A Resource Allocation Model for Energy Management Systems

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Abstract— **Energy Management Systems monitor and control the behavior of an underlying system, allowing it to fulfill its primary purpose at the same time balancing across multiple constraints including cost optimization, system reliability, and environmental considerations. Examples of such systems include building energy management systems, where electrical and HVAC resources are optimized to deliver human comfort; microgrid management, where generators, energy storage, and renewable energy resources are balanced with loads to provide electrical service; and datacenter energy management, where electrical and cooling resources are balanced to provide a reliable computing resource. This paper analyzes these disparate energy management systems and defines a model for resource allocation that can be used for these and other energy management systems. The paper then shows how this model can be used across these domains.**

Keywords: Energy management systems, resource allocation, Lagrangian

I. Introduction

Energy management systems monitor and control energy production and consumption in generation, transmission, and customer facilities. Using such systems can lead to significant savings:

- In 2005, data centers used 1% of all the electricity generated worldwide [1].
- Many commercial companies are using energy management systems to realize significant impacts to their bottom lines [2].

This paper presents a theoretical model for resource allocation in energy management systems. It is an abstract model which can be applied to many different energy management domains. The paper then presents three ongoing research activities related to energy management and describes how the abstract model can be applied to them.

II. Basic Model

A. Definitions

We define a basic system model as follows, illustrated in figure 1. A *device* consumes *fuel* to produce a *resource*, which in turn is consumed by a *load*. For example, a generator (device) consumes coal or natural gas (fuel) to produce electricity (resource), which is then consumed by an industrial process (load).

Devices have limits in terms of the maximum amount of resources that can be delivered. Let max_d represent the maximum output of a particular device d. Devices consume fuel at a variable rate proportional to the amount of resources produced. The fuel used by a device is described by a fuel consumption curve, $fc_d(x)$ where x is the consumption level.

The load is not constant -- it varies stochastically. Assume that the load follows a probability distribution. If the load follows a probability distribution function f, we are interested in the *Q-function* of f, the probability that the load exceeds a certain value. This function can be calculated as

$$Q(x) = \int_x^\infty f(u)du. \tag{1}$$

$Q(max_d)$, therefore, is the probability that the load exceeds the maximum production capacity of device d. It is often impractical to keep the maximum load open-ended, so a *Service Level Agreement* (SLA) can be used between the resource supplier and the consumer. The SLA defines a guaranteed amount of resource that can be consumed. If the producer fails to meet the SLA, the producer incurs a penalty. If the consumer attempts to exceed the resource level defined in the SLA, the excess resources may or may not be delivered. If a producer has more capacity for resource generation than is required by the SLA, the excess capacity goes to waste. The producer is said to be *over provisioned*.

Fig. 1 gives an example with a Normal probability distribution function f. If the maximum load is the line labeled 'Underprovisioned', the shaded area represents Q for that load.

In order to provide a common basis for comparison, we would like to use the cost, in dollars, of various quantities.

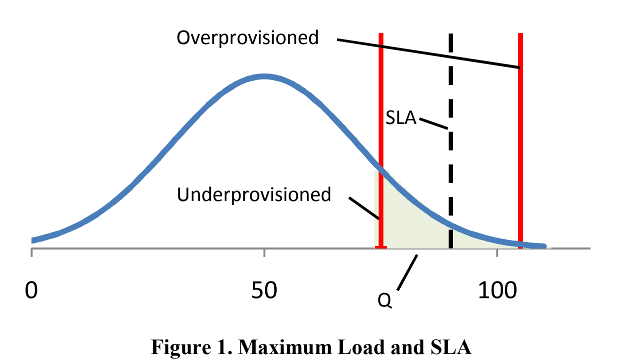

Figure 1. Maximum Load and SLA

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Devices have both a fixed cost and a variable cost. The fixed cost is the depreciation cost of the equipment. The variable cost is the cost of the fuel to meet a specific load, and has been defined previously as $fc_d(x)$. Finally, there is a penalty incurred if a load is not met. To keep the model simple, we assume this penalty is constant and denote it as Y.

B. Derivations

The resource allocation model can now be used to answer some economic questions about system operations. For example, to calculate the cost of unmet load:

$$C_{unmet\ load} = Q(max_d)*Y \quad (2)$$

Another interesting question is whether the system can take on additional customers, that is, what is the risk of taking on more load without increasing capacity:

$$C_{incremental\ load} = (Q_2(max_d)-Q_1(max_d))*Y \quad (3)$$

Q_1 and Q_2 are calculated from the initial probability distribution and the probability distribution of the new load, respectively.

Both of the above scenarios assume the maximum load was held constant. There are two strategies to increase the maximum load for the system. First is to increase max_d for a single machine, perhaps with an upgrade. The second strategy is to add more devices.

Upgrading a single machine keeps the system architecture simple. There may be limitations to the ultimate capacity possible, if there are limits on available devices. Moving to multiple devices increases overall system complexity, yet increases overall system reliability, as the loss of a single machine can be spread across multiple devices. If the load can be easily spread across multiple devices, a multiple machine strategy can have a higher maximum system capacity.

For multiple devices, the maximum system capacity is the sum of the capacities of the individual devices:

$$max_{system} = \sum_{i=0}^{n} max_i \quad (4)$$

Finding the system-wide fuel cost is more complicated. This can be expressed as an optimization for a particular load, L:

$$minimize \sum_{i=0}^{n} fc_i(\pi_i)\ \ subject\ to\ \sum_{i=1}^{n} \pi_i = L \quad (5)$$

Where π_i is the production level for device i. This can be solved by forming a Lagrangian function l that combines the objective functions and constraints [3]:

$$l(\pi_1, \pi_2, \ldots, \pi_N, \lambda) = \sum_{i=1}^{n} fc_i + \lambda(L - \sum_{i=1}^{N} \pi_i) \quad (6)$$

Setting the partial derivatives of the function to zero will allow us to find the optimum:

$$\frac{\delta fc_i}{\delta P_i} - \lambda = 0\ \forall i = 1, .. N \quad (7)$$

From (5), we also know that

$$\sum_{i=1}^{n} \pi_i = L \quad (8)$$

The values of π_i, are the optimal production values for each device i, and λ is the aggregated per-unit fuel cost at a particular load.

III. Application Domains

The resource allocation model described above is very simple. The probability distribution example is based on a Normal distribution, and the formula used to calculate optimal production in a multi-device environment has implicit assumptions about the behavior of the fuel consumption curves – specifically, that they were differentiable and convex. In order to apply the model to real-world problems, either the simple models need to be validated, or the models need to be more complex to more closely reflect reality. The alternative energy research group at Colorado State University has ongoing projects in three areas to validate the resource allocation model. These projects are described below.

The **Building Energy Management** project collects energy consumption data from several buildings across campus and develops models to predict energy consumption based on weather and other external factors. The goal is to use these models to allow finer-grained control of the HVAC system to maintain human comfort at improved energy efficiency.

Describing the building energy project in resource allocation model terms, the devices are the HVAC equipment, the fuel is either natural gas (for heating), or electricity (for air conditioning). The resource produced is either warm air or cold air, and the setting of the thermostat can be considered the SLA. Complicating this view is the fact that electricity is also used for other purposes – lighting, elevators, office and IT equipment, etc. Work is ongoing to develop a sensor network to collect data on human activity in the buildings, and define more sophisticated models to take this additional data into account.

A *microgrid* is an electricity generation system that has multiple generation assets and loads that can be managed as a single entity. The **Microgrid Energy Management** project examines strategies to effectively control the generation assets and loads, specifically to optimize fuel consumption. In terms of the resource allocation model, the devices are generators, the fuel natural gas, and the resource produced is electricity. This project is currently validating the optimization model, which provides the theoretically optimal settings for a group of generators, against various real-world generator dispatch strategies. Ongoing work is focused on running these dispatch strategies against actual generator hardware in the InteGrid [4] to show how the theoretical models reflect actual implementation practice.

The **Datacenter Energy Management** project is focused on modeling energy consumption in data centers, with a goal to optimize electricity consumption. Electricity is consumed in a datacenter both directly by the IT equipment itself, and indirectly by the air conditioning equipment to remove the heat generated by the IT equipment from the datacenter environment. From a resource allocation model perspective, the devices are the IT equipment, the fuel is electricity, and the resource produced is "compute power." This project has just begun, and is focused on collecting data to define basic fuel consumption curves – determining electricity consumption for IT equipment based on various load levels.

IV. Future Work and Conclusion

A. Future Work

Future work is being performed on two broad fronts – improving the theoretical models and fully validating the models against the application domains. We are looking at improving the theoretical models by incorporating metrics for system-wide reliability, which will drive more sophisticated modeling of system topology. We are also looking at more sophisticated cost models, incorporating different supplier pricing strategies such as peak load pricing or time of use pricing, which will make the theoretical models more reflective of reality and thus more useful.

To further validate the approach, we are developing a software test bed which will allow for controlled experiments. This test bed will be flexible enough to communicate to various sensors and devices over multiple protocols, and will be integrated into a general purpose programming language for ease of experimentation.

B. Conclusion

Energy management systems (EMS) show promise in making significant improvements in energy savings across many domains. A sound underlying model is a critical component for an EMS, as is proof of implementation in a wide variety of uses. This paper has presented a basic theoretical model and described its use in building energy management, managing microgrids, and datacenter energy management.

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