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# Path Planning Support of Intelligent Battery Tray to Autonomous Combat Vehicles

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## ABSTRACT

*Path planning is critical for mission implementation in various robot platforms and autonomous combat vehicles. With the efforts of electrification, battery energy storage as power sources is an ideal solution for robots and autonomous combat vehicles to improve capability and survivability. However, the battery's limited energy and limited instantaneous power capability could become limiting factors for a mission. The energy and power constraints are also affected by the environment, battery state of health (SOH), and state of charge (SOC) significantly; in the worst case, a well-tested mission profile could fail in the real world if all aspects of the battery are not considered. This paper presents a framework to model the battery's capability to support a whole mission and specific tasks under various environments. This real-time battery model can be built into an intelligent battery management system to support system-level mission planning, real-time task selection/ teleoperation, post-mission evaluation, and maintenance assistance. Furthermore, case studies are presented to show that the simple rule-of-thumb approach would not provide an optimal solution and that a comprehensive battery model is necessary. Transparent to vehicle's system control, this model framework provides a simplified parameter set for existing path planning approaches to achieve optimum battery usage, which leads to the improved range, duration, and reliability for a mission.*

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## 1. INTRODUCTION

Mission planning and path planning play vital roles in ensuring that autonomous vehicles and mobile robots can accomplish a mission while meeting certain requirements, such as travel time, energy consumption, and risks/uncertainties [1,2,3]. Researchers have developed various path-finding methods to support the navigation of vehicles or robots in both known and unknown dynamic environments under various settings and different priorities for initial mission scheduling and real-time planning [4,5]. The majority of the studies focused on the mission and tasks themselves, and the energy and power of the vehicle were not the priorities.

When the vehicle or robot is battery operated, the energy and power constraint of the battery poses additional challenges in the mission planning process. Although energy consumption has been considered in some path-finding methods [6], battery energy and power limitation have not been fully accounted for in the mission planning of battery-operated vehicles. This is partially due to the complexity of the battery and the lack of mission-oriented models to describe battery performance in the dynamic environment.

Recent advances in electric vehicles and fuel conservation have considered power usage [7]. However, those applications almost always include high energy reserves and a controlled environment. For example, on electrical vehicles, the battery pack environment could be tightly controlled so its performance could be better predicted.

Electrification improves vehicles and robots' capability and survivability, and battery energy storage is an ideal solution for those platforms. When battery packs are used as power sources, the assumptions in traditional path planning algorithms might not always be valid. Specifically, the battery pack has limited energy due to system-level constraints such as weight and size. Meanwhile, the vehicle is expected to have maximum range and duration. Therefore, if the path planning does not consider the limitation of the battery, the battery might not support all planned tasks. Further, during the mission, the battery pack's capability will be significantly affected by the environment, its state of charge (SOC) and state of health (SOH). For example, the battery might not be able to complete a high-power task when it is close to empty while it is capable of at a high state of charge due to high output resistance and low voltage at low SOC besides battery management system protections.

Another example is safety. IATA shipping guideline requires Lithium-ion battery with low SOC during shipment to reduce hazards. Studies also show that, besides chemistry itself, a Li-ion battery cell's responses to nail penetration tests vary concerning SOC, and, when impacted, cells with SOC less than 50% could be less likely to cause fire with other conditions equal [8,9]. Therefore, although the outcomes of severe abuses such as direct projectile penetration event might be the same, during path planning, it might still be advantageous to schedule safety-critical tasks when battery SOC is low if permitted.

Therefore, autonomous combat vehicles including battery-powered robotic systems present an energy and power-constrained setting, which is not common in traditional applications.

This paper presents a battery model framework. It provides a performance index for the battery's real-time power and energy capability and performance forecast. This index allows the system to view the battery box as a black box. The path planning algorithm can include the index in its existing global planning, real-time short-term task evaluation/teleoperation, and/or post-mission evaluation with low additional overhead. Further, weak batteries in the battery pack can be identified for maintenance. As a result, mission interruption and maintenance costs will be reduced. This model is included in the battery pack's battery management system as an intelligent battery tray (IBT).

In real applications, mission planning and path planning have different meanings. For example, in a typical traveling salesman problem, the tasks have the same priority so the order of the tasks can be changed to achieve the shortest path. In other missions, the tasks could be highly correlated, so the order is not interchangeable. The paper will show that the model we propose for the IBT is beneficial for both scenarios. For simplicity, path planning and mission planning will be used interchangeably in the paper unless otherwise noted.

Further, the available energy might have different meanings at system level from battery capacity. For example, the system might set a reserved energy threshold for system level objectives such as battery cycle life, mission certainty, etc. In this case, the mission planning should plan with the available energy.

The background is presented in Section 2. The model is shown in Section 3. Case studies are discussed in Section 4. Section 5 shows the ongoing work on testing and verification. The conclusions are given in Section 6.

## 2. BACKGROUND

Various algorithms have been developed to find the optimal or near-optimal mission paths, including graph search methods (e.g., A* family algorithms [10], sampling-based methods [11], and trajectory optimization methods [12].) In addition, to minimize energy consumption, some energy-efficient path-finding algorithms have been developed. For example, Sun and J. Reif studied the problem of finding energy optimal paths on terrains where the energy cost depends on friction and gravity [13]. Niu et al. considered speeds and vehicle characteristics in the energy consumption model and proposed an algorithm to find the minimum energy path [14]. However, the above-mentioned methods do not account for the battery's instantaneous power capability, which depends on other factors such as the state of charge and environmental factors.

On combat vehicles and robotic platforms with the battery as the power source, the battery pack has limited power, limited energy, and an uncontrollable environment:

Limited energy: It is reasonable to assume that the on-vehicle battery storage is fully charged at the beginning of a mission. During the mission, the battery power will be consumed to empty for maximum range and endurance. Therefore, the mission planning should consider the energy used and reserved energy.

Limited power: Similar to limited energy, when the battery's SOC is low, it would not be able to conduct certain tasks which is capable of when the battery is full, especially the high current draw tasks. For example, the battery's voltage is low at low SOC and is much more likely to trigger shutoff due to large current draws [15]. On the other hand, when the battery SOC is high, the regenerative power capability of a battery-power vehicle is limited because the battery charging capability is reduced or disabled to prevent overcharge. During the lifetime of a battery, its SOH should also be considered during planning and post-mission evaluation.

Uncontrolled environment: The combat vehicle would operate in a wide range of environments, be it hot or cold. If climate-control is not available on the vehicle platform such as a medium-size robots, the battery energy and power capabilities will be directly affected by environmental factors. For example, a Li-ion battery could go into protection when the battery is too hot, while its capability will severely diminish in a cold environment.

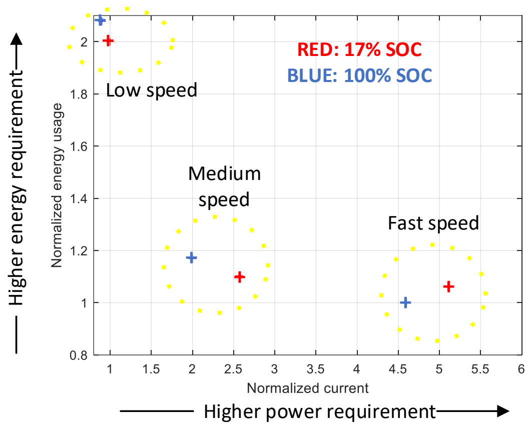


Fig. 1 Normalized power and energy consumption for the same travel distance with different speeds and different SOCs.

Table 1: Normalized power and energy consumption show in Fig. 1

| SOC=100% | Speed | | |
|---|---|---|---|
| | Low | Medium | Fast |
| Current | **1** | 2.57 | 5.10 |
| Energy usage | 2.00 | 1.10 | 1.06 |

| SOC=17% | Speed | | |
|---|---|---|---|
| | Low | Medium | Fast |
| Current | 0.90 | 2.60 | 4.60 |
| Energy usage | 2.08 | 1.17 | **1** |

Fig. 1 shows the normalized experimental results of average current usage vs. energy usage for a robot with slow, medium, and fast speed under 17% SOC and 100% SOC for the same distance. Table 1 shows the normalized data. The power requirements are normalized to the current at 100% SOC and Fast speed. The energy consumptions are normalized to that of 17% SOC and Low speed. The energy consumption has an overhead portion, which is the idle current usage to power the onboard system. Under both 17% and 100% SOC, the overhead at low speed is high because of its long travel time. Furthermore, the higher motion-only energy at low speed is also robot-specific. Therefore, the energy usage is lower at higher speeds, and the peak current is around twice the average current. Clearly, the Fast speed will require much higher currents, and the high energy usage might trigger battery shut-off at low SOC. For this task, the medium speed setting might be a better choice for the balance of power and energy consumption. In a real-world application, the terrain condition must be considered with different energy vs. power profiles with respect to mission tasks. The intelligent battery tray can monitor and predict the battery pack's power availability and energy availability in real-time and during path planning to ensure minimum reserved capacity and, in the worst case, the optimal motion option to limp home.

Besides the above power and energy considerations, the environmental factor should also be considered.

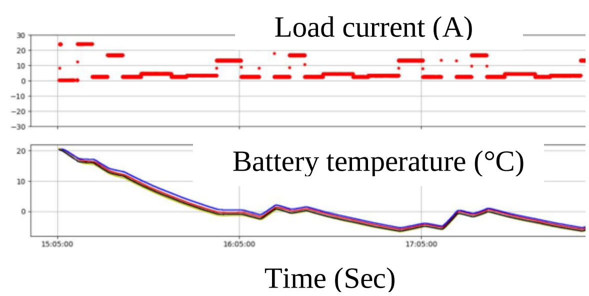


Fig. 2 Experimental battery temperature operating in -20°C environment with starting battery temperature of 20°C

Fig. 2 shows an example of battery temperature during a multi-task mission. The battery is charged full and conditioned at the temperature of 20°C. It is put into a -20°C environment. At the end of the mission, the battery temperature is cooled down to -10°C while the Li-ion battery's capacity is reduced at lower temperatures. Also, when the task current is high, the battery temperature increases. As an intuition, an optimal path planning algorithm should schedule the tasks so that the battery has a higher temperature during the majority of the time to have higher available capacity.

Optimizing for battery temperature during mission planning is particularly important for applications such as small-size and medium-size robots' battery tray, where heavy insulations are not available due to platform's size and weight limits. Additionality, fully-sealed climate-control enclosures may not be possible due to other operations requirements: for example, some applications requires that battery modules can be easily swapped out during the mission by operator without needing special tools.

## 3. MODEL SUPPORTING PATH PLANNING

### *3.1. Model and its outputs*

The path-planning supporting battery model generates a battery performance index

$$\begin{pmatrix} P_0 & E_0 & H_0 & t_0 \\ P_n & E_n & H_n & t_n \end{pmatrix} = f(inputs)$$

Where P is power, E is energy(SOC), and its health index at a given time, *t*. The data in $t_0$ is the real-time information while that in $t_n$ is for performance prediction at a given time. Depending on the complexities of the implemented model, the prediction could be multiple time points or only one or two critical times such as battery low warning and battery temperature warning.

The health index, *H*, is used to model the probability of whether the desired task can be completed reliably and safely, and possibly also its long-term effects on battery life. Instead of performing simple constraint checks related to battery power limits, a 'score' is given to indicate the impact of the task on the battery's short-term and long-term health. By using a numerical value instead of a simple go or no-go, we can take more factors into account such as battery-to-battery variations, battery variations during its life cycle. By lumping all the battery constraints and operation impacts into one health index 'score', we also simplify the mission planning algorithms design by keeping the battery details in the battery model only. The mission planning algorithm can be ported to a different battery system relatively easily, without having to re-write the algorithms solely due to a new set of battery constraints, or different battery characteristics.

Based on its usages, the model can be tailored for different complexities:

1) During global task scheduling, the model can be run offline. Its power and energy capability can be used as go/no-go criteria for tasks. The impact on the battery is also calculated.

2) During real-time task planning /teleoperation, the power and energy capabilities are used to ensure the task can be implemented. More importantly, the health index will be used to evaluate the effects of the execution of the current task on following tasks.

   After the mission, the health index can be used for battery maintenance and mission planning update.

### *3.2. Inputs to the Model*

The external inputs to the model are the mission conditions including environmental temperature, task profiles, and its related power profiles.

The following battery characteristics are included in the model as identified as the key parameters that affect mission planning:

1) Li-ion battery capacity modeling: The capacity of the battery pack is a function of design capacity, battery ageing, and temperatures.

2) Battery discharge and charge limit modeling: The battery charging and discharge pulse current limits including high-C are functions of the battery SOC and temperature.

   For example, for a Li-ion battery, when SOC is close to 100%, the charging current limit is reduced to zero. A pulse discharge limit is usually a constant number as reduced to zero as SOC approached 0%. The actual usable capacity is also affected by discharge rate. For high C-rate discharge, the battery is likely to shutdown at a higher SOC, which effectively means lower energy delivered.

The battery cell-to-cell variations and variations over the lifetime also have significant effects on almost all the above key characteristics, thus they should be included in the model for an accurate estimate.

Additionally, battery packs on the robotic vehicles are usually constructed by interconnecting hundreds or even thousands of cells. Pack-level statistic models are needed, which will make it possible for the mission planning tools to make the decision based on qualitative results on questions such as how likely a mission can be completed within certain SOC or power limits.

The cells in the battery pack are usually managed by a pack battery management system, which performs active functions such as cell balancing and cell fault mitigations. Each manufacturer usually designs algorithms in the BMS with specific calibrations determining the real-time various energy and power thresholds that ensure safe battery operation. These calibrations, along with the physical parameters of the battery design, are both key inputs to the model.

## 4. PATH PLANNING WITH BATTERY USAGE OPTIMIZATION

### *4.1. Case study 1: Pathfinding optimizing battery energy usage*

<u>Problem Statement:</u>
Assume that a robot is conducting surveillance operations, the robot will return to base to be recharged when the battery is low. Let's assume that the priority is maximum surveillance time for each mission. At the same time, the robot should be able to reach home before the battery is empty.

<u>Analysis:</u>
Fig. 3(a) shows an example of a simplified terrain map with slope information in each cell. Its related energy consumption for a reference vehicle was calculated. To simplify the case study, the terrain map only contains positive slopes, thus the energy consumption is a function of speed and slope. For the case study, a constant vehicle speed is assumed. If a terrain map with downhills is considered, the energy consumption model also needs to account for regenerative energy and is out of the scope of this paper. In addition, the instantaneous power capacity of the battery limits the maximum slope that the vehicle can climb at a certain state of charge and temperature.

At high SOC, the power capacity allows the vehicle to traverse any cells in the terrain map, with the steepest slope of 30°. The minimum energy path was calculated using the A* algorithm, as shown in Fig. 3(b).

When SOC is low, some cells in the terrain map become unpassable because of the battery's reduced power capacity. Fig 3(c) shows an example of a minimum energy path that avoids any slope greater or equal to 25°.

| | | | | | |
|---|---|---|---|---|---|
| 20 | 20 | 20 | 20 | 20 | 20 |
| 16 | 18 | 24 | 26 | 28 | 18 |
| 12 | 16 | 22 | 30 | 25 | 16 |
| 8 | 14 | 20 | 22 | 18 | 14 |
| 4 | 18 | 16 | 20 | 16 | 12 |
| 0 | 6 | 12 | 22 | 26 | 18 |

(a) Terrain maps with slope (°) indicated in each cell

| | | | | | |
|---|---|---|---|---|---|
| 282 | 282 | 282 | 282 | 282 | 282 |
| 251 | 267 | 313 | 328 | 344 | 267 |
| 221 | 251 | 298 | 359 | 321 | 251 |
| 190 | 236 | 282 | 298 | 267 | 236 |
| 159 | 267 | 251 | 282 | 251 | 221 |
| 128 | 174 | 221 | 298 | 328 | 267 |

(b) Path with minimum energy consumption. The shaded cells indicate the path. The energy consumption is 1714.

| | | | | | |
|---|---|---|---|---|---|
| 282 | 282 | 282 | 282 | 282 | 282 |
| 251 | 267 | 313 | | | 267 |
| 221 | 251 | 298 | | 321 | 251 |
| 190 | 236 | 282 | 298 | 267 | 236 |
| 159 | 267 | 251 | 282 | 251 | 221 |
| 128 | 174 | 221 | 298 | | 267 |

(c) Minimum energy path when SOC is low. The black cells indicate unpassable cells (i.e. slope >=25°). The energy consumption is 1721.

Fig. 3 An example of terrain map (a) and its path with minimum energy consumption (b)(c).

| | | | | | |
|---|---|---|---|---|---|
| 282 | 282 | 282 | 282 | 282 | 282 |
| 251 | 267 | 313 | | | 267 |
| 221 | 251 | 298 | | 321 | 251 |
| 190 | 236 | 282 | 298 | 267 | 236 |
| 159 | 267 | 251 | 282 | 251 | 221 |
| 128 | 174 | 221 | 298 | | 267 |

Fig. 4 An example of real-time rerouting due to impassable cells. The robot is rerouted to the path shaded in yellow after the SOC is dropped. The energy consumption is 1934.

As an input to the model, the energy consumption rate can be used as the input to the battery pack to reduce BMS's computation overhead. Alternatively, the calculation can be conducted on BMS with the terrain data received from the controller.

In real-time operations, the battery needs to continuously monitor the power and energy capacity. Fig. 4 shows an example of rerouting after power capacity drops and prevents the vehicle from continuing the original assigned route that includes steep slopes.

<u>Benefits of the IBT model:</u>

As in the problem statement, ideally, the robot should return home when the battery has the minimum energy left upon home. Any additional reserved energy means less mission time.

The IBT model can be beneficial in the following ways:

1) The path-finding algorithms can take the power and energy capabilities of the battery into consideration to identify a feasible path.

2) If only limited or one path option is available, the IBT model can provide a go/no-go decision. For example, it will provide warnings if the robot is likely to get stuck at a steep slope when the battery is close to empty as shown in Fig. 4.

3) The IBT model can predict the battery capability. Therefore, the planner might choose to get the robot back a lot sooner to get it recharged to reduce the uncertainty of the later sections of the mission. Though it would turn the mission into multiple trips, the operator can plan it ahead, which could still be valuable for certain applications.

As a result, the robot can maximize the mission time and safely return home.

### *4.2. Case study 2: Task scheduling with optimized battery usage*

A simple traveling salesman problem (TSP) is presented here to demonstrate the effects of battery models on path planning. The battery power limits were considered first. Then the effects of environmental temperatures are presented. The results show that a battery model is important for optimal path planning, and the traditional rule-of-thumb approach would not provide the optimal solution.

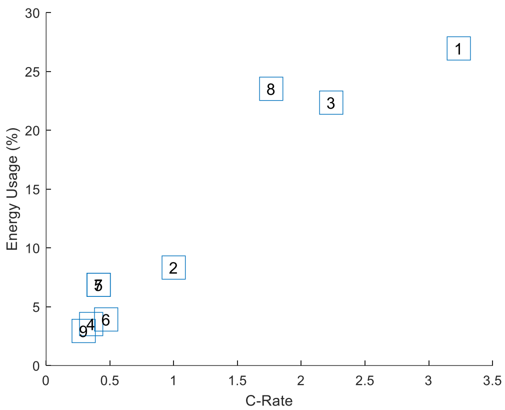


Fig. 5 Power and energy consumption for the nine tasks defined for the case study for path planning. The tasks are labeled with numbers 1 to 9 in the graph. The numbers don't represent the task priority.

Fig. 5 shows tasks 1-9 defined for the case study. The power and energy levels are chosen so that the case study simulates a typical real-life robotic mission, including both low power/energy idling tasks such as silent watch and simple arm operation, and high power and energy burst tasks such as high speed with a heavy load, fast rotation, movement on rough terrain, etc. To simplify the analysis, it is assumed that the energy usage between the tasks is negligible.

#### 4.2.1 Task scheduling considering power limits

As shown in Fig. 6, given a 10 by 10 grid network, nine tasks are expected to be completed with the same priorities. The starting node is **0**. In this section, it is assumed that the nine tasks have the same priority so their order can be interchanged.

Of those, three tasks (1, 3, and 8 in Fig. 5) require high instantaneous power; therefore, it might be preferred to be conducted when SOC is high.

The other six tasks (2, 4, 5, 6, 7, and 9) have low power consumption so they can be implemented at low SOC. The example tasks include surveillance, simple arm operation, and camera operation.

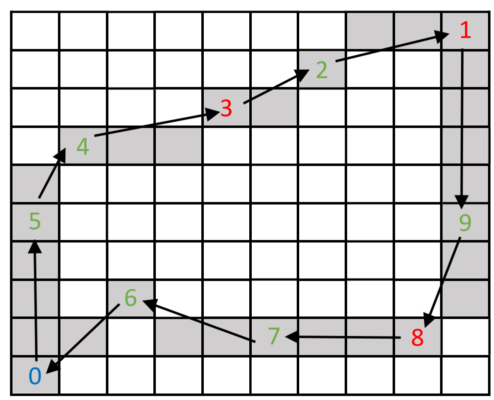

Fig. 6 Path selection without considering battery power limits at low SOC (TT=33.2)

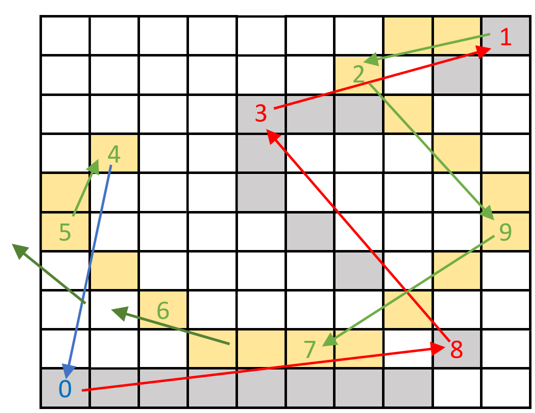

Fig. 7 Path selection with high power task scheduled first (TT=50.7)

If the power limit at different SOCs is not considered, the mission planning problem is solved as a typical TSP. The total travel distance is 33.2, as shown in Fig. 6. However, when reaching the location of Task 8, the SOC will drop to 33% and the robot is at high risk of entering a power-limiting state while completing Task 8.

If power limit at different SOCs is considered, one simple strategy is to implement the high-power tasks first, as shown in Fig. 7. The robot will perform tasks 8, 3, then 1. After that, the robot will perform the remaining tasks, which require less power and energy, before returning to the base, **0**. As a result, the total travel distance is 21.9 (high power tasks) + 22.4 (low power tasks) + 6.4 (return to **0**) = 50.7.

### 4.2.2 Task scheduling's effects on battery thermal performance

As shown in Fig. 6 and Fig. 7, the previous section assumes that the order of the tasks can be changed, which is not always true. The tasks in a mission can have strong dependencies, and the order changing will have a much-limited number of choices.

When the order of the tasks cannot be changed, this IBT model can help planning algorithms to evaluate uncertainty and to provide go/no-go decisions based on power and energy similar to the previous section.

Further, our battery model also shows the task sequence's impacts on the temperature profile of the Li-ion battery when climate-control is not available on the vehicle platform.

Keeping the Li-ion battery cell temperature within the optimum range is especially important in extreme cold or hot weather operations since temperature impacts the battery capacity, operation safety, and life. The Li-ion battery will shut off when the temperature is too high, while its energy and power capacity will be significantly reduced below a certain low temperature.

As a case study, we compare the temperature profiles predicted by the battery model under various task scheduling strategies for a cold-weather operation scenario.

Fig. 8 shows simulated battery temperature when the tasks were run with the power consumption from high to low corresponding to the strategy in Fig. 7. Similar to Fig. 2, it is assumed that the battery is conditioned at 20°C and is put into operation in a -20°C environment. It shows that the battery temperature falls quickly at the later part of the operation to below -15°C. Though it is safe to conduct the low SOC task, its power reserve is reduced due to low temperature so real-time task rescheduling is difficult.

Fig. 9 shows simulated battery temperature in the reverse sequence of Fig. 6, where the high-power tasks are performed at the end. Contrary to rule-of-thumb, the battery is kept warm, especially at the end of the operation because of the high-power tasks, which implies higher available energy and power when a new mission arises during operation. However, as described in section 4.1, it is undesirable to carry out these tasks at the end of the mission due to low battery SOC.

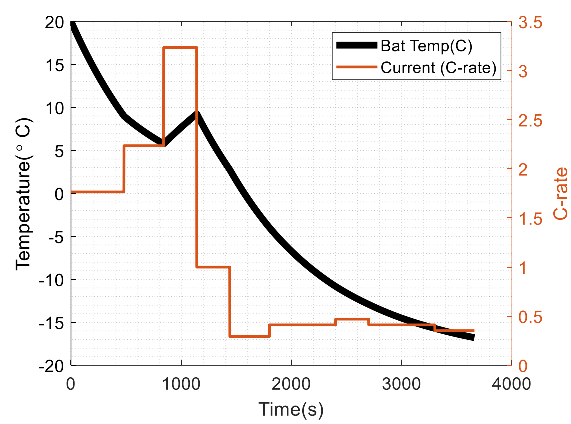

Fig. 8 Temperature profile operating in -20°C environment with an initial battery temperature of 20°C with the strategy of scheduling the high-power tasks with highest priorities.

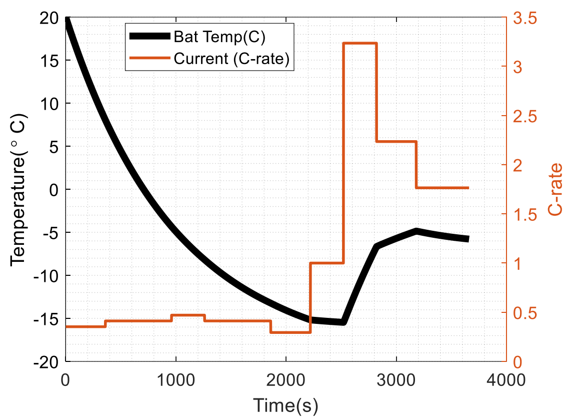


Fig. 9 Temperature profile operating in -20°C environments with an initial battery temperature of 20°C with scheduling high power tasks at the lowest priority

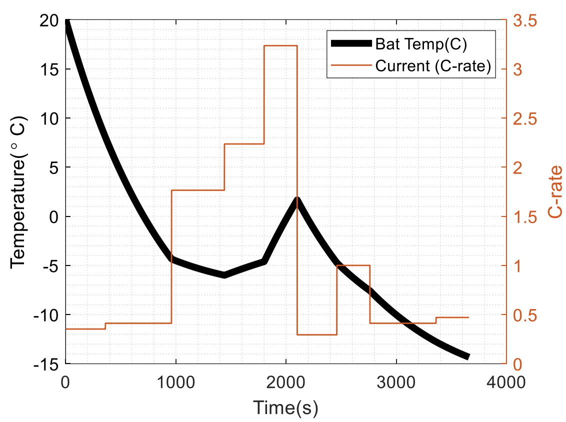


Fig. 10 Temperature profile operating in -20°C environments with an initial battery temperature of 20°C with scheduling high power tasks at medium priority

With our model, Fig. 10 shows simulated battery temperature when the high-power tasks are assigned with medium priority. The sequence ensures that the high-power tasks 1, 3, 8 are still performed at good battery SOCs, while they are also mixed with 'idle' tasks so that the battery temperature never drops too low during those idle tasks. The battery temperature is kept above -15C for the whole operation. With the model, the vehicle could operate with a balanced performance with high power and energy reserve for new tasks.

## 5. MODEL VERIFICATION

As part of ongoing development, the proposed models will be verified at the IBT level and also at the robotic vehicle system level for path planning.

The IBT model will output real-time power and energy capacity and health index and predict future performance. With pre-defined mission profiles, the model outputs and experimental results will be compared. The initial set of model parameters is derived from manufacture data and module-level battery lab testing data and will be further validated and calibrated to match the test data from IBT when more data is available.

At the path planning level, we are developing a generic path planning model so the IBT model can be adopted in wide range of robotic and autonomous combat vehicle platforms. The interaction and efficiency will be evaluated. Both optimizations with task sequence and go/no-go for fixed task sequence will be studied.

## 6. CONCLUSIONS

This paper presented a battery model framework to support path planning. By presenting mission planning case studies, we showed that including the battery model is important in predicting mission feasibility. The case studies also show that different mission planning strategy impacts battery's health and life greatly. Thus, a model that predicts battery's power, energy, and health index should be provided to autonomous combat vehicles and robots to improve mission execution.

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