Chapter 23
Applications of Reinforcement Learning and Bayesian Networks Algorithms to the Load-Frequency Control Problem

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ABSTRACT

Load-Frequency Control (LFC) is an essential auxiliary service to keep the electrical system reliability at a suitable level. In addition to the regulating area frequency, the LFC system should control the net interchange power with neighboring areas at scheduled values. Therefore, a desirable LFC performance is achieved by effective adjusting of generation to minimize frequency deviation and regulate tie-line power flows. Nowadays such an LFC design is becoming much more complicated and significant due to the complexity of interconnected power systems. However, most of the LFC designs are based on conventional Proportional-Integral (PI) controllers that are tuned online by trial-and-error approaches. These conventional LFC designs are usually suitable for working at specific operating points and are not more efficient for modern and distributed power systems. These problems apply to design of intelligent LFC schemes that are more adaptive and flexible than conventional ones. The present chapter addresses the frequency regulation using Reinforcement Learning (RL) and Bayesian Networks (BNs) approaches for interconnected power systems. RL and BNs are computational learning based solutions which can adapt with environment conditions. They are a kind of Machine Learning (ML) techniques which have many applications in power system engineering. The main advantages of these intelligent-based solutions for the LFC design can be simplicity and intuitive model building that is closely based on the physical power system topology, easy incorporation of uncertainty, and dependent to the frequency response model and also to the power system parameter values.

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INTRODUCTION

The main frequency is an important parameter of an electrical power system. It can change over a small range due to generation-load mismatches. Therefore, system frequency control on an isolated power system is particularly one of the important power system control problems and has an important role to enable power exchanges and to provide better conditions for the electricity trading (Bevrani, 2009).

However existing Load Frequency Control (LFC) solutions that use classical or trial-and-error approaches to tune the PI controller parameters are more difficult and time-consuming to design. They are usually suitable for working at specific operating points, and are not more efficient for modern power systems, considering increasing size, changing structure, and new uncertainties. These controllers are designed for a specific disturbance, if the nature of the disturbance varies, they may not perform as expected. Also most of the applied linear modern/robust control techniques suggest complex control structure with high-order dynamic controllers too which the importance and difficulties in the selection of weighting functions of these approaches and the pole-zero cancellation phenomenon associated with it produces closed loop poles and reduce their applicability (Daneshfar & Bevrani, 2012). Therefore, it is expected that using intelligent controllers in modern and distributed environment to be more adaptive/flexible than conventional ones. This chapter addresses two different learning based algorithms, Reinforcement Learning (RL) and Bayesian Networks (BNs) to satisfy LFC objectives in distributed environments. These approaches are intelligent and systematic learning based methods so that they can learn and update their decision-making capability (Ernst et. al., 2004). Also they have many applications in power system frequency control (Bevrani et. al., 2012; Daneshfar & Bevrani, 2010; Daneshfar et. al., 2011).

RL is one of the adaptive and nonlinear algorithms that is independent of environmental conditions (Sutton & Barto, 1998). It is a learning method which is suitable for unknown environments with nonlinearities and many conditions. It also allows the machine or software agent to learn the behavior based on feedback from the environment. This behavior can be learnt once and for all, or keep on adapting as time goes by. Again reinforcement learning differs from the other kinds of learning algorithms in several ways. The most important difference is that there aren't any pairs of input/output. Instead, after choosing an action, the agent received the immediate reward and the subsequent state, but is not told which action is the best choice. The agent should gather useful experience about the possible system states, actions, transitions and rewards actively to act optimally (Sutton, 1996).

This automated learning scheme implies that RL algorithm works well in nonlinear conditions and can easily be scalable for large-scale engineering systems. Also there is a little need to a human expert who knows about the domain of application and much less time will be spent for designing a solution, since there is no need for hand-crafting complex sets of rules as with expert systems, and all that is required is someone familiar with reinforcement learning (Dung et. al., 2008).

Many authors have been utilized RL algorithm for LFC problem until now. Ahamed et. al., (2002) presented a learning controller for LFC with discrete variables. They have demonstrated a controller based on reinforcement learning for the discrete state space considering a two-area power system. Again Ahamed et. al. (2003) presented another learning controller for LFC based on RL with discrete variables. The aim of this paper was to demonstrate an alternative RL-LFC design which is simpler than the first proposed one. The proposed RL based solution effectiveness was demonstrated by considering a four-area hydrothermal system whose dynamics