Chapter 9
Power Systems Operation and Control: Contributions of the Liège Group, 1970–2000

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9.1 Introduction

An electric power system (PS for short) is the combination of *generation* of electricity, *transmitted (high voltage networks) and distributed (medium and low voltage networks)* to *loads (or consumers)*.

The electricity may be generated by hydro, nuclear, gas turbines, biomass, geothermal, solar, wind, waves, and others.

A main PS characteristic is that, so far, electrical power at the disposal of customers cannot be cheaply stored. Only storage of primary energy is available for free. This makes electricity something different from other goods.

Another feature of PSs is that the only way of studying comprehensively the involved physical phenomena is *simulation*. Testing PSs is often not feasible (creating blackouts to study dynamic aspects would not be appreciated . . .).

Throughout the years, simulations have essentially been relying on *digital models*.

They are used as a reference tool for both deterministic and machine learning methods described below in the context of transient stability.

By way of comment, let us mention what Faraday answered Gladstone, the then Chancellor of the Exchequer who was asking him *"What is electricity?"* Faraday said: *"One day, Sir, you may tax it!"*

Much later, in the 1970s, Fred Schweppe, a famous MIT professor in aeronautics, when attempting to apply aeronautic techniques to power system state estimation said: *"Electric power systems are the most complex damn systems man ever designed . . . ."*

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Power system operation and control encompasses a large variety of aspects, characterized by different electrical-mechanical parameters and different time scales evolution.

This contribution focuses on the study of transient stability. Transient stability phenomena are characterized by a very rapid time evolution and catastrophic consequences if appropriate actions are not taken early enough.

The described methodologies aim at assessing real-time system stability and, if necessary, at stopping instability by designing and applying suitable control actions.

9.2 Transient Stability

Transient stability (TS) is one aspect of *PS security*. *Security* may be defined as the system robustness to operate in an equilibrium state under normal and perturbed conditions.

TS is associated with the operation of the synchronous machines, and may be defined as the PS's ability to maintain machines' synchronous operation under normal operating conditions, and to regain an acceptable equilibrium state after being subjected to a severe disturbance (such as opening a heavily loaded line and accidental disconnection of a generator).

The occurrence of a severe disturbance (or "fault") may result in large excursions of the system machines' rotor angles and, whenever corrective actions fail, loss of synchronism among machines.

In practice, transient instability typically leads to the loss of synchronism of all the generators of a power plant with respect to the rest of the system. When a generator loses synchronism, its rotation speed increases rapidly, which triggers an automatic shut-down of the generator to avoid its mechanical destruction. An undesired shut-down of all generators of a large power plant may lead to a partial or even a full system blackout.

TS is studied in terms of highly nonlinear differential equations that can be represented by the following two generic sets of equations:

$$\dot{x} = f\,(x, y, p)\,,$$
$$0 = g\,(x, y, p)\,.$$

The first set of equations consists of the differential equations (generators, motors, including their controls, and other devices whose dynamics are modeled); the second set comprises the algebraic equations of network and "static" loads. The dimension of vector x depends on the modeling detail; it is lower bounded by twice the number of modeled system machines (e.g., typically greater than 50), but may be orders of magnitude larger. The dimension of vector y is lower bounded by twice the number of nodes of the power system grid model (e.g., typically greater than 1000). Vector p explicitly represents parameters whose influence on dynamic security may be studied (e.g., generator output, load level, and interface flows) as well as disturbances (represented as a sequence of "instantaneous" changes in *p).*

The reference approach to TS analysis is *time-domain simulation*, using numerical integration of the nonlinear differential equations representing the system dynamic model. Within this approach, to assess the system robustness vis-à-vis a given disturbance and its clearance, one simulates the system dynamics in the *during-fault* (e.g., 100 ms) and *post-fault* (some seconds) configurations.

A typical measure of system robustness is the *Critical Clearing Time* (CCT): this is the maximum fault elimination time without the system losing its capability to recover normal operating conditions.

Transmission system operators perform off-line time-domain simulations for a few dangerous scenarios (faults) and design remedial actions for the critical ones, i.e., the ones with a too small CCT.

Time-domain (TD) simulation is flexible, and it can consider detailed mathematical modeling for almost any component of the power system. However, this detail comes at a cost, a high computational time. Moreover, TD simulation cannot provide a direct indication of the CCT; thus, the system equations should be solved for different fault elimination times to search for the critical time. Besides, it does not provide guidelines to control, i.e., "appropriate actions," to stabilize the PS.

This led to the development of other classes of stability analysis techniques: the *direct methods* and the *machine learning methods*.

In the area of direct methods, we distinguish the following:

– Lyapunov-like direct methods applied to multimachine PSs (for the record)
– OMIB approaches, relying on a *One Machine Infinite Bus* (OMIB) equivalent

Within the realm of machine learning approaches, we focus on decision trees.

9.3 Direct Methods

9.3.1 Multimachine Lyapunov-Like Techniques

Studying TS of multimachine power systems by the Lyapunov direct method started being proposed as early as 1947 (Magnuson), 1958 (Aylet), 1966 (El-Abiad & Nagappan), and later in 1971 (Ribbens-Pavella); for a survey see Ref. [1] and the references therein. These forerunner studies have been followed by an impressive number of (often PhD) studies, yielding an outburst of publications for many more decades.

Broadly, the Lyapunov direct method relies on the construction of a Lyapunov function (V), which is a scalar function of the system state vector. Figure 9.1 illustrates it for a simple hypothetical OMIB with two state variables:

– Machine rotor angle, δ: the angle between a reference rotating at synchronous speed and an axis fixed on the machine's shaft

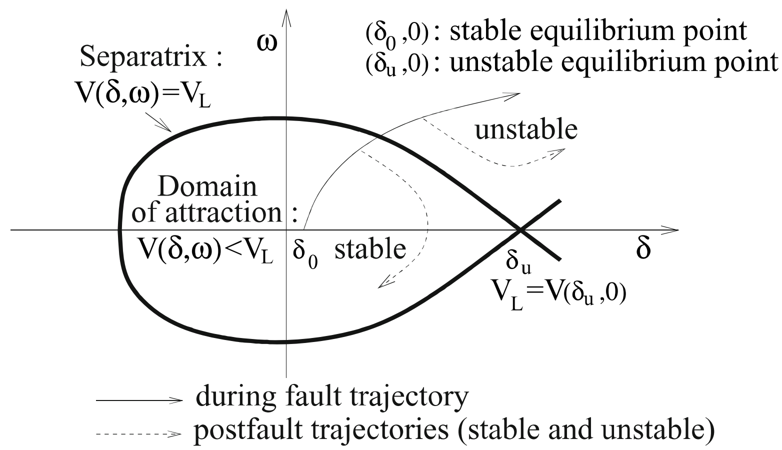

Fig. 9.1 Stability domain of an OMIB system in the phase plane. (Adapted from Ref. [2])

– Machine rotor speed, ω: the derivative of δ, i.e., difference between the actual speed of rotation of the machine and the synchronous speed

In brief, the Lyapunov criterion applied to TS consists of assessing whether the system state is inside the stability domain at the moment when the fault is eliminated. In turn, this allows restricting to a single time-domain simulation for the during-fault period, upper bounded by the CCT, provided that the limit value V_{L} is easy to compute. Assuming this constraint is met, the time-domain computation needed to determine the CCT is restricted to a very small percentage of the simulation time required by a pure time-domain assessment.

Unfortunately, despite their attractive potentialities, the multimachine Lyapunov-like approaches have shown two main types of difficulties.

The first type is related to the suitable estimation of the stability domain and hence of the system's TS assessment. This provides conservative estimation, and, in addition, it implies important computing burdens. The difficulties come (i) from the necessity of computing all the "unstable equilibrium points" (δ_{u},0), i.e., unstable solutions of the nonlinear algebraic system equilibrium equations, and (ii) of choosing the solution which is "relevant" to the system's instability. For want of guidelines, one then is often led to choose the solution which provides the most pessimistic stability answer, thus generally leading to an overconservative assessment.

The second type of difficulties stems from the fact that developing Lyapunov functions for a multimachine system is made possible only with oversimplified modeling. Indeed, all well-known construction methods of Lyapunov functions have shown to be effective only under the oversimplified machines' modeling: electromotive force behind transient reactance. They yielded the so-called energy-type Lyapunov function.

Despite intensive (essentially academic) research work all over the world, these two difficulties persisted tenaciously, thus canceling out the expected advantages of Lyapunov direct methods.

9.3.2 OMIB and OMIB-Driven Techniques

To overcome the difficulties linked to the multimachine stability domain estimate, a loophole has been proposed by Y. Xue in his PhD thesis [3]. It relies on the observation that estimating the stability domain becomes trivial when it comes to an OMIB.

All OMIB techniques rely on the observation that the loss of synchronism of a multimachine PS originates from the irrevocable separation of its machines into two groups, namely, the machine's group that drives the system to instability and the group of remaining machines. Further, these techniques replace the two groups by a two-machine system and then by an OMIB equivalent. Thus, an OMIB may be viewed as a transformation of the multidimensional multimachine dynamic equations into a single dynamic equation. This latter takes on various forms, depending upon the PS modeling and the assumed behavior of the machines within *each group.*

We distinguish three types of OMIB: *time-invariant, time-varying, and generalized* ones. The TS study of all these OMIBs relies on the classical well-known equal-area criterion.

9.3.2.1 Time-Invariant OMIB: The EEAC Method

A time-invariant OMIB is obtained under the assumptions: (i) simplified PS modeling; and (ii) coherency of the machines within each one of the two groups, so as to "freeze" their relative motion in the fault-on and post-fault periods. The dynamic equations of a multimachine PS may therefore be transformed into an equivalent OMIB differential equation of the form:

$$M\ddot{\delta} = P_{\mathrm{m}} - P_{\mathrm{e}} = P - P_{\max} \sin(\delta - \nu)$$

where M, P, $P_{\max}$, and ν take on constant values (possibly different for the fault-on and post-fault periods).

The *Extended Equal Area Criterion* (EEAC) method uses a time-invariant OMIB, to which it applies the classic Equal Area Criterion (EAC) concept to find the critical clearing angle. The system CCT can then be obtained by numerical integration of OMIB equations. EEAC is an interesting approach that provides not only valuable information, but also a graphical representation of system dynamics [4].

9.3.2.2 Time-Varying OMIB: The DEEAC Method

Applying EEAC to part of the French power system has shown to provide appealing results, by very significantly speeding up the CCT computations with respect to the time-domain simulation approach and correctly assessing TS, thus circumventing Lyapunov method's conservativeness. This led to increased practical interest for the EEAC and prompted further research aiming to refine the EEAC system modeling. It resulted in the development of the DEEAC (*Dynamic EEAC*) [5], which uses a time-varying OMIB model. This model is obtained by keeping the simplified system model of the previous section while allowing the temporal variation of the parameters P, $P_{\max}$, and ν. The differential equation describing the OMIB dynamics thus becomes piece-wise sinusoidal. Yet, DEEAC allowed only limited refinement of system's modeling.

Reference [6] provides thorough developments of EEAC and variants. It revisits the EEAC from a functional point of view. First, the definition of the OMIB model of a multimachine power system is redrawn in its general form. To achieve fast, transient stability analysis, EEAC relies on approximate models of the true OMIB model. These approximations are clarified, and the EAC concept is redefined with a general definition for instability, and its conditions. Based on the defined conditions and definitions, functions are developed for each EEAC building block, which are put out together to provide a full-resolution, functional scheme. This functional scheme not only covers the previous literature on the subject, but also makes it possible to introduce several possible new EEAC approaches and provides a detailed description of their implementation procedure. A number of these former and novel approaches are applied to the French EHV network, and the quality of these approximations is examined.

9.3.2.3 Generalized OMIB: SIME

SIME (for *SIngle Machine Equivalent*) is a generalized temporal-direct method: temporal, since it relies on the multimachine system evolution with time; direct, like the EEAC from which it originates. In short, it consists of feeding the EEAC method with information derived from time-domain simulation (or measurements) of the multimachine system, in order to free the OMIB computation from mathematical modeling restrictions, at the cost of computational sophistication.

SIME was elaborated by Y. Zhang in her PhD thesis, and further developed, modified, and improved ever since.

The method thus derived has been called SIME for *SIngle Machine Equivalent* [7].

SIME's main advantages are as follows: reliable CCT assessment; unambiguous identification of the system's critical machines (responsible for the system's instability); *and size of the instability* (i.e., of the stability margin). These piece of information are of paramount importance. Indeed, they open means toward TS control of two types:

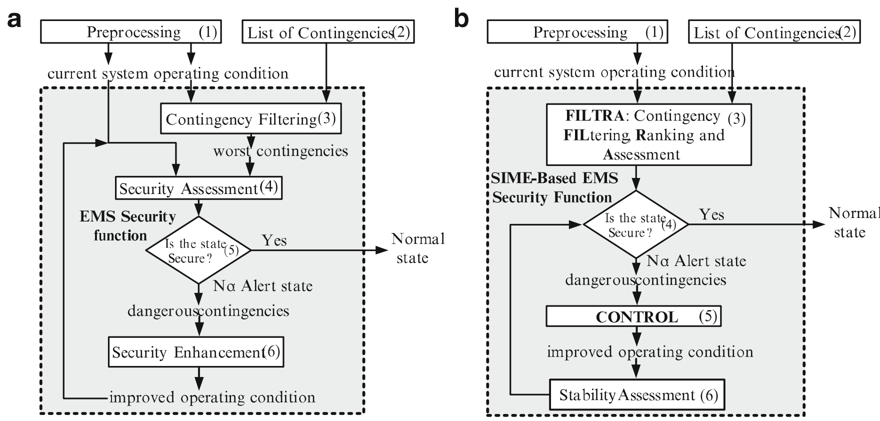

Fig. 9.2 Structure of two on-line security assessment and control functions. (**a**) General structure of an on-line security function. (**b**) SIME-based on-line transient stability function. (Adapted from Ref. [8])

– *Preventive* control, by combining SIME with a time-domain numerical simulation program using the desired details of power system modeling. This is the *Preventive SIME*, or PSIME
– *Emergency* control, by combining SIME with information provided in real time by *Phasor Measurement Units* (PMUs) (the *Emergency SIME*, or ESIME)

Both PSIME and ESIME provide possibilities never achieved before.

9.3.2.4 Preventive SIME (PSIME)

The TS assessment of the current power system state is performed with respect to a set of probable contingencies, chosen by the system operator.

TS assessment aims at responding to the question "What would happen to the system stability if a contingency, out of a set of probable contingencies, would take place?", before this contingency occurs.

Determining the security level of the current system operating condition is a very hard task: the security function usually has to analyze a set of probable "next contingencies" in a very short time. The number of contingencies composing the contingency list is usually very large, on the order of thousands [8]. This implies designing preventive control actions capable of stabilizing all the harmful or dangerous contingencies.

In 1998, a project, sponsored by the Belgian government [9], showed that PSIME may advantageously replace the traditional structure of an on-line TS assessment and control function, whose general structure is schematically described in Fig. 9.2a.

The major components of the on-line TS function, their operation, and the SIME-based components are described below.

– *Contingency Filtering* (*Block (3) of* Fig. 9.2a). Using the current steady-state operating condition of the power system and a fast approximative screening tool, select the worst contingencies (the ones that could threaten system security) from an initially large list of contingencies.
– *Security Assessment* (*Block (4) of* Fig. 9.2a). Determine whether the system operating state is stable or unstable with respect to each one of the list contingencies.
– *Security Enhancement* (*Block (6) of* Fig. 9.2a). If there is at least one contingency that can cause a potential problem, determine a countermeasure able to improve system TS using a preventive control action (usually a generation re-dispatching). This last step is sequentially repeated in a loop, along with the TS assessment block (*Block (6) of* Fig. 9.2b), until all contingencies are found to be harmless for the last improved operating condition, and the system is now declared to be in the normal state.

The initial Contingency Filtering and Stability Assessment blocks of Fig. 9.2b, which are the most time-consuming and computationally demanding tasks, were efficiently implemented in a single, coordinated process named FILTRA (for Contingency FILTering-Ranking-Assessment), a technique developed in an Electric Power Research Institute (EPRI) project [10–12]. FILTRA has the major advantage that both filtering and assessment tasks are performed using SIME simulations with the complete detailed dynamic power system model. Therefore, results from the filtering phase are fully compatible and useful to be employed in the assessment block.

If FILTRA detects one or more contingencies on the list capable of destabilizing the system, PSIME-based preventive control countermeasures should be determined.

Reference [13] describes many on-line security functions implemented in real power system control centers around the world.

9.3.2.5 Emergency SIME (ESIME)

A brief description of this method's essentials is summarized below.

Objectives
Upon a disturbance inception and its clearance, ESIME aims to assess whether the system is stable or is driven to instability; in the latter case:

– Assess "how much" unstable the system is going to be, and accordingly:
– Assess "where and how much corrective action" should be (immediately) taken (for preassigned type of actions).
– Continue assessing whether the executed corrective action has been sufficient or whether to repeat it (with appropriate size).

Main Steps
– 1st step: *prediction* of (in)stability.

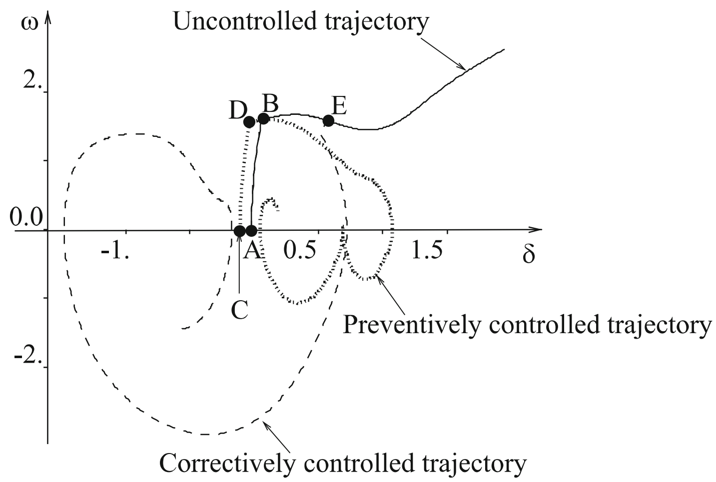

Fig. 9.3 Difference between preventive and emergency control. Illustration on the OMIB phase plane computed for the 88-machine EPRI test system. (Adapted from Ref. [2])

– 2nd step: *appraisal* of the size of control needed.
– 3rd step: *design* of appropriate control actions to take.
– This "three-step procedure" may be repeated in a closed loop, until power system stabilization has been ascertained.

Means
– *Phasor measurement devices* placed at the main system's power plant stations
– *Communication system* to transmit (centralize-decentralize) information about the status of the main power plants
– *Suggested rate* of receiving measurements: 1 cycle
– *Expected time* elapsed between disturbance clearance and execution of control action: 500 ms.

Preventive Versus Emergency Control
Figure 9.3 shortly illustrates the evolution of a power system subject to a disturbance in the following three cases: no control action, preventive control action, and emergency control action. The curves are drawn on the OMIB phase plane, computed for the 88-machine EPRI test system.

Observe how clearly this phase plane describes the physical phenomena.

Additional interesting information is provided by the control efficiency curve of Fig. 9.4. It displays the control effort, ΔP_c, necessary to preserve the system's integrity as a function of the "control time," t_{ct} (duration elapsed between the contingency inception and the actual application of the control action). Notice that in this curve, the preventive action is supposed to correspond to t_{ct} equal or smaller than 0.

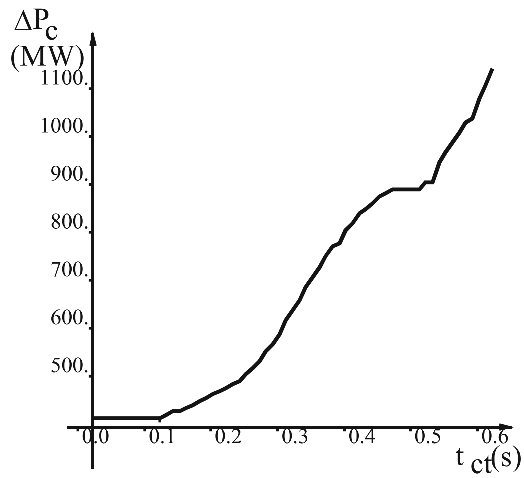

Fig. 9.4 Control efficiency curve. (Adapted from Ref. [2])

A practical implementation of SIME-based functions has been realized using security generation re-dispatch, during the OMASES EU project, in the control systems of Greece and Italy [13].

9.4 Machine Learning Techniques

9.4.1 Problem Statement

Contrary to direct methods, machine learning methods are model-free, i.e., free from any assumption about the physical system mathematical modeling.

Machine learning (ML) in general is concerned with the design of machines (here we do not mean "synchronous" machines, but "machines" like computers, smart devices, and intelligent robots) able to learn a task from a learning set of solved cases of this task. One may, for example, distinguish *symbolic machine learning*, *artificial (deep) neural networks, statistical pattern classification, and regression techniques.*

In the context of PSs security applications, an ML-based approach is schematically described in Fig. 9.5. Random sampling techniques screen all relevant situations in a given context. Numerical simulations are carried out to generate a *Data Base* (DB) of case-by-case simulations from the screened situations. ML methods are then used to extract and synthesize relevant information and reformulate it in a suitable way for decision-making. This transforms the DB of simulation results into a PS *Knowledge Base* (KB). The final step consists of using the extracted synthetic information so as to enhance the physical insight of human experts and support them to take suitable reliability management decisions.

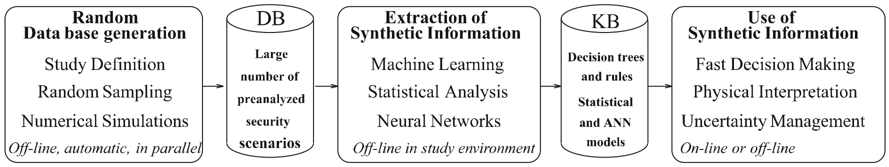

Fig. 9.5 Machine learning approach to power systems security. (Adapted from Ref. [2])

9.4.2 Decision Trees

Decision trees (DTs) are members of ML techniques. The idea of using automatically learnt decision trees to assess power system *TS* was first proposed by L. Wehenkel in his Master's thesis, whose results were further published in [14].

In this very first attempt, Wehenkel constructed a DT to study the TS of an OMIB system. The obtained results were very interesting. This prompted further exploration along this totally new research direction in the realm of PSs.

DTs in general aim to provide solutions (rules) in a form compatible with typical human reasoning, easy to understand and interpret.

Applied to TS, the method consists of constructing off-line DTs, to assess on-line the TS of an unknown case.

The DT construction relies on the following:

– A (learning) set composed of stable and unstable cases pre-classified by means of time-domain simulations.
– A (restricted) number of selected parameters (list of candidate "attributes"); these are parameters assumed to possibly drive a system's TS.

A DT comprises "test nodes" and "terminal nodes"; it involves dichotomic tests automatically carried out during the building procedure, illustrated in Fig. 9.6. It starts at the tree top node, with the entire learning set, and consists of identifying a candidate attribute along with its threshold value so as to decompose the mixture of stable-unstable cases into the two most purified subsets; in turn, these latter are directed toward the two successor nodes. The dichotomic procedure is repeatedly applied, until a subset results whose further splitting is deemed statistically meaningless. This "purified enough" subset becomes a terminal node, labeled stable or unstable according to its majority population (e.g., in Fig. 9.6 the leftmost terminal node D9 is an unstable node).

At each test node, a "test attribute" is selected along with its threshold value that provides the two most purified subsets; e.g., in Fig. 9.6, the test attribute Ps (denoting a generated power) appears at the top node, and also at other lower-level test nodes, with different threshold values.

Besides identifying the test attributes, the DT appraises their respective influence on TS in terms of *Information Quantity* (IQ). This is a measure of "purification ability," which takes into account the size of the learning (sub)sets of concern: typically, the higher the position of a test attribute in the tree, the larger its IQ—

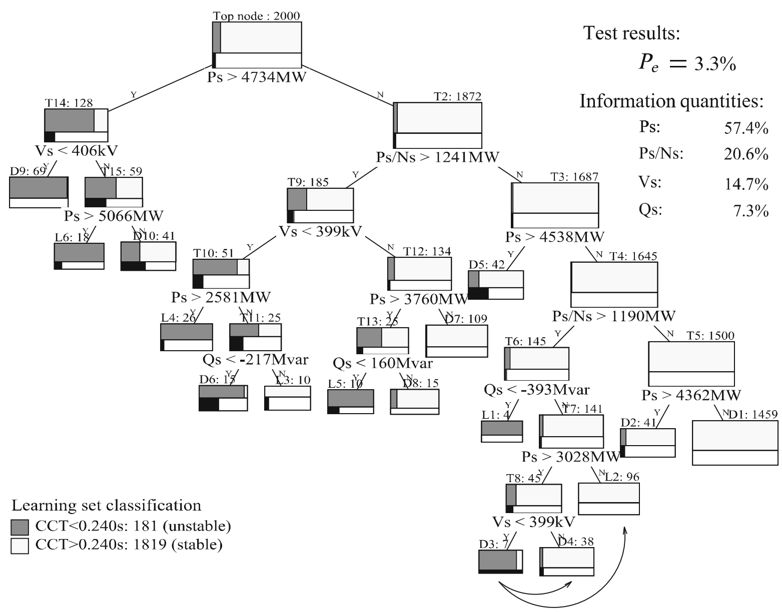

Fig. 9.6 Example DT for TS assessment and control. (Adapted from Ref. [2])

its influence on TS. Note also that the IQ of a test attribute that appears at many tree nodes is the sum of its partial IQs.

According to the above description, a DT provides the following information:

– A subset of relevant attributes (system parameters) that drive TS.
– A synthetic description of TS.
– The straightforward classification of a new, unseen case, by placing it at the top node, letting it progress down the DT by submitting it to the successive tests that it meets: it finally reaches a terminal node, labeled stable or unstable.
– Means to control: to stabilize an otherwise unstable case, the DT informs about the attribute(s), along with the(ir) value(s), to stabilize it.

It is important to emphasize that the successful application of the DT method depends on the close collaboration between its designer and the expert(s) of the physical problem under study. Incidentally, during our implementations of the DT approach to PSs, the experts were pleased and at the same time proud to observe that the relevant attributes selected by the DT, as well as their degree of influence, corroborated nicely with their own intuition. This was certainly one of the best incentives in favor of the adoption of the approach in practice [15].

9.5 Hindsight

We have described one of the main R&D subject matters (physical problems) studied by the Liège group, and we have given an outline of two methodological approaches developed over the years to carry them out.

The first methodology emanates from the Lyapunov direct criterion. It gave rise to the EEAC and its variants, then further revisited and yielded SIME. SIME is a hybrid approach aiming at combining advantages of direct methods and of time-domain numerical information, by coupling them together. The obtained advantages go far beyond those of the two approaches put together.

The other methodology calls upon machine learning techniques. Decision trees are a member of this set of techniques. We proposed them about four decades ago to tackle transient stability. Today, the outburst of machine learning gives rise to a rapidly growing number of applications in many domains including in the field of electric power systems reliability management [16].

In the meantime, the morphology of the electricity sector has undergone two major upheavals.

One is *the liberalization of the electricity sector*. This has profoundly changed its very organization, going from

- *Vertical, monopolistic organization, which is* managed by a single operator, the Electricity Company, to
- *Horizontal, unbundled organization*, which depends on many different players, such as *generation companies*, *transmission and distribution companies, transmission and distribution operators*, *suppliers, aggregators*, *market operators, and regulators*. (Incidentally, unlike the “ancient” vertical structure, this “modern” organization does not have the legal obligation to cover consumption needs at all times by adequate generation-transmission-distribution-supply schemes.)

The other upheaval comes from a profound *change in the morphology of the electrical generation;* it is linked to the advent and dazzling increase in *renewable energies* aimed at taking the lion’s share of the total electricity production.

The management of this new multifaceted morphology brings up new, much tougher challenges: increasing complexity in size and in uncertainties; decreasing security of operation, etc.

Nevertheless, the tailor-made SIME approach is still adaptable.

Regarding machine learning methods, their last decades’ extraordinary outburst undoubtedly benefits enormously various aspects of power system operation and control, including transient stability.

Acknowledgments This contribution is a small sample of the R&D work carried out collectively by the Liège group, mainly PhD students, in 1970–2000.

I (Mania Pavella) am greatly pleased to express my sincere appreciation for the enthusiastic motivation, inspiration, and dedication in their research work, and the constantly smiling and cordial behavior of all my PhD students. Warm thanks go (in order of thesis defense) to: Thierry

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Mania Pavella (Remembrances of a professional life) arrived in Liège (Belgium) at the end of September 1952. It was foggy, rainy, and chilly—quite different from the Greek sunny and warm weather I had just left. Deciding to study outside Greece was motivated by my curiosity to see whether "abroad" would correspond to the descriptions of my French and English Professor.

My parents did not dissuade me, despite the fact that I was their only child and still under 18.

On my arrival in Belgium, I had to suddenly adjust to my new and quite different surroundings. However, having to attend first-year University courses as a "free student" while at the same time working for my University entrance exams left me no time to experience homesick feelings.

At the end of my undergraduate studies, with my diploma of electrical engineer in hand, I was leaving for my vacation in Greece without worrying about "what to do next." So, when my main electrical engineering professor suggested that I apply for an assistantship, I did so without hesitation.

During my first years of assistantship, I explored possible thesis topics related to my basic training (Electronics Engineer). However, after a while, I realized that I was reaching a dead end. I thus turned to the realm of Power Systems. My thesis subject was found, its elaboration accomplished, followed by its defense and my PhD graduation (1969).

(Let me mention for fun, that at those times, the computing center of my university possessed a sole computer, which had the responsibility of executing all manner of tasks. Theses' calculations would be considered after executing all other tasks. So, usually, during my thesis elaboration, I was allowed to go and use the computer around 4 am or 5 am—and not for as long as I needed.)

After my PhD graduation, I joined academia as an associate professor. This was the real start of my professional career and the origin of the Liège group.

My first trip to the States was quite an experience. The purpose was my participation in the 1971 Institute of Electrical and Electronics Engineers (IEEE) Power Engineering Society (PES) Winter meeting in New York, and presentation of a paper summarizing my PhD thesis. Strangely enough, being among an almost totally male assembly without knowing anyone did not affect me. However, I was in shock at the end of my presentation, when a participant started criticizing my work, quite violently. I was flabbergasted inasmuch as I did not understand a single word of what he was saying, and therefore unable to answer. The intervention of a participant whom, of course, I did not know either, saved the situation, apparently by his explaining the interest in applying the Lyapunov theory. Later, I learned that he was Petar Kokotovic, a professor at the University of Illinois, who was an expert in Lyapunov theory.

Petar invited me to pay a visit to his CSL (Coordinated System Laboratory) in October of the same year, and to contribute a paper in the Allerton Conference, held at the "Allerton house"—an idyllic place in the middle of a superb forest.

This was my first encounter with the international community of scientists and researchers. It was a period of hard work and intense professional activities locally and internationally. I even had to give up my bridge card game that I was so fond of.

The second decisive encounter took place in 1975, during the COPOS conference in San Carlos, Brazil, where I met Tom Dy-Liacco.

Tom, in his thesis, a masterpiece published in 1968*, laid the foundations of the overall organization of power systems, identified needed techniques to operate them from the control center, and promoted innovative theoretical approaches to meet these needs. By 1975 he was recognized to be the "father of power system control centers." This is still valid today.*

Tom kindly invited me to go to Cleveland and visit the Cleveland Electric Illuminating (CEI) company and also his home, where I met his wonderful wife and children. I accepted his invitation enthusiastically. This was the beginning of collaborations and meetings at numerous conferences. These efforts gave me the opportunity to appreciate even more Tom's exceptionally gifted personality: a polyglot, a deep connoisseur of fine arts, an enthusiastic lover of the "art de vivre," and an extremely kind and benevolent human being.

This was a long time ago. At present, after many years of professional retirement, I would like to throw a hindsight, and share some personal thoughts.

Looking back at the professionally active part of my life, I realize that my career has seldom been planned. Rather, it has consistently been guided by luck, whenever luck has been encountered and recognized.

Among the happier circumstances, were my interactions with three exceptional personalities.

- As a teenager, my cosmopolitan French and English Professor. He instilled in me the love of foreign languages, and introduced me to and made me adore French literature.
- During my university studies and my assistantship, my main Professor of EE, F. Dacos. He instilled in me the love of physics, and introduced me to Einstein's relativity, Eddington's small flatfish, and the magic of physics.
- Later, as a senior researcher and professor, Tom Dy-Liacco. A dear friend and guiding light.

I am and will always be most grateful to them and appreciative of the chance of having crossed their paths and benefited from their personalities.

My deepest feelings of love go to my passed parents, for their unconditional and tactful love, and also for the confidence they put on me, which has been the dominant strength in my life. I will be thankful to them forever.

Finally, the warmest thoughts and love go to my daughter Clio.

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