Toward Customized Hybrid Fuel-Cell and Battery-powered Mobile Device for Individual Users

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Rapidly evolving technologies and applications of mobile devices inevitably increase the power demands on the battery. However, the development of batteries can hardly keep pace with the fast-growing demands, leading to short battery life, which becomes the top complaints from customers. In this article, we investigate a novel energy supply technology, fuel cell (FC), and leverage its advantages of providing long-term energy storage to build a hybrid FC-battery power system. Therefore, mobile device operation time is dramatically extended, and users are no longer bothered by battery recharging. We examine real-world smartphone usage data and find that a naive hybrid power system cannot meet many users' highly diversified power demands. We thus propose an OS-level power management policy that reduces the device power consumption for each power peak to solve this mismatch. This technique trades the quality-of-service (QoS) for a larger FC ratio in the system and thus much longer device operation time. We further observe that the user's personality largely determines his/her satisfaction with the QoS degradation and the operation time extension. Thus, applying a hybrid system with fixed configuration (i.e., peak throttling level coupled with corresponding FC/battery ratio) fails to satisfy every user. We then explore customized hybrid system configuration based on each individual user's personality to deliver the optimal satisfaction for him/her. The experimental results show that our personality-aware hybrid FC-battery solution can achieve 4× longer operation time and 25% higher satisfaction score compared to the common setting for state-of-the-art mobile devices.

CCS Concepts: • **Hardware** → **Batteries; Fuel-based energy**; • **Human-centered computing** → **User models**;

Additional Key Words and Phrases: Mobile devices, fuel cell, battery, customize

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1 INTRODUCTION

Today's mobile device technology are evolving rapidly, and more cutting edge technologies (e.g., the augmented reality, voice control, hologram) are being introduced to the devices, which inevitably increases the power demands for the battery. Moreover, the mobile device producers are pushing toward lighter and thinner devices to improve usability, which makes the battery design even more challenging, since it needs to provide a large amount of energy under very strict constraints. Unfortunately, the state-of-the-art battery for mobile devices, i.e., the Li-ion batteries, could not keep up the pace, and battery life is usually sacrificed to meet those increasing power demands and design constraints. As a result, the battery life becomes one of the top complaints about modern mobile devices. An ideal energy supply system should be able to provide the long-term energy storage for the mobile devices and meanwhile still meet the high power demands.

Besides Li-ion batteries, there have been various alternative energy supply technologies. Among them, super capacitors (SCs) and fuel cells (FCs) are generally considered as good candidates for energy storage in computer systems. Figure 1 compares the specific energy (in Wh/kg) and specific power (in watts per kilogram) of SCs, Li-ion batteries, and FCs. *Specific energy* denotes the amount of energy provided by a unit of weight, and *specific power* denotes the maximal power supported by a unit of weight. As shown, SCs have the highest specific power (two order-of-magnitude higher than the Li-ion batteries) but very low specific energy (one to two order-of-magnitude lower than the Li-ion batteries). Due to their extremely low specific energy, SCs can only provide short-term energy storage. Meanwhile, their high specific power is far beyond the power demands of mobile devices. Thus, SCs are not suitable for mobile devices. Instead, they are promising to be used in cases where burst-mode power delivery is needed, e.g., data centers [33]. FCs have one- to two-orders-of-magnitude-higher specific energy than the Li-ion batteries, but their specific power is slightly lower. Because of the obvious advantage of high specific energy (i.e., the long-term energy storage), FCs have been viewed as one of the most promising candidate for mobile devices. However, FCs also suffer some major disadvantages, i.e., low specific power and slow dynamic responses, which must be taken into consideration when using them as the energy source for mobile devices.

It is well known that mobile device are not active and running applications all the time; their power demands remain low during the idle state and will experience a rapid increase when there is a user action. Leveraging this unique characteristic, in this work, we propose the hybrid FC and battery design to power the emerging mobile platforms. FCs will provide the basic power and batteries are used to compensate the slow dynamic response of FCs and satisfy high power demand. FC and battery hybrid system has been widely studied before for portable device, electric cars, unmanned aerial vehicles, and so on [16, 31, 39]. However, how to design the optimal hybrid energy solution for each individual mobile user based on his/her usage still needs to be investigated.

We then investigate the real-world smartphone usage data and observe the highly diversified user power demands due to distinct user behaviors. A naive hybrid power system design with either huge FCs or large battery fails to meet many users' power requirements. We then explore an OS-level power management policy that reduces the device's peak power consumption by $\alpha\%$

Fig. 1. The specific energy and specific power of super capacitor (SCs), Li-ion batteries, and fuel cell (FCs).

to solve those mismatches between the power supply in the hybrid system and the power demands. With a large throttling level, high power demand is reduced and small battery size in the hybrid system suffices. Therefore, there is a one-to-one mapping between peak throttling level and FC/battery ratio. We define the pair of $\langle \alpha\%, \eta\% \rangle$ as the **configuration** of our hybrid system, where $\alpha\%$ specifies the peak throttling level and $\eta\%$ indicates the portion of battery in the hybrid system. Obviously, a high peak throttling level $\alpha\%$ will cause more quality-of-service (QoS) degradation. However, since $\eta\%$ can also be decreased accordingly, and, thus, there is more room for FC and the operation time are extended. As a key observation in this study, we find that *the user's personality largely determines his/her perception on the QoS degradation and the long operation time brought by our novel power system*. For example, people exhibiting strong trait on neuroticism can tolerate the high QoS loss caused by an aggressive peak throttling technique, as they have relatively light device usage thus enjoy its benefit on the long device operation time. To the contrary, the conscientious people prefer the high QoS, since they are highly organized and usually have regular charging behavior, and, thus, the long operation time is less attractive to them. As can be seen, adopting a hybrid system with fixed configuration for all users fails to consider their personality and thus cannot deliver the optimal user experience.

In this study, we explore a customized hybrid FC and battery system configuration for each individual user according to his/her personality, therefore achieving optimal user satisfaction. We conduct a comprehensive survey on 60 users and build a linear regression model to find out the optimal peak throttling level given a user's personality. Evaluated with the real-world mobile user data, we find that our customized hybrid FC and battery power system based on each individual user's personality is able to achieve 4× longer operation time and the overall satisfaction score is improved by 25% comparing with the baseline case of using the LCO battery to power the device on average across all investigated users.

To summarize, this article makes the following contributions:

- We propose and implement a hybrid fuel cell and battery power system for emerging mobile devices.
- We propose an OS-level power management policy that reduces the peak power consumption to solve the mismatch between the power supply in our hybrid power system and mobile users' power demands.
- We further explore customized hybrid FC and battery system configuration for each individual user according to his/her personality, which achieves the optimal user satisfaction per user.

Fig. 2. The characteristics of DMFC.

2 BACKGROUND

2.1 Fuel Cells

A fuel cell is a device that can convert the chemical energy in the fuel to electricity. It has been recognized as one of the most promising energy sources in the 21st century and is widely used in many fields, including power stations, vehicles, un-interruptible power supplies (UPS), and so on, due to its high specific energy [12, 13, 59]. There are various types of fuel cells, such as the direct methanol fuel cell (DMFC), the hydrogen-based polymer electrolyte membrane fuel cell (PEMFC), and so on. DMFC is considered more suitable for mobile devices, as it not only can operate at room temperature but also uses methanol as the fuel, which is easy to store and transport without additional fuel reforming process like hydrogen-based PEMFC [25]. The DMFC has very high specific energy, up to ~ 5000 Wh/kg, compared with ~ 150 Wh/kg for the common Li-ion batteries used in modern mobile devices [5, 10, 62]. It contains two electrodes, i.e., anode and cathode, which are separated by the electrolyte, as shown in Figure 2(a). The following chemical reactions occur at the anode and cathode of DMFC, respectively:

Fuel cells have some special characteristics, which must be taken into consideration when using them as the energy source for mobile devices. To analyze and illustrate these characteristics, we simulate a passive air-breathing DMFC using the analytical model developed in Reference [42]. Fuel cells can stack multiple layers of flow beds. Common designs of flow beds include serpentine, parallel, interdigitated, and pin [27, 30, 32]. For micro DMFC, the single-serpentine flow bed design is considered to be the most favorable [53]. To make the size of DMFC comparable to the smartphone battery, we consider such design with total active area of 16 cm^2 . Under room temperature, its efficiency is $\sim 20\%$, and, thus, its effective specific energy is ~ 1000 Wh/kg, which is **6X** that of common Li-ion batteries. For FCs, there exists a Maximum Power Point (MPP). With current density smaller than the MPP, the output power grows when the current becomes larger. If the current density is beyond the MPP, then the output power will drop sharply. Maximum Power Point Tracking (MPPT) is usually adopted to pull the most power out of FCs [18, 26]. The dynamic performance of our DMFC is shown in Figure 2(b). It illustrates the simulated voltage curve with current load-up and load-down (the baseline for per unit output power is 1W). FCs are sluggish in responding to load changes. It fails to provide enough power in the next few seconds after sharp

load-up, while still generates excessive power after load-down. The voltage needs around 5 s to keep up and stabilize, which is clearly too slow for CPUs. The reason for this phenomenon is that many dynamic processes, e.g., gas diffusion effects, liquid water transportation and flooding, and so on, take place during the load-up and load-down, and these processes take seconds to finish [57]. Besides the slow dynamic response, FCs usually fail to provide enough power for mobile devices. Our DMFC has around 1 W of maximal output power; however, the power traces of real smartphone users suggest that the power consumption of mobile devices can be up to ~ 4 W [48].

2.2 Batteries

Batteries, as the most commonly used energy supply for today's mobile devices, are devices that can convert the stored chemical energy into electricity and vice versa. The former process is called battery discharging and the latter is charging. The current level during charging (discharging) is usually called the C-rate. For example, a 5C charging (discharging) rate will replenish (deplete) the battery in 1/5 hour. The endurance of battery can be measured by the battery lifecycle, i.e., the number of complete charge/discharge cycles that a battery can use. Lithium-ion batteries are widely used for portable devices because of their relatively high specific energy (Li is the lightest metal) and great stability, comparing with other types of batteries, e.g., lead acid. Even lithium-ion batteries have different types, e.g., lithium cobalt oxide (LiCoO_2 or LCO), lithium titanate ($\text{Li}_4\text{Ti}_5\text{O}_{12}$ or LTO), and so on. The LCO battery is the most popular choice for smartphones because of its low cost. It has high specific energy (~ 150 Wh/kg) but low discharging rate (1C) and low lifecycle (~ 750) [5, 44]. Today's smartphones can equip around 3500 mAh LCO battery [15]. Still, it can only last for around one day under normal usage. The LTO battery has low specific energy (~ 75 Wh/kg) but high discharging rate (30C), long lifecycle (~ 5000), and also around 98% re-charge efficiency [3, 44]. The LTO battery is seldom used for smartphones due to its low specific energy; however, it becomes more useful when high charging rate and long endurance are needed.

2.3 The Diversified Power Demands of Mobile Users

To design an energy source for mobile devices, real-world smartphone usage must be examined. It has been found that different mobile users have highly diversified application usage [17]. C. Shepard et al. [48] presented LiveLab traces, which recorded iPhone usage data of 24 Rice University students from February 2010 to February 2011 and 10 Houston Community College students from September 2010 to February 2011, including the application usage, power, charging, WiFi connection, Web surfing history, and so on. We investigate the power traces of the 15 most popular applications for all users in the LiveLab data and find diversified power demands of these applications, e.g., the camera consumes ~ 1.8 W while the weather application only consumes ~ 0.8 W on average across all users. Even for the same application, its power varies substantially for different users. For example, the power for Pandora ranges from 0.4 to 1.8 W.

Figure 3 further presents the distribution of device power for each user in the LiveLab data. As shown, the percentage that device power exceeds 2 W is low ($< 10\%$) for all users, although modern smartphone's peak power can achieve ~ 4 W. This suggests that the high output power capability of batteries is not always needed. Then, we focus on the distribution of the power in the range $[0\text{W}, 2\text{W}]$ and it is obvious that users have totally different power profiles, as shown in the figure. Some users (e.g., B00, D07) have quite light usage with their smartphones running at super low power mode (< 0.2 W) almost half of the operation time, and their smartphones remain idle for up to 70% of the time (when the smartphone is idle, its power is generally around 0.5 W or less). To the contrary, some users (e.g., A09, D05) heavily use their smartphones, and the idle time only accounts for 25% of the total operation time.

Fig. 3. The distribution of device power for all users in the LiveLab trace. On the x -axis, the users are ranked as A00-A12, B00-B11, and D00-D09 from left to right (different colors are for easy reading and have no specific meaning).

3 DESIGN OF HYBRID FUEL CELL AND BATTERY POWER SYSTEM FOR MOBILE DEVICES

In this section, we first introduce the architecture of hybrid FC and battery power system. To enable such a hybrid system for mobile devices, we also design an OS-level power management policy. Then, we further quantitatively study the relationship between the configurations of the hybrid system and the power management policy.

3.1 The Architecture of the Hybrid Power System

Although FCs have remarkably high specific energy, their slow dynamic response and low specific power make them unsuitable to be the sole energy source for mobile devices. However, Li-ion batteries, especially LTO batteries, can support high C-rate (i.e., high specific power) and long endurance, which can offset the disadvantages of FCs. Thus, we explore a hybrid FC and battery power system for the mobile devices, which leverages the advantages and combats the disadvantages of these two power supplies to substantially extend the device operation time, hence, greatly improving the user experience.

The architecture of our hybrid FC and battery power system is shown in Figure 4. In this hybrid system, the LTO battery, whose specific energy is roughly 1/2 of the LCO battery, will collaborate with our passive air-breathing DMFC as discussed in Section 2.1, which has 1 W of maximum power and $6\times$ specific energy comparing with LCO batteries. Without explicitly mentioning, batteries in the following sections means the LTO batteries. The output voltage of a single DMFC cell is only around 0.4–0.8V, and converting such low voltage to the required voltage of mobile devices can yield high loss [44, 62]. Thus, four DMFC cells are stacked in sequence, which can provide 0.8 to 2.4 V and improves the converting efficiency. Battery charging is controlled by switch Q_1 , and the top converter is used to convert the FC stack output voltage to battery charging voltage. Switches Q_3 and Q_2 , together with the other two converters, are responsible for enabling FC stack and battery output and transforming their voltages to the required load voltage, respectively.

The core of our hybrid system is the Energy Management System (EMS). It takes the device power P_{load} and battery State-of-Charge (SoC) as inputs. Based on the power management strategies, EMS generates the reference currents. Then proportional-integral (PI) controllers and Pulse

Fig. 4. The overview of the hybrid FC and battery power system.

Width Modulations (PWMs) are used to determine the duty cycle of converters. The detailed states and corresponding management strategies are as follows.

State 1: Load power P_{load} is higher than the maximal power of FC stack P_{FC_Max} and SoC of battery is higher than the lowest operating threshold, i.e., battery is not empty. In this case, the battery will be responsible for compensating the slow dynamic response of FC and satisfying high power demand. Q_1 is off, while Q_2 and Q_3 is on. EMS adjusts the water to methanol molar ratio r to a value R_{Max} , such that FC outputs the maximal power. It also sets the reference current I_{ref_load} , which corresponds to the MPP.

State 2: Load power P_{load} is lower than the maximal power of FC P_{FC_MAX} , and the battery is not full. In this case, the FC will provide the load power and charge the battery in the meantime. Q_1 and Q_3 is on, while Q_2 is off. EMS sets $r = R_{Max}$. It also sets I_{ref_load} , which corresponds to the P_{load} , and I_{ref_charge} , which corresponds to the $P_{FC_Max} - P_{load}$.

State 3: The power of load P_{load} is lower than the maximal power of FC P_{FC_MAX} and the battery is full. In this case, the battery will provide the load power. Q_1 and Q_3 are both off, while Q_2 is on. The SoC of battery need to be reduced to certain threshold, such that the battery can take the excessive power of FC during load-down.

State 4: The battery is empty. In this case, the FC will provide the load power and charge the battery in the meantime. Q_1 and Q_3 are on, while Q_2 is off, $r = R_{Max}$, and EMS also sets I_{ref_load} , which corresponds to the P_{load} . The device is forced to operated at idle state and the change of state is prohibited.

3.2 OS-Level Power Throttling Policy

The hybrid system can ensure normal functioning of the device except in state four when the battery is empty. For users with heavy power demand, a hybrid system with insufficient battery size will frequently enter state four, which causes great dissatisfaction. To solve such a mismatch, we further introduce an OS-level power throttling policy that can effectively throttle the peak power $P > P_{FC_Max}$ by a level of $\alpha\%$, as shown in Figure 5. Notes that when $P \leq P_{FC_Max}$, it will not be throttled.

First, we need to estimate the peak power of mobile devices, which is the total power consumption of the major components, including CPU, GPU, screen, WiFi/cellular, camera, bluetooth, and GPS [6, 36, 58]. The CPU, GPU, screen, and WiFi/cellular are the most frequently used, while others, e.g., GPS (even when using application like Google Map, the GPS is connected intermittently rather than continuously), are infrequently used. CPU power P_{cpu} consists of uncore and core

Fig. 5. The illustration of different peak throttling levels.

power consumptions, so we have $P_{cpu} = P_{uncore} + P_{core}$ [7]. The core power P_{core} can be further expressed as the total power of all active cores and idle cores, thus, $P_{core} = \sum P_i$ [20]. For idle cores, their power can be approximated by constants depending on their state [63]. For active cores, their power consumption can be estimated by $P_{dynamic} + P_{static}$, and the dynamic power can be further estimated by $P_{dynamic} = \alpha * CV^2f$, where α is a constant, C is the capacitance, V is the voltage, and f is the frequency [28, 41]. The voltage scales linearly with the frequency under different granularity, i.e., $V_i = \theta_1 * f + \theta_2$ [23, 29]. If per-core voltage scaling is supported, then f is the core frequency. If per-cluster voltage scaling is adopted, then f is the maximal frequency in the cluster. Similarly, the GPU power model can follow the same methodology as multi-core CPU, except state-of-the-art GPUs only support per-chip voltage and frequency scaling [35, 52]. The screen power can be modeled by the multiplication of a quadratic function of the brightness and a linear combination of the average red, green, and blue color intensities of all pixels [58]. The WiFi/cellular power is simply a linear function to the transmission rate D [58]. The powers of CPU, GPU, screen, and WiFi/cellular can be controlled by setting proper frequency (for CPU and GPU), brightness (for screen), and maximal connection speed (for WiFi/cellular) in the OS. For the infrequent used ones, their powers can be simply modeled by some constant values if they are on [36, 58].

With peak throttling level $\alpha\%$, the power of each major running components in the device is capped by $1 - \alpha\%$. The power of screen and WiFi module can be reduced by adjusting the brightness L and the transmission rate D , respectively. The power of GPU can be reduced by adjusting the chip frequency and voltage together. For CPU with per-core frequency and voltage scaling capability, to achieve the overall power cap, the frequency and voltage of each active core will be reduced by a percentage calculated by $\alpha * P_{cpu}/P_{active}$, unless the lowest possible frequency is reached for some cores. If it happens, then the frequency and voltage of the core with the highest frequency will be further reduced until overall power cap is met.

3.3 Bridging the Ratio of FC/Battery and Peak Throttling Level

We first denote $\eta\%$ as the percentage of size allocated for the battery in the hybrid system. Then, the percentage for FC will be $1 - \eta\%$. If equipped on mobile devices, then a hybrid system with certain FC/battery ratio should be coupled with corresponding $\alpha\%$ peak throttling level power management policy to avoid frequently enter state four. In this section, we quantitatively study their relationship to enable the hybrid system for mobile devices. Clearly, with a large throttling level, high power demand is reduced and small battery size in the hybrid system suffices. Therefore, there is a one-to-one mapping between them, and we define the pair of $\langle \alpha\%, \eta\% \rangle$ as the **configuration** of our hybrid system, where $\alpha\%$ specifies the peak throttling level and $\eta\%$ indicates the portion of battery in the hybrid system.

Fig. 6. The percentage of the users whose power requirements are served given battery capacities under different peak throttling levels.

Fig. 7. FC/Battery ratio with different peak throttling levels. Different curves correspond to different coverages.

As discussed in Section 2.3, mobile users have highly diversified power demands. The percentage of users whose power requirements can be satisfied (i.e., the hybrid system never enters state 4) given different battery capacities under 10%, 20%, 30%, and 40% peak throttling levels is plotted in Figure 6. The battery is simulated by a classic model Dualfoil, which models the diffusion processes inside the battery and achieves very high accuracy [55]. The LTO battery's specific energy is roughly 1/2 of the LCO battery, and thus the maximum LTO battery capacity is 1750 mAh. However, with 0% or even 10% peak throttling, it is impossible to satisfy all the users even with a 1980-mAh LTO battery. With 20%, 30%, and 40% peak throttling, 1350-, 490-, and 270-mAh batteries are needed, respectively. If the criteria of satisfying 100% of the users, i.e., 100% coverage, is relaxed to 90%, then 0% is still impossible. We can get the required battery size as 1440, 650, 230, and 80 mAh when applying the 10%, 20%, 30%, and 40% peak throttling, respectively.

Figure 7 further displays the data pairs of FC/battery ratio and its corresponding peak throttling level and fitted curves to maintain 100%, 90%, and 80% coverages. The first curve is for 100% user coverage, and it can be observed that at least an 18% peak throttling technique has to be adopted. To cover 90% of users (the second curve), at least 8% peak throttling is needed. If further relaxing to cover 80% (the third curve) of users, then 0% peak throttling can be allowed. Given a coverage, FC/battery ratio generally follows exponential relationship with peak throttling level. Thus, we

introduce the following exponential model:

$$\eta = d_1 * e^{(1-c*\alpha)} + d_2, \quad (1)$$

where c , d_1 , and d_2 are parameters. The curve also becomes steeper with higher user coverage, e.g., the curve for 90% user coverage is steeper than the one for 80% user coverage. Overall, given a coverage level (e.g., 90%), there is a set of available configurations, for example, $\langle 10\%, 82\% \rangle$, $\langle 20\%, 37\% \rangle$, $\langle 30\%, 13\% \rangle$, $\langle 40\%, 5\% \rangle$.

4 CUSTOMIZING THE HYBRID SYSTEM FOR INDIVIDUAL MOBILE USERS

Since mobile users have highly diversified demands, a hybrid system with fixed configuration can hardly satisfy everyone. In this section, we build a user satisfaction model, and identify that user satisfaction is strongly affected by the personality. Finally, we explore the customized configuration of a hybrid FC/battery system for individual users based on his/her personality to deliver optimal user satisfaction.

4.1 The Tradeoff between QoS and Operation Time

We define the quadruple of CPU frequency, GPU frequency, screen brightness, and Internet connection speed as the **Quality-of-Service (QoS)**. Without explicit mentioning, the QoS degradation or operation time extension are compared against the baseline case, i.e., no peak throttling plus LCO battery. Considering a hybrid system with configuration $\langle \alpha\%, \eta\% \rangle$, the battery percentage in the hybrid system $\eta\%$ can translate to operation time extension t by the following formula:

$$t = f_1 * (1 - \eta) + f_2 * \eta, \quad (2)$$

where f_1 and f_2 are the ratios of specific energy of FC and LTO battery to the baseline LCO battery, respectively. In our hybrid system, we have $f_1 = 6$ and $f_2 = 0.5$. Meanwhile, a peak throttling level of $\alpha\%$ causes a QoS degradation of $\alpha\%$. With Equation (2), we can quantitatively evaluate the tradeoff between QoS and operation time.

Obviously, adopting a fixed configuration can hardly satisfy every user. Some users may be satisfied with trading more QoS for a longer operation time, while some may be quite sensitive to the QoS degradation and even willing to tolerate the short operation time. In the next section, we build user satisfaction model and identify the best configuration for individual users.

4.2 Modeling User Satisfaction

To evaluate users' satisfaction and find the best configuration for them, we conduct a survey on 60 users with half male and half female. Their average age is 25.5 years old, with the youngest 17 years old and the oldest 49 years old. These users are invited to test four peak throttling levels, 10%, 20%, 30%, and 40%, with the 10 most popular applications as mentioned before, including Gmail, Google Map, Youtube, Facebook, Google, Google+, Google Text-to-speech, WhatsApp, Google Play Books, and Messenger, on a Samsung Galaxy S9 smartphone [4]. Here we set the peak throttling granularity as 10%, which is good enough for our modeling purpose. Each participant's satisfaction score with the QoS, ranging from 1 (lowest satisfaction) to 10 (highest satisfaction), is recorded for each peak throttling level. To eliminate the impact of prior experiences with the participants' own devices and make a fair comparison, the satisfaction level for 0% peak throttling is always set to the highest score 10. In other words, the satisfaction score is a relative value based on the common baseline with no peak throttling. Meantime, using Equation (2), the device operation time extensions correspond to these four configurations are 1.6 $\times$, 4 $\times$, 5.3 $\times$, and 5.7 $\times$, respectively. Users are instructed with these device operation time extensions and their satisfaction scores are recorded as well. Again, to make a fair comparison, the satisfaction level for 1 $\times$, i.e., no operation

time extension, is always set to 1. Now, for each participant, he/she has two sets of satisfaction scores, with one set for QoS and another for operation time extension. The overall satisfaction score per configuration for certain participant can be acquired by simply adding his/her two scores together, and the optimal configuration for him/her is the one with the highest overall satisfaction score. Normal distribution is widely adopted to model survey scores [22]. Empirically, we find each participant's scores can well fit the normal distribution with respect to the peak throttling level $\alpha\%$. Thus, the total satisfaction score S_{total} for a group of n users can be modeled as the summation of each user's satisfaction score S_i , i.e.,

$$S_{total} = \sum_{i=1}^n S_i, \quad \text{where } S_i = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(\alpha_i - \alpha'_i)^2}{2\sigma^2}}. \quad (3)$$

In this formula, α_i and α'_i are the real and optimal peak throttling levels, respectively. Clearly, to optimize s , we simply need to set $\alpha_i = \alpha'_i$ for each i . Then, the next question becomes how to find the optimal peak throttling level for each user. **As our key observation, we find that the mobile user's personality has great impact on his or her preference with QoS and operation time.** Leveraging this observation, we can customize the optimal hybrid FC and battery system for each individual user.

4.3 Predicting Optimal Peak Throttling

Personality refers to *individuals' characteristic patterns of thought, emotion, and behavior, together with the psychological mechanisms—hidden or not—behind those patterns* [19]. To describe someone's personality, Big-Five traits are widely used, which include Extroversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N), and Openness to Experience (O) [34]. Extrovert people are usually recognized as active, assertive, energetic, enthusiastic, outgoing, talkative, and so on. Agreeable people are often viewed as more appreciative, forgiving, generous, kind, and sympathetic. Conscientious people tend to be organized and have a strong sense of duty. They are normally described as efficient, organized, planful, reliable, responsible, and thorough. Neurotic people are typically anxious, self-pitying, tense, touchy, unstable, and full of worry. People who are open to experiences are commonly artistic, curious, imaginative, insightful, and original and have wide interests.

In the past, many tests have been proposed to evaluate the Big-Five personality traits. For example, the Coopersmith Self-Esteem Inventory (SEI) [9] contains 25 items and the NEO-Personality-Inventory (NEO-FFI) [11] includes 60 items. Recently, a brief Ten Item Personality Inventory (TIPI) has been proposed by Gosling et al. [47], which significantly reduces the effort required to complete the personality test. The 10 items in the TIPI are as follows: (1) I am reserved, (2) I am generally trusting, (3) I tend to be lazy, (4) I am relaxed, handle stress well, (5) I have few artistic interests, (6) I am outgoing, sociable, (7) I tend to find fault with others, (8) I do a thorough job, (9) I get nervous easily, and (10) I have an active imagination. Each of these 10 items will be answered by the participants with a scale from 1 (strongly disagree) to 7 (strongly agree). With all the scales for the 10 items, the personality scores could be calculated based on the model described in Reference [47]. For each of the five personality traits, its score also ranges from 1 to 7.

We also let the test users, as mentioned in Section 4.2, take TIPI questionnaires, and their personality scores (i.e., the scores of the Big-Five traits) are calculated by the model from Reference [47]. The mean personality scores of the survey participants are E:3.8, A:4.4, C:5, N:4.5, O:4.6 with the standard variation of E:1.7, A:1.6, C:1.4, N:1.5, O:1.1. After analyzing the personality and users' optimal peak throttling levels, we observe a strong correlation. We identify that the conscientiousness score is negatively related with the peak throttling level, which means conscientious people prefer high QoS over long operation time. The reason is that this type of user is highly

Fig. 8. The prediction accuracy for all participants in the testing set.

organized and usually has a regular charging behavior, and, thus, the long operation time is less attractive to them. The Neuroticism score is positively related with the peak throttling level, because it has been found that neurotic people generally use smartphones less often, and, thus, they prefer long operation time rather than high QoS. For people with high Openness-to-Experience and Extroversion scores, they tend to choose peak throttling level between 20% to 30%, because both QoS and the operation time matter to them.

Finally, we build a linear regression model to predict users' optimal peak throttling level based on their personality. We denote the personality scores for all survey participants as P . The optimal peak throttling levels of all participants are denoted as $\hat{\alpha}'$. We randomly split the data with 80% for training set and 20% for testing set. The parameter β can be acquired by minimizing the means square error as follows:

$$\min_{\beta} \|\hat{\alpha}' - P * \beta\|^2. \quad (4)$$

With new data p (i.e., personality score), his/her optimal peak throttling level can be predicted by $p * \beta$. The prediction accuracy for all participants in the testing set is shown in Figure 8, and the average accuracy is >89%.

5 EVALUATION

5.1 Experiment Setup

We build a prototype to evaluate the hybrid FC and battery system. For the FC subsystem, we use the Horizon hydrogen FC charger to simulate the DMFC, since the commercial DMFC is not available for the smartphone yet and the methanol and hydrogen based FCs have similar characteristics [46]. The Horizon FC charger uses USB output, which is 5 V by its standard, and, thus, the design of the prototype is slightly different from Figure 4. We use a Texas Instrument (TI) TPS22944 0.2-A current limit load switch (its input voltage ranges from 1.62 V to 5.5 V), which can limit the FC output power to 1 W. Since the device we use requires a 5-V input, the output voltage of the FC does not need to be further regulated. We use the TI TPS63024 buck/boost converter, which can convert the 5-V output of the FC to 2.9 V (the charging voltage of the LTO battery), as the DC-DC converter for the battery charging. For the battery, we use a 1,500-mAh LTO battery managed by the TI BQ27532EVM battery charging solution evaluation module, which can charge the battery and also provide the battery status, including remaining capacity, and so on, to the EMS via the TI EV2300 interface board. The output power of the battery is only 2.4 V, which is converted to 5 V by the TI TPS61230EVM boost converter. The converters can be controlled by enabling signals, and, thus, there is no need for extra switches. The voltage and current sensors are LTC2990. We implement the EMS based on the micro-controller TI MSP-EXP430.

We use the Odroid XU3 ARM development board as the device whose configuration is on par with the state-of-the-art smartphones. The CPU of the board is the Exynos5422 SoC, which

Fig. 9. The personality scores (i.e., the score for each personality trait) for all test users.

contains one out-of-order quad-core Cortex-A15 cluster and one in-order quad-core Cortex-A7 cluster (ARM BIG.little architecture). The GPU is Mali-T628 GPU, and the main memory is 2G LPDDR3 RAM. It contains built-in power monitors for CPU, GPU, and memory. The Odroid XU3 board is cooled by a fan, which is powered separately in our platform, since they are usually not available for smartphones. Also, we connect the ARM board with a 5-in. multi-touch screen and a WiFi module; their power are measured by REGOL DM3058 multi-meter separately.

We compare five fixed configurations, including baseline (no peak throttling plus a 3,500-mAh LCO battery), C1 (<10%, 82%>, i.e., 10% throttling plus 82% LTO battery), C2 (<20%, 37%>), C3 (<30%, 13%>), and C4 (<40%, 5%>), with a personality-aware configuration, which selects the optimal one of these five for each individual user based on his/her personality.

To evaluate our proposed technique, we recruited another 34 test users, who are different from the previous survey participants. We recorded their smartphone usage, i.e., when and which application they are using, for 3 weeks. We did not record the actions, e.g., touch, swipe, and so on, since replaying these actions in a different platform is impractical due to system configuration and software version variation. Instead, we create a base benchmark for each application, e.g., Facebook, in our experiment platform. We first run each base benchmark for a sufficiently long time with the default interactive governor on the ARM board. Meanwhile, we use the HiroMacro auto-touch to record the actions, e.g., touch, swipe, and so on, of a specific test user using our experiment platform. We also use the Linux perf tool to record the progress of execution by periodically dumping the instruction count. Then, we can link the user actions to the instruction count rather than time, since the time can change with different frequencies. The base benchmark is used to replace an execution trace of corresponding application. For example, as user “U1” uses Facebook for 10,000 instructions (under default interactive governor), we can simply cut 10,000 instructions from our base benchmark and use it for “U1.” In this way, we can re-generate the execution traces for all the users.

5.2 Personality Scores and Optimal Peak Throttling Levels

The personality scores for all the test users are shown in Figure 9.¹ As shown, these users have different scores on the five traits. For instance, “U07” exhibits quite strong tendency toward the extroversion trait, while “U26” leans more toward the conscientiousness trait. The predicted optimal throttling

¹Our test users have agreed on the disclosure of their personality and preference data.

Table 1. The Predicted Optimal Peak Throttling Levels for All the Test Users

UID	Opt	UID	Opt	UID	Opt	UID	Opt
U01	20%	U10	10%	U19	0%	U28	20%
U02	10%	U11	20%	U20	10%	U29	10%
U03	20%	U12	20%	U21	20%	U30	40%
U04	40%	U13	30%	U22	40%	U31	30%
U05	20%	U14	30%	U23	30%	U32	30%
U06	20%	U15	30%	U24	40%	U33	40%
U07	30%	U16	20%	U25	30%	U34	30%
U08	40%	U17	10%	U26	0%		
U09	20%	U18	30%	U27	20%

Fig. 10. The operation time in days for all the test users with different configurations.

levels for test users are shown in Table 1. As shown in the table, some users may prefer high QoS (i.e., 0% peak throttling), while others desire longer operation time (i.e., 40% peak throttling). Obviously, any fixed configuration can only fully satisfy a small group of users, and partially satisfy or even completely dissatisfy others. While setting the optimal peak throttling level for each individual user can always fully satisfy all the users, and, thus, is better than any fixed configurations.

5.3 Results

In this study, we evaluate three most important metrics for the hybrid system: the operation time, the battery lifecycle, and the user satisfaction score.

The operation time for each test user is shown in Figure 10, and the average results are shown in Figure 13(a). Since the optimal peak throttling level per user is already listed in Table 1, the operation time under a personality-aware optimal configuration is equal to one of the throttling levels from 0% to 40%. Therefore, Figure 10 does not show its operation time to avoid the redundant result presentation. For the baseline LCO battery, the averaged operation time is slightly less than 1 day, and it can be extended to 1.3 days with 10% peak throttling. With 20%, 30%, and 40% peak throttling, as the percentage of the FCs gets larger, the averaged operation time is further improved to 3.9, 5.6, and 6.5 days. The personality-aware peak throttling can power the device for 4.3 days on average across all users. For some users with light usage, e.g., “U21” and “U27,” the baseline LCO battery can last for 1.24 and 1.39 days, respectively. With 40% peak throttling, their operation time can be even extended to 8.86 and 9.25 days, respectively. For some users with heavy usage, e.g., “U02” and “U03,” the baseline case can only last for around 0.6 days, and the hybrid system with 40% peak throttling can last more than 4 days.

The battery lifecycle is also an important metric, because battery aging is a significant problem, and it needs to be frequently charge/discharged in our hybrid system. The battery lifecycle for each user is shown in Figure 11, and the average is shown in Figure 13(b). Similarly, Figure 11

Fig. 11. The battery lifecycle in years for all the test users with different configurations.

Fig. 12. The normalized user satisfaction score for all test users with different configurations (normalized to the highest score).

does not present the battery lifecycle under the personality-aware optimal configuration to avoid showing the redundant result. Excitingly, the LTO battery in the hybrid system can endure much longer than the LCO battery. Even with 40% peak throttling that uses the smallest LTO battery requiring quite frequent charging/discharging, the LTO battery can still last for around 8.4 years compared with only 1.8 years of the LCO battery. With 10% peak throttling, the LTO battery can last for more than 20 years on average. For some user, like “U27,” the LTO battery can last for 50 years. Since the FC does not have the same significant aging problem as the battery, the hybrid system is expected to last much longer than the LCO battery [46].

The satisfaction score normalized to the highest one for each user is shown in Figure 12, and the average is shown in Figure 13(c). Again, the score under the personality-aware technique is not shown in Figure 12 to avoid the redundant result presentation. The baseline case has the lowest score 0.75. The optimal has the highest satisfaction score of 1, and the second optimal is the 20% peak throttling with a satisfaction score of ~ 0.85 .

Overall, our personality aware optimal configuration can achieve $4\times$ longer operation time, $6\times$ longer battery lifecycle, and 25% higher user satisfaction score compared with the baseline LCO battery. C2 ($<20\%$, 37%) achieves the higher QoS score than other fixed configurations. Our optimal configuration can achieve 11% improvement on operation time extension, 15% higher user satisfaction score comparing with C2. Although the battery lifecycle of optimal configuration is 20% lower than C2, 12.5 years of battery lifecycle is more than enough for normal users, and the disadvantage of 3 years’ shorter battery lifecycle is negligible.

Finally, to analyze the cost of the hybrid system, we consider the cost of the fuel (methanol), the cell (e.g., the anode, the cathode), and the LTO battery. The cost of the methanol is negligible, and the cost of cell itself is around \$2 for the size required by smartphones [8]. The cost of the LTO battery is about \$2.5/Ah compared to \$1.5/Ah for the LCO battery. Thus, for the personality-aware optimal configuration, the overall cost is only about half of the LCO battery. Here we only consider the cost of some basic components, which is scaled from the existing products. In real world, the cost is highly related with some other factors, e.g., the maturity of technology, which is beyond the discussion of this article.

Fig. 13. The average (a) operation time, (b) battery lifecycle, and (c) user satisfaction score with different configurations.

6 RELATED WORK

In the past, there were many work using the DMFC for the portable devices [1, 2, 12, 14, 43, 54]. Some prototypes of the passive air-breathing DMFC have been built for mobile devices [1, 14, 54]. C. Chen et al. identified that the passive air-breathing DMFC's low specific power is highly related to the fabrication conditions and further explored proper manufacturing process by adjusting its physical parameters [12, 13]. In addition, a more efficient catalyst has been proposed to boost the performance of the DMFC [43]. K. Lee et al. have designed a fuel cell and battery hybrid system; however, the usage characteristics of mobile devices are not considered [31]. Also, many studies have been conducted to introduce the personality into the mobile computing. S. Walsh et al. investigated the impact of the personality on smartphone usage for Australian youth [56]. The personality also has been found to be highly related with the usage of games and the Internet [24, 45]. However, smartphone usage can be used to infer the users' personality and even stress level [21, 40]. K. Yan et al. have re-defined the QoS definition for mobile devices and explored the optimal management policy based on users' personalities [60].

There have been many studies on the mobile architecture and system. Some studies have been performed to analyze and model the energy consumption of mobile devices [6, 36, 58]. Y. Zhu et al. proposed the event-based scheduling strategy to optimize the energy-efficient QoS. The accelerators (or IP cores) in the mobile devices also attracted a lot of attention recently. A domain-aware coordinated DVFS policies, which can coordinate the DVFS state for each component of the mobile devices, was proposed to achieve high energy efficiency for the frame-based applications [37]. A new IP virtualization framework (VIP) was proposed for mobile devices, which allows many IPs to be chained together and be virtualized as a single one [38]. DORA, a dynamic frequency controller for energy efficient mobile web browsing was introduced [49]. For streaming-based mobile applications, a combination of race-to-sleep, content, and display caching techniques was proposed to improve energy efficiency [61]. Human factors were also considered for architecture design and power management. Some hardware, e.g. eye tracker, force sensor, and so on, have been used to collect human physiological traits, which guide the control of CPU frequency [51]. Further, the link

between micro-architecture level measurement and user satisfaction was explored, which does not rely on external hardware [50]. However, none of these works targets fuel cell and a battery hybrid system for mobile devices or considers user personality.

7 CONCLUSION

In this study, we develop a hybrid FC and battery system as the power supply for the mobile devices to significantly extend the device operation time, while still satisfying users' diversified power demands. The hybrid system uses passive air-breathing DMFC and an LTO battery, which achieves both high specific energy and specific power. We examine real-world smartphone usage data, LiveLab, and find that a naive hybrid power system cannot satisfy many users' high power demands. We then propose an OS-level power management policy, which reduces the device power consumption by $\alpha\%$ for each power peak to solve the mismatch between the power supply and power demands. This technique trades the QoS for a large FC size, thus much longer device operation time. Furthermore, we observe that user personality largely affects his/her satisfaction with the QoS loss and the operation time extension. Thus, applying a hybrid system with fixed configuration (i.e., peak throttling level coupled with corresponding FC/battery ratio) is unable to satisfy each user. We then explore customized hybrid FC and battery system configuration for each individual user according to his/her personality, which achieves the optimal user satisfaction per user. The experimental results show that our personality-aware hybrid FC and battery solution can achieve 4 $\times$ longer operation time and 25% higher satisfaction score comparing with the baseline LCO battery.

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