ONLINE LEARNING OF TIMEOUT POLICIES FOR DYNAMIC POWER MANAGEMENT

Abstract

This thesis proposes a novel machine learning based approach for the Dynamic Power Management (DPM) of a computing system to reduce its power consumption during runtime while maintaining the overall performance at an optimal level. This work mainly focuses on two major aspects of dynamic power management: (i) obtaining different solutions corresponding to power consumption and performance with a user-selected criteria, and (ii) dynamically reconfiguring the system during the operation so that a user-specified constraint (or level) of power consumption or performance is achieved. Considering the dynamic nature of real environments, this DPM technique uses a Reinforcement Learning (RL) based approach to adapt to the environment and adjusting the DPM decisions online during the system’s operation. The DPM decisions in this learning framework, referred to as Online Learning of Timeout Policies (OLTP), include the optimal selection of timeout values in the different device states. As opposed to the widely used static timeout policies, the OLTP learns to dynamically change the timeout decisions in the different device states including the non-operational states.

The proposed DPM approach is further able to adapt the user-specified power/performance constraints online via an Online Adaptation of Power/Performance (OAPP) framework. Additionally, the compatibility and effectiveness of the proposed OLTP/OAPP framework for a system having a higher number of power/performance states has also been demonstrated in this thesis. The proposed techniques have been implemented and evaluated on an embedded traffic surveillance platform called MobiTrick.