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ADAPTIVE AGENT-BASED CONTROL FOR LITHIUM-ION BATTERIES IN NAVAL MICROGRIDS

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ABSTRACT

This paper presents an adaptive agent-based control scheme for operating distributed energy storage in naval power systems. The adaptive agent-based control scheme enables batteries distributed throughout an electrical grid to autonomously communicate and align each other to operate in the most effective way possible. To achieve this, each battery is assigned an agent capable of controlling the battery's output with the goal of maximizing the life of the battery while supplying the required power to the load. Along with the goals of the individual agents, system-level alignment strategies are employed to maximize certain aspects of the battery operations. The employed system-level alignment strategies are duration, ready, and aggressive. The duration strategy maximizes the longevity of grid resources of expected battery degradation and electric generator component wear by utilizing the system in a manner that optimizes system-level longevity. The ready strategy maximizes the amount of power being kept in reserve for use when needed while the Aggressive strategy maximizes power output by allowing the batteries to be used to their limits to deliver as much power as possible. Moreover, an adaptive strategy was also created by mapping the previously mentioned static strategies to the levels of power demand. This adaptive strategy allows the batteries to operate in the most efficient manner while adapting to the power demand from the load. To analyze these strategies, the chosen performance metrics were 1) battery and generator remaining useful life (RUL), 2) average battery temperature, and 3) percent of time the requested load profile was achieved. Results demonstrate that the adaptive strategy operates with better overal efficiency by maintaining the 2^{nd} highest battery RUL, the 3^{rd} highest generator RUL and the 2^{nd} lowest average temperatures. It was also the only strategy to fulfill the maximum pulse seen from the load.

Keywords: Agent-based control, Microgrid, Lithium-ion, Distributed energy storage, Prognostics

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1. INTRODUCTION

Lithium-ion batteries are the dominant energy storage (ES) solutions being implemented into electrical grids. Most research in this area is done with optimizing ES control for renewable energy implementation in mind. This usually entails optimizing the right times to store and release energy into a grid to make up for the varying energy supply of renewable sources [1, 2], or supporting smaller energy generation plants with renewables coupled with batteries [3, 4]. However, optimizing distributed battery operations in a vehicle or plant-based microgrid with non-renewable energy sources is less-studied. An example of this type of microgrid would be naval platforms that integrates electric propulsion systems with other dynamic loads (e.g., radar, pulsed weapons). Effective control schemes for this class of microgrids would enable more efficient ES allocation, longer lifespan for grid components, and more robust grid operations in general.

Typically, a battery management system is used to control a designated battery pack. However, in larger grids with multiple distributed battery packs throughout, an overall control scheme is needed to monitor and operate the distributed energy storage resources. The larger the grid, the harder for traditional battery management systems to solve energy distribution efficiently. Unavoidable issues such as distorted voltage profiles and power fluctuations during a ships operation can also decrease the effectiveness of a control system. A multi-agent system is a control system that can address these problems by dividing the complex large-scale systems into smaller subsystems [5]. The application of multi-agent systems in microgrids is becoming popular due to the agent's ability to cooperate and respond to fluctuations in the grid, while working autonomously in remote grids [6]. Research shows that this control scheme can ensure safe grid operation while reacting to disturbances on a decentralized energy storage system [7].

Multi-agent systems have been implemented before in managing the power flow of a simulated microgrid comprised of various renewable energy sources and batteries. In Necmi et al, The researchers created three different agents (battery, grid, and load) which worked together to effectively distribute power throughout the grid during different scenarios. The results demonstrate that a multi-agent approach improves stability and power quality of the microgrid [8]. Machine learning methods have been utilized to further improve the coordination of agents to distribute power throughout a simulated microgrid. Reinforcement-learning has been implemented to help better coordinate agents, forming an overall strategy that can change depending on the state of the power grid. Preliminary simulation results showed that the agents are capable of suppling power to a load under fixed and variable communication interruptions [9]. Efficiently supplying power throughout a ship's grid is essential when performing maritime operations. Failures caused by damage or inefficiency in the grid can lead to downtime which can cause degradation and be potentially fatal to the crew. These failures or efficiencies can be avoided by the use of an Agent based control.

Energy storage system (ESS) agents can be implemented to monitor and control a battery pack and its power converter interface. These agents can communicate to each other and adapt to meet the grid's required power demand. With this communication, the energy contributions of each battery pack can be controlled to optimize the battery pack's state within the grid leading to a more robust and efficient grid.

In this paper, an adaptive agent-based control scheme is developed to optimize distributed battery implementation into naval microgrids. The agent-based control scheme enables communication between three battery energy storage systems, a generator, and load within a simplified electrical grid. An adaptive strategy is also developed to allow the agent-based control scheme to be completely autonomous. The contribution of this paper is the development of a control scheme in which distributed battery energy storage agents throughout a grid can autonomously communicate and adapt in order to increase the grid's readiness and longevity.

2. METHODS

This work contains an adaptive agent-based control scheme for battery implementation into electrical grids. The control scheme and simplified electrical grid is developed and tested in MATLAB's Simulink environment.

2.1 Energy Storage System Agents

There are three energy storage system agents used in the control scheme. The ESS agents will monitor the outputs of the battery models and communicate the temperature and state of charge (SOC) to the other agents. With this information exchange the agents will organize themselves into a run order based off the priority of their batteries. The priority of the batteries is determined by their current state of charge and temperature. The purpose of this priority-based run order is to allow the batteries to shift the load onto the strongest battery(s) in order to let other batteries recuperate their charge or cool down.

2.2 Agent's Logic

The agents will monitor the outputs of their battery in terms of the power output, current state of charge, and the battery's temperature. The agent will decide on its battery's new output, based off the monitored values and priority order. After the outputs of the battery has been captured and the priority number assigned; the first step is to run a battery status check. The system check will verify whether the battery and its connections to the grid are operational. If the check comes back as both are operational, then the decision tree, seen in Figure 1, will determine which mode the battery should be in.

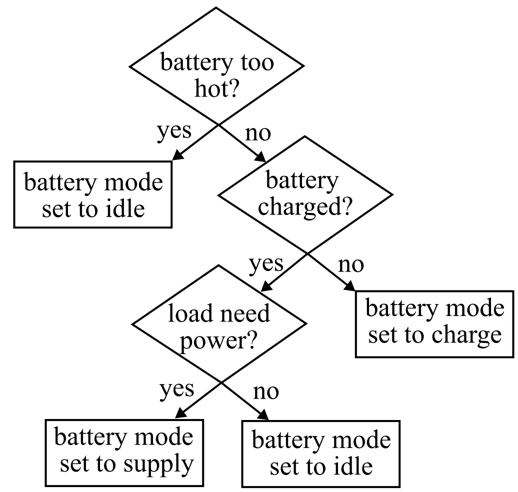

FIGURE 1: Decision tree for selecting the battery mode.

The battery can be in one of three modes charging, supply, or idle. The battery will enter charging and supply mode when it needs to charge or supply power. The battery can also enter idle mode for when the battery does not need to be supplying power or charging. This mode is also used to disconnect the battery when it becomes too hot; it will reconnect when it has cooled back within a safe temperature. Once the battery mode is selected the agent will then determine the output of its battery and proceeds to send the power to service the load. Then the process starts over again for the next iteration of the model.

2.3 Simplified Microgrid

The microgrid is composed of simplified models of key power components. The components are three energy storage systems (ESS), a generator connected to the bus through an AC-DC converter, and a variable load. The ESS components are composed of a battery, DC-DC converter, and contactors. The grid layout can be seen in Figure 2.

The generator model is an ideal power source for the batteries to charge from and does not aide in fulfilling the load. There is an implemented counter to count the start-stop cycles to produce a RUL measurement to help gauge the battery's performance in the micro-grid. Every time the generator is turned on and then off is counted as one cycle. The cycle life of the generator was chosen to be 100 start-stop cycles and is considered to be the time between maintenance intervals.

The battery models are simplified to meet the needed outputs for the agents to measure. They calculate the state of charge, RUL, and the temperature of the battery. The equations used can be

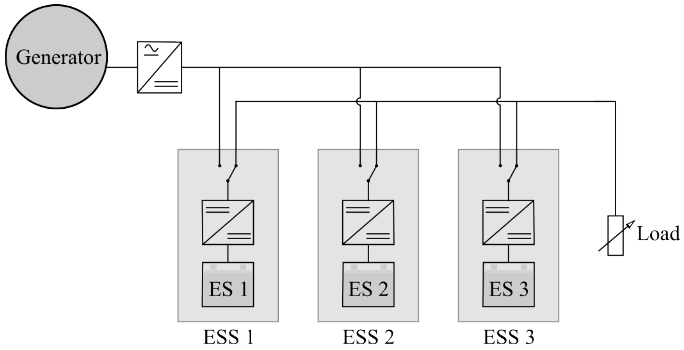

FIGURE 2: Diagram of the simplified microgrid.

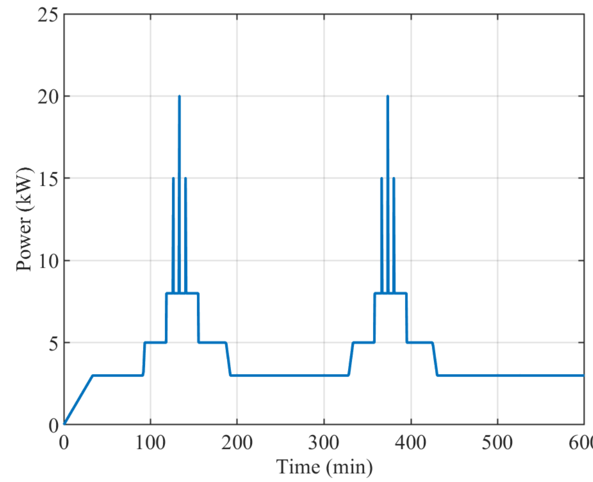

FIGURE 3: The load profile used to test the control scheme.

seen in equation 1. For temperature, currently only joule heating is calculated.

$$T_{\text{batt,f}} = \frac{h_{\text{batt}} A_{\text{batt}} (T_{\text{amb}} - T_{\text{batt,i}}) + P_{\text{Transfer, batt}}}{m_{\text{batt}} c_{\text{batt}}} \tag{1}$$

where h_{batt}, A_{batt}, m_{batt}, T_{amb}, $T_{\text{batt,i}}$, and c_{batt} is the convective heat transfer coefficient, surface area, mass, ambient temperature, initial temperature, and specific heat capacity of the battery respectively. $P_{\text{Transfer, batt}}$ is the power flowing through the battery.

The state of charge calculation is based off the power output. SOC and SOC_0 are the current and beginning state of charge of the battery. The time integral of the power transfer is added to the beginning state of charge to determine the current state of charge. This is seen in equation 2.

$$SOC = SOC_0 + \int P_{\text{Transfer}} \text{dt} \tag{2}$$

The RUL is calculated from cycle count and power output. This equation is seen in equation 3, where E_{max}, C_{life} and RUL are the max energy capacity, cycle life and RUL of the battery.

$$RUL = 1 - \frac{\int P_{\text{Transfer}} \text{dt}}{E_{\text{max}} * C_{\text{life}}} \tag{3}$$

The load in the model is a variable resistor subjected to a predefined power profile. The load profile can be seen in Figure 3. The idea behind the load profile is a simple 10-hour mission for a naval ship. With a standard operating load of 3.8 kW and two short engagements at around 150 and 380 minutes. At the beginning of each engagement the ship will increase speed thus increasing the load power level to 5 kw. It then elevates its awareness by turning on sensors and then proceeds to fire pulsed weapons. At the end of each engagement the ship returns back to the standard operating load.

2.4 Strategies

The agents will initially be aligned to an overall strategy during the duration of the test. Three static strategies have been developed to prioritize certain aspects of the batteries. Table 1 shows the three strategies. The power output values were decided on by the operational limits of the Simpliphi 3.8 battery which has maximum continuous discharge of 1.9 kw and maximum discharge of 4.1 kw for 10 minutes. The duration strategy is designed to prioritize the RUL of the battery by having a lower power output and limiting the useable state of charge range between 20% and 80%. The ready strategy prioritizes keeping as much energy in the batteries as possible. This is done by increasing the power output to a 1.1 C-rate (where C is battery capacity) and reducing the useable state of charge range from 100% to 80%. The reason for the increase in power output instead of a decrease is due to the batteries being the sole energy supply to the load. In order to satisfy the load with a smaller SOC range the increase in power output was needed. The aggressive strategy is developed to prioritize the maximum amount of output power. To do this, the state of charge range was enlarged to be from 0.5% to 100%, while the power output was kept at a 1.1 C-rate. To enable a fully adaptive control scheme, an adaptive strategy was created based off the load profile. The static strategies were mapped to power ranges. The duration strategy covers the 0 to 3.8 kw range, the ready strategy covers the 3.9 to 5 kw range and the aggressive covers 5 kw and above.

TABLE 1: The parameters set for each static strategy.

	strategies duration	 ready	 aggressive
max power output	1.9 kw	4.1 kw	4.1 kw
max temperature	40 °C	60 °C	60 °C
SOC range	80 %-20 %	100 %-80 %	100 %-0.5 %
load factor	0.6	0.7	0.9
temperature factor	0.4	0.3	0.1

3. RESULTS AND DISCUSSION

Figure 4 shows the performance of the different static strategies in addition to the adaptive strategy. This shows the combined output power of the batteries to the load compared to the load profile. From this figure it can be seen how well the static strategies and the adaptive strategy were able to supply the demanded power. For the duration strategy the load is under-met for a good portion of the load above the standard operating power

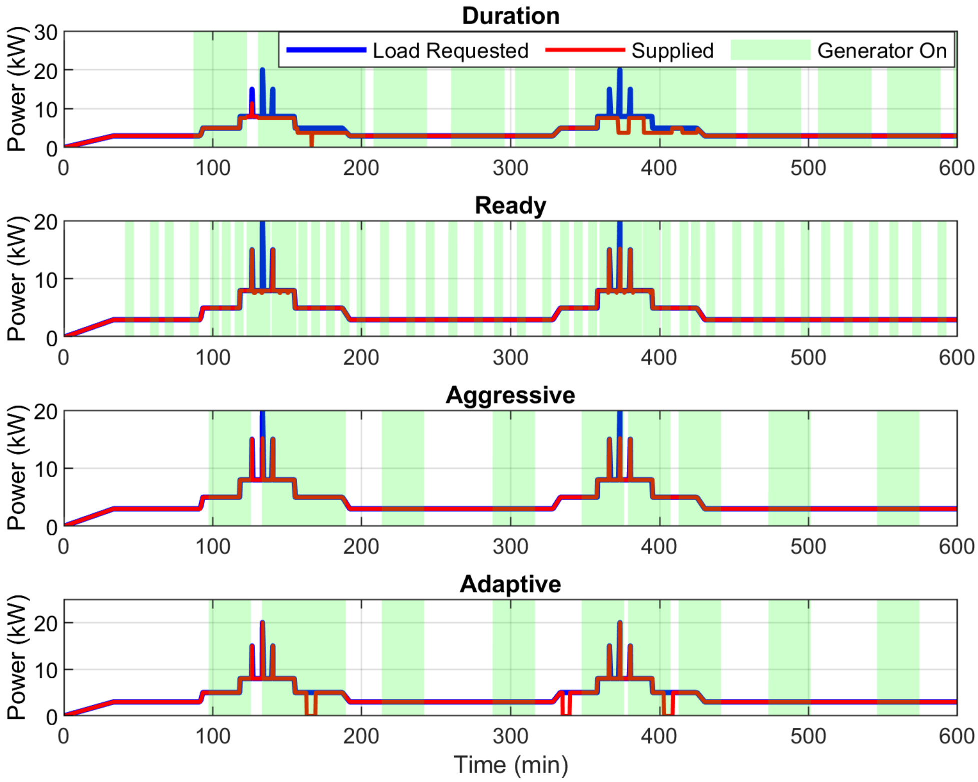

FIGURE 4: The strategy's performance against the load profile.

level. This is expected since the duration strategy was created to maximize the longevity of the batteries. This leads to the trade off of failing to meet the higher requested load levels in order to operate the batteries in an efficient manner. The ready and aggressive strategies were able to fulfill most of the load profile due to their higher output allowance. However, they both fail at different points during the pulsed loads. This is because due to the agents trading off which agent is charging their battery while the other two are discharging. This cycle of one battery charging while the others discharge leads to only two batteries at a time having the ability to fulfill the pulsed loads. In order to meet the smaller pulse two batteries have to max out their output rating and during the larger pulse all three batteries need to be discharging to meet it.

The adaptive strategy was able to meet both the smaller and larger pulses. Since the adaptive strategy transitions through the three static strategies the agents were able to prepare for the incoming pulses. This is due to the agents entering the ready strategy when the load power level surpassed the standard operating level of 3.8 kW. Which allowed the batteries to maintain a high SOC of above 80% in anticipation of incoming pulses while still fulfilling the current load with higher power outputs. When the load power level surpassed 5 kw the agents entered the aggressive strategy which allowed them to discharge past the 80% lower SOC bound from the ready strategy and successfully fulfilled the pulsed loads. The adaptive strategy did however fail at a couple of points during the mission at times 160, 335, and 403 minutes. This is a failure of strategy transition. At 160 minutes, the agents are shifting out of the aggressive strategy and into the ready strategy. As the agents are in the aggressive strategy they are free to discharge their batteries down to 0.05% SOC where as the lower bound for the ready strategy is 80% SOC. When the batteries get to this transition point, they are typically under this lower bound which leads to the agents immediately charging their batteries and dropping the load. This same failure is seen at 403 minutes. At 335 minutes the same out of bounds failure occurs but this time its during the transition from the duration to ready strategy. This failure can be remedied with a smooth transition of slowly shifting each battery into the new strategy over a certain time period; this method is being further investigated.

To gauge the performance of the agent strategies in optimizing the battery usage for their intended priorities are shown in Figure 5. The duration strategy was created to increase the longevity of the batteries that the agents control. The strategy has proven to be successful and can be seen in Figure 5 as it achieved the highest battery RUL, generator RUL, and the lowest average temperatures for the batteries.However, this performance comes with the trade off of being the worst in load fulfillment.

The ready strategy was created to maximize the energy reserved in the batteries to increase readiness while fulfilling the load. The ready strategy has successfully achieved this goal and can be seen in the metrics that the batteries were maintaining a

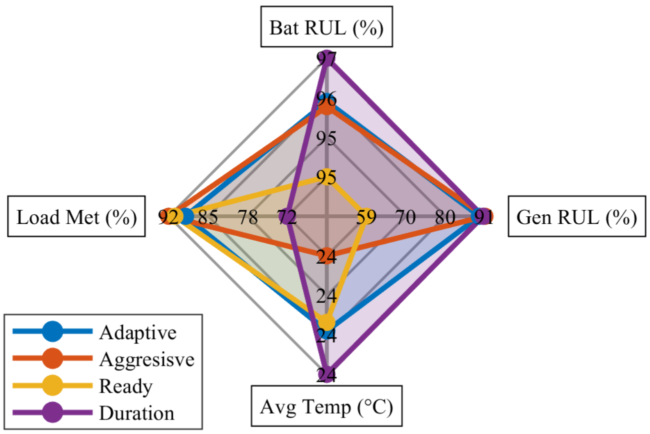

FIGURE 5: The performance metrics of the strategies against the load profile.

higher energy level by using the generator the most. while maintaining a higher energy, level the ready strategy was still able to achieve the 2nd highest load fulfillment. In meeting the goal of maintaining high energy level the strategy traded off battery and generator RUL to do it.

The aggressive strategy was created to maximize the power availability and the fulfillment of the load. The aggressive strategy successfully achieved this goal by fulfilling more load than other strategies and using the generator the least, however this came with the trade off of having the highest average battery temperatures and the 2nd lowest battery RUL.

The adaptive strategy was created to capitalized on the other strategies' benefits. It can be seen that the adaptive strategy is the middle ground between all the strategies by taking up the most area in Figure 5. It achieved a close 3rd in battery RUL, generator RUL and load met. It also achieved the 2nd lowest average battery temperature. The metrics that the adaptive came in 3rd are very close in value to the 2rd-place strategy. This is due to the simplicity of the load profile and as well as the simplicity of the battery and generator models. The difference in the metric values are expected to expand as the load profile becomes more complex and with more detailed battery RUL models that incorporate the nonlinear behavior of the battery's RUL in the more aggressive uses in both temperature and discharge rates. In future works this control scheme and the strategies will be tested on more complex load profiles and the detail of the RUL models will be increased.

4. CONCLUSION

This paper presents and tests an adaptive agent-based control scheme for distributed battery energy storage systems within a simplified microgrid; where the batteries were assigned agents to allow for control and communications. The agents were aligned to overall strategies to operate the batteries in unison to maximize certain aspects. The static alignment strategies are duration, ready, and aggressive which maximizes remaining useful life, energy reserves, and power output respectively. The adaptive strategy was created by mapping the static strategies to certain power ranges. Allowing the agents to adapt to the power demand. A load profile was defined and used to test and compare the strategies. The adaptive strategy resulted in the 2nd highest battery remaining useful life and the 3rd highest generator remaining useful life while maintaining the 2nd lowest average battery temperatures. It was also the only strategy to fulfill the maximum pulse from the load. This demonstrates that the adaptive strategy is a good mix between maximizing battery remaining useful life, energy reserves, power output and minimizing average battery temperatures. Future work will focus on adding more complexity to the overall system and models as well as further refinement of the adaptive strategy. Experimental validation will be undertaken on a microgrid with distributed energy systems.

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