OPTIMIZING THE EFFICIENCY OF PROTOTYPE BATTERY SYSTEM IN INDUSTRIES

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Abstract:

Large-scale battery packs with hundreds/thousands of battery cells square measure unremarkably adopted in several rising cyber-physical systems like electrical vehicles and good small grids. For several applications, the load necessities on the battery systems square measure dynamic and will considerably amendment over time. A way to resolve the discrepancies between the output power provided by the battery system and also the input power needed by the masses is vital to the event of large-scale battery systems. Historically, a voltage regulators square measure typically adopted to convert the voltage outputs to match loads' needed input power. The potency of utilizing such voltage regulators degrades considerably once the distinction between provided and needed voltages becomes giant or the load becomes lightweight. During this paper, we have a tendency to propose to deal with this drawback via associate degree adaptive reconfiguration framework for the battery system. By abstracting the battery system into a graph illustration, we have a tendency to develop 2 adaptive reconfiguration algorithms to spot the required system configurations dynamically in accordance with the period of time load necessities. We have a tendency to extensively value our style with empirical experiments on an image battery system, electrical vehicle driving trace-based emulation and battery discharge trace-based simulations. The analysis results demonstrate that, betting on the system states, our planned adaptive reconfiguration algorithms square measure able to come through 1× to 5× performance improvement with relevancy the system operation time.

Introduction:

Large-scale battery systems with tons of or thousands of batteries square measure currently widely employed in electric vehicles, energy storage in each macro and small good grids. For several of those applications, the load demand on the battery system is dynamic and will considerably amendment over time. For instance, betting on the driving states, the specified voltage output of electrical vehicles could vary from around seventy V to quite 700 V. Such dynamic masses create the matter of optimizing the energy potency of large-scale battery systems even a lot of vital and difficult that is attracting increasing attentions of funding agencies, and analysis efforts. a conventional technique of handling dynamic masses is to adopt voltage regulators to simply accept voltages provided by the battery pack and change them to the specified levels because of the input to the masses. Sadly, the energy potency of voltage regulators could degrade considerably beneath 2 scenarios: (i) the distinction between the provided and needed voltages is giant, and (ii) the load is lightweight and also the system operates in a very low power mode. In distinction, dynamically adjusting the connections among batteries within a battery system supported the period of time load necessities, referred because the adaptive system reconfiguration, is an alternate approach to handle the pair between the availability and also the demand. The adaptive recon-figuration not solely avoids the low potency issue of the standard regulator-based approaches, however conjointly will increase the system lustiness in this failing batteries may be by-passed while not considerably degrading the system performance, abundant analysis has been conducted to style battery systems that provide higher configuration flexibility with fewer supplementary electronic elements like connectors and switches, that has already been enforced in several off-the-peg battery packs. Besides providing configuration flexibility, there nonetheless exists another open challenge in maximizing energy potency that is to optimally verify battery system configurations in accordance with a period of time load necessities. Intended by this, during this paper, we have a tendency to advance the progressive by ad-dressing the subsequent analysis question: with a given if the flexibility of A battery system, a way to adaptively determine the best system configuration supported voltage load necessities. We have a tendency to initial prove that this drawback is NP-Hard generally, and so we have a tendency to effectively solve it supported 2 empirical observations on battery systems. We have a tendency to propose a near-optimal adaptive reconfiguration algorithmic rule supported the classic 0-1 whole number programming drawback for the one load amendment state of affairs. For the state of affairs wherever multiple masses amendment at the same time, we have a tendency to extend our style with a greedy heuristic to spot the required system configurations.

We propose a generic graph illustration of large-scale battery systems, that facilitates the of battery system reconfigurations. For the state of affairs wherever solely one load changes, we have a tendency to remodel the matter of distinguishing the best system configuration to a path choice problem within the corresponding graph. We have a tendency to initial prove that the matter is NP-Hard. We have a tendency to then propose a much possible answer supported 2 empirical observations that is ready to come back a near-optimal system configuration through Depth-First-Search with pruning technique and 0-1 whole number programming formulation. Extending our investigation to the state of affairs of multiple load changes, we have a tendency to propose a greedy answer to spot the required system configuration by covetously choosing the load to be processed and increasingly achieving the required configuration. We have a tendency to extensively value our style with empirical experiments on a image battery system, electrical vehicle driving trace-based emulation, and battery discharge trace-based simulations. The analysis results demonstrate that the planned adaptive reconfiguration algorithms are able to do 1× to 5× improvement within the system operation time.

System Model and Style Principles:

We take into account large-scale battery systems that may support multiple masses at the same time during this work, as shown in Fig. 1. The battery pack within the system has multiple output terminal pairs, and every terminal combine is connected to a special load. For the ith terminal combine, we have a tendency to denote the load's needed voltage and power magnitude relation. The battery pack consists of a complete variety of N batteries, and also the voltage of the ith battery at the choice time is $v_i \in [vc, vf]$, wherever vc and vf square measure the battery cutoff voltage one and full charge voltage, severally. I follow the chance for multiple masses to alter at addressing constant time is comparatively low. The ultimate goal of adaptive system reconfiguration is to maximize energy potency by adopting the best configurations in accordance with period of time load necessities. Energy potency of A battery system is put together determined by several the cutoff voltage usually defines the empty state of the battery. Factors like adopted electronic elements, battery temperature, loads, battery chemical properties, etc. to cover these complicated factors from sensible implementation, and we have a tendency to propose the subsequent rule-of-thumb style principles.

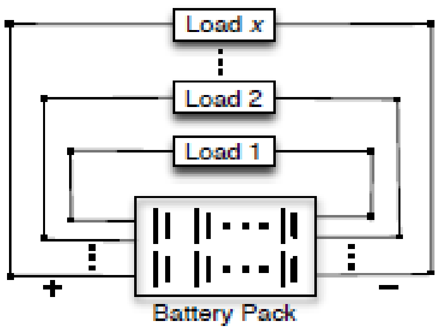


Fig. 1. System model.

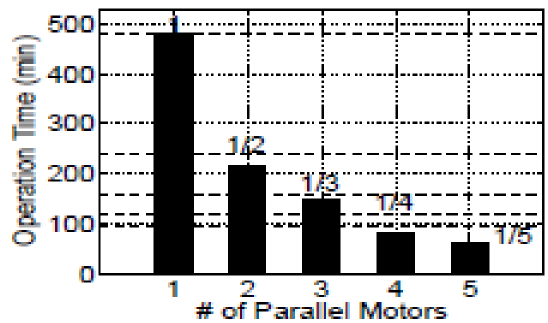


Fig. 2. Reducing discharge current improves energy efficiency.

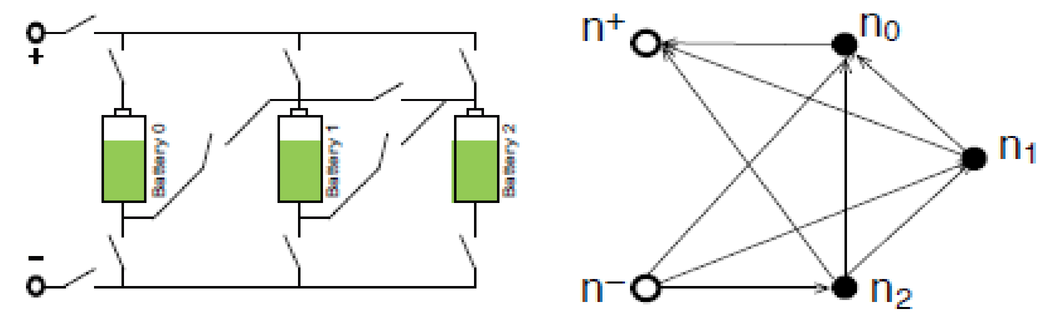
Matching provided and required Voltages: exploitation volt-age regulators to convert the battery pack provided voltages to the load's required levels could also be a typical approach in follow. However, the voltage regulators introduce more energy loss once ever-changing voltages, and conjointly the energy loss on regulators can increase as a result of the excellence between the provided and required voltages can increase. This truth is to boot according in. Thus, to optimize the system energy efficiency, it's key to match the provided voltage with the load's required voltage the most quantity as potential.
Minimizing the Discharge Current of Individual Batteries: giant discharge current degrades battery performance in some ways, e.g., increasing the inner energy loss, reducing the deliverable battery capability, inflicting important temperature rise, and introducing further energy overheads because of the next system observation frequency. As a result, the theoretical relationship among the operation time T, the battery capability alphabetic character, and also the discharge current I is indeed T < chi in apply. To understand the impact of discharge current on battery performance, we tend to conduct a group of measurements as follows. we tend to adopt 2 series connected and initio totally charged 2450mAh AA batteries to power many parallel connected motors with an operation voltage of vi V. during this manner, the battery discharge current will increase with a bigger variety of motors. We tend to record the time that the batteries will support the hundreds, i.e., the operation time, with the motor numbers varied from one to five. The measuring results are shown in Fig. 2. It's intuitive that the operation time decreases with heavier hundreds. Moreover, the operation time decreases quicker than the rise of loads: normalizing the operation time with one single motor because the unit time one, the operation time with c parallel motors (and so a c× battery discharge current) is smaller than 1c . This super-linear decreasing speed of the operation time indicates that it's extremely fascinating to attenuate the battery discharge current to optimize the performance. To support a given load demand, the battery pack equipped current is often restricted to an explicit range; but, we are able to cut back the discharge current of individual batteries within the pack by optimizing the system configuration.

Reconfiguration with Singe-Load-Change:

We investigate the accommodative system reconfiguration within the state of affairs with solely one load modification during this section. We tend to 1st abstract the battery system into a weighted directed graph, with that the matter of distinguishing the optimum system configuration is remodeled to seek out as several as attainable disjoint methods orthodox to a given weight demand.

Drawback Formulation: Given the 2 style principles delineated in Section, our drawback in distinguishing the optimum system configuration will be developed as 2min we tend to then show that the matter will be solved during a near-optimal manner by a mixture of a Depth-First-Search (DFS) with pruning and 0-1 number programming. We need to contemplate the voltage imbalance issue once the parallel association of multiple series strings ar adopted, which can cause the reverse charging of batteries if the voltage of those strings deviate an excessive amount of from one another. Matching provided and needed Voltages: exploitation volt-age regulators to convert the battery pack provided voltages to the load's needed levels may be a common approach in follow. However, the voltage regulators introduce further energy loss once changing voltages, and also the energy loss on regulators will increase because the distinction between the provided and needed voltages will increase. This truth is additionally according in. Thus, to optimize the system energy potency, it's key to match the provided voltage with the load's needed voltage the maximum amount as potential. Minimizing the Discharge Current of Individual Batteries: Large discharge current degrades battery performance in many ways, e.g., increasing the internal energy loss, reducing the deliverable battery capacity, causing significant temperature rise, and introducing additional energy overheads due to a higher system monitoring frequency. As a result, the theoretical relationship among the operation time T, the battery capacity Q, and the discharge current I (i.e., $T = \frac{Q}{I}$) is in fact $T < \frac{Q}{I}$ in practice. To understand the impact of discharge current on battery performance, we conduct a set of measurements as follows. We adopt two series connected and initially fully charged 2450mAh AA batteries to power several parallel connected motors with an operation voltage of 6 V. In this way, the battery discharge current increases with a larger number of motors. We record the time that the batteries can support the loads, i.e., the operation time, with the motor numbers varying from 1 to 5. The measurement results are shown in Fig. 2. It is intuitive that the operation time decreases with heavier loads. Furthermore, the operation time decreases faster than the increase of loads: normalizing the operation time with one single motor as the unit time 1, the operation time with c parallel motors (and thus a c× battery discharge current) is smaller than $\frac{1}{c}$. This super-linear decreasing speed of the operation time indicates that it is highly desirable to minimize the battery discharge current to optimize the performance. To support a given load requirement, the battery pack supplied current is normally limited to a certain range; however, we can reduce the discharge current of individual batteries in the pack by optimizing the system configuration.

Graph Representation: We propose an abstracted graph model for the battery system to facilitate in optimizing its performance. Given a battery pack and the battery voltages at the decision time, we construct a corresponding weighted and directed graph. The above constructed graph only incorporates the batteries in the system. To further include the terminal pairs on which the load has changed into the graph representation, we further extend the graph with the following three steps. First, we add two vertices n^+ and n^- to V, representing the two output terminals. Then to capture the connectivity of the two terminals, we add edge $n^+ \rightarrow n_i$ and $n_i \rightarrow n^-$ (i = 1, 2, · · · , N) to E if the output terminals can be directly connected to the ith. The extended graph captures all the potential system con-figurations, and the out-degree of vertices is a direct metric to quantify the configuration flexibility offered by the system. Note that any specific battery pack can be mapped to only one corresponding graph, while one graph may have multiple battery pack implementations. This is because the edges in the graph only reflect the logical connectivity between batteries, but do not specify how to physically achieve such connectivity. Problem Transformation: With the constructed graph, the problem formulation (2) can be transformed to identifying the maximal number of disjoint simple paths connecting n^+ and n^- with weight sum in the range of [V, (1 + σ)V]. Specifically, we say a simple path connecting n^+ and n^- is feasible if the weight sum of involved vertices is within [V, (1+σ)V]. The requirement on the disjoint paths is to avoid involving the same battery in multiple series strings, which increases its discharge current and unbalances the battery utilization. Identifying the Optimal Configuration: We first show that identifying the optimal configuration is NP-hard, and then based on two important observations on battery system, we propose a solution which is feasible in practice and achieves the near-optimal performance.



(a) Circuit design proposed in [26]

(b) Abstracted graph

Fig. 3. An example on the graph representation of battery systems.

a) n = 1 and σ = 0; b) the weights of all vertices are 1; c) V is an integer larger than 1. If a polynomial time algorithm Ψ exists for the special case of Y, we can apply Ψ on the Longest Path Problem with path length increasing from 1 to |V|, until no solution can be returned. In this way, we solve the Longest Path Problem in polynomial time, which contradicts with its NP-hardness. As a result, we show that no polynomial time algorithm exists for the special case of Y, and thus prove its NP-hardness. First, we identify all feasible paths in the graph, then we find their largest disjoint subset. Each path in the returned subset represents a series string of the corresponding batteries, and all these strings are connected in parallel to support the load. Although the original problem is NP-hard, our solution is feasible in practice based on two important observations on battery systems.

Finding All Feasible Paths: We implement a DFS with pruning method to identify all the feasible paths in the graph. If using the basic DFS idea to identify all the feasible paths, we need a computational time of O (N^{N-1}) to identify all the feasible battery strings (note that we assume fully connected output terminals, and the computation time to identify all the paths is quite different from graph traversal). However, the following two observations on battery systems assist in reducing the computation complexity in practice. Finding the Largest Set of Disjoint Feasible Paths: Due to the requirement on disjoint paths for balanced battery utilization, if we include a specific path into the system configuration, other paths with overlapping vertices will not be able to be added to the configuration later. Thus our next step is to find the largest disjoint subset of all these feasible Paths. Assuming M feasible paths have been identified, which are denoted as P = {$path_1$, $path_2$, · · ·, $path_{\mathbf{M}}$}. This transformed problem is a classic 0-1 integer programming problem. As the DFS with pruning method identifies all the feasible paths in the graph, we can see that the optimality of the identified configuration only depends on how optimal a solution the 0-1 integer programming can return. Fortunately, efficient 0-1 integer programming solvers exist in the literature, and thus the near-optimality of the identified configuration can be guaranteed.

Reconfiguration with Multi-Load-Changes:

We have investigated the scenario where only a single load changes in the previous section. To complete our investigation, in this section, we extend our design to the scenario where multiple loads may change simultaneously.

Problem Formulation: The graph representation of the battery pack can be ex-tended by adding 2U vertices in V and extending the edge set E and weight set W in the same way as in the single load change case. An important difference between the scenarios of a single and multiple loads changes is that the battery discharge currents are likely to be heterogeneous in the latter case. This is because the loads on different terminal pairs are quite likely to be heterogeneous, and the number of series strings for each load in the adopted system configuration may be heterogeneous as well. As a result, we need to minimize the maximal discharge current of batteries in this multiple loads changes case to improve the overall battery utilization efficiency. We can use the same DFS with pruning method as in the single load change scenario to identify all the feasible paths for each load, denoted as Q, The first constraint means that a path can be selected only for the load it can support, the second constraint requires that each of the M paths can be adopted by at most one load, and the final constraint requires the same vertex to be involved in almost one selected path. This min-max optimization problem cannot be efficiently solved by 0-1 programming. We thus propose a greedy algorithm to identify the desired system configurations in this case.

Greedy Solution: After identifying the path set Q, the greedy solution adds paths into the system configuration in a step-by-step manner until no more paths can be added. Because the inclusion of a specific path prevents other paths sharing common vertices from being included in the future, the sequence with which the paths are added into the configuration plays a critical role i n determining the final results. Thus, two sub-questions need to be addressed are: (i) which load should be selected to explore for each step, and (ii) which path should be included into the configuration for the selected load. Our solution greedily addresses these two sub-questions: we greedily select the load with the largest battery discharge current for each step, and then greedily include the path with the least conflict on other paths into the system configuration.

- ✓ Select the Load with the Largest Current: Given the load requirements and the paths that have been already included into the system configuration, in each step, we can calculate the discharge current of the batteries supporting each load. Specifically, let $n^1_{\mathbf{p}}$, $n^2_{\mathbf{p}}$, · · · , $n^{\mathbf{U}}_{\mathbf{p}}$ denote the number of selected paths for each load. With a small σ, the discharge current of batteries supporting individual loads can be approximated. Then we select the load with the largest discharge current for individual batteries for each step, specifically, the selected load is

✓ Select the Path with the Least Conflict: After selecting the load, the next step is to select a feasible path for the load and include the path into the system configuration. The selection of a specific path prevents other overlapping paths to be selected in the future due to the disjoint paths requirement. Thus, we select the path that has the least negative impact on other paths. We define the conflict matrix C in the same way as (5). When the kth load is selected in a specific step, we select the path according to where $Q_{\mathbf{a}}$ is the set of paths that are still available for selection before this step. Note that the inclusion of a specific path into the configuration changes the values of (7), and thus we need to re-select the load to be processed for each step. If no path can be selected for the load under consideration, we mark the load as saturated, and re-select the non-saturated load with the largest discharge current for individual batteries as the next to process. This process continues until no paths can be selected for any loads.

Discussion: Energy Overhead of Reconfiguration Overhead The adaptive system reconfiguration is achieved by the operation of supplementary electronic components such as switches and connectors, which also consumes energy. Because the energy consumption on these supplementary components is normally smaller than the battery capacities in orders of magnitudes, we can separate the identification of optimal configurations from minimizing the operation costs of supplementary components as two independent problems in practice.

Time Overhead of Reconfiguration Besides energy loss, the system reconfiguration also requires certain time duration to accomplish, i.e., the reconfiguration latency. This reconfiguration latency introduces two additional challenges: how to minimize the latency and how to supply the load during the transient phase. A possible approach to address the first question is through the coordinated supplementary component operations, and the second question can be addressed by incorporating super-capacitor based secondary power supply systems.

Battery Charging through System Reconfiguration Battery charging is another important issue for battery-powered systems, which is desired to be fast (i.e., accomplished in short time) and efficient (i.e., more energy is charged into the batteries). It is also possible to apply the idea of system reconfiguration to assist the charging of batteries: the charging current/voltage can be controlled by adjusting the way in which the batteries are connected.

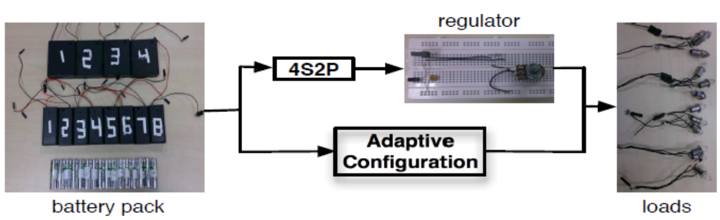


Fig. 4. Experiment method.

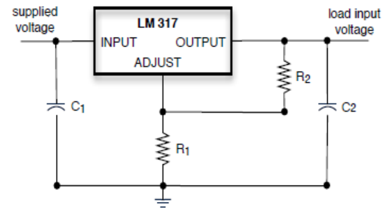
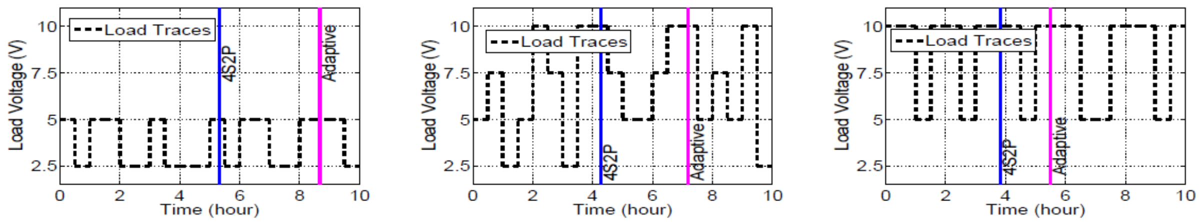


Fig. 5. Adjustable voltage regulator.



(a) Light Loads (b) Mild Loads (c) Heavy Loads

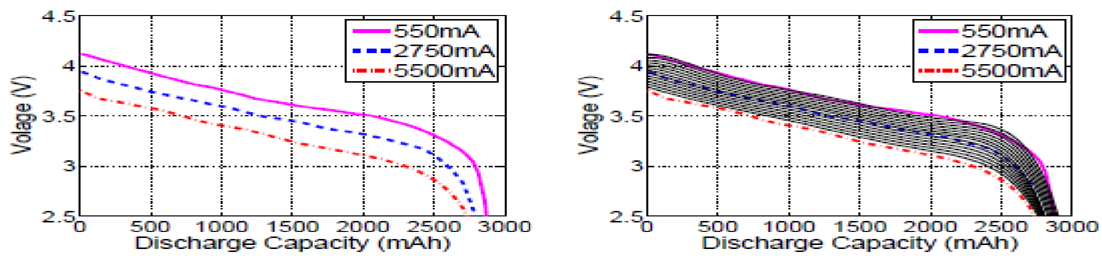
Fig. 6. Operation time with different loads.

Results:

To investigate the performance of the adaptive configure algorithm with different load conditions, we randomly generate three load traces with light, mild, and heavy loads respectively. Specifically, with light load, only 1-2 bulb modules are series connected as the load. The numbers of bulb Models adopted with the mild and heavy loads are randomly chosen from 1-4 and 2-4, respectively. In this way, the number of bulb modules used in the light, mild, and heavy loads is 1.5, 2.5, and 3 in average, respectively. The load lasting time t_i is set to 30 minutes. The operation times obtained with the two configuration methods for each load trace are shown in Fig. 6. The advantage of the adaptive configuration over the baseline is obvious, and an average operation time increase of 3.06 hour is obtained over the three loads conditions. This operation time improvement is due to two reasons: first, by adaptively converting the supplied voltages to the load required levels, the energy loss on the voltage regulator is reduced; second, by minimizing the discharge current of individual batteries, more battery capacity can be delivered and the heat dissipation on other system components is also reduced. Furthermore, we can observe that the lighter the loads, the more improvement can be obtained, which can be explained by the following two facts. First, with the 4S2P configuration n, the lighter the loads, the larger the gap between the supplied and required voltages, which degrades the regulator efficiency. Second, the lighter the loads, the fewer batteries are needed to form a single series string to support the loads. This in turn offers more space for the adaptive configuration to identify more parallel connected strings, and thus reduces the battery discharge current. Another observation from our experiment result is that with the 4S2P configuration, the temperature of the LM 317 IC easily rises to 44°C at the maximum. Such a high temperature not only indicates significant energy loss (and thus supports our design principle in matching supplied and required voltages), but also reduces the system stability.

Simulation Evaluations:

In this section, we evaluate the proposed adaptive reconfiguration algorithms through extensive trace-based simulations. We first evaluate the adaptive reconfiguration based on battery discharge traces obtained from the data sheet of off-the-shelf battery products. Then, the efficiency of the adaptive reconfiguration is further verified base on two sets of electric vehicle traces collected during driving.



(a) Provided in [7] (b) Approximated

Fig. 7. Battery discharge traces.

Simulation based on Battery Discharge Traces

- o Trace-based Battery Model: Analytical modeling of battery properties is computational expensive, and thus we use a trace-based method to track the battery states. We simulate a battery pack consisting of 2, 900mAh Panasonic NCR18650Li-ion batteries, whose discharge curves with discharge currents of 550mA, 2, 750mA, and 5, 500mA are provided in its data sheet. The full and cutoff voltages are v_f = 4.25 V and v_c = 2.5 V, respectively.
- ✓ To obtain more fine grained battery discharge traces, we divide the current interval [550, 5500] mA into 99 intervals with a gap of 50mA each, and proportionally approximate the corresponding discharge traces based on the three traces provided in the data sheet. Note that we could further reduce the current gap to improve the approximation accuracy. A subset of the obtained discharge curves is shown in Fig. 7 (not all the curves are shown for figure clarity).
- ✓ Simulated Battery Packs: The simulated battery pack consists of 64 batteries and can support three loads simultaneously. The current drawn from each battery can directly reach two other batteries on average (i.e., an average vertices out-degree of two in the graph). The simulation follows these settings unless otherwise specified. The initial battery voltages are randomly generated in the range where α is a control parameter that determines the battery voltage diversity and is set to 1.2 unless otherwise specified.
- ✓ Load Traces: Similar to the traces in the experiment, we randomly generate load traces in the form of {t^j_i , V_i^j , P_i^j } for each loads, where t^j_i is the lasting duration of the ith trace for the jth load, and V_i^j and P_i^j are the required voltage and power of that trace, respectively. A unit time interval of 10 minutes is adopted for loads' lasting time, i.e., t_i only takes the values of 10 min, 20 min, and so on. The system configuration is updated every 10 minutes by first updating the battery voltages according to the traces in Fig. 7, and then adaptively reconfiguring the battery pack. The required voltage

- ✓ V is randomly generated from 15-20 V unless otherwise specified. The tolerable jitter voltage is 2.5 V (i.e., v_c) by default. The required power P is randomly generated from 15 V × 550mA = 8.25 W to 20 V × 5500mA = 110W.
- ✓ Baselines: We implement the following three system configurations as baselines.
- ✓ Serial: The batteries are evenly assigned to individual loads, formed, and then these strings are assigned to individual loads in a round-robin manner.
- ✓ Oracle: Given the range of all possible load required voltage, we can calculate how many batteries are needed for a string to be able to support any potential loads, and then we form as many as possible such strings. The remaining batteries (those are not enough to construct another such string) form the last string. This oracle configuration maximizes the number of parallel connected strings while guaranteeing each string is able to support the load requirement. These strings are then assigned to individual loads in a round-robin manner.
- ✓ Performance Evaluation: We evaluate the impact of different system parameters on the performance of adaptive reconfiguration.

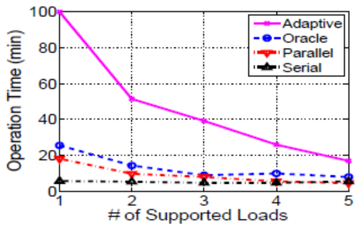


Fig. 8. Impact of supported loads #.

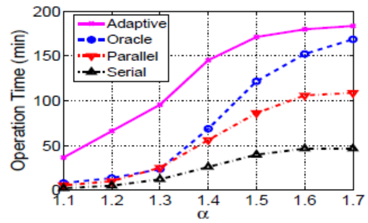


Fig. 9. Impact of initial battery voltages.

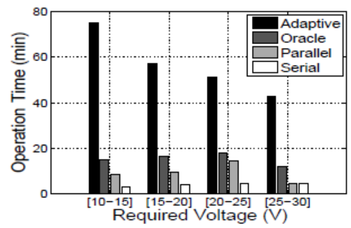


Fig. 10. Impact of required voltage.

Number of Loads: We first examine the impact of the number of supported loads on the system operation time. The results with 1 to 5 simultaneously supported loads are shown in Fig. 8. Note that it is not necessary for all these loads to change at the same time. The operation time decreases as more loads have to be supported, which is intuitive because increasing the number of supported loads essentially indicates heavier loads for the battery system. Furthermore, we can see that compared with the baselines, the adaptive reconfiguration achieves around 4× gain in operation time when only one load is supported. Although the gain decreases as more loads need to be supported, the adaptive reconfiguration still obtains a 2× operation time even with a load number of 5.

Battery Voltage Diversities: We then explore the impact of battery voltages on the operation time. The battery voltages are controlled by the parameter α in (10), and a smaller α indicates both a higher voltage diversity among batteries and a lower average battery voltages. The operation time with α varying from 1.1 to 1.7 are shown in Fig. 9. Note that with α = 1.7, it indicates that the battery voltages are randomly generated from [2.5 × 1.7, 4.25] = {4.25 }, meaning all the batteries are initially fully charged. The operation time increases as α increases because of higher initial battery voltages, and the adaptive reconfiguration outperforms the baselines in a ll the explored cases. Furthermore, we can see the advantage of adaptive reconfiguration is more obvious with smaller α. This is because the smaller α is, the more likely that certain batteries are close to depletion. Depleted batteries significantly degrade the system performance if the configuration is not adjustable. On the other hand, the adaptive reconfiguration can bypass low-voltage batteries when necessary, which reduces the impact of the near-depletion batteries on system performance.

Loads Requirements: The operation time with different load required voltages and powers are shown in Fig. 10 and Fig. 11, respectively. The load required power is set to 55 W in Fig. 10 and the required voltage is 20 V in Fig. 11. Again, significant improvement on the operation time can be observe d with the adaptive reconfiguration, which is about 3×-5× of those obtained with the baselines. Furthermore, the operation time decreases as the loads become heavier, as a result of the increase in either the required voltage or power. Note that Fig. 10 shows that when the required voltage is relatively low (e.g., 10– 25 V), the operation time obtained with the non-reconfigurable baselines slightly increases with a higher voltage. This is because when the required voltage increases, the load current decreases with a fixed required power, which in turn leads to a longer operation time. However, as the required voltage continuously increases (e.g., [25, 30]), the probability for the fixed configuration to not able to support such required voltage increases, and thus the operation time is reduced.

Configuration Flexibilities: We investigate the impact of system configuration flexibility on the adaptive reconfiguration in the following. The operation time with different configuration flexibilities (i.e., the vertices out-degree in the graph) are shown in Fig. 12, with an average out-degree of 1, 2, and 3, respectively. Significant increase in system operation time can be observed when the configuration flexibility increases. However, the increase in operation time slows down with larger average out-degrees. This implies that an excessive high configuration flexibility may not be desirable, especially when considering the fact that the configuration flexibility does not come without costs, e.g., the implementation complexity would be dramatically increased.

Besides the average configuration flexibility, the distribution pattern of these flexibilities also affects the system performance. Fixing the average vertices out-degree as 3, we explore three cases on how the configuration flexibilities are distributed among batteries, as shown in Table I. The resulting operation times under these three cases are shown in Fig. 13. We can see that the flexibility distribution significantly affects the performance. An important observation is that when the configuration flexibility is more evenly distributed among batteries, the performance becomes better. This is because such an evenly distribution pattern alleviates the negative impact due to bottleneck batteries on the system performance. This observation serves as guidance in practical battery system design.

Emulation based on Electric Vehicle Driving Traces: We further evaluate the adaptive reconfiguration based on empirical electric vehicle driving traces. We collect two driving traces of around 900 s and 2400 s each, containing the corresponding operation voltages and powers during that time period, as shown in Fig. 14 and Fig. 15, respectively.

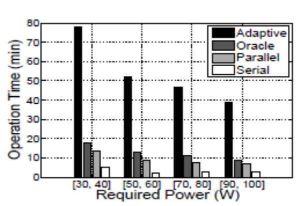


Fig. 11. Impact of required power.

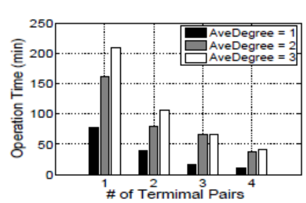


Fig. 12. Impact of ave. configuration flexibility.

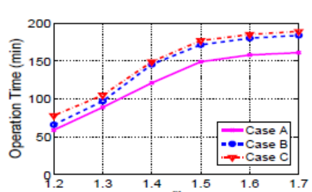


Fig. 13. Impact of flexibility distributions.

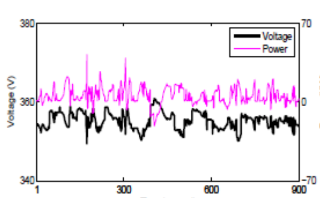


Fig. 14. Electric vehicle driving traces #1.

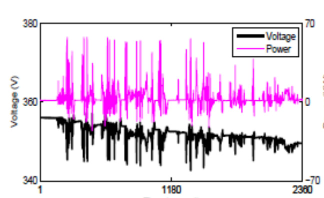


Fig. 15. Electric vehicle driving traces #2.

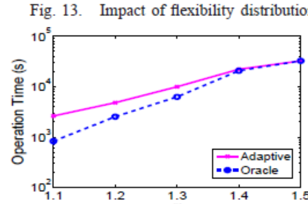


Fig. 16. Operation time.

We generate the load traces for our emulation based on these two raw traces. First, both the discharging and charging of battery pack happen during the driving of electric vehicles. This is reflected in the traces that the both positive and negative values exist in the power trace. Because we only focus on the discharge management in our design, we set all the negative powers and the voltages at the corresponding time instance in the traces to zeros. The battery packs for electric vehicles normally take the hierarchical architecture: it can be divided into a set of battery modules which in turn are consisted of individual batteries. In our emulation, we form a battery pack consisting of 64 modules each with 16S4P connected batteries. The battery discharge property conforms to the discharge traces shown in Fig. 7. Again, we take the non-reconfigurable Oracle baseline for comparison. The operation time with varying initial battery voltages is shown in Fig. 16. Obvious advantage of the adaptive reconfiguration can be observed, especially when the battery initial voltages are low, which agrees with the observation in Fig. 9. The operation time obtained with the two configuration methods converge as increases, because in this case the battery pack has sufficient energy supply to survive the load even without the assistance of adaptive reconfiguration.

Large-scale battery systems are commonly adopted in practice, and many research efforts have been devoted to improve the system performance focusing on the battery discharge scheduling, the effective system monitoring, the design of battery management systems, etc. Due to the load dynamics in large-scale battery systems, traditionally, the battery supplied voltage is adjusted to the load. Required level by adopting additional electronic components, e.g., voltage regulators. However, the additional component introduces additional energy consumption/loss, and thus degrades the battery energy utilization efficiency. Another approach to provide the dynamic load requirement is to adaptively adjust the battery connections in the system. Investigations on this adaptive system reconfiguration have been reported in, targeting on small multicell battery systems such as mobile devices. In our work, we extend the investigation to large-scale scale battery systems. Two necessary conditions must be satisfied to effectively and adaptively reconfigure the system. First, the system has to offer certain configuration flexibility on which the adaptive reconfiguration can operate. However, the system configuration flexibility is achieved by adopting more electronic components such as connectors and switches, which not only introduces additional energy costs, but also increases the system implementation complexity. Research efforts have been devoted to effectively offer configuration flexibility with less additional costs. Based on the system design, six switches are enough to connect a battery in any manner: series, parallel, or by-passed. Our work advances the state-of-the-art by proposing adaptive reconfiguration algorithms t hat return the desired system configuration based on the offered configuration flexibility and the real time load requirements. Second, the system has to be aware of individual battery conditions to carry out the adaptive reconfiguration. Many works on battery modeling and simulation exist in the literature. However, most of these models are computational extensive, and the simulators require practical parameters to implement. Furthermore, most of these models/simulators are for specific battery types, and thus their universalities are limited. Our proposed adaptive reconfiguration algorithms hide the complex low level battery properties by focusing on two rules of thumb in identifying the desired system configurations: matching the supplied an d required voltages and minimizing the discharge currents. The most similar works are, a power tree representation of the battery pack is proposed to assist the effective system reconfiguration when the battery failures happen. We tackle the system reconfiguration with a different objective, i.e., optimizing the system energy efficiency, and our solutions can also effectively handle the case with battery failures. An optimization formulation w.r.t the energy efficiency is presented in [19], which requires low level battery properties such as the state of charge, the state of health, etc. Our work hides the complex battery properties from engineering and thus facilitates its practical implementation. A reconfigurable series-connected battery string is proposed in [28] to adjust the supplied voltage to the load required level. We advance the investigation by further exploring minimizing the battery discharge current to improve the system energy efficiency.

Conclusions:

In this paper, we've got explored the adaptation reconfiguration of large-scale battery systems to dynamically offer the load's needed voltages, that avoids the low potency issue of the normal voltage regulator-based solutions. Supported 2 through empirical observation discovered style principles, our approach hides the complicated battery properties from engineering, and so makes it additional sensible for implementation. Specifically, by abstracting the battery system into a graph illustration, we've got investigated each situations with one and multiple load changes, and planned corresponding adaptation reconfiguration algorithms. Through model implementation and intensive simulation, we've got shown the planned adaptation reconfiguration algorithms will considerably improve the performance w.r.t. system operation time. Within the future, we are going to investigate the trade-off between the system energy potency and implementation quality.

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