these methods is that they make use of mature results for the local controller design and provide necessary coordinations. A major feature added here is that the local controls are coordinated in optimal control schedules. In the development of generic techniques of control, very little recognition is made of underlying bifurcation structure, except in examples. A further feature to provide here is that the controller architecture be fully sensitive to bifurcations of various kinds.

Following development of the main ideas, two important problems in power system control will be used for illustration, namely transient stability control and network control. Power system dynamics is commonly studied in terms of bifurcations occurring as power levels are raised. Transient stability and voltage regulation are both important properties to guarantee in power system control, but they are studied via different model descriptions and related to different stages of system operation (i.e. the transient period, post-transient period, mid-term and long-term behaviour). In this chapter, we design a global controller to co-ordinate the transient stabilizer and voltage regulator in the transient period. Earlier control results deal with the two problems separately, or employ a switching strategy of two different kinds of controllers, which causes a discontinuity of system behavior. The designed controller is smooth and robust with respect to different transient faults.

To enhance the transient stability of power systems, in recent years a great deal of attention has been paid to the application of feedback linearization approaches [10], see e.g. [11–13]. Compared with use of conventional approximate linearization, which can only deal with local stability around an operating point, the controlled system can endure large disturbances and retain a steady post-fault condition. Inevitably, in order to enhance the stability, the power angle has to be one of the feedback variables whereas the generator voltage is not needed. In such transient stabilizing control, a common phenomenon is that the post-fault voltage value varies considerably from the prefault one [14]. From the practical point of view, voltage quality is a very important index of power supply in power system operation; so the post-fault value is expected to reach the normal value as closely as possible. In [14–16], voltage regulation was achieved by introducing voltage feedback. However, the voltage controllers are only effective around a working region, i.e., they work well when a small disturbance occurs and at the post-fault stage, but cannot survive a large disturbance. Different behavior of nonlinear power systems in different operating regions requires different control objectives and consequently different control actions must be employed in each operating region. How to achieve a satisfactory control performance over a wide range of anticipated operating conditions is demonstrated using global control.

The second major illustration introduces use of optimal control to achieve coordination of local physically based controllers. A method of optimal coordination is presented for load shedding, capacitor switching and tap changer operation using a dynamic system model in order to preserve or retain long-term voltage stability. Voltage stability is well-known to be related to bifurcations encountered as the loading of the system is increased. The method is based on model predictive control and a tree search. A model of the controlled system, including the network and load dynamics, is used to predict the future system behaviour based on the current state and applied control actions. The optimal control state according to these predictions is then obtained using a search method similar to those used in chess playing computers.

The structure of the chapter is as follows. Section 2 will discuss global control in general terms. Sections 3 and 4 present the specific illustrations of transient stabilisation with voltage regulation and network control with dissimilar devices respectively. Section 5 gives some conclusions. The presentation is somewhat descriptive to enable presentation of ideas which have scope for further development theoretically and in applications. Earlier versions of this chapter have been presented in conference form [7,8].

2 Global Control Ideas

2.1 Introduction

Global control is a further development of modern control design towards the capability to handle complex systems. Like power systems, many practical systems have the following four major characteristics: 1) substantial nonlinearity; 2) large-scale; 3) uncertainty in the model; and 4) hybrid or heterogeneous form. The last aspect refers to a mixture of control actions, i.e. discrete and continuous, and control requirements, possibly in different regions of operation. Adaptive, robust, intelligent and stochastic control are well-known methodologies which overcome parametric variation, unstructured uncertainty, unknown models and random disturbances respectively. Here it is of interest to note more recent developments in so-called multi-model, switching and hybrid control [20–24] as at least partially able to address the problems of complexity in a holistic way. No attempt is made to give extensive references; some representative results directly supporting this discussion only are chosen for reference. It remains to develop these methods to address systems of serious large-scale and mixed uncertainty types such as appear in power systems. In practice, a framework is needed for designing controls of a truly global kind which act in a coordinated way across the whole system geographically and for all operating situations, ie for all states and in-the-large (in the sense of stability theory) as parameters and conditions vary. This appears possible by combining ideas already developed for power systems with some of the newer techniques in control.

There are several special features of power systems which are noteworthy for the study of complex systems: 1) the system has a large-scale network structure; 2) many of the controls are embedded in the system with some having scope for tuning; further control design must allow for and enlist where possible these existing controls; 3) the overall control scheme will have a hierarchical structure; 4) the control actions available physically are already largely determined and have diverse timing, cost and priority for action; 5) the control goals are multi-objective with local and global requirements which vary with system operating state, e.g., normal and insecure states in power systems. Of course, many systems in industry, such as chemical processes, share these features. A related issue which is often mentioned in more practical discussions of general control science needs is "reconfigurability". It is recognised that the control designers have a huge toolbox of techniques for developing the models and local controllers throughout a system. There needs to be more effort on the higher levels of control to deal with failures and external events. Power systems engineers certainly need no reminding of this issue.

In general, we need a high-level version of distributed adaptive optimal control which "swarms" around the complex system attacking problems as they arise, but keeping a meta-view so that other problems are not ignored while attending to a particular one. Needless to say the implementation requires accounting for physical features like physical sparseness and time-scales as always to reduce computation demands. Thus, the approach favoured exploits model-based approaches as much as possible, only appealing to notions from intelligent control to deal with interpolation on extrapolation from known models.

2.2 Hybrid models

The use of hybrid models in power systems is already well-accepted to capture the use of mixed continuous and discrete control actions [70]. The equations often take a differential-algebraic-difference (DAD) form as follows

$$\dot{x} = f(x, w, z(k); \lambda) \tag{1}$$

$$0 = g(x, w, z(k); \lambda) \tag{2}$$

$$z(k+1) = h(x, w, z(k); \lambda) \tag{3}$$

The dynamic state variables x are variables that appear as derivatives in the differential equations and cannot change instantaneously. On the other hand, the algebraic state variables w do not appear as derivatives, and can thus change instantaneously due to changes in x or $z(k)$. The discrete state variables $z(k)$ have discrete-time dynamics and can change only at fixed time instants given by a selected sample time. The dynamic state variables relate to generator flux, continuous control and load dynamics; algebraic state variables relate to network voltages and currents, and the discrete states $z(k)$ typically arise from discrete control logic such as relay controls. The parameters are denoted λ and may include control parameters, independent parameters and action variables. We can write $\lambda = (\theta, \vartheta, u)$ where θ represents tunable parameters, ϑ represents the (structured) uncertainty and u the control variables which are yet to be designed. The basic DAD model will include control algorithms (discrete and continuous) for which no further tuning is planned.

The use of hybrid or DAD models has been discussed in more general terms for power systems in [25,26]. In particular, the discrete time actions can be generalised to allow for switching and reset events which depend on system behaviour. Recent advances in modeling software make use of hybrid models more straightforward. For instance, we can use the modeling and simulation tool Dymola, which has a power systems library [27].

As exists for differential equation models and DA models, e.g. see [28], a basic set of analysis tools for DAD systems is needed. This is currently the subject of active research. Some results have been summarised in [29,30].

2.3 Control elements

One of the problems with applying modern control methods like adaptive, fuzzy or robust control to power systems is that they are established in a generic framework which is not sensitive to the structure of particular practical systems. Hence many practitioners get the impression that these methods, while sounding appealing at first, are really impractical. Part of the problem is that they are presented as replacement rather than additional control. A more specific challenge is to blend these new ideas into the overall scheme of control which exists, i.e. excitation control, PSS, security control and network regulators such as tap-changers. Typically, much of this is already trusted and we only need some new control modules and overall co-ordination.

Co-ordination has not been a strong point of power system control in the past. Generally a sequential design approach has been taken rather than a holistic (or global) approach. It has often been the case that the solution to the last problem has caused the next problem, e.g. fast excitation systems for transient stability led to self-excited oscillations. Of course there were limitations in control technology which prevented use of a more comprehensive approach and the ingenuity of engineers to overcome these problems has been impressive. However, it might be that this approach has about met its limit with recent changes in the industry leading to much greater complexity. On the other hand, modern information technology for control, communication and computing (CCC) gives us possibilities to use intelligent distributed algorithms to complement more traditional approaches. It is worth noting that many of these issues have been dealt with in a simpler form in development of coordinated PSS schemes in the 1980's [31–33]. The PSS modules were designed largely according to local stability criteria. They could be designed sequentially or simultaneously to accommodate the effect of interactions, but this could be a large computational task either way. The simultaneous approach amounts to an optimisation of any tunable parameters within certain operating constraints to position the closed loop modes of the system with adequate damping. In Russia, such algorithms were highly developed for coordinating stability on large systems and robustly with respect to changes of system structure - see [34] and especially the references within. In this particular problem, it is interesting to note that system structural conditions were found, related inter alia to loading levels, under which the designs could be largely decoupled [35]. Typically, such decoupling does not apply in heavily loaded systems, but its presence in any degree maybe useful.

In looking to generalise these ideas to the whole control problem of maintaining stability while providing specified performance, we start by identifying the basic *control elements,* i.e. those existing controllers and their tunable parameters which are free to adjust for system-wide purposes.These will be based on physical devices or at least the designs for them. The controller could have the form

$$u_i = U_i(x_i, w_i, z_i(k); \theta_i, \vartheta_i) \tag{4}$$

where subscript i refers to a geographical part of the system and/or some special control task, e.g. transient stabilisation in an area of a power system. The controller is typically expressed as a function of state variables or as a dynamical system driven by certain system outputs. This controller could be anything from a simple classical PID controller to the most sophisticated nonlinear controller (including rule-based, fuzzy or model-based designs such as feedback linearisation). The controller is required to perform well in spite of the uncertainty ϑ_i. The parameters θ_i are available to implement co-ordination with other controllers.

2.4 Bifurcations and global control

The development of nonlinear control theory has generally evolved along several lines of thought. There are many books on this topic - see for instance the recent ones [10,36–38]. Emerging from mathematics of dynamical systems and the study of some specific systems, there has been an extensive study of nonlinear systems dynamics in terms of underlying bifurcations in the models [37]. This line has been extensively pursued for power systems analysis [39]. While bifurcation control has been developed for special systems of scientific interest [40], it has not been developed for power systems in any practical way. Most work on generic nonlinear control does not deal with the bifurcation structure. In fact, many assumptions used in the development of nonlinear control algorithms effectively rule out bifurcations of dynamical behaviour. When we consider the possibility of parameters crossing bifurcation boundaries, we should develop control on at least two levels, as is commonly discussed for power systems: the first level uses continuous and switching type control to establish an appropriate equilibrium operating point (or manifold); the second level deals with the system dynamics around these operating points and uses techniques from stabilisation and local bifurcation control. We could classify controllers as: 1) bifurcation avoiding; 2) bifurcation delaying; 3) bifurcation eliminating; 4) bifurcation accepting. Loosely speaking, the controller could keep the system well away from the bifurcation boundaries, as is typical for power systems, push the boundaries further away in parameter space, eliminate certain boundaries, or devise a scheme for operating across the boundaries. The study of performance of the various forms of textbook control tools in these situations is incomplete, but intuitively they will have many problems dealing with such complexity in their basic form. For example, adaptive control is clearly challenged by the unknown parameters encountering a bifurcation.

Our global control objective is to achieve good control performance over a wide range for the anticipated operating region with robustness to different faults whose sequences are not known apriori. The bifurcation boundaries define domains of operation where the dynamical behaviour is qualitatively different, see [39] for review papers. A possible control strategy, accepting the boundaries, is to design controllers for each structurally stable region and switch between them in some way. A scheme which has the abovementioned two-level structure has been presented and used for a standard example in [5]. The switching controller has a weighted Sugeno type form used in fuzzy control, but is motivated by the need to allocate control effort according to dynamical behaviour. Assuming the state-parameter space is partitioned into two domains, the control u takes the form:

$$u = u_e + \mu_1 u_1 + \mu_2 u_2 \tag{5}$$

where u_e provides the new equilibrium manifold; μ_1 and μ_2 are functions of an indicator variable expressing the closeness to a particular region or control concern; and $u_1$and u_2 are the local controllers which can have the general form (4). The overall control for a specific design is just a special form of nonlinear controller which may have tunable parameters. There may be many such controllers acting on the complex system.

More generally the domain boundaries could be defined by regions where modeling is unknown and typically behaviour changes in some major way, so switching control again becomes natural. Between these discrete models the models are incomplete and uncertainty must be allowed for. A complete model becomes an interpolation which can be expressed in various ways, e.g.

see [9,41] for use again of fuzzy-control type membership functions to switch between local controllers.

Another possible control architecture employs a neural network to choose between local controllers according to pattern recognition of dynamical behaviour. This idea has been studied for a power system application [74].

2.5 Optimal coordination and swarming

Once all the local controllers are designed and teamed up where needed, e.g. as in (5), the freedom to use them flexibly should be fully exploited. It is of no great concern that the controllers might be complex in themselves. Besides the argument that they can often be expressed in software code, at a system-wide level the controller complexity is related more to the number of parameters that need tuning. This may involve simply tuning of free parameters, as in the PSS case mentioned above, or a more complicated scheduling exercise which allows for any control redundancy to use scaling and timing according to control costs, dynamic properties and priority. The latter idea is familiar at least for static scheduling in operations research, but is quite complicated for dynamical systems as it requires the solution of the optimal control problem [42,43]. In [1,3], a technique along these lines has been developed for optimally coordinated voltage security control of power systems using differential dynamic programming (DDP) and trajectory sensitivity methods to set-up the staged use of available controls in an optimal way. However, there is a wealth of techniques which can be explored here: in particular, all ideas in modern control which boil down to use of optimal control. In Section IV, we will illustrate further work on the voltage security problem using Model Predictive Control (MPC) and search techniques as a way to set up the optimal tuning. The connection between DP and MPC can be made [44], but each has been developed with a set of techniques for implementation with various forms of complexity. There are many special ideas which can be mentioned to implement optimal coordination. One useful one, which suits the current framework, was formulated in the Russian literature and used for adaptive nonlinear control [45,46]. The control objective is expressed in memoryless or integral form. The control algorithm takes a two-level structure with a controller of the form (4) and a so-called speed-gradient parameter update.

The switching idea expressed above can be interpreted as allowing the controller to adjust the individual contributions of the local controllers according to the particular problem being faced at a given time. For instance when an instability occurs in a certain domain or in a certain variable type, e.g. voltage instability, the indicators driving the weighting functions will automatically adjust the control to emphasize the appropriate actions. When optimal coordination of many such controllers is considered, we can think of numerous controller elements in a complex system as swarming [47] to deal with problems as they arise.

It is beyond the scope of this chapter, but it is straightforward to see special forms of adaptive and learning control as specific examples of the above coordinated tuning of control elements framework. The theory of aspects of optimal control for structured nonlinear systems with variable parameters needs further development, but many ideas have already been established in the development of adaptive control- see for instance [20,48,49].

3 Global Transient Stability and Voltage Regulation

3.1 Introduction

In this section, we design global control to maintain transient stability and achieve satisfactory post-fault voltage level of a power system when subjected to severe disturbances. The control signal from the global controller has the form (5), i.e. the weighted average of the signals from the local control laws. Since the membership functions can be determined by direct measurable variables of power systems, it has several appealing properties compared with the switching control strategy proposed by [14]. For example, to achieve control action switching, the fault sequence needed to be known apriori; also as long as the switching time is fixed according to a certain fault, the system may not survive another different fault. The global control law overcomes these disadvantages by sensing the relevance of stabilisation and regulation and automatically shifting to the appropriate controller. By a smooth transition between pure control regions, our global control objective is achieved. It is important that it adopts a mature control strategy in each local region, i.e. familiar schemes can be preserved.

The results presented here are based on the paper [6].

3.2 Dynamical model of power systems

We consider the particular SMIB power system arrangement shown in Figure 1. The actual dynamic response of a synchronous generator in a practical power system when a fault occurs is very complicated including many nonlinearities such as the magnetic saturation. However, the classical third order dynamic generator model has been commonly used for designing the excitation controller. More complete models are used in the simulations to evaluate the design in the presence of other effects.

The classical third-order dynamical model of a SMIB power system (Figure 1) can be written as follows [52–54]:

Mechanical equations:

$$\dot{\delta} = \omega \tag{6}$$

$$\dot{\omega} = -\frac{D}{2H}\omega + \frac{\omega_0}{2H}(P_m - P_e) \tag{7}$$

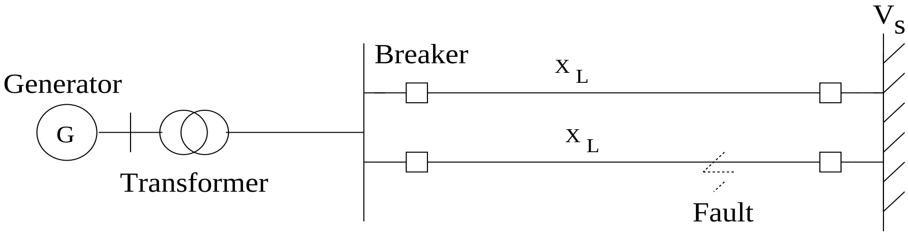

Fig. 1. A single machine infinite bus power system.

Generator electrical dynamics:

$$\dot{E}_q^{'} = \frac{1}{T_{do}^{'}}(E_f - E_q) \tag{8}$$

Electrical equations:

$$E_q = \frac{x_{ds}}{x_{ds}^{'}}E_q^{'} - \frac{x_d - x_d^{'}}{x_{ds}^{'}}V_s \cos\delta \tag{9}$$

$$P_e = \frac{V_s E_q}{x_{ds}} \sin\delta \tag{10}$$

$$I_q = \frac{V_s}{x_{ds}} \sin\delta = \frac{P_e}{x_{ad} I_f} \tag{11}$$

$$Q_e = \frac{V_s}{x_{ds}} E_q \cos\delta - \frac{V_s^2}{x_{ds}} \tag{12}$$

$$E_q = x_{ad} I_f \tag{13}$$

$$E_f = k_c u_f \tag{14}$$

$$V_t = \frac{1}{x_{ds}} \left[x_s^2 E_q^2 + V_s^2 x_d^2 + 2 x_s x_d x_{ds} P_e \cot\delta\right]^{\frac{1}{2}} \tag{15}$$

where $\delta(t)$ is the power angle of the generator (in *radian*), $\omega(t)$ is the relative speed (in *rad/s*), P_m is the mechanical input power (in *p.u.*), P_e is the active power delivered to bus (in *p.u.*), E_f is the referred field excitation voltage, $E_q^{'}$ is the transient EMF in the quadrature axis (in *p.u.*), and V_t is the terminal voltage of the generator (in *p.u.*). The notation for other variables and parameters are standard and readers are referred to [14,54,55].

The fault considered in this chapter is a symmetrical three phase short circuit fault which occurs on one of the transmission lines.

In the next section, we test the existing controller performances on different fault sequences, and then in Section 3.D a new global controller will be presented and tested.

3.3 Local controllers

A. Nonlinear controller for transient stability

As discussed in [10], feedback linearization is a quite appealing design method for nonlinear systems. Since it avoids the local nature of approximate linearization and transforms the system to be linear over a very wide range, it has been applied to power systems by different authors shortly after it was available – see e.g. [11–15,56–59]. In the following, we briefly describe a design based on so-called direct feedback linearization (DFL) compensators [14,13]. This more easily allows particular physical states to be preserved than the geometric algorithm version in [10].

By a DFL transformation [13], (6)-(8) becomes

$$\begin{aligned}
\dot{\delta} &= \omega \\
\dot{\omega} &= -\frac{D}{2H}\omega - \frac{\omega_0}{2H} \triangle P_e \\
\triangle\dot{P}_e &= -\frac{1}{T'} \triangle P_e + \frac{1}{T'} v_f
\end{aligned} \tag{16}$$

where

$$\triangle P_e = P_e - P_{m0} \tag{17}$$

$$T^{'} = \frac{x^{'}_{ds}}{x_{ds}} T^{'}_{d0} \tag{18}$$

$$\begin{aligned}
v_f &= \frac{V_s}{x_{ds}} \sin\delta \left[k_c u_f + T^{'}_{d0}(x_d - x^{'}_d)\frac{V_s}{x_{ds}} \sin\delta\ \omega \right] \\
&\quad + T^{'} \frac{V_s}{x_{ds}} E_q \cos\delta\ \omega - P_{m0}
\end{aligned} \tag{19}$$

Note that the mechanical power control is represented as a constant power P_{m0}, i.e. the governor loop is relatively slow acting.

Now, we note (16) is a linear system with the new input v_f. Robust control techniques for linear systems [60,61] can be employed. By solving an algebraic Riccati equation (ARE) – see [13,55] for details, the control law is obtained as

$$v_f = -k_\delta \delta - k_\omega \omega - k_P \triangle P_e \tag{20}$$

where k_δ, k_ω, k_P are the linear gains obtained from the solutions of ARE.

The real excitation control u_f can be obtained from (19) to give

$$\begin{aligned}
u_f &= \frac{x_{ds}}{k_c V_s \sin\delta} \left[v_f - T^{'} \frac{V_s}{x_{ds}} E_q \cos\delta\ \omega + P_{m0} \right] \\
&\quad - T^{'}_{d0}(x_d - x^{'}_d)\frac{V_s}{k_c x_{ds}} \sin\delta\ \omega
\end{aligned} \tag{21}$$

The DFL nonlinear control (21) with (20) guarantees the transient stability of power system (6)-(8) for admissible uncertain x_L and V_s – proof is given in [13].

However, since V_t is a nonlinear function of δ, P_e and the system structure, any change in the system structure will cause the voltage to reach another post-fault equilibrium point even if δ and P_e are forced to go back to their prefault steady values. So the generator terminal voltage V_t could stay at a different post-fault state which is undesirable in practice.

From the above, we can see that although the DFL nonlinear compensator is effective for stability, it cannot guarantee voltage regulation. The simulation results shown later in this section will verify that the DFL nonlinear controller enhances the transient stability of power systems but cannot by itself achieve a satisfactory post-fault voltage level.

B. Voltage controller

Voltage regulation is an important property particularly in the post-transient period. The basic objective is to regulate the voltage to reach its nominal value. Voltage controllers have been given in [15] using LQ-optimal techniques and in [16] using a linear robust control technique. Both of them have the problem that they deteriorate transient stability over the whole operating region.

For example, as proposed in [16], differentiating equation (15) gives

$$\triangle \dot{V}_t = f_1(t)\omega + \frac{f_2(t)}{T'_{d0}} \triangle P_e + \frac{f_2(t)}{T'_{d0}} v_f \tag{22}$$

where $f_1(t)$ and $f_2(t)$ are highly nonlinear functions of δ, P_e and V_t – see [16] for details. Since $f_1(t)$ and $f_2(t)$ are dependent on the operating conditions, their bounds can be found within a certain operating region. So a new linearized system which is represented by the vector $[\triangle V_t, \omega, \triangle P_e]$ can be developed. Robust linear control techniques can be applied to obtain

$$v_f = -k_V \triangle V_t - k_\omega \omega - k_P \triangle P_e \tag{23}$$

where k_V, k_ω, k_P are linear gains dependent on the bounds of $f_1(t), f_2(t)$. The real excitation input u_f is chosen as defined in (21).

Since the voltage is introduced as a feedback variable in (23), the post-fault voltage is prevented from excessive variation. It is unnecessary to keep the power angle regulated once transient stability is assured.

However, since the design of the voltage controller involves estimating nonlinearity bounds within a certain operating region, it is only effective locally. In another words, when serious disturbances occur which cause the system to operate in a wider range outside the estimated one, the designed system may not perform well.

In conclusion, the voltage controller achieves voltage regulation, but it is only valid locally. This point will be verified in the simulations in Section 3.3.

C. Coordinated control by switching

By now it can be seen that the DFL nonlinear controller and voltage controller achieve different control objectives in different regions of the states. In [14,55], a nonlinear coordinated control scheme was proposed where a switching strategy is used between the different control actions to guarantee transient stability enhancement and voltage regulation.

The simple switching scheme is as follows:

Step 1: When the fault occurs at $t = t_0$, the DFL nonlinear controller u_f (21) with (20) is employed to maintain the transient stability of power systems;
Step 2: At $t = t_s$, the control law switches to the voltage controller u_f (21) with (23) to maintain the desired post-fault voltage level.

Since the switching time is physically fixed according to one particular fault sequence, it may not be suitable for a different fault sequence, which may then destabilize the power system. Also, the switching time fixed in the first post-transient period cannot achieve voltage regulation over the whole working region allowing for later faults. In summary, the switching strategy with the switching time fixed is not robust with respect to different faults.

How to design a universal control law which is robust with respect to uncertain faults is a challenging problem. Before stating our global controller which overcomes these obstacles, we show in the next subsection simulation results of the controllers which were discussed above.

D. Simulations of local controllers

The parameters of the SMIB power system which is shown in Figure 1 are as follows:

$$\begin{aligned} &x_d = 1.863, \quad x_d^{'} = 0.257, \quad x_T = 0.127, \\ &T_{do}^{'} = 6.9, \quad x_L = 0.4853, \quad H = 4, \quad D = 5, \\ &K_c = 1, \quad x_{ad} = 1.712, \quad \omega_0 = 314.159. \end{aligned} \tag{24}$$

The physical limit of the excitation voltage is taken as

$$-3 \leq k_c u_f \leq 6 \tag{25}$$

The operating point of the power system used in the simulations is:

$$\delta_0 = 72^\circ,\ P_{m0} = 0.9 p.u.,\ V_{t0} = 1.0 p.u. \tag{26}$$

The fault sequence consists of two symmetrical three phase short circuit faults–one temporary and then one permanent (Case 3 in [6]):
Stage 1: The system is in a prefault steady state;
Stage 2: A fault occurs at $t = t_0$;
Stage 3: The fault is removed by opening the breakers of the faulted line at $t = t_1$;

Stage 4: The transmission lines are restored at $t = t_3$;
Stage 5: Another fault occurs at $t = t_4$;
Stage 6: The fault is removed by opening the breakers of the faulted line at $t = t_5$;
Stage 7: The system is in a post-fault state.

The nominal switching time for the controller has been set at $t_s = t_2$. We choose in the simulation $t_0 = 0.1s, t_1 = 0.25s, t_2 = 1s, t_3 = 1.4s, t_4 = 2.1s, t_5 = 2.25s$.

The fault location is indexed by a positive constant λ which is the fraction of the line to the left of the fault. The nominal fault location for the given fault sequence is $\lambda = 0.04$.

The controllers employed in the simulations are [16]:

$$\begin{aligned} &Transient\ controller:\\ &v_f = 22.36\ \delta + 12.81\ \omega - 82.45 \triangle P_e \quad (27)\\ &Voltage\ controller:\\ &v_f = -40.14 \triangle V_t + 10.11\ \omega - 30.81 \triangle P_e \quad (28)\end{aligned}$$

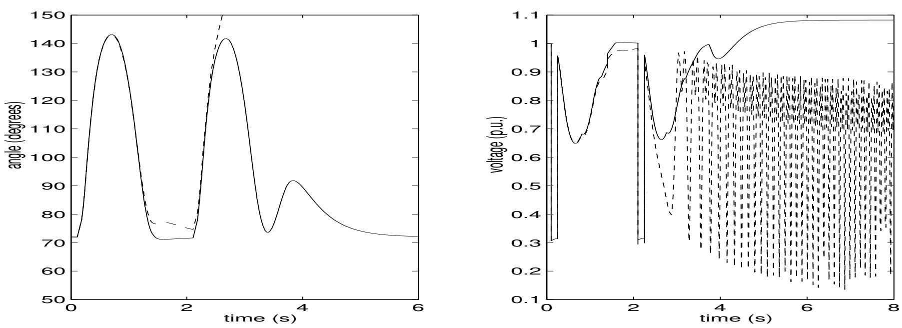

Fig. 2. Power system responses: '—' DFL nonlinear controller; '- -' voltage controller.

The power system responses with the three different controllers are shown in Figures 2-3. (The highly oscillatory voltage response, caused by the unstable local controller, would be prevented by protection actions in practice.)

From the simulation results it can be observed that the transient nonlinear controller stabilizes the disturbed system but the post-fault voltage differs from the prefault value by 10%-20%, which is not acceptable in practice. The voltage controller cannot stabilize the system. For the switching controller, the switching time is seen to be important since an inappropriate one causes the loss of synchronism of generators. This point is clearly shown in Figure 3 where the switching controller with nominal switching time $t_s = 1s$ destabilizes the system, but $t_s = 1.3s$ stabilizes it.

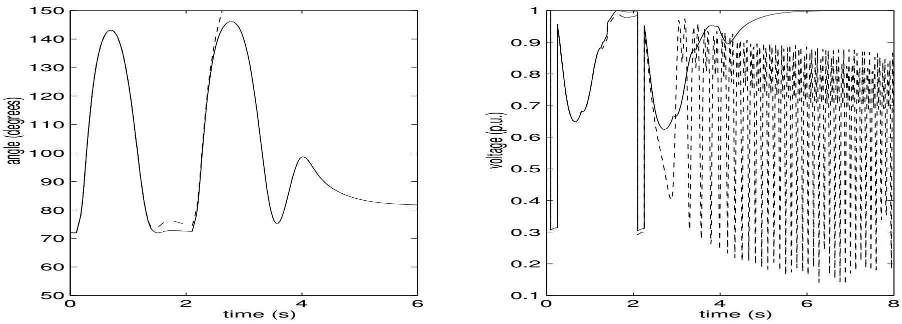

Fig. 3. Power system responses for switching controller: '—' $t_s = 1.3s$; '- -' $t_s = 1s$.

The simulation results are consistent with the analysis stated early in this Section. The strategy of simply switching between different control actions is not reliable due to the non-existence of a universal switching time. In the next Section, we will propose a new global control strategy which achieves transient stability enhancement and voltage regulation simultaneously and robustly.

3.4 Global controller

Our global control objective is to achieve good control performance over a wide range for the anticipated operating region. Specifically, we have the following control task:

Global control problem: *Design a smooth nonlinear feedback control law for the excitation system (6)-(8), such that the closed-loop power system is transiently stable when subjected to a severe disturbance, and restores the steady prefault voltage value after the disturbance.*

Desired properties of the global controller include robustness with respect to different faults whose sequences are not known apriori.

A. Operating region membership function

We want to achieve both transient stability enhancement and good post-fault performance of the system. Good post-fault performance means that after the transient period we wish to control the excitation unit to regulate the generator terminal voltage V_t. According to the qualitatively distinct operating conditions and the corresponding control objectives over each region, local controllers are designed and coordinated through some strategy. We firstly need to define the operating regions and membership functions.

We use the following trapezoid-shaped like membership functions which are able to indicate different operating stages.

$$\begin{aligned} \mu_V(z) &= \left(1 - \frac{1}{1+\exp(-120(z-0.08))}\right) \cdot \left(\frac{1}{1+\exp(-120(z+0.08))}\right) \\ \mu_\delta(z) &= 1 - \mu_V \end{aligned} \tag{29}$$

where

$$z = \sqrt{\alpha_1 \omega^2 + \alpha_2 \left(\triangle V_t\right)^2} \tag{30}$$

and α_1, α_2 are positive design constants providing appropriate scaling which can be chosen according to different sensitivity requirement of power frequency and voltage. This surprisingly simple choice of dynamical indicator function z works quite well.

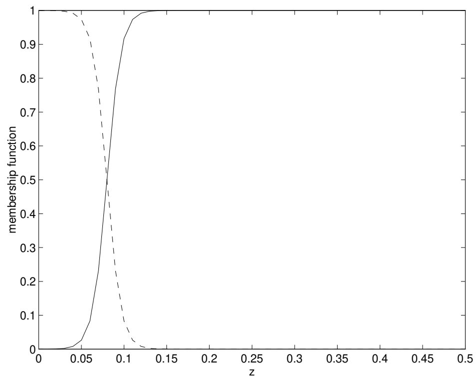

Fig. 4. Membership functions: '–' μ_δ, '- -' μ_V.

Membership function (29) is plotted in Figure 4. It can be seen that $\mu_\delta(z)$ gets its dominant value when z is far away from the origin, which corresponds to the transient period; on the other hand, $\mu_V(z)$ does so when z is close to the origin, which indicates the post-transient period. Since the membership function values are determined by the directly measurable variables, ω and $\triangle V$, the fault sequence need not to be known beforehand.

Therefore, the whole operating region is partitioned into the following two subspaces by the membership functions, where S_1 indicates the transient period and S_2 indicates the post-transient period.

$$\begin{aligned} S_1 &= \{(\omega, \triangle V) | \mu_V \leq \mu_\delta\} \\ S_2 &= \{(\omega, \triangle V) | \mu_V > \mu_\delta\} \end{aligned} \tag{31}$$

The characteristic function of each subspace S_l $(l = 1, 2)$ is defined by:

$$\tau_l = \begin{cases} 1 & z \in S_l \\ 0 & \text{otherwise} \end{cases} \tag{32}$$

Note that $\tau_1 + \tau_2 = 1$.

It should be pointed out that ω and $\triangle V_t$ are chosen as the indicator variables in (30) since they sufficiently represent the operating status for the problem of transient stability and voltage regulation. If the problem under consideration is voltage stability, reactive power could be included in the indicator. Similarly, the proposed method can be extended to other power system control issues. The chosen membership functions have a trapezoid-like shape which is well known in fuzzy control to separate operating conditions. From our simulation experience, the system performance is not sensitive to different parameters α_1 and α_2.

B. Global control law

After the state space is partitioned, it is desirable that in the transient period, which corresponds to subspace S_1, the transient stability controller takes effect; while in the post-transient period, which corresponds to subspace S_2, the voltage controller dominates. The global control law is the average of the individual control laws, weighted by the operating region membership functions, i.e., the input v_f takes the form:

$$v_f = \mu_\delta v_{f1} + \mu_V v_{f2} \tag{33}$$

where v_{f1} is the nonlinear controller (20) and v_{f2} is the voltage controller (23). The real excitation control u_f can be implemented by (21).

The global control (33) has the following interpretation: in the transient period, the system is far away from the equilibrium; the primary goal is to control the states to enter a neighborhood of the equilibrium without large oscillations; then in the post-transient period around the equilibrium, the voltage needs to be tuned to reach the prefault level. The membership functions play the role of appropriate weighting and smooth interpolation of the two controllers. One of the appealing abilities of the method is that the operating status is automatically distinguished by the membership functions which are functions of directly measurable variables. The form of control law (33) is such that a smooth transfer between the local controllers is automatically achieved.

The global heterogeneous control for transient stability and voltage regulation is illustrated in Figure 5, where block #1 and #2 represents local controllers, and membership functions play the role of appropriate coordination.

The proposed global control law (33) features the following properties:

- Control action is determined by online measurement of power frequency and voltage, which makes it unnecessary to know the fault sequence beforehand;
- The controller is globally effective in the presence of different uncertain faults;

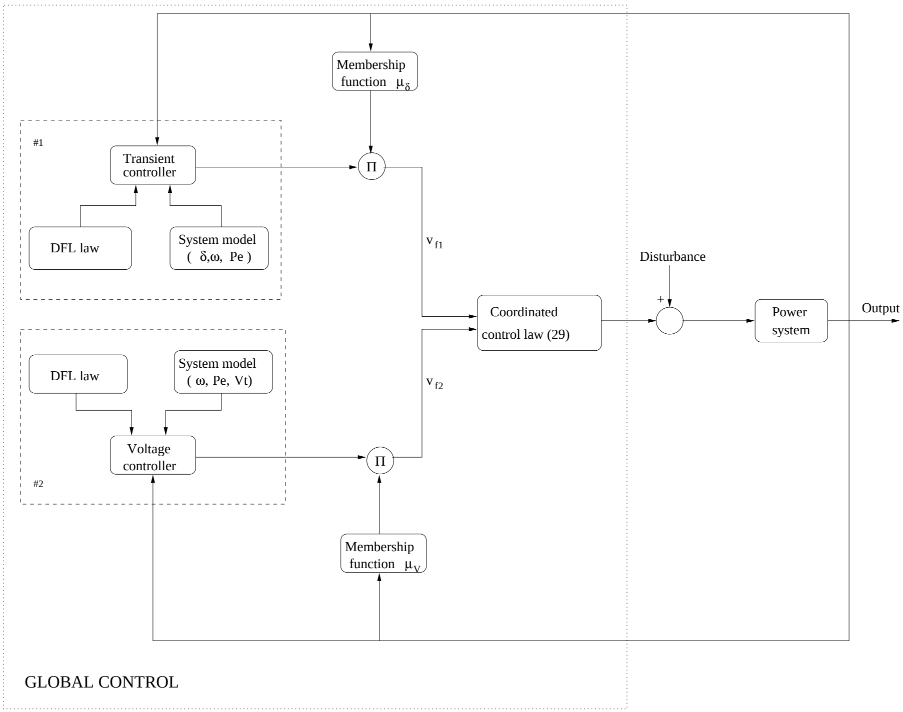

Fig. 5. Global controller for transient stability and voltage regulation.

- The controller inherits the properties of local controllers, i.e., it is robust with respect to parameter uncertainties.

Simulation results follow to demonstrate the effectiveness of the heterogeneous control law.

C. Simulations

In this subsection, we exhibit the closed-loop power system performance with the global controller. The power system parameters and fault case are the same as in Section 3.3. The global control law employed is (33) with v_{f1} and v_{f2} from (27) and (28) respectively. Figure 6 shows the system performance. In contrast with Figures 2 and 3, both transient stability and normal post-fault voltage values are achieved. From the simulations, we can see the global controller achieves the proposed control task. In [6], it is also shown that the global controller is robust with respect to different fault sequences and their locations.

D. Discussion

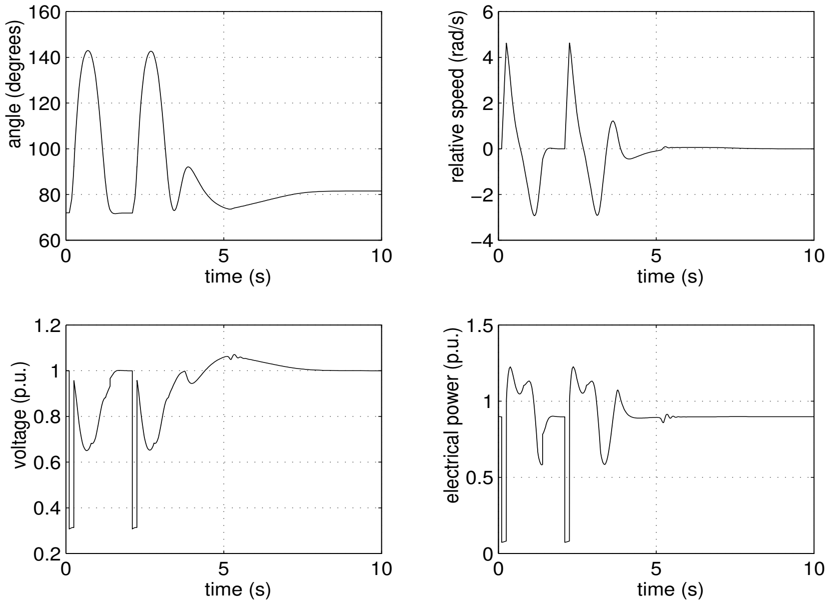

Fig. 6. Power system responses: global control law.

The global control design procedure involves the following three steps:

- Qualitatively distinct operating regions are identified by membership functions of directly measurable indicator variables, and the region partitionings admit overlap;
- The control law in each region is specified to be a usual type of controller developed from model-based nonlinear control techniques;
- The global control law is the weighted sum of local controllers, which achieves smooth transitions between the different operating conditions.

The full power of the control law (4), (5) has not been used here, namely the equilibrium controller u_e and the coordination/optimisation of tunable control parameters. The former is illustrated in [5]. The optimal scheduling of controller flexibility is illustrated in the next section. These ideas are clearly applicable in other application areas.

4 Emergency Voltage Control

4.1 Introduction

Electric power systems are designed, through careful planning and preventive control schemes, to survive most foreseeable disturbances [54]. Not all possible disturbances, however, can be foreseen at the planning stage and these may result in instability that will eventually lead to collapse or islanding of the system. The objective of an emergency control system is to detect such situations and carry out control actions necessary to prevent collapse of the system. Here we consider the problem of emergency voltage control in the long-term time period.

The emergency controls considered here are: switching of capacitor banks, tap changer operation and load shedding. The principles of using these as efficient emergency controls in a dynamical context have been established in [62–65]. Similar principles are used to the discussion in Section 2.4. The control includes switching to establish a viable equilibrium combined with dynamic stabilization about that equilibrium; proximity to bifurcation boundaries must be evaluated. The highly nonlinear nature of the problem calls for sophisticated methods based on a dynamic system model rather than the adhoc methods used in practice. In particular, proper coordination of all controls would minimize the amount of load shed thus minimising impact on customers and cost. Most controls are inherently discrete in their nature; for example, capacitor banks and tap changers must be switched in fixed steps.

Methods for coordination of secondary voltage control and load shedding using static system models have been described, e.g. in [66]. Coordination of dissimilar controls in the emergency state based on a dynamic system model has so far received little attention. A method based on differential dynamic programming and a security measure as the distance to the closest bifurcation has been derived in [1,3,67]. None of the above mentioned references fully take account of the discrete nature of controls or the inherent dynamics of the loads.

This section demonstrates the application of model predictive control (MPC) combined with search techniques to optimise emergency state voltage control. General model predictive control is well established for process control (see, e.g. [18,19,68]) but the application to power systems network control is novel. A model of the controlled system, including the network and load dynamics, is used to predict the future system behaviour based on the current state and the applied control actions. The optimal control actions can then be obtained from the solution of a combinatorial optimization problem by a search method. Various predictors are employed, ranging from a detailed predictor based on simulation of the system to more computationally tractable linearized versions. The results presented here are based on the paper [2].

4.2 System modeling

Again we use a single system to illustrate the ideas. Consider the power system in Figure 7. There are two loads, four capacitor banks and two on-load tap changing transformers considered as actuators. These can be operated in the discrete fixed steps given in Table 2.

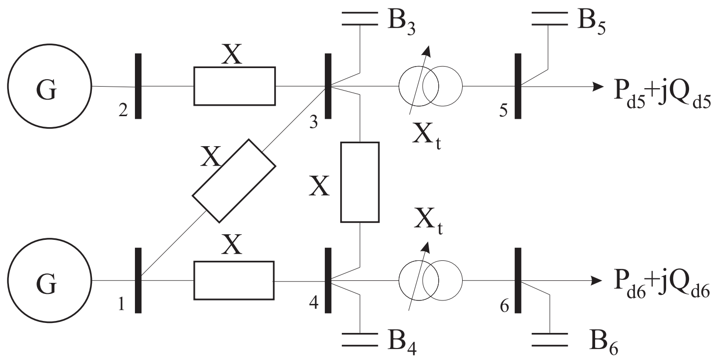

Fig. 7. Example power system studied.

The generator at bus 1 is modeled as an infinite bus with fixed voltage and voltage angle while the generator at bus 2 is modeled using the standard sixth order dq-model with first order excitation system, an over-excitation limiter and a first order governor. The loads are modeled using the aggregate exponential recovery model [69]

$$T_p \dot{x}_p + x_p = P_s(V) - P_t(V) \tag{34}$$

$$P_d = k_l(x_p + P_t(V)) \tag{35}$$

where x_p is a continuous dynamic state that can be interpreted as a measure of the energy deficit in the load and $P_s(V) = P_0 V^{\alpha_s}$ and $P_t(V) = P_0 V^{\alpha_t}$ are the steady-state and transient voltage dependencies respectively. P_d is the actual active load power and T_p is the active power recovery time constant. For the reactive load power, a similar model is used with corresponding characteristics Q_d, x_q, $Q_s(V) = Q_0 V^{\beta_s}$, $Q_t(V) = Q_0 V^{\beta_t}$ and time constant T_q. The scale factor k_l models load shedding and is applied to the reactive as well as to the active load model. The transformers are modeled as pure reactances in series with an ideal turns ratio change.

For the purpose of control determination, generators and their associated control systems are modeled more simply, using their quasi-steady state approximations given in [70], i.e, the derivative terms in the mechanical and flux equations are neglected. The power system network model is conveniently expressed in the hybrid differential-algebraic-difference form given by equations (1)-(3).

4.3 Control problem formulation

Our global control objective is to coordinate all the control devices to ensure voltage regulation in the face of large disturbances. Specifically, we have:

Global Control Problem: *Design a scheduling control law for the system (expressed in the DAD form) such that the voltages are regulated to within* *a practically small region of the set-point values following a large disturbance. The voltage error will be determined by discrete controller steps.*

It is convenient to review the basic principle of Model Predictive Control (MPC) illustrated in Figure 8. A model predictive controller uses a system model to predict the future output trajectories (dotted lines) based on the current state and several different candidate input sequences. A cost function is defined based on the deviation of each predicted trajectory from a desired trajectory (dashed line). The optimal control sequence, in the sense that it minimizes the defined cost function, is then obtained by solving an optimization problem on-line each time a new instance of the control sequence is to be determined. The optimal control is then applied to the system, until the next sample time. The interval between the current time t^* and the prediction horizon $t^* + t_p$ is referred to as the prediction interval, and is chosen based on the settling time of the slowest dynamics. Usually, the prediction interval is chosen as a multiple of the sample time.

In the standard formulation, it is assumed that all control signals are continuous, i.e., can assume all values within some fixed range. In the case of a linear system this leads to an optimization problem that can be solved using quadratic programming; nonlinear programming is naturally required with a nonlinear system. The application here differs from the general nonlinear case in that the control variables are constrained to fixed discrete values which makes it necessary to resort to a combinatorial optimization method. A sequence of control inputs, for the first n samples during the prediction horizon, is obtained from the optimization. The first control step in this sequence is then applied to the plant and the rest are ignored. In order to save computation time, various devices can be used which restrict controller complexity.

A. Combinatorial optimisation

Accordingly, the problem of selecting the new control vector u^+ at the operating point $(x^*, u^-) = (x(t^*), u(t^*))$ can be formulated as the combinatorial optimization problem

$$\begin{aligned} \text{minimize} \;\; & J(x^*, u) \\ \text{subject to} \;\; & u \in \mathcal{S}(u^-) \end{aligned} \tag{36}$$

where u is the optimization variable corresponding to the new control state to be used during the interval $[t^*, t^* + t_p]$. u^- denotes the control state presently in use, i.e. before the optimization starts at time t^*. $\mathcal{S}(u^-)$ is the set of available control states at time t^* and is normally a function of u^-. The scalar function $J(x^*, u)$ is referred to as a cost function and should evaluate the candidate control state u such that a smaller result indicates a more desirable state. Typically the cost function should include a component based

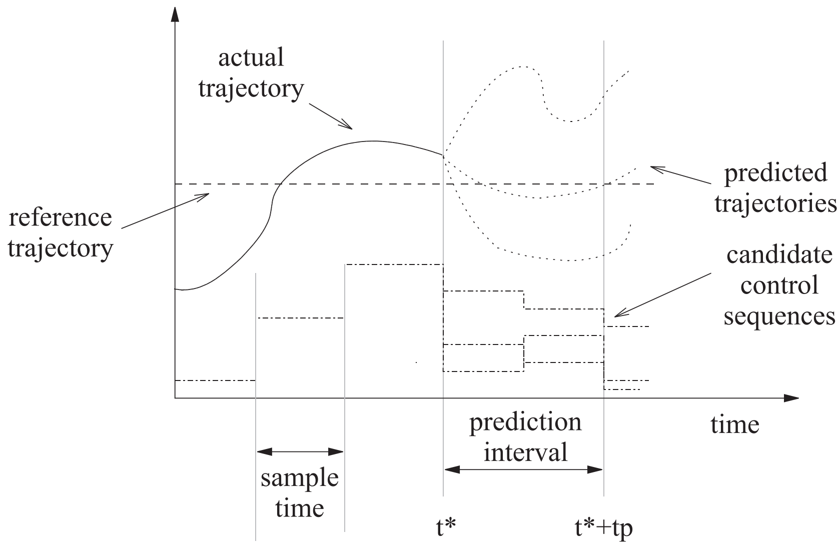

Fig. 8. Principle of Model Predictive Control.

on the deviations of the chosen outputs from their reference trajectories and a component based on the control variations.

Constraints can be imposed on inputs as well as states and outputs as follows:

- Input constraints.
  Actuator limits, for example, are modeled using the set of available control states. Since the set may be a function of the present control state, actuator ramp limits can also be handled. More specific constraints can also be represented. For instance, a useful constraint is to set priorities for control actions as in [1,3,67].
- Output and state constraints.
  These could be modeled as hard constraints in the optimisation However, it is generally not desirable to impose hard constraints on the outputs or states since they may be impossible to strictly satisfy, and for large disturbances no control could be determined. Therefore output and state constraints are modeled as soft constraints by adding terms to the cost function [71]. If this cost is dominant over other terms in the cost function, the primary aim of the controller will be to minimize any constraint violation.

Control actions are divided into two classes:

- Normal control measures that will be routinely scheduled; capacitor and tap changer operations belong to this category.
- Emergency control measures that will be scheduled only when required for the satisfaction of a constraint. This control is activated only if the

constraint cannot be satisfied using any combination of the normal control measures. Load shedding belongs to this category.

The cost function is defined in the form

$$J(x^*, u^+) = \int_{t^*}^{t^*+t_p} \big((\hat{y} - y_r)^T \mathbf{Q}(\hat{y} - y_r) \\ +(u^+ - u^-)^T \mathbf{R}(u^+ - u^-) + P(t, x^*, u^+)\big) \, \mathrm{d}t \qquad (37)$$

where $\hat{y} = \hat{y}(t, x^*, u^+)$ is a prediction of the output trajectory using information up to time t^* if the new piecewise constant control u^+ is applied during the prediction interval. The control state presently in use is denoted u^-, the reference trajectory y_r, and the weighting matrices for output errors and control variations $\mathbf{Q}$ and $\mathbf{R}$ respectively. A special penalty term $P(t, u^+, x^*)$ is introduced whenever a constraint violation or a singularity-induced bifurcation is predicted to occur within the prediction horizon ($t \in [t^*, t^* + t_p]$). A suitable selection of $\mathbf{Q}$, $\mathbf{R}$ and $P(t, u^+, x^*)$ ensures that none of the emergency controls are scheduled unless necessary to remove a constraint violation during the prediction interval.

B. Predictors

The cost function is calculated from predictions of the output trajectories. Several different methods of obtaining (approximations of) these trajectories are possible [2]. The benchmark method is Nonlinear MPC (NLMPC) The system (1)–(3) is a hybrid nonlinear system and it is therefore generally impossible to find an analytical expression for the trajectories ($\hat{y}(t, u)$). The most straightforward method is to obtain them numerically. This requires simulation of the hybrid DAE model over the prediction interval for each evaluation of the cost function.

The NLMPC predictor makes use of the full simulation model and thus accounts for hybrid as well as nonlinear behaviour of the system. In [2], the performance of NLMPC is compared with various approximate prediction methods:

- Euler State Prediction (ESP);
- MPC using off-equilibrium linearisations (LMPC);
- Euler state prediction – linear output approximation (ESPLO).

The details are more to do with numerical methods than the ideas of this chapter. Nevertheless, it is an important topic for practical implementation – see [2] for further discussion.

4.4 A tree search method

The combinatorial optimization problem (36) is a search problem where the search state-space is determined by the control constraints. For illustration,

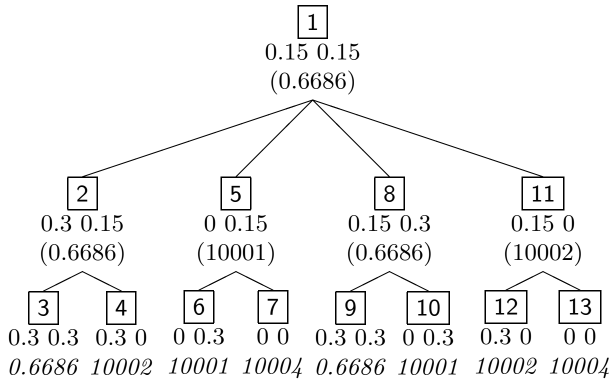

Fig. 9. Search example.

the set of available control states $\mathcal{S}(u)$ is explored for a best control state using the standard recursive depth-first algorithm [72] shown in Table 1. The algorithm relies on two types of auxiliary functions:

- s(u) which generates all control states , i.e., a subset of $\mathcal{S}(u)$, reachable from the current state u with a single switching of one control.
- c(u) which evaluates the state u, according to the cost criteria (37).

Figure 9 shows the search tree for a simplified search problem where only the controls B_3 and B_4 in Figure 7 are enabled; the additional constraint that each control may only change once in the tree has been imposed. The number shown below each node corresponds to the result reported by the function *search*. The search starts at the initial state (1) with $B_3 = 0.15$, $B_4 = 0.15$, corresponding to the root of the tree. From here four new states can be reached (2, 5, 8, 11) by changing either B_3 or B_4 one step up or down. From each of these four states another two can be reached by changing the other control. Here the optimum is found in nodes 3 and 9 for $B_3 = 0.3$, $B_4 = 0.3$. Note that the search tree (13 nodes) is larger than the state space ($3^2 = 9$ possible combinations) since it contains not only all possible control states but also all paths to them. The example search requires 13 evaluations of the cost-function.

For this simple example, the search state space is kept small by the control constraints because of the small number of controls. However, the tree grows exponentially with the number of controls and an exhaustive search of the tree is not feasible for practical cases. With a larger number of controls, the size of the tree is limited by applying a maximum search depth which corresponds to the maximum number of controls that may change in one search.

Table 1. Pseudocode for construction and traversal of the search tree.

```
[f_out] = function search (f_in, u_in, m);
  f = call c(u_in)
  if m = 1 /* the node is a leaf node */
    best = f
  else
    best = min(f, f_in)
    for u_i = call s(u_in) do
      f_tree = call search(f_in, u_i, n − 1)
      best =min(f_tree, best)
    end
  return f_out = best
```

f_{in}	- best value found prior to search of tree
u_{in}	- initial (root) control state
m	- search depth
f_{out}	- best value found after search of tree

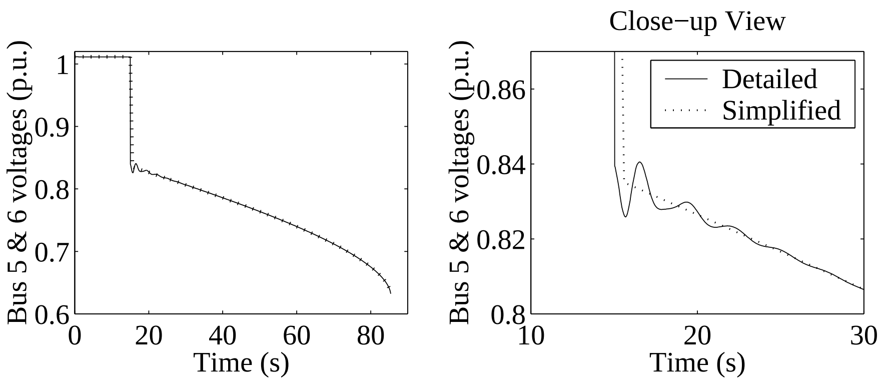

Fig. 10. Voltage response without voltage control.

4.5 Simulation results

To illustrate the performance of the emergency controllers, results from simulation of the system in Figure 7 are presented in Figures 11-12. The disturbances applied are changes of the four line impedances from X=0.2 to X=1.0 p.u. When computing the new control signal, it is assumed that it will be in use during the entire prediction interval (that is, $n = 1$). If no emergency actions are taken, voltage collapse will occur at simulation time 70 s as shown in Figure 10. This figure also shows the response with a more detailed model including the fast electromechanical oscillations. The simulations have been carried out with a 30 s sampling interval of the controller,

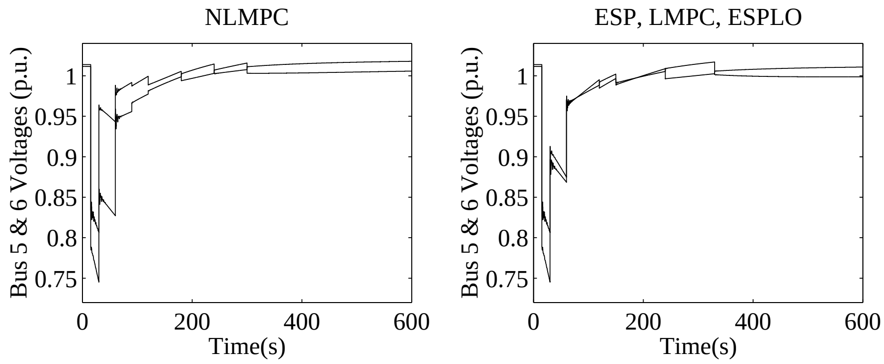

Fig. 11. Voltage response at buses 5 and 6 with all controls enabled.

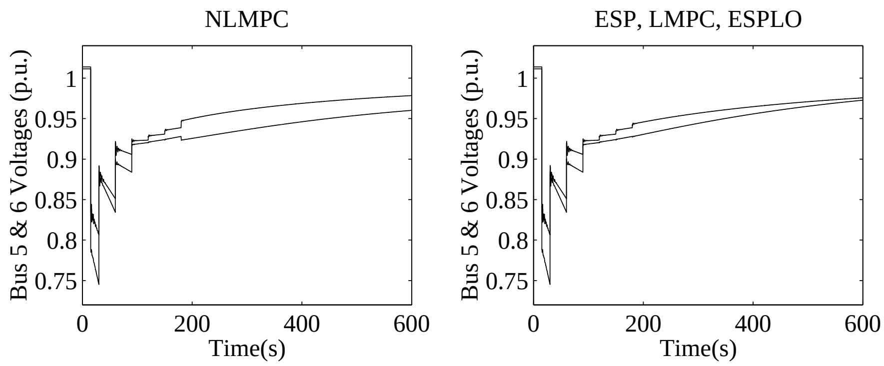

Fig. 12. Voltage response at buses 5 and 6 with B_5 and B_6 disabled. The three methods in the right hand figure yield identical results.

i.e. the tree-search optimization is carried out periodically every 30 s. By the use of voltage constraints, load shedding is authorized if the voltages at bus 5 or 6 are predicted to be lower than 0.9 p.u. at the prediction horizon. The search depth is 4, the prediction horizon 120 s and the weight matrices and penalty terms were chosen according to particular tuning procedure in [2], with the output vector y containing the voltages of buses 5 and 6.

Figure 11 shows the voltage response at buses 5 and 6 with all controls enabled. In this case, it is possible to stabilize the system without resorting to load shedding. All the predictors yield near identical results. The NLMPC version stabilizes and restores the voltages close to their pre-disturbance levels using 5 capacitor bank steps and 6 tap changer operations. In [2] it is shown that more approximate predictors are capable of stabilizing the voltage with less computation, but use an extra capacitor switching for a total of 6 switchings.

Figure 12 shows the voltage response to the same disturbance but with capacitor controls B_5 and B_6 disabled. The NLMPC stabilizes the voltages using 4 capacitor steps, 5 tap changer operations and 4 load shedding steps. Here, the tap changer positions are explicitly controlled by the emergency controller. Normally, the two tap changing transformers would be under feedback control by relays such as those described by for example [73]. Thus, the emergency control applicable to tap changers would normally be tap locking.

Reference [2] discusses use of search heuristics to reduce computation.

5 Conclusions

This chapter has given a conceptual framework, called global control, for the control of complex systems. Some illustrations are given using simple power system problems. The further development for large systems is occurring [75,76]. The term global refers to scale (in dimension or geographically) and size of disturbances as is clearly needed for the world's larger power systems. The combination of ideas developed in control science, optimisation and related to the specific structure of power systems provides the possibility of more advanced control in the era of deregulation where more complexity is going to be inevitable. The framework involves hybrid system modeling, bifurcation analysis, switching control and optimal coordination and scheduling of control. Two special control tasks were investigated in more detail. Firstly, we showed how global control can even improve the coordination of multi-objective control of a single machine on an infinite bus power system. We defined our global control objective as achieving satisfactory control performance over a wide range of anticipated operating conditions; specifically, transiently stabilizing the power system when subjected to a severe disturbance and retaining good voltage level after the disturbance. The controller was of the switching kind using membership functions. The applicability of the ideas to more complex systems should be clear even if there are nontrivial issues to resolve in any design.

The second illustration demonstrates use of coordinated control by the application of Model Predictive Control combined with search techniques to emergency voltage control. The controller optimally coordinates capacitor switching, tap changer operation, and load shedding in different geographic locations, ensuring minimum usage of emergency controls such as load shedding. A search method is employed to minimize a cost function based on predictions of the system's future behaviour. The results presented here consider emergency state operation. The same methodology can be used in an implementation that provides control coordination aimed at loss minimization in the normal state and arrest of voltage collapse in the emergency state. The cost function would be based on system active power losses and two sets of voltage constraints would be used, for the normal and emergency states respectively. In principle the methodology described here could be applied to any kind of stability problem in power systems and similar problems that arise in other applications.

6 Appendix: System Data

Table 2. Control Variables (All data given in p.u.)

symbol	control	initial value	lower limit	upper limit	control step
B_3	cap. 3	0.00	0.00	0.30	0.15
B_4	cap. 4	0.00	0.00	0.30	0.15
B_5	cap. 5	0.00	0.00	0.30	0.15
B_6	cap. 6	0.00	0.00	0.30	0.15
k_{t35}	tap 3-5	1.04	0.80	1.20	0.02
k_{t46}	tap 4-6	1.06	0.80	1.20	0.02
k_{l5}	load 5	1	0.85	1	0.05
k_{l6}	load 6	1	0.85	1	0.05

Table 3. Network, Generator and Load Parameters

Load	**Generator (at bus 2)**
$P_{05} = P_{06} = 0.6$ p.u.	$V_r = 1.05$ p.u.
$Q_{05} = Q_{06} = 0.3$ p.u.	$P_m = 0.3$ p.u.
$T_{p5} = T_{p6} = 60$ s	$H = 3.54$ MVA/MWs, $D = 0.0$ p.u.
$T_{q6} = T_{q6} = 60$ s	$r_a = 0.00327$ p.u.
$\alpha_{s5} = \alpha_{s6} = 0$	$x_d = 1.76$ p.u., $x_q = 1.58$ p.u.,
$\alpha_{t5} = \alpha_{t6} = 2$	$x'_d = 0.42$ p.u., $x'_q = 0.30$ p.u.
$\beta_{s5} = \beta_{s6} = 0$	$x''_d = 0.10$ p.u., $x''_q = 0.20$ p.u.
$\beta_{t5} = \beta_{t6} = 2$	$T'_{d0} = 6.66$ s, $T'_{q0} = 0.44$ s
Network	$T''_{d0} = 0.02$ s, $T''_{q0} = 0.03$ s
$n_{max} = 1.2$ p.u.	
$n_{min} = 0.8$ p.u.	**Exciter & AVR (at bus 2)**
$X_t = 0.1$ p.u.	$T_{exc} = 2.5$ s
$T_t = 30$ s	$K_{avr} = 100$
$X = \begin{cases} 0.2, \, time < 15 \text{ s} \\ 1.0, \, time > 15 \text{ s} \end{cases}$	$E_{fmax} = 3.5$ p.u.
$V_1 = 1.05\angle 0$ p.u.	$E_{fmin} = -3.5$ p.u.

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