Joint User-Channel Assignment for Efficient Use of Renewable Energy in Hybrid Powered Communication Systems

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***Abstract*—In this paper, we introduce a new green resource allocation problem using hybrid powering of the communication system from renewable and non-renewable sources. The objective is to efficiently allocate the power delivered from different micro-grids to satisfy the users' requirements. Minimizing a defined power cost function instead of the net power consumption aims to encourage the use of the available renewable power through collaboration between base stations within and outside the different micro-grids. The different degrees of freedom in the system, ranging from assignment of users to base stations, possibility of switching the unnecessary base stations to the sleep mode, and dynamic allocation of the available bandwidth, allow us to achieve important power cost savings. Although the formulated optimization problem is a mixed integer-real problem with a non-linear objective function, we propose an efficient two-step algorithm to jointly assign users to base stations and the shared bandwidth among users. The users-to-base stations assignment is inspired from the *bin-packing* approach while the bandwidth allocation is performed through the *bulb-search* approach. Simulation results confirm the important savings in non-renewable power consumption when using the proposed approach.**

***Index Terms*—Green communications, smart grids, efficient bandwidth allocation, power efficiency.**

I. Introduction

The dramatic increases in power generation costs coupled with the increasing awareness about the negative impact of carbon dioxide emission on the environment prompted researchers to think of new, innovative ways that can make substantial reduction in power consumption when designing modern communication systems [1–4]. As a result, the development of techniques that can still achieve high system performances while minimizing energy consumption has been the design focus of various networking systems, including sensor networks [5–8], cognitive radio networks [9–11], femtocell networks [12–15], cloud networks [16–18], and others.

Relying on renewable energy sources has recently emerged as one of promising solution to address this energy consumption issue [19, 20]. However, their limited energy efficiency makes them unreliable for long-term use. With the technological advances achieved in improving their energy efficiency, renewable sources contributed about 19% of the global world energy consumption in 2012 [21]. Communication systems are one of the biggest power consumers and CO_2 producers. In 2014, radio access networks contributed about $84\ TWh$ in the total world energy consumption and about 170 $Mto\ CO_2e$ in the total carbon emissions [22]. Those numbers are expected to exponentially increase in the coming years with the continuous growth of the telecommunications market driven by the multiplication and variation of the telecommunication services and the exponential increase of the required Quality of Service (QoS). According to [23, 24], base stations (BSs) are the highest components in terms of power consumption in the mobile networks. It is responsible for about 60% of the total power consumption. For that, many research attempts have focused on reducing BSs' energy consumption through efficient resource allocation, increasing collaboration between BSs to serve users, optimizing the geographical positions taking into consideration the distribution of the served users, and improving the use of renewable sources.

For instance, Holtkamp *et al.* [25] proposed an optimized radio resource allocation where the achieved gain ranges between 20 to 40% depending on the load. Micallef *et al.* [26] and Saker *et al.* [27] proposed to switch BSs to sleep mode when the traffic load decreases. They proposed different switching scenarios to sleep mode that allow to obtain a considerable gain of energy consumption. Other research works focused on power sources; Chamola and Sikdar in [28] proposed to power BSs using solar energy while Yu and Qian studied wind-powered BSs' performance in [29]. The authors in [23, 30] considered user-BS associations in cellular networks whose BSs are powered by both on-grid power and green energy.

One of the limits of renewable sources is the discontinuity of the power generation which affects reliability of the service. Thus, hybrid powering is required. The emergence of smart grids represents also an opportunity to enhance power usage in telecommunication systems by exploiting the dynamic power pricing information. A recent survey, Erol-Kantarci and Mouftah [31], showed that although green communications is one of the hot topics in the last few years, only few research groups have focused on optimizing the use of smart grids in communication systems. Of these works, Bu *et al.* [32] presented a study of the best scheme to power base stations using smart grid with consideration of real-time power prices provided by the smart grid and pollution level resulting from the power generation while Ghazzai *et al.* [33] presented a complete framework for a smart-grid powered LTE system and introduced a power allocation strategy based on evolutionary algorithms.

In this work, we consider a communication system where BSs connected to different micro-grids cooperate to minimize the global power cost while ensuring a reliable service to the requesting users. Each micro-grid is equipped with renewable sources but has the ability to procure non-renewable power from the main grid when needed. The main task is to optimize resources allocation through collaboration between BSs to satisfy the required QoS of the different users while minimizing the non-renewable energy consumption by profiting from the available renewable power. The challenge consists in determining the users' assignment to BSs depending on their relative channel gains as well as the renewable power availability at each micro-grid. The main contribution of this paper is to propose efficient algorithms for dynamic power and bandwidth allocation for a wireless communication system using cooperation between BSs to efficiently use the renewable power and minimize usage of exceeding non-renewable energy. Turning the unnecessary BSs to the sleep mode capability is also exploited. Furthermore, we study the possibility of allocating the available bandwidth dynamically to further improve the power usage, although this step represents an additional challenge.

This paper is organized as follows. Section II introduces the system model and micro-grid powering architecture. Section III gives the mathematical problem formulation of the system and models that govern the power cost in the system. In Section IV, we detail and analyze the proposed algorithms for resource allocation while in Section V we present simulation results and gains achieved with the proposed schemes. Finally, the conclusion is drawn in Section VI.

II. System Model

We consider a set of L base stations aiming to serve K users through N sub-channels ($N >> K$). We assume that the base stations are connected through M power-grids where each micro-grid m powers a group of L_m base stations. Each micro-grid uses renewable power to generate electricity needed to feed the connected base stations. In addition to that, it is responsible for purchasing the back-up power from the main grid when needed as shown in Fig. 1.

It is to be noted that BSs' clustering into the micro-grids is out of the scope of this paper. But, results of this work could be exploited to optimize the clustering of the BSs as we will show in the simulation results' section. We consider to focus on the instantaneous management of the available power. Thus, we assume that BSs do not have the ability to stock power. The available instantaneous renewable power at a micro-grid m is denoted by P_m^{renew} assumed to incur free cost of usage while the non-renewable power has a unitary cost denoted α_m per power unit. Thus, the cost of the power consumed by each micro-grid is equal to the cost of the power consumed by all BSs belonging to the micro-grid exceeding the available renewable power. Mathematically, the cost of the power at the micro-grid m is written as

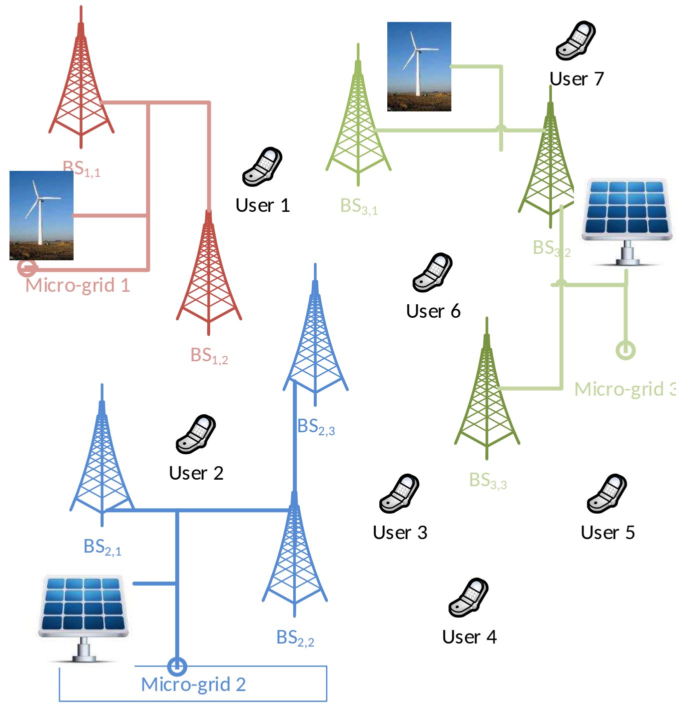

Fig. 1. System model.

$$C_m = \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+, \quad (1)$$

with $[x]^+ = \max(x, 0)$ and where P_l represents the power consumption of the base station l, $b_{m,l}$ is an index of the base stations connected to the micro-grid m (i.e., $b_{m,l} = 1$ if base station l is connected to micro-grid m and $b_{m,l} = 0$, otherwise), and P_m^{renew} represents the generated renewable power at this micro-grid.

We consider a simplified model for the base station power P_l. According to Arnold *et al.* [34], the power consumption of a base station consists of basically two components. The first term is function of the transmitted power which depends on the served users while the second is independent from the load and serves to ensure powering of the base station and ensuring some functionalities such as cooling. Assuming the possibility of switching the base station to a sleep mode when not serving any user, this component is divided into two terms, one represents the power needed to turn the base station ON from sleep mode and one for the power consumed even if in sleep mode. Thus, assuming a linear model function of the transmitted power, the base station power can be written as follows

$$P_l = \xi_l \sum_{k=1}^{K} a_l^{(k)} P_l^{(k)} + P_l^{on} \Big(\sum_{k=1}^{K} a_l^{(k)} > 0 \Big) + P_l^{idle}, \quad (2)$$

where $a_l^{(k)}$ is the assignment index for users to base stations (i.e., $a_l^{(k)} = 1$ if the k-th user is served by the base station

l and $a_l^{(k)} = 0$, otherwise), $P_l^{(k)}$ is the power transmitted by base station l to the k-th user, and ξ_l is the amplification factor for the transmitted power by the base station l while P_l^{on} is the power consumed when the base station is not at sleep mode (i.e., at least one user is served) and P_l^{idle} is the power consumed by the l-th base station when idle.

III. Problem formulation

The aim of our work is to improve the usage of the available renewable power in different micro-grids through collaboration between the base stations in the same micro-grid and in different micro-grids. Consider Eq. (1), the total cost of the procured non-renewable power by all micro-grids can be written as follows

$$C = \sum_{m=1}^{M} \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+ . \tag{3}$$

The Quality of Service (QoS) is ensured by a minimum throughput r_k^{req} that needs to be guaranteed for each user k for its successful communication. The QoS may differ from one user to another depending on the user's running applications. The minimum rate constraint for each user is expressed as

$$R(k) \geq r_k^{req}, \tag{4}$$

where $R(k)$ is the achieved throughput by user k, given by

$$R(k) = \sum_{l=1}^{L} a_l^{(k)}\ b_c\ n_l^{(k)}\ log_2\left(1 + \frac{P_l^{(k)}\ g_l^{(k)}}{N_0\ b_c\ n_l^{(k)}}\right), \tag{5}$$

where $n_l^{(k)}$ is the number of sub-channels allocated to user k, b_c is the sub-channel bandwidth, $g_l^{(k)}$ is the channel gain between the base station l and the user k supposed to be the same for all channels (fast fading variations are not considered as we aim relatively large time-slot transmissions), and N_0 is the noise power density. To avoid interference, we assume channel re-use not allowed and all channels shared orthogonally between all base-stations. Thus, an additional constraint is considered for channels' sharing

$$\sum_{l=1}^{L} \sum_{k=1}^{K}\ a_l^{(k)} n_l^{(k)} \leq N. \tag{6}$$

Then, the problem consists of minimizing the cost function under minimum rate per user constraint, total bandwidth constraint and the assumption that each user must be served only from one base station.

$$\min_{\left\{a_l^{(k)}, n_l^{(k)}\right\}_{\substack{1 \leq l \leq L \\ 1 \leq k \leq K}}} \quad \sum_{m=1}^{M} \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+ \tag{7a}$$

$$\text{s.t.} \sum_{l=1}^{L} a_l^{(k)} b_c n_l^{(k)}\ log_2\left(1 + \frac{P_l^{(k)}\ g_l^{(k)}}{N_0 b_c n_l^{(k)}}\right) \geq r_k^{req}, \quad \forall k \tag{7b}$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K}\ a_l^{(k)} n_l^{(k)} \leq N \tag{7c}$$

$$\sum_{l=1}^{L}\ a_l^{(k)} = 1, \quad \forall k. \tag{7d}$$

The last constraint is added to indicate that each user is served by only one base station. In this case, the allocated power is deduced from the rate constraint (7b) as follows

$$P_l^{(k)} = a_l^{(k)} \left(2^{\frac{r_k^{req}}{n_l^{(k)} b_c}} - 1 \right) \frac{N_0 b_c n_l^{(k)}}{g_l^{(k)}}. \tag{8}$$

IV. Efficient Users and Channels Assignment

The optimization problem (7) is a non-linear integer minimization problem to determine the assignment of each user to the best BS in addition to the number of sub-channels per user. The objective is to ensure the required data rates for all users while minimizing the consumption power cost by profiting from the available renewable power in the different micro-grids and variability of the channels' gains between the different users. In conventional power allocation problems, users-to-BSs assignment depends mainly on the channel gains between the users and the BSs (i.e., each user will be assigned to the BS with the best channel gain). In our problem, the dependency of the cost function on the available renewable power makes the problem more challenging. In addition, further power cost reductions are possible by keeping unneeded BSs in the sleep mode and using adaptive bandwidth allocation. As the problem is complex, we propose to firstly assume uniform bandwidth assignment among all users and focus on assigning the users to BSs. Then, we will present a two-step approach to jointly optimize the users-to-BSs assignment and allocated bandwidth to further optimize the cost of the power consumed by profiting from dynamic spectrum assignment.

A. Uniform Bandwidth

In this part, we consider a uniform bandwidth sharing between the users (i.e., $n_l^{(k)} = \frac{N}{K}$). The optimal solution to determine the best users-to-BS assignment is to perform an exhaustive search of all the possible assignments and take the combination that incur the least total cost. Obviously, this is not a practical solution as its complexity is exponential. Alternatively, we propose a polynomial approach based on the *bin-packing* to determine the users that will be assigned to each base station. In our case, the BSs represent the bins while the users are the objects to be packed. The difference, is that objects occupy different volumes depending on the pack as the power consumed differs from a BS to another. Our metric criterion for the decision is the resultant global power cost in the whole network. Thus, each user will be assigned to the base station incurring the lowest power cost according to Eq. (3). As in usual bin-packing algorithms, the order of packing objects influences the obtained performance. For that, we propose two approaches:

- **Random users assignment:** In this approach, we simply assign the users in random order. Although, this method is limited in performance, it is suitable for online assignment as we need to assign users in their order of request of service without waiting for all users to search the best order of assignment.
- **Best users assignment:** In this approach, as described in Algorithm 1, we search for the user that will incur the lowest power cost by checking with all users. Then, assign it and repeat the procedure until assigning all users. Although the complexity is multiplied by a factor capped by the number of users (we need to parse, at each step, all users and compute the resultant power cost), this process enhances notably the performance as the order of assignment of the users is very important to efficiently use the renewable power in the micro-grids.

Algorithm 1 Users-to-base stations assignment.

INPUT: Number of sub-channels per user: $\{n_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

OUTPUT: Users-to-BSs assignment: $\{a_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

repeat
  for all users $k = 1 : K$ **do**
    Determine base station l_k to be assigned to user k incurring lowest power cost: $l_k = \arg\min_l c_l^{(k)}$
  end for
  Assign user k^* such that $k^* = \arg\min_k c_{l_k}^{(k)}$
until All users assigned

B. Bandwidth Allocation

Dynamic spectrum allocation has shown its importance for power savings. Thus, we propose to assign the bandwidth adaptively between the users in order to further reduce the global power cost. As discussed earlier, solving the global problem optimally is computationally complex, therefore we propose to use an iterative two-step algorithm. In the first step, we optimize the users-to-BSs assignment similarly to the previous section. While in the second step, we propose to optimize the bandwidth allocation. For the bandwidth allocation, inspired by the bubble sort, we propose an algorithm that consists of searching recursively the best possible sub-channels changes until convergence. At each step, we parse all users and search, for every user, the best channel swap with another user that results in the largest reduction in power cost. We apply that change and restart the search again until no further power savings could be achieved.

Algorithm 2 Bandwidth allocation.

INPUT: Users-to-BSs assignment: $\{a_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

OUTPUT: Number of sub-channels per user: $\{n_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

repeat
  for all users $k_1 = 1 : K$ **do**
    search for the best sub-channel swap with another user k_2 such that:

$$k_2 = \arg\min_{k_2} C(n_l^{(k_1)} \Leftarrow n_l^{(k_1)} + 1, n_l^{(k_2)} \Leftarrow n_l^{(k_2)} - 1)$$

  end for
until no possible cost decrease ($k_2 = k_1,\ \forall k_1$).

V. Simulation Results

We consider a circular area of diameter $6\ Km$ where K users and $L = 8$ base stations are placed randomly. The channel gains are derived based on the pathloss model $g_l^{(k)} = c_0 \left(\frac{d_0}{d_{l,k}}\right)^\eta$, where c_0 is the channel gain for the reference distance d_0, $d_{l,k}$ is the distance between the base-station l and the user k, and η is the path-loss set to 3. We consider a total bandwidth $B = 20\ MHz$ divided into sub-channels of per sub-channel width $b_c = 15\ KHz$. The noise power is taken $-120\ dBm/Hz$. The minimum required throughput rate per user is set to $r_k^{req} = 50\ Mbps$.

We consider that for an average load, the dependent transmission power term represents $2/3$ of the base-station total power. The remaining 1/3 is divided equally between the idle power and the sleep-mode power. Thus, when in sleep mode, base stations can save 1/6 of the consumed power and the consumed power when idle is equal to 1/6 of the average consumed power. The efficiency of the base station amplifiers is set to $\frac{1}{\xi} = 33.33\%$. We consider that the base stations are grouped into $M = 4$ micro-grids so each micro-grid supplies two base stations. We assume that the non-renewable power cost, α_m, is equal for all micro-grids to focus on the effect of the renewable power availability.

To illustrate the results, we consider the scenario where renewable power is not considered in optimization and compute the incurred power cost and consider that as a reference. We represent the obtained performance as the relative cost gain with comparison to this reference cost.

Fig. 2 illustrates the normalized power cost gain as a function of the number of users in the network with different algorithms. First, we note the net cost gain achieved by incorporating additional features in the optimization algorithm. In particular, the best user selection method for the users-to-BSs assignment outperforms the random selection. In addition, optimizing the allocated bandwidth for each user allows further cost savings. Second, as the number of users requesting to be served increases, the cost gain decreases due to the increase of the consumed power which, at a certain step, harvests all the available renewable power. In this case, the problem reduces to

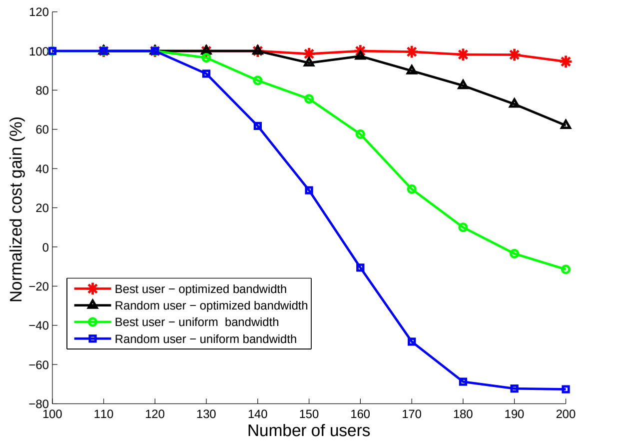

Fig. 2. Relative power cost gain as function of the number of served users with constant renewable power for all micro-grids.

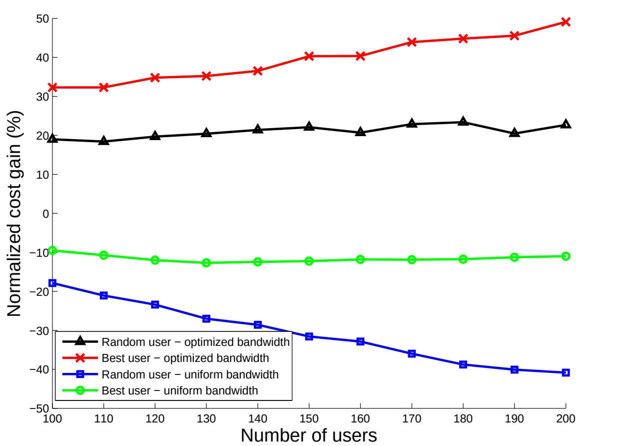

Fig. 3. Algorithms optimality: Relative power cost gain when renewable power is not available.

a total power minimization problem and our approach becomes limited in performance compared to the optimal approach.

In order to show the optimality of the proposed algorithms, we consider the case where the renewable power is not available at all (i.e., $P_m^{renew} = 0,\ \forall m$). In this case, the problem is exactly the same as the total power minimization which we take as a reference for computing the cost gains. We present the results in Fig. 3 which shows that without bandwidth optimization the best user selection algorithm incurs a loss of around 10% while adding the bandwidth optimization allows a gain between 30 to 45% which represents the net gain of the dynamic allocation of the bandwidth.

In the previous figures, we studied configurations where the same renewable power amount is available in each micro-grid. In the following, we propose to study a more practical scenario where the available renewable power is variable across the different micro-grids. We present in Fig. 4 the cost gain with increasing variability of the renewable power level across

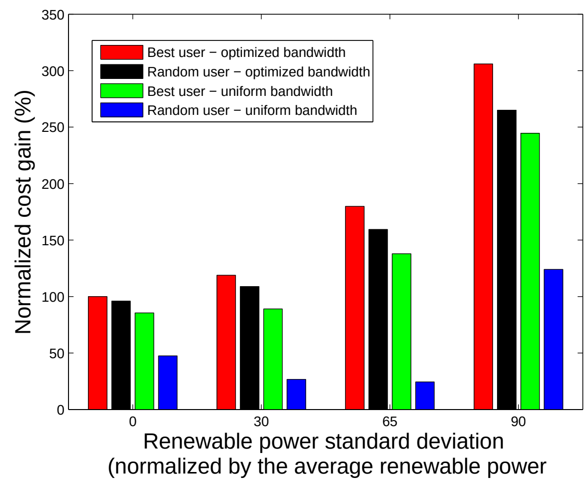

Fig. 4. Cost gain percentage as function of the renewable power standard deviation for $K = 150$ users.

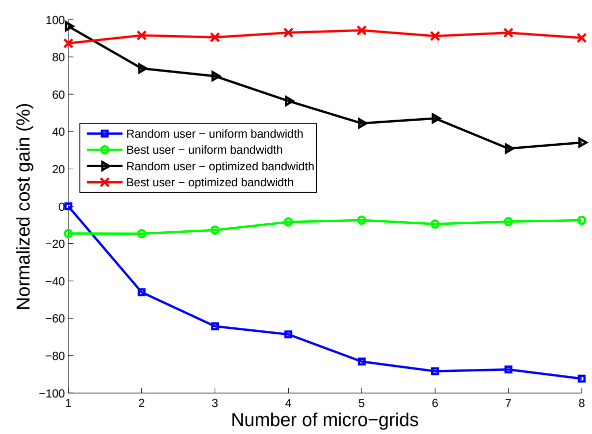

Fig. 5. Cost gain percentage for different number of micro-grids for $K = 200$ users.

the micro-grids. We note that with the best user assignment algorithm, the cost gain increases when the variance increases. This is explained by the fact that order of assignment of users-to-BSs becomes more important in this case than in the equal renewable case for which, due to the random distribution of users, optimal assignment will be most likely based on channel gains rather than renewable power availability.

In Fig. 5, we vary the number of micro-grids while keeping the same number of base stations and the same total renewable power over all micro-grids to observe the effect of collaboration between the base stations. As the number of micro-grids increases, the cost gain is expected to decrease as in the random users assignment due to non-possibility of exchanging energy between BSs. But, with the best user assignment, the gain remains approximately constant. The algorithm succeeds to compensate the loss incurred by the absence of collaboration between BSs by classifying the users before assigning them.

VI. Conclusion

We have introduced in this paper a new model for powering base stations using hybrid renewable and non-renewable power sources. While base-stations are clustered in groups of micro-grids, we proposed efficient assignment algorithms and bandwidth allocation that minimize the global power cost and satisfy users requirements through cooperation between BSs in the same micro-grids and between the different micro-grids. Important power cost gains are achieved through the proposed approach. Although we consider in this paper a simple cost function, the work can be applied also for more complex power cost functions.

VII. Acknowledgment

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