WiP Abstract: Mobility-based Load Balancing for IoT-enabled Devices in Smart Grids

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***Abstract*—There is an unprecedented load variability in the smart grids due to device (e.g. electric vehicles) mobility across different grid-locations. As a consequence, utility service providers have started exploring solutions such as dynamic pricing mechanisms, grid extensions and redistribution across micro-grids. However, most of these solutions do not exploit the transient nature of mobile devices. In this work, we propose an alternate mobility-based load balancing mechanism that exploits device-level flexibility. With recent advancements in Internet of Things (IoT) technology, we assume these devices to be equipped with IoT capabilities. We present an abstract model to capture the demand from these IoT-enabled devices in the form of a *utility function*. Our objective is to cater to the demand by incentivising device mobility without exceeding the peak load capacity across all grid-locations such that the overall utility of the devices is maximized.**

***Index Terms*—Load Balancing, IoT, Smart Grids, Electric Vehicles, Decentralized Optimization**

I. Introduction

Load balancing has always been a major research area in the smart grids domain. The issue is gaining further traction due to the electrification of public transport, shift towards electric vehicles and increased use of personal mobility devices (PMD). The problem is inherently complex due to the stochastic nature of the device (or vehicle) demand. Several research studies have been carried out to tackle this dynamic load balancing problem. Some of the existing techniques introduce incentive schemes [1]–[3] to encourage load shifting to non-peak times. Other methods incorporate mobile energy sources [4] to augment the existing capacities of the grid, often known as *grid-extensions*. Some studies [5] focus on energy redistribution across different micro-grids. However, most of these works handle the load variability only from the grid perspective. The solutions that consider load-shifting due to inherent device mobility are least explored.

In this work, we present a novel decentralized mobility-based load balancing algorithm that maximizes the overall *utility* of the devices across all grid-locations. We assume that the devices are equipped with IoT capabilities which allow them to be connected in a network and communicate with other devices in the same network. The system architecture and device interaction is shown in Figure 1.

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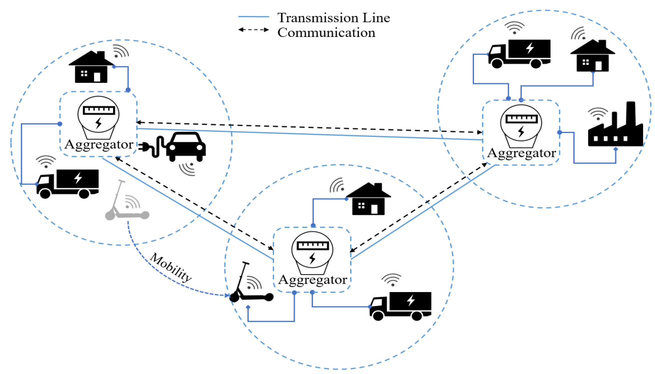

Fig. 1: The grid aggregator and the devices (including mobile devices formed into clusters)

Without loss of generality, we assume the grid is subdivided into multiple clusters (micro-grids), each having a peak load capacity and managed by an aggregator unit. The aggregator provides the grid status (*e.g.* load constraint, pricing, etc.) and the electricity supply to the devices. Each cluster comprises both stationary and mobile devices. Mobile devices have a storage unit (battery) that enables them to move across clusters. Mobile devices could either have a fixed route (*e.g.* public transport) or a dynamic route (*e.g.* taxis) defined by the devices. Thus, resulting in a fixed or a stochastic load. We define a *utility function* for each device that abstracts the energy demand of the device, utility losses due to deadline misses and device mobility (information obtained from aggregator). The algorithm aims at maximizing the cumulative device utility while ensuring that the peak load capacity across different clusters is not violated.

II. Mobility-based Load Balancing

We consider a 2-tier hierarchical architecture as shown in Figure 1. We assume a finite timeline $\mathcal{T}$ that is divided into time slots of fixed duration T_0.

A. System Model

Suppose the system comprises L clusters and K devices. We denote the set of aggregators and set of devices as $A = \{a_l\}$ and $D = \{d_k\}$, respectively. At any point in time, each device d_k is connected to at most one aggregator a_l for power and communication. Let d_k^l denote the set of devices connected to aggregator a_l. Each aggregator has a limited power capacity denoted as $\hat{\alpha}_l$.

Each device requests for an energy demand of E_k within its deadline T_k^d and has a set of power modes $\alpha_k = \{\alpha_k^0, \alpha_k^1, \ldots, \alpha_k^{max}\}$ associated with it. Each such request is denoted by,

$$\theta_k = \left(T_k^d, b_k^m, E_k, \alpha_k\right) \tag{1}$$

where b_k^m is a binary variable that denotes whether the device is stationary ($b_k^m = 0$) or mobile ($b_k^m = 1$).

We define a mobility cost vector $C_k^m(i,j)$ for each device that moves between cluster i and cluster j as $< \mathfrak{t}_{h,i,j}^m, c_{h,i,j}^m >$, where $\mathfrak{t}_{h,i,j}^m$ denotes the movement duration and $c_{h,i,j}^m$ denotes the utility loss per time slot. We use the notation h to denote different transition options (*i.e.* cost vs. duration trade-off).

B. Utility Function

The utility function of a device is defined per time slot. For time slot $t \in \mathcal{T}$, it is given as:

$$u_k(t) = \psi_k(t)\gamma_k + \beta_k(t) + (1 - b_k^m)(1 - \delta_{i,j}(t))\beta^{max} \tag{2}$$

1) Positive Utility: It consists of a progress function $\psi_k(t)$ and a priority function γ_k. The progress $\psi_k(t)$ is given by

$$\psi_k(t) = \frac{\alpha_k(t)T_0}{E_k} + \frac{\beta_k^m T_0 c_{h,i,j}^m(t)}{E_k} b_k^m$$

where β_k^m is a negative constant used to capture utility loss due to mobility. The accumulated progress (utility gain) Ψ_k up to the time slot t_c is given as $\Psi_k(t) = \sum_{t=0}^{t_c} \psi_k(t)$. The priority function γ_k assigns different utility value to devices based on its requested energy E_k and is used to differentiate devices with same/different energy requirement.

2) Negative utility: The $\beta_k(t)$ incorporates the penalty for missing the deadline. We assume the utility of the device becomes negative if it cannot be served within its deadline.

$$\beta_k(t) = \begin{cases} \mathfrak{F}(t), & (t > T_k^d) \wedge (\Psi_k(t) < 1) \\ 0 & \text{otherwise} \end{cases}$$

where $\mathfrak{F}(t) = \beta[\exp(\kappa(t - T_k^d)) - \exp(\kappa((t-1) - T_k^d))]$ is penalty per time slot and β is a negative constant. The κ is used to differentiate devices with the same deadline. Higher κ leads to a higher penalty denoting higher priority.

The third term in Eq. (2) is to ensure the stationary device does not move from its cluster. They are penalized if they move, say from $i \rightarrow j$. Thus, $\delta_{i,j}$ is 1 if $i = j$ and 0 otherwise. We define β^{max} as a very large negative number.

C. Problem Formulation

Our objective is to maximize the cumulative device utility across all clusters over all time slots:

$$\max \sum_{t \in \mathcal{T}} \sum_{d_k \in D} u_k(t) \tag{3}$$

$$\text{s.t.} \quad \sum_{d_k \in d_k^l} \alpha_k(t) \leq \hat{\alpha}_l, \qquad \forall t, \forall a_l \quad \text{(i)}$$

$$0 \leq \Psi_k(t) \leq 1, \qquad \forall t, \forall d_k \in D \quad \text{(ii)}$$

$$((a_k(t) \neq 0) \wedge (c_{h,i,j}^m(t) \neq 0) = 0), \qquad \forall t, \forall d_k \in D \quad \text{(iii)}$$

$$d_k^i \cap d_k^j = \emptyset, \qquad \forall \{a_i, a_j\} \in A, \forall t \quad \text{(iv)}$$

$$\alpha_k(t) \in \alpha_k, \qquad \forall t, \forall d_k \in D \quad \text{(v)}$$

$$(\mathfrak{t}_{h,i,j}^m, c_{h,i,j}^m) \in C_k^m(i,j), \qquad \forall t, \forall d_k \in D \quad \text{(vi)}$$

Eq. (i) constrains the total power consumption of all devices in l to the maximum aggregator power capacity $\hat{\alpha}_l$ at all time slots. The accumulated progress is limited between $0 - 100\%$ in Eq. (ii). This also ensures the mobile device cannot move until it has accumulated at least the mobility cost as utility. Eq. (iii) captures that a device must never move and consume power at the same time. Eq. (iv) captures that each device is associated to at most one aggregator at any time. Eq. (v) restricts the power consumption to be among the different modes defined in α_k. Eq. (vi) restricts the choices of transition from cluster i to other cluster j to be among the mobility cost vector.

III. Summary and Future Work

Constant upgrades to the grid are expensive and not a feasible load balancing solution as the number of mobile devices increases. To overcome this limitation, we propose a mobility-based load balancing scheme. As a part of our research, we plan to develop a decentralized solution to the presented optimization problem where devices communicate among each other to make decisions at every time slot. We also plan to incorporate incentive schemes for mobility and take into account the pre-defined routes (relaxes stochastic requirement) for mobile devices.

In the poster, we plan to show the detailed model of the mobility-based load balancing along with a solution. The results from the optimization will also be included to demonstrate the performance of the formulation.

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