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Dynamic power management with fuzzy decision support system

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Abstract: In this paper, we propose a new dynamic power management (DPM) system based on fuzzy decision support system. Different dynamic power management policies may be implemented in the system. Based on the system requirements for each application class, one of the policies may be selected automatically. The approach, which is not dependent on the system under management, can be utilized in different systems. To show the efficacy of the fuzzy decision support system, we have compared its performance with fixed DPM policy systems. The results show that considerable improvements may be achieved in this approach compared to those systems with one DPM policy.

Keywords: DPM, power management, decision support system, fuzzy

Classification: Integrated circuits

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1 Introduction

Battery life times in portable systems can be prolonged using dynamic power management (DPM) systems. Dynamic power management (DPM) uses the runtime behavior to reduce power when systems are serving light workloads or are idle. The DPM system can be considered as a policy for selective shutdown, slowdown, or taking to other lower power states of the system components that are idle or underutilized. The policy should be determined in order to minimize the power consumption under a given performance constraint.

Much of the power dissipation in a portable electronic device comes from non-digital components. For example, the power breakdown for a well-known laptop computer shows that, on average, 36% of the total power is consumed by the display, 18% by the hard drive, 18% by the wireless LAN interface, 7% by non-critical components (such as keyboard and mouse) and only 21% by digital VLSI circuitry (mainly memory and CPU) [1]. Reducing power in the digital logic portion of this laptop by 15X would reduce the overall power consumption by less than 20% while if we reduce the power consumption of the non VLSI components (such as LCD and HDD) only by a factor of 2X leads to more than 25% reduction in the total power dissipation [1]. Each of DPM policies has its own advantages and disadvantages in terms of delay, power, and computation overheads.

In this work, we propose the use of a fuzzy decision support DPM system which can support different DPM policies. In this system, based on the requirements of different conditions, the best DPM policy would be adopted. The rest of the paper is organized as follows: Section 2, we review some of the dynamic power management algorithms while Section 3 describes fuzzy based DPM system. The simulation results are discussed in Section 4 and finally the summary and conclusion are given in Section 5.

2 Dynamic power management

First let us introduce Break Even Time (T_{BE}) which is one of the parameters used in DPM algorithms. It is the idle time for which using or not using the DPM policy leads to the amount of power consumption. One of the simplest algorithms of dynamic power management is the Timeout algorithm. The Timeout policy has a timeout value, τ, where the device goes into the sleep state if the idle time exceeds τ. The basic assumption is, if the device remains idle for τ, it stays idle further for at least a time equal to T_{BE}. The drawback

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of this policy is that while waiting for the timeout to expire, we waste energy. For this algorithm, the most important problem is to determine the optimum value for τ.

Another DPM method, called L-shop, shuts down the system, if the active interval is less than a predefined threshold. The system continues its work if the active interval is greater than the threshold [4]. There are several adaptive Timeout methods. One of these methods, called AT0, decreases the timeout period if the active interval is greater than a predefined threshold and increases the timeout period, if the active interval is less than the threshold [2]. There is another method in this category, called AT1, which counts the number of ons and offs of the system. If the counter exceeds a threshold, it multiplies the timeout period by a constant and if the counter decreases much, it divides the timeout period by a constant [3].

The Probability algorithm calculates the probability distribution function of the times between the arrivals of the user requests, and predicts the next time for the user request. There is another algorithm called Exponential Average which predicts the next idle time defined with $\mathrm{T_{Pred}}$ as [2]

$$T^{N}_{\Pr ed} = aT^{N-1}_{idle} + (1-a)T^{N-1}_{\Pr ed} \tag{1}$$

Where the superscripts (N and N − 1) show the indices for the actual and predicted idle times and a is a weighting coefficient. If the value of $T_{\Pr ed}$ is larger than TBE, the algorithm will shutdown the component.

3 Proposed DPM system

A powerful dynamic management of a system may satisfy global objectives with unequal significance and usually contradictory in different conditions. To achieve this goal, the management system should use different approaches to satisfy different goals of the system. In this paper, our objectives include low power consumption, high speed in responding to the service requests, low computational cost, and low switching rate. The significances of these requirements may differ in different applications. For this we incorporate different DPM policies in the system based on the requirements one of the policies is selected. The manager of the system, therefore, should define certain value for each goal and then the system chooses the best DPM algorithm for that particular situation. In this work, we use the fuzzy decision support system for selecting one policy among the supported DPM approaches which include Timeout, AT0, AT1, L-shop, Exponential, Probability, and ANFIS (Adaptive Neuro-Fuzzy Inference System). Now, we briefly explain the last approach. In the absence of an expert, generating the rules for the decision making may be difficult. To deal with this problem, a neuro-fuzzy system in which the rules can be generated in a train and learn process may be utilized. ANFIS known as a powerful neuro-fuzzy system may be used to achieve this goal. As mentioned above, each one of these approaches has its own performances in terms of the parameters of our interests. To make our decision making correct, first, we should estimate the ability of each ap-

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proach to satisfy each goal. Next using these estimations, we rank approaches to determine the best policy satisfying our requirements.

The first step in the decision making process is to extract some features of the service requests. For the convenience, we consider idle times ($\mathrm{T_{idle}}$) as time series. The features used for the power estimation of different approaches are given in the following:

- The oscillation rate of idle time ($\mathrm{T_{idle}}$) series around T_{BE}: If most of the idle times are greater than T_{BE}, then the Timeout algorithm is not an efficient DPM policy. In these cases, the approaches which estimate the idle time for shutting down the system should be used.

- Sever peaks in the time series: The existence of sever peaks in the idle time series makes the approaches based on the prediction less efficient, and adversely affect the adaptation ability of adaptive approaches. In these cases, approaches which use fixed parameters are more efficient.

- Rate of movements in the average of idle time series: The performance of some approaches is adversely affected by an increase or decrease in the average.

Then we compute the magnitude of each feature in the time series in each time slot to obtain some measures for decision making. We must estimate performance of all approaches in fulfilling different goals. To do this, following approaches can be used

- Using a fuzzy rule base, reflecting an expert knowledge or experiments done: In this case, in different situations, power of an approach can be estimated by using features extracted from requests and fuzzy rules.

- Using a neuro-fuzzy system: In absence of an expert, generation of rules for power management may be difficult. To deal with this problem, a neuro-fuzzy system can be utilized. Using this method, the rule can be generated in a train and learn process. ANFIS can be used to fulfill this purpose. In this paper we use this approach and train system with some data.

In the decision making system, a crisp number is estimated as the ability of an approach in achieving the goal. To convert this number to a fuzzy number, the following method is used. The developed fuzzy number is a triangular number whose core is the number generated by the estimation approach, and whose support is the interval produced by the minimum and the maximum of the performance measure of the approach in the N preceding moments. The Support of a fuzzy set F is the crisp set of all points in the Universe of Discourse [5]. In the initial states of the system, due to lack of an interval of N moments, crisp numbers are converted to fuzzy singletons (a fuzzy set whose support is a single point). The decision making using these fuzzy triangular numbers is expected to be more accurate. This is due to the fact that the decision making based on momentary information is not a good

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measure for decision making. The general diagram of the decision support system is shown in Fig. 1. After estimating the ability of each algorithm in achieving the desired goals in each time slot, the decision support system decides to use which algorithm. We use only one algorithm in each time slot and hence the extra overhead of the new approach, compared to using the algorithm itself, is the overhead due to the decision making process.

The decision making may be characterized as a process of choosing 'sufficiently good' alternative(s) or course(s) of action, from a set of alternatives, to attain a goal or goals [5]. The decision making deals with a set of conflicting goals that usually are difficult to achieve simultaneously. In fact, the total goal is to select an alternative with the best tradeoff between all goals. To evaluate the concepts like dominance, similarity, and contrast between different alternatives, some criteria can be defined [6]. The fuzzy set theory has been used widely in decision making problems. This is due to usual ambiguity in the goal definition and powerful representation of the concepts in the existence of uncertainty by the fuzzy set theory. System parameters used for the management can be injected to the system in the form of linguistic terms.

Usually, the goals of a system under the decision making do not have equal significance. The way that is normally used to assess the relative importance of different goals, is to dedicate a value to each goal. To define these values, different approaches have been developed which some of them include eigen vector, weighted least squares, entropy and Analytic Hierarchy Process (AHP) [7]. AHP approach was proposed to face with complicated problems systematically [8].

Assume that a set of approaches are denoted by Ai ($\mathrm{i} \in \{1, 2, \ldots, \mathrm{n}\}$) and goals of C_j with ($\mathrm{j} \in \{1, 2, \ldots, \mathrm{m}\}$). After estimating the performance of each approach by regarding each goal, a decision matrix given by (3) may be generated.

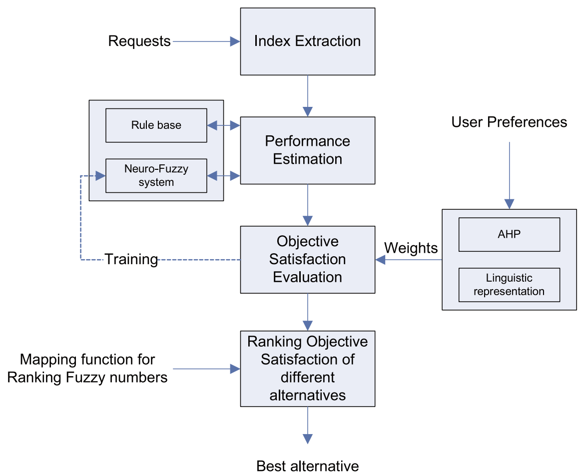

Fig. 1. Decision support system.

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$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \tag{2}$$

Here, x_{ij} is a representative of the performance of the approach i regarding the goal j. The weighting coefficients are represented by a vector as

$$W = (w_1, w_2, \dots, w_m) \tag{3}$$

Where W_j is the significance of the goal C_j. The performance matrix is produced by multiplying (2) by (3).

$$Z = \begin{bmatrix} w_1x_{11} & w_2x_{12} & \dots & w_mx_{1m} \\ w_1x_{21} & w_2x_{22} & \dots & w_mx_{2m} \\ \dots & \dots & \dots & \dots \\ w_1x_{n1} & w_2x_{n2} & \dots & w_mx_{nm} \end{bmatrix} \tag{4}$$

The sum of each row of the performance matrix is an estimation of the corresponding approach performance. In the proposed approach, we choose a DPM policy which maximizes the ability function, J. This method is called SAW (Simple additive weight) [9]. The ability function defined as:

$$J_i = \sum w_j.x_{ji} \tag{5}$$

$$\text{Optimum index} = i \ \forall (k \in \{1, 2, \dots, n\}) : (J_i > J_k) \tag{6}$$

We use this ability function to compare the algorithms. For computing x_{ij}, we use the following parameters:

Goal I : Power

$$\mathrm{Power_{Used}} = T_{active} \times P_{active} + T_{idle} \times P_{idle} + N_{Switch} \times (P_{up} + P_{down})$$

$$\mathrm{Power_{Save}} = 1 - (\mathrm{P_{used}}/\mathrm{P_{max}})$$

Goal II : Speed

$$\mathrm{Delay} = \sum T_{falsealarms} + N_{Switch} \times (T_u + T_d)$$

$$\mathrm{Speed} = 1 - (\mathrm{Delay}/\mathrm{Delay_{max}})$$

Goal III: Computation

$$\mathrm{Computation_{Efficiency}} = 1 - (N_{operations}/N_{max})$$

Goal IV: Toggle

$$\mathrm{Switching_{Efficiency}} = 1 - (N_{Switch}/N_{Switchmax})$$

4 Result and discussion

In this section, to evaluate the efficacy of the proposed DPM system, the simulation results for different approaches are presented. Hard disk we used

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Table I. Weighting coefficients of the goals.

Goals		Power	Speed	Switching	Computation
Weight	System I	Fairly High	High	Low	Fairly Low
	System II	High	Fairly High	Fairly Low	Low
	System III	High	Low	Fairly Low	Fairly High

Table II. Results of Table I.

Algorithm	*Ability Function (%)*		
	System I	*System II*	*System III*
Timeout	39	33	76
AT0	24	23	65
AT1	83	90	90
Competitive	30	30	65
Lshop	83	90	90
Exponentioal	71	86	61
Probability	42	77	43
ANFIS	60	80	35
DSS	90	95	73

has two states of spinning and sleeping and two transition states of spinning up and spinning down [3]. Note that although we have used a two-state HDD, the proposed algorithm however can be applied to multi-state systems. We compare the objective functions for different algorithms in different situations using (5). The goal is to reduce the power consumption, delay, switching rate, and computation. In each T_{idle}, our algorithm chooses the best DPM approach which has the best ability at that time. We test our system with many cases. Table I contains the weighting coefficients for these systems. The importance of the power saving is more than the speed in system. I. In system II, speed of the policies is the point, and computational cost is the great issue in the third system. The values of the normalized ability function for the DPM algorithms are shown in Table II. It should be mentioned that in all cases, we optimize the time constant for the timeout-based algorithms. As shown in Table II, the proposed algorithm works more efficiently than other policies. Although our proposed algorithm has a high computational cost, the results are satisfying in system III.

5 Conclusion

In this paper a new approach for power management based on fuzzy decision support system is presented. This approach can be utilized in different systems and is not dependent on the system under management. In addition, management goals can be altered conveniently. This algorithm can be used in different systems with different importance of goals and user can select the importance value of each goal such as speed, power, computation or toggle rate. Good results will be achieved by considering simulation results.

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