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Extending Mission Duration of UAS Multicopters: Multi-disciplinary Approach

Marc Lussier
University of Nebrska-Lincoln, marclussier92@gmail.com

EXTENDING MISSION DURATION OF UAS MULTICOPTERS: MULTI-DISCIPLINARY APPROACH

by

Marc Lussier

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Marc Lussier, MS

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Adviser: Justin Bradley and Carrick Detweiler

Multicopters are important tools in industry, the military, and research but suffer from short flight times and mission durations. In this thesis, we discuss three different ways to increase flight times and therefore increase the viability of using multicopters in a variety of missions. Alternate fuel sources such as hydrogen fuel and solar cells are starting to be used on multicopters, in our research we simulate modern fuel cells and show how well they currently work as the power source for multicopters and how close they are to becoming useful in Unmanned Aircraft System (UAS) technology. Increasing the efficiency in which the available energy is used can also increase mission duration. Two characteristics that effect the efficiency of a mission are the flight speeds of the multicopter and the payload it carries. These characteristics are well known in larger rotor crafts but often ignored in smaller multicopters. In our research, we explore the effect of flight speed on the dynamics of a multicopter and show that higher speeds lead to higher flight times due to the effect of translational lift. Lastly, we developed an online updating multi-flight planning algorithm for stop and charge missions, a method that can potentially indefinitely extend a mission. The multi-flight planning algorithm, the variable resolution horizon, reduces the computing resources necessary to 15% to 40% of a typical optimal planner while having a maximum 5.6% decrease in expected future reward, a metric for accuracy. The results of this thesis help guide decisions in fuel type for multicopter missions, show examples of how

to increase flight time through increasing efficiency, and develop the framework for multi-flight missions.

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Chapter 1

Introduction

The diversity of desired missions and associated requirements for multicopter Unmanned Aerial Systems (UASs) is expanding rapidly. We see this in companies such as Amazon suggesting the future of delivery lies with multicopter UASs [1, 2]. Researchers and engineers have begun using them for inspection [3, 4] of structures and environmental areas. Search and rescue teams have adopted the technology for use in floods, earthquakes, and avalanches [5, 6]. Here in the NIMBUS lab, we have used multicopters to set prescribed fires [7], take water samples [8], gather weather data [9], and plant sensors [10], the last of which is the motivation behind this thesis. Multicopters work terrifically in the above situations, where interacting with the environment is necessary because of their agile flight and hovering ability. The energy and power requirements needed to enable this type of mission, however, are a major weakness. These limitations greatly restrict multicopter UAS mission types. The restrictions impact the distance the vehicle can travel, flight speed, and flight time – the consequences of which means multicopters are primarily good for short, nearby, slow missions, preferably with minimal payload and unaggressive maneuvers. To power multicopters lithium polymer, or Li-Po, batteries are the standard because they are capable of producing large amounts of power and therefore can handle the power requirements of multicopters. However, their energy density is low, thus limiting the mission range. If we are to expand the domains in which multicopters can be used extending the possible mission duration is imperative. This can be achieved by finding a better power source, increasing the mission efficiency, or creating a way to work within the current restrictions. In this thesis we explore an approach in each of these domains to increase mission duration by considering: Alternative fuel sources such as hydrogen fuel cells and solar power, using flight characteristics to optimize power usage, and building a multi-flight planner to be used in stop and charge missions.

In terms of alternate fuel sources both solar cells and hydrogen fuel cells are potential solutions for the low energy density problem of Li-Po batteries, either by replacing or supplementing them. Solar cells can also be used to indefinitely extend mission life by supplementing a battery in cases where landing and charging during daytime hours is an option. Currently, however, they cannot provide nearly enough power for continuous operation of a multicopter. As a result a vehicle must stop, possibly in an undesirable location or time, and recharge. Hydrogen fuel cells are compelling because of their large energy density compared to current battery technology. Hydrogen based fuel cells can contain more than 1000 $\frac{\mathrm{W\,h}}{\mathrm{kg}}$ compared to ∼200 $\frac{\mathrm{W\,h}}{\mathrm{kg}}$ for typical Li-Po batteries used in most multicopters [11]. This presents an opportunity to significantly extend the range of capabilities if the technology can be made to work with a multicopter UAS. Solar cells present a different set of challenges as they require a large surface area to be useful but provide continuous energy in sunlight. This has some potential on flight if a solar cell can be added and carried stably. More interesting to us is the potential to use a deployable solar cell as a charger in stop and charge, multi-flight missions. This could potentially extend missions indefinitely, making the limiting factor wear and tear on the multicopters themselves. To effectively use a stop and charge method multicopter UASs will need to autonomously decide which route will optimize their ability to carry out the task at hand.

Learning flight characteristics of different multicopters is another avenue that could bear fruit in terms of increasing mission duration. The flight characteristics of helicopters are very well known [12, 13], in fact each helicopter model has their own set of instructions on best flight speeds for endurance and distance depending on their remaining fuel. Pilots are required to be familiar with the specifications to avoid being stranded without a landing spot and to complete missions efficiently. The primary characteristic which affects helicopter efficiency according to the FAA is the idea of translational lift [14]. As the helicopter moves forward the airspeed over the spinning blades increases therefore requiring the propellers to pull through less air themselves to achieve lift. This phenomena causes helicopters to be more efficient while flying than while hovering. While the dynamics of multicopters are well known [15], formal research into characteristics such as the effect of flight speed on multicopters is scarce. One would expect though, that they act similarly to their larger counterparts. Learning the most efficient ways to fly a multicopter would greatly aid in the ability to increase the length of their missions.

How a UAS responds to a payload is another important aspect of their utility. The majority of mission types with UASs requires carrying some sort of payload, whether it is a package, some sort of camera or sensor, or a robotics payload designed to interact with the environment, most multicopter UASs will be carrying extra weight. That extra weight will greatly effect the possible flight times for UASs and the shapes of the payloads will add to the drag effects during flight. Most UAS companies in fact release figures showing their flight times at different payload weights in the specifications. Our hope in this section is to validate our model and the flight time numbers suggested by the developer of our test multicopter, DJI.

Developing a stop and charge multi-flight planner brought up an interesting problem, how to deal with stochastic and dynamic environments. The planner must address uncertainty because conditions such as wind that effect the flight dynamics or even the battery life aren't always completely known making all decisions probabilistic. The planner is also going to be effected by changes in the environment. For example changing weather will effect the ability to charge, air traffic will effect possible flight paths, and changes in viability of different landing spots can pop up. The dynamic nature of real world problems needs to be considered.

Decision making in stochastic environments is well explored and frameworks such as Markov Decision Processes (MDPs) have received wide attention [16, 17]. MDPs though, are not without limitation. State space explosion hampers their usefulness as the state space grows exponentially with each variable upon which it is dependant. In these cases, researchers have developed tools to reduce the state space, therefore, reducing the computing resources necessary to solve for the optimal policy [18, 19]. For example, factoring the MDP [20] allows independent variables to be considered separately, while reward gradients allow policies to be estimated [21]. Because of their size, MDPs are generally solved ahead of time and the optimal policy uploaded to the vehicle to be executed at run time. This means MDPs must be carefully designed since, once the policy is uploaded, if anything in the MDPs changes it must be resolved offline for a new optimal policy. This then affects their ability to adapt in dynamic conditions or evolve through reinforcement learning techniques as they cannot compute large MDPs on the fly. In these cases a suboptimal MDP design is chosen and an imprecise, small MDP that can be solved online is created. The other option is to build a precise MDP and solve it offline without allowing for adjustments to the model. As a part of this thesis we suggest a new technique for building MDPs and solving them online which can produce near optimal policies while limiting the state space size. This new technique, which we call the Variable Resolution Horizon (VRH), enables us to indefinitely extend missions with an intelligent multi-flight planner.

Chapter 2

Related Work

This thesis touches on a broad range of topics with the hope of increasing the mission duration of multicopters. In this section we discuss a number of areas that informed our work. For the alternate fuel source section the common uses of fuel cells in industry and research, the use of fuel and solar cells in fixed winged UASs, the types of fuel cells available and their advantages, and the use of solar cells in flight are all important context for our research. We use these contexts to build the case that alternate energy is a critical advancement in multicopter UASs, and we indicate which current capabilities could translate to these advancements. The second section, flight characteristics, is primarily motivated by what is known about how helicopters react to different flight speeds. Translational lift is common knowledge amongst pilots and power curves to optimize efficiency are widely used. We expand upon this later in this section. Lastly we discuss where our mission planning work fits in the broader context of UASs, how MDPs with large state spaces are dealt with in computer science, and the inspiration for the variable resolution approach.

2.0.1 Alternate Fuel Sources

Using hydrogen and solar energy to power vehicles has been most prominently done in automobiles. Their lack of green house gas emissions and ability to run quietly have helped fuel their development as we push forward into a greener world. Tollefson explored the prospects of hydrogen cars on behalf of Nature [22]. Hydrogen fueled automobile research seemed to pass its peak after initial investment in the early 2000's but has made a comeback as fuel cell technology has rapidly improved in the last decade. Fuel cells are getting smaller and more efficient addressing previous concerns.

There are still many obstacles for hydrogen fuel cells to overcome before they become a commercially viable option for cars but they are already a great alternative in other sectors, especially the military. A recently declassified review of potential military uses for fuel cells by the Australian government confirmed that Departments of Defense across the world are intrigued by fuel cell potential [23]. In this review Campbell, Crase and Sims discuss the advantages of replacing typical fuel and batteries with a number of different fuel cells. The positives are shown specifically in missions that require silent power. Fuel cells and batteries are excellent options for these cases as both run quietly while gasoline and other combustible fuels do not. Fuel cells though, have a much higher energy density and do not require a long charging times. Instead they can be refueled by filling or changing the tank. This is important for vehicles where space and weight come at a premium or vehicles that cannot afford a long down time.

Kim and Kwon's recent paper [24] shows the potential for using fuel cells as alternates to battery power to increase flight times on unmanned winged aircrafts. The researchers showed that hydrogen fuel cells can be quite effective at this goal especially when a hybrid power system is used to overcome the pitfalls of the cells. This technique combined with the replacement of some materials with lighter acrylic will be useful in adapting fuel cells for multicopter UASs. Such work isn't uncommon as fuel cells on winged aircrafts have been explored for over a decade. The different generations of fuel cells that have been used on winged flight can be seen in [25], [26], and [27].

Other work into exploring the effectiveness of fuel cells for flight have shown promising results. The authors in [11] presents a detailed analysis of the benefits and pitfalls of different fuel sources for UASs. In this paper they compared $LiCoO_2$, $LiFePO_4$, Li-Po, and Li-ion before determining that Li-Po and Li-ion are typically the best battery types for flight applications due their high energy density, stability, and ability to maintain their effectiveness over many charging cycles. When compared to a fuel cell the primary advantage of Li-Po batteries is its ability to supply very high power at low weights (power density) and its efficiency at discharging usable energy. However, energy density in the fuel cell was shown to be much better and the weight needed to achieve a specific flight time much lower. In [11] battery and fuel cell weights are compared for different flight time requirements. For 1 hour flight time the Li-Po battery required enabled a slightly lighter craft than the fuel cell. However, after that point the weight of the Li-Po battery required grew much quicker to 10 kg for a 10 h flight as opposed to 4 kg for the fuel cell.

Similar research has looked into using different sources of hydrogen with fuel cell flight in mind. In [28], the authors create and test a hydrogen fuel cell system to help increase the performance of a winged UAS. They surmise that the potential in fuel cells for military applications comes from their low noise and heat signature being ideal for covert ops alongside the high energy density compared with batteries. In their experiment [28], the authors use a hydrogen based solution and explore how to best maximize the fuel. Such methods will be useful to future research and applications as this technology grows. The authors also discuss their use of a hybrid power system allowing the fuel cell to stay constantly at peak performance, sharing the load with the battery when necessary, and charging the battery when supplying excess power. Such a system would likely significantly increase flight times even in multicopter applications.

There are also other fuel cell types that could possibly be used. In [29], a number of different types of fuel cells were explored for the purpose of extending the flight of UASs. Electrolyte Membrane Fuel Cell or Proton Exchange Membrane Fuel Cell (PEMFC), Alkaline Fuel Cell (AFC), Phosphoric Acid Fuel Cell (PAFC), Molten Carbonate Fuel Cell (MCFC), and Solid Oxide Fuel Cell (SOFC) were all considered. These different fuel cells use different chemical or electrolytic processes to achieve the same result, turning hydrogen into water and energy. PEMFC were determined to be likely the best for this application due to its temperature range (between 30 °C and 100 °C) and its potential for large power outputs. This paper found that using a continuous power for the fuel cells is the most efficient use. Increasing the load too quickly causes a sharp fall off in productivity and can cause a quick drop in power produced. This finding reaffirms the usefulness of a hybrid power system which allows a battery to account for fluctuations in the load.

Gong and Verstraete also explore the historical uses of hydrogen fuel cells and compare different fuel cell tanks and fuel sources [30]. They show that PEM fuel cells are the most popular because they have the best operating power, energy density and power density when compared to other fuel cell types. When considering brands, their comparison shows Horizon Aerostack A-1000 and Protonex ProCore VI as the two best in terms of specific power having $571\,\mathrm{W\,kg^{-1}}$ and $1961\,\mathrm{W\,kg^{-1}}$ respectively. The ProCore VI is the fuel cell used on the Aerovironment Puma UAS, a UAS that was able to fly 9 h non-stop. When considering fuel types Gong and Verstraete explored pressurized hydrogen, chemical hydrogen and liquid hydrogen. Pressurized hydrogen is the most commonly used and is quite efficient but has the issue of requiring a large bulky tank which negatively affects its specific power and energy. Chemical hydrogen has the advantage that you can safely store high density hydrogen at a low pressure. Chemical hydrogen removes the need for a pressurized tank but requires a chemical reaction to separate the hydrogen for use. Liquid hydrogen, however, may not make sense because of the extremely low temperatures in which it must be stored.

For winged aircraft there is now a fleet of hydrogen powered UASs being deployed by some militaries. [31] discusses the shift of military research to creating drones powered by fuel cells. Military projects have ranged from small UASs such as the Swedish HyFish to larger High Altitude, Long Endurance (HALE) UASs. This shows the range that fuel cells can be useful. The power requirements from some of these projects are as small as 50 W while other can be in excess of 10 kW. [31] illustrates that these fuel cells have become a huge area of interest to the military because of increased flight time and ease of adding more fuel, thus limiting down time. The ability to use different fuels such as different hydrides, which are stable compounds, or just pure hydrogen also gives a tactical advantage as it can be adjusted for the situation. In a spot where having soldiers carry pure compressed hydrogen may be too dangerous, safer alternatives can be found.

Solar power has become prevalent in military research of UASs. The potential for winged aircrafts to fly continuously without refueling during the day gives solar power a unique advantage over other forms of fuel. In fact a number of papers present analysis and experiment for exploring the viability of using solar cells on winged UASs [32–34]. Some results show the ability to create an aircraft that can continuously fly for 6 hours on a day with solar radiation conditions that are about the world average. In fact winged UASs aren't the only UASs that can be powered by solar energy. [35] demonstrated that purely solar powered flight was possible for a multicopter by creating a quadcopter to run purely on solar energy. In their paper, they explain the selection of solar panels and how to properly protect them from in flight vibrations.

For the purposes of this paper, knowing that sustained solar-powered flight is possible, gives us an experimental example of increasing the flight time of a multicopter using solar cells.

2.0.2 Flight Characteristics

Multicopter UAS efficiency is another important area to consider. Strong efficiency will help overcome some of the limitations of alternate fuel sources. The fuel source, the motors, the propellers all add to the overall efficiency of the aircraft. The efficiency of different propellers on different multicopters was done by S. Z. Sverdlov in [36]. Zulkipli, Raj, Hashim, and Huddin describe their experiments to pick the most efficient motor [37] where they show the efficiency of different motors at different power levels.

The efficiency of flight is not only dependant on the quality of the parts. Characteristics of flight such as angle of attack and speed can have a huge affect. The authors in [38] explored the angle of attack idea and showed how the yaw tilt of a multicopter UAS can change the efficiency of flight. In helicopters the idea of translational lift is very important and well known. As a helicopter moves forward the increased airspeed over the propellers increases the amount of air being pulled through naturally, reducing the amount of power necessary to generate lift and therefore increasing the efficiency compared to a hover. In fact helicopters have handbooks [12, 13] which describe this characteristic with power curves allowing pilots to calculate the most efficient speed to fly to optimize flight distance or time depending on the weight of the craft. The dynamics of multicopters is quite well known [15, 39] but little comprehensive research into how translational lift affects their flight has been done. Some path planning research has considered the affect to make their algorithms energy aware [40, 41]. This research was done on each groups respective UAS of choice and shows how beneficial considering flight speeds in path planning can be on their respective airframes. Considering that translational lift in rotored aircrafts is a vital concept, a comprehensive model of our multicopter platform's characteristics should help to greatly increase flight efficiency.

2.0.3 Multi-flight Path Planning

Path planning to both maximize mission efficiency and allow for multi-flight planning for autonomous UAS missions has developed as its own distinct area in research. This area is quite broad and many different strategies have been applied, for example missions such as surveillance or collecting sensor data have been broken down into a shortest path problem [42, 43]. The authors in these papers plan their paths exclusively over the most efficient way to cover an area using one or multiple agents. This approach has proven effective in environments with little uncertainty and where each goal has the same priority. Others such as [44] use combinatorics to solve more complex problems such as multiple goal UAS swarm routing. This method treats actions as a chromosome like structure and uses random mutations and rewards to determine the best possible outcome. This technique works well in solving their swarm problem but isn't suitable for online updating as it requires large computations. To deal with uncertainty and different valued goals, many researchers [45, 46] have taken a different approach opting for the power of MDPs in these situations. This approach suffers from the same problem we are attempting to solve, the explosion of the state space as dimensions are added. Jeong, Ha, and Choi solve this problem using task allocation as their method of reducing the state space. This method chooses to only compute over accessible states, a similar goal to our receding horizon.

Plenty of research has been focused on reducing the state space and computing power necessary to use MDPs. For example, in [47] the state space is reduced by finding hidden structures within it. Their algorithm will search a state space by considering the problem deterministic. Any states that the planner would never consider due to their lack of path towards a viable goal are removed. Trimming the state space as such is always an advantage when possible. In many MDPs where there are only a couple viable routes, this can bring the state space down to a manageable size. This goal also drives the research in [48]. Instead of looking at possible paths to a goal state though, Dean, Givan, and Kim remove states and actions which will not produce meaningful rewards. Like these papers above we hope to reduce the size of the state space by not including unimportant information. In our research though, we determine that there is unnecessary detail in our state space as you move away from the current state and remove that detail as our means of problem space reduction.

To deal with excessively large state spaces in control theory, receding horizon approaches have been utilized throughout the field. This approach breaks a problem into chunks manageable by the CPU by only looking at the next couple of steps instead of the problem as a whole. This technique has been used in many different ways. [49] suggests it as a solution for dealing with feedback control for non-linear systems. Receding horizons are also familiar territory when flight planning, for example [50] uses a receding horizon approach to create trajectories for UASs when using mixed integer linear programming optimization. The receding horizon approach has also been applied as a useful technique to solve MDPs where the state space is considered infinite. Chang and Marcus proposed their solutions to this problem in [51] and [52]. By using a small, moving horizon at each decision all computations stay small enough to fit the processor. This paper discusses two solutions. First, a roll out policy is created by considering the average future reward of each state in the space. This estimates a finite horizon and creates a base policy and then builds on that base policy as needed. In some cases the receeding horizon encounters a problem where they can not confidently predict what the best base policy is. For these cases a parallel roll out strategy is implemented using multiple base policies to track the different trajectories and rank the policies. Techniques such as this which allow you to make micro decision that will help proceed towards a macro goal are incredibly useful in cases where things need to be calculated dynamically. In our research we leverage the idea of a receding horizon to determine where we include highly detailed information. Like the roll out strategy we are able to recompute and adjust the policy as we move throughout the state space.

Usually a state space is just arbitrarily defined as a discrete system since considering it continuous means an infinite state space. In control theory multi-resolution approaches have been used as a way of discretization. They have been applied in models from economics to vehicle control [53–55]. Both the paper written by Grune and Semmler and the paper by Nash use a multigrid approach to increase resolution for control problems. This method has proved valuable in controls as it can lower computation power necessary while increasing accuracy. Munos and Moore suggest a slightly different approach, looking at each state as a node on a decision tree, splitting each node whenever one of the three criteria they propose is met. The corner value theorem and the value non-linearity theorem they suggest give useful tools to create a near optimal policy while not over loading the CPU. Munos and Moore's corner value theorem was a significant inspiration to our work. The value difference method we use to determine the discretization of the state space uses their idea that large value differences between neighboring states imply important information is missing between them. This is the basis of how we determine the best possible discretization within our resolution horizon. Unlike the above work, which uses changing resolution throughout the whole problem space and solve, we only increase along a moving horizon.

Chapter 3

Extending Endurance with Alternate Fuel Sources

3.1 Introduction

Extending mission duration starts with better energy sources. Current LiPo batteries are great for meeting the power requirements necessary for multicopters but fail to sustain the power requirements for very long due to low energy densities, typically about $\sim 200\,\frac{\mathrm{W\,h}}{\mathrm{kg}}$. Higher density energy sources, such as hydrogen gas greatly outperform LiPo batteries with an energy density on the order of $\sim 30\,000\,\frac{\mathrm{W\,h}}{\mathrm{kg}}$. Hydrogen gas though need to be converted to electrical energy to be used and requires heavy fuel cells and storage containers to do so, fuel cells which grow with the power requirements, dropping the energy density of the entire set up significantly. Other options such as solar cells can give 250 W for 0.174 kg of weight and theoretically supply unlimited energy but require large surface areas. In this chapter we discuss and analyze through simulation how hydrogen and solar on multicopters would work and how future advancements are likely to vastly improve the industry.

3.2 Theory

Here we develop the equations and theory that determine hover endurance of a multicopter. We consider the power required to hover, the multicopter's efficiency, and discuss how to determine the energy contribution from each source. Using this we derive equations for the life of the battery in hybrid power systems, which is generally a necessity as current fuel cells struggle to provide the necessary peak power and adjust to changing conditions without a battery.

3.2.1 Power to Hover

In this section we derive the equations which describe the power necessary to hover, similar to the work done in [56] and [57]. To start, we consider the lift generated by the air moving through the rotors of our multicopter, which in a hover will equal the weight of the craft. Rearranging this with M being the mass of the craft, m being the mass of air being moved and using v as the velocity of the air we get

$$\frac{Mg}{v}\,dt = dm, \tag{3.1}$$

Considering the infinitesimal changes of the kinetic energy formula we get

$$dE = \frac{1}{2}dm\,v^2. \tag{3.2}$$

To solve for air velocity, consider the equation for torque from a propeller rearranged for velocity

$$v = \sqrt{\frac{T}{\rho A}}. \tag{3.3}$$

Where ρ is the density of air and A is the area of the propeller. Note that this is the force of thrust for each single propeller. The thrust from all the propellers will equal the gravitational force for hovering. Therefore $bT = Mg$ where b is the number of propellers on the multicopter. Knowing the area of a circle and that power is energy per second we derive

$$P = \frac{M^{\frac{3}{2}}}{r}\sqrt{\frac{g^3}{4\pi b\rho}}, \tag{3.4}$$

where the constant $\sqrt{\frac{g^3}{4\pi b\rho}}$ will be often denoted as k.

3.2.2 Efficiency

Using Equation 3.4 we calculate the theoretical power that is necessary for the multicopter UAV to hover. To find the theoretical energy used in a battery this theoretical power is multiplied by the time the multicopter can hover in seconds, $E_T = Pt$. The hover time is taken from each multicopter's specifications provided by the manufacturers. The actual energy that the multicopter uses is equal to the amount of energy the batteries can provide, also taken from the manufacturers specification, leaving us with the actual energy used or E_A, and the theoretically required energy, E_T. Efficiency is then

$$\eta = \frac{E_T}{E_A}. \tag{3.5}$$

This calculated efficiency will be assumed to stay constant for all the energy sources we use for the remainder of this paper.

3.2.3 Time of Flight

Since alternate fuel sources can struggle to deliver sufficient peak power or adjust to quickly changing conditions fast enough the multicopter will only fly as long as its battery can provide the power. Therefore the flight time is calculated by dividing the energy in the battery, E_B, by the power required from the battery, P_B. Therefore,

$$t = \frac{E_B}{P_B}. \tag{3.6}$$

Using the assumption that the supplementary fuel source's power, P_S, will be directly applied to the multicopter and that the efficiency in which the power is used is the same as the battery we get

$$P = \eta(P_B + P_S) \tag{3.7}$$

This equation though, is only valid for $t < t_S$ where t_S is the lifetime of the supplementary power source, after that $P_S = 0$. In all cases explored in this paper the lifetime of the supplementary power source is much larger than that of the battery.

3.2.4 Solar Cells

Recent improvements in solar panels make them a viable option for supplementing power for a multicopter. Solar cells have become so light weight, flexible and efficient that their addition can often add much more power to the system than is required to carry them. To calculate the added flight time we make the following assumptions. First, since taking load off the battery is a common goal of solar-supplemented flight, power from the solar cells can directly be applied to the multicopter, therefore skipping the loss in efficiency that charging the battery would face. Second, we assume that the multicopter uses the power from the solar cell with the same efficiency that it uses power from the battery. It is believed that the low efficiency is primarily due to the multicopter's dynamics so the source that is delivering power should not have a huge impact. Finally, we assume that the solar cells are working as efficiently as claimed by their manufacturer. This assumes they are constantly in direct sunlight during flight which may not always be the case.

Two specifications are necessary when trying to determine the added flight time; power per area, p_d, and mass per area, m_s. Using these we can determine the total power added

$$P_s = p_d A_s, \tag{3.8}$$

and the total mass added

$$M_s = m_s A_s. \tag{3.9}$$

Where A_s is the area of the solar cell.

Adding solar cells also creates a distinct advantage to other power sources; near unlimited energy. Every other option has a limited fuel supply limiting their potential. With the solar cells there is the option to park and charge as many times as necessary. This allows for missions outside of the typical range by using multi-flight planners [46]. Solar cells are not without drawbacks though as they need direct sunlight and mounting a large enough panel in a way that does not affect stability is difficult.

3.2.5 Hydrogen Fuel Cells

The hydrogen fuel cells present another option for increasing the flight times. They are lightweight, can be scaled up to provide a lot of power to take the load off a battery and have a much higher energy density than the batteries used on current multicopter, providing up to 4 times as much energy per kg in some cases [11]. There are limitations though, as mentioned in the related work section. Fuel cells are not as good at quickly adjusting to changing loads as batteries are and can and often struggle to deliver enough peak power to keep a multicopter running by itself. To complete the calculations, the fuel cells will be assumed to be running at full power at all times, a reasonable assumption considering the power they provide is generally less than the power required by the multicopter to hover. Energy the fuel cell can provide will be its nominal power multiplied by the number of seconds it can operate, t_s giving us

$$E_H = P_H t_S. \tag{3.10}$$

We use P_H as the supplementary power source in Equation 3.10 which will then hold valid as long as $t < t_S$. After that point though the multicopter goes back to being operated purely on battery power or battery and solar if a solar cell is attached.

3.2.6 Ideal Battery Size

The battery is the limiting factor of multicopter flight time due to its ability to deliver peak power and quickly adjust to changing conditions. It may be beneficial to increase the size of the battery even though the batteries comparatively inefficient source of energy. To find the ideal battery size for each alternate power source we derive equations for the total battery life, B, which will also be the total hover time

$$B = \frac{E_B}{\frac{P}{\eta} - P_S}. \tag{3.11}$$

where $E_B = M_B d$. Since the goal is to get battery life as a function of the battery's mass we split up the mass of the battery from the mass of the system. This gives $M = M_B + M_S$. These equations are substituted into Equation 3.4 to get

$$B = \frac{M_B d}{(M_B + M_S)^{\frac{3}{2}} \frac{k}{\eta r} - P_S}. \tag{3.12}$$

We then use this equation to graphically demonstrate results for specific cases below.

Table 3.1: Multicopter Specifications

Make/Model	Airframe mass	Total standard mass	Standard flight time	Max Takeoff Weight
DJI Matrice 600	5.96 kg	9.5 kg	32 min	15.1 kg
DJI M200	2.76 kg	3.80 kg	27 min	6.1 kg
Kitty Hawk	4.08 kg	9.15 kg	30 min	18.6 kg

Table 3.2: HES Aerostak Fuel Cell Specifications

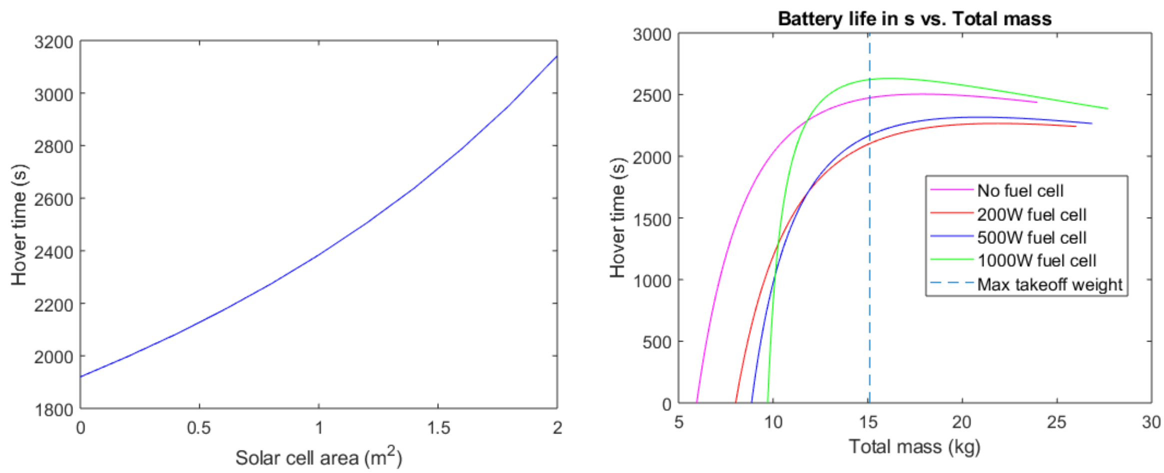
Power	Mass(Original/New)	L/min	Operating pressure	Equivalent volume at STP	Time at max power
200/250 W	2.06/1.93 kg	2.8	0.5 bar	1200 L	25714 s
500 W	2.90/2.12 kg	6.5	0.5 bar	1200 L	11077 s
1000 W	3.75/2.97 kg	14	0.55 bar	1091 L	4675 s

3.3 Case Study

Our case study consists of three parts: initial investigation, current advancements, and future advancements. The initial investigation contains our simulations and analysis on the systems available at the beginning of 2018. For the current advancements we consider the newest available technology as of November 2018 in our simulations. Finally in future advancements we explore what the future landscape of hydrogen powered multicopters could look like with some small improvements to technology.

3.3.1 Initial Investigation

We apply our theory to three different multicopters, a DJI Matrice 600, DJI M200, and a KittyHawk HDX4. Each of these multicopters are different sizes and allow three distinct cases to support our theory. For auxiliary power supplies, only commercially available products are explored to show current viability. Alta Devices technology solar panels are considered to model the equations and theory. The solar panels that they supply are highly efficient compared to the industry standard, about 28.8-31.6% giving a power output of about 250 $\frac{\text{W}}{\text{m}^2}$ while weighing 0.174 $\frac{\text{kg}}{\text{m}^2}$ [58]. The fuel



(a) Flight time with solar cell

(b) Flight time with fuel cell and increasing battery size

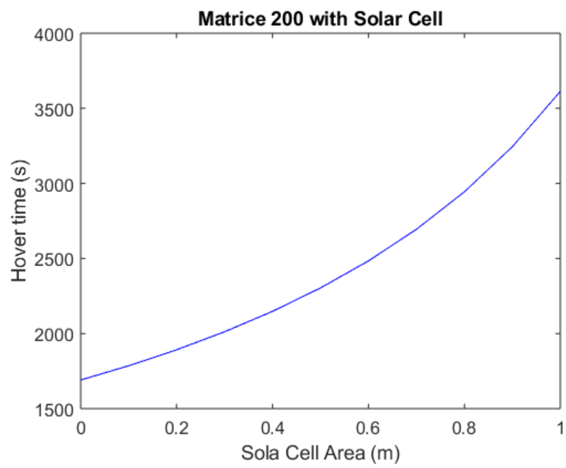
Figure 3.1: Matrice 600

cells used are HES Aerostaks and have a Ultra-Light Composite Storage Cylinder (E-Series) tank [59]. The 200 W, 500 W and 1000 W cells equipped with a tank that can hold 2 L at a pressure of 300 bar (Model # 3271522) are considered for this case study. Larger tanks could be useful in future research or if the plan is to park to charge but will not be included in this analysis.

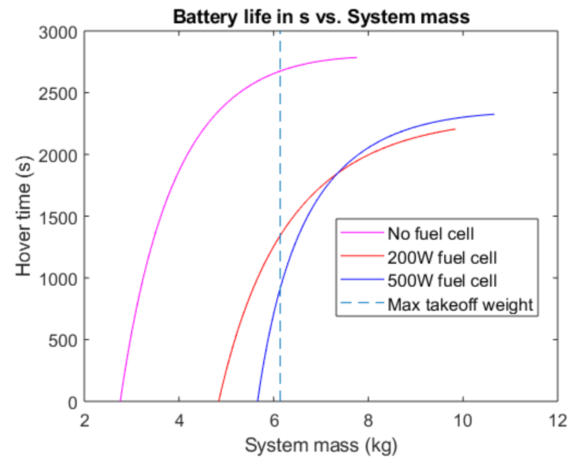
Table 3.2 shows the specifications of the fuel cells that will be used. All calculations for fuel cells are made based on these specifications. The time at max power is the operating time each of these fuel cells can achieve. This is much greater than the overall flight time of the multicopter and therefore will not be considered in analysis.

The Matrice 600 specifications can be seen in Table 3.1. Plugging in these numbers, along with the added power and mass of the solar cell into Equation 3.12 a curve describing the relationship between solar cell area and flight time is shown in Figure 3.1a. We note that the quadratic shape will not hold if the size of the solar cell continues to increase, this is due to the $M^{\frac{3}{2}}$ relationship as seen in Equation 3.4 . That though, is not of concern due to the relatively small amounts of area available on the multicopter. Figure 3.1a shows the flight time was increased by 64% when a $2\,\mathrm{m}^2$ solar cell was added and about 24% when there is $1\,\mathrm{m}^2$. The requirements of needing direct sunlight still exists but in good conditions one can expect a significant boost to the flight time. With such little weight added also there is very little fall off from standard performance if those conditions are not met. Knowing the potential to increase flight time also lends itself to the idea of multi-flight planning missions where there are scheduled charge times as mentioned earlier. In practice integrating enough area of solar cells to effectively harvest energy could be challenging on a multicopter.

For the fuel cells to add value a larger battery becomes useful. In Figure 3.1b, the graph of total mass including the fuel cell, the multicopter and the increasing battery size is plotted vs total time of hover in seconds. The multicopter's default battery specifications, particularly its energy density, is used as the standard in this case study. Figure 3.1b shows the 200 W and 500 W fuel cells are less effective than just increasing the size of the battery. This is a product of the battery life. The smaller fuel cells only take a small load off of the battery but leave unused excess energy when the battery dies. For the fuel cell to be effective it needs to take the majority of the load off of the battery. The 1000 W fuel cell shows good potential for increasing the flight time topping out at 2601 s with a total mass of 16 kg. This 16 kg is comprised of 3.75 kg for the fuel cell, 5.96 kg for the multicopter and the remaining 6.29 kg for the battery. This configuration increases the flight time by about 11.33 min, or by 35.5%. Although 16 kg is above what DJI suggests as the maximum take off weight, tests we conducted with this vehicle anecdotally show it can take off and is stable at that weight. Worth discussing is the case where the size of the battery is increased. At under 11.8 kg the increased battery size, 5.84 kg of battery, outperforms any of the other options besides the 1000W fuel cell, and improves flight time by 19.5% from 1920 s to 2294 s.



(a) Flight time with solar cell



(b) Flight time with fuel cell

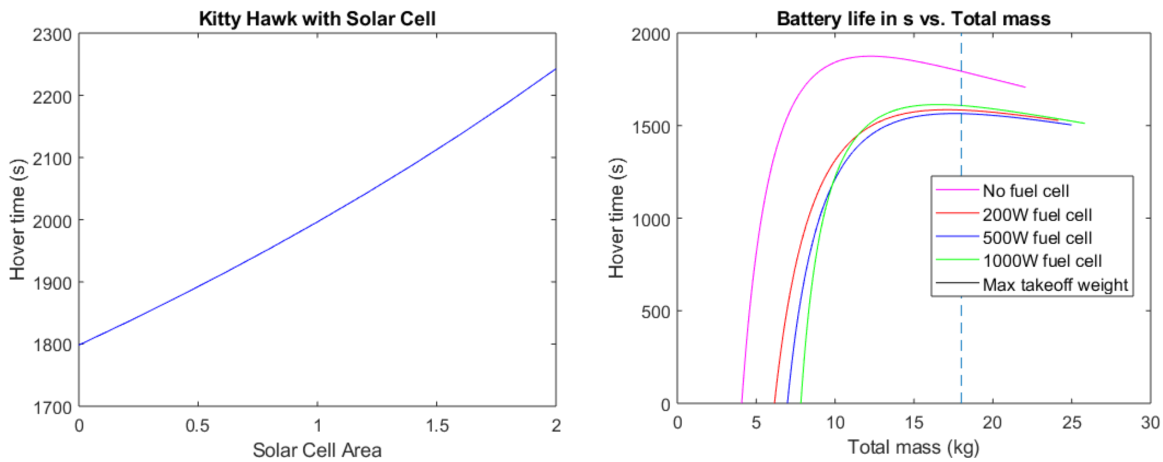
Figure 3.2: Matrice 200

Though the area available to fit a solar cell on the M200 is small, improved flight time could still be realized. In Figure 3.2b a 19% increase in hover time is shown for as small as $0.3\,\mathrm{m}^2$ of solar cell area. Anything larger will be a challenge to fit on the limited area but the added extra 6 min could prove to be useful in certain situations.

In contrast to the M600, the M200 is not suitable for the fuel cell. Being a much smaller craft, as seen in Table 3.1, it requires less power to hover but cannot carry nearly as much. Considering the load restrictions of this vehicle, a 1000 W fuel cell is unreasonable to carry. For this reason analysis will be kept to the 200 W and 500 W fuel cell. As seen in Figure 3.2b the M200 does not seem like a viable option to run on hydrogen. The weight added by either fuel cell actually adds less power than is required to carry it. This is a problem small multicopters will face as the base weight of a fuel cell large enough to help is much higher than what they can carry.

The KittyHawk is a prime candidate for solar cells. In the right conditions a theoretical increase in the KittyHawk's flight time occur with every reasonable denomination of solar cell area.

From Figure 3.3a, with $2\,\mathrm{m}^2$ of solar cell, up to 2243 s of theoretical flight time



(a) Flight time with solar cell

(b) Flight time with fuel cell

Figure 3.3: Kitty Hawk

can be achieved. This is about a 25% increase from the original 1800 s that the specifications show. This gives some confidence that solar cells, as light as they have become, will add extra flight time to a system of this size. However, the lack of efficiency from the aircraft creates serious obstacles for applying a fuel cell. The KitttyHawk had a calculated efficiency of about 25%, compared to about 31% for the Matrice aircrafts. This difference causes the fuel cell effectiveness to be severely limited because of the inability to use most of its power. The results, shown in Figure 3.3b, demonstrate that the fuel cells require more power to carry than can be used from them.

Increasing the size of the battery for this multicopter is the most effective way to increase the flight times. When the system weight, including increased battery, is at 12 kg a max flight time of 2343 s can be realized. This includes a base weight for the aircraft of 4.08 kg and 7.92 kg of battery. For the 1000 W fuel cell we max out at a flight time of 2149 s at 14.13 kg showing the fuel cell's inability, in this case, to outperform the battery even with its superior energy density. This, like in previous cases, is due to limitations of the battery as the fuel cell has an excess of energy when the battery dies.

3.3.2 Current Advancements

HES Energy Systems has reduced the weight of their new line of fuel cells. Their Aerostak 200 W system has been increased to 250 W at 0.13 kg less than the previous iteration. The Aerostak 500 W system weighs 0.4 kg less than the previous iteration and the Aerostak 1000 W system weight went down 0.78 kg. For this analysis we assume these fuel cells have a F2 F-series tank also from HES fuel systems.

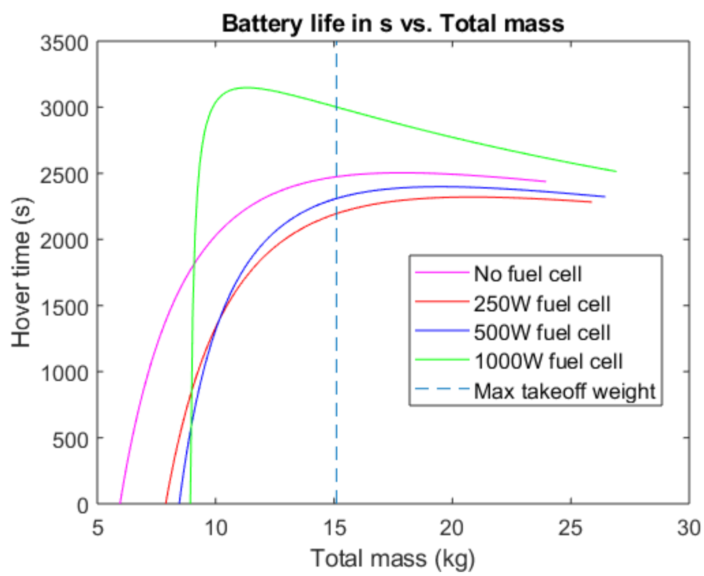
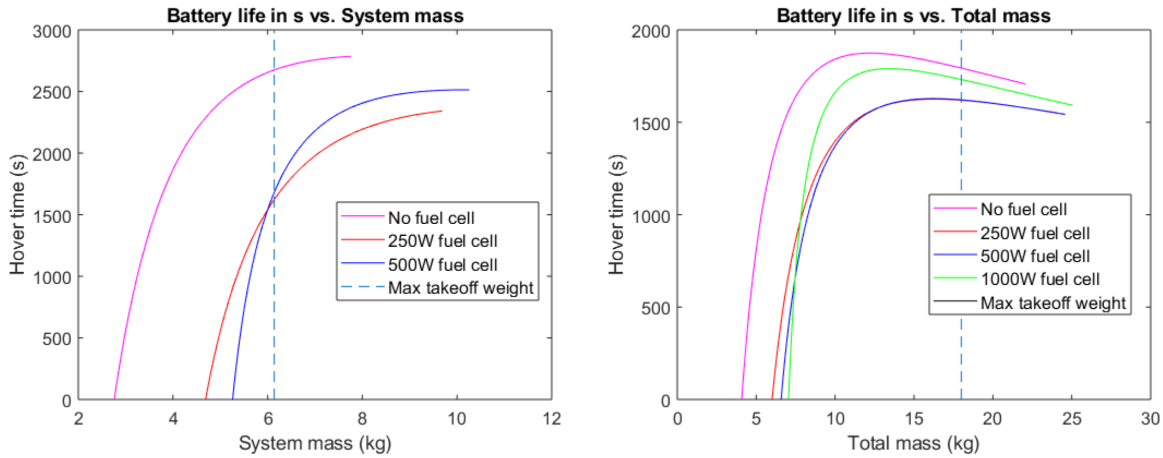


Figure 3.4: Matrice 600 flight time with current fuel cell

Since less weight requires less power, a smaller, lighter battery is sufficient to hover, and the vehicle can take advantage of the high energy density of the fuel cells. In Figure 3.4 there is a significant difference the lighter 1000 W fuel cell makes on the Matrice 600. Hover time peaks at 3148 s, or 52.5 min, as compared to 43.4 min for the last generation of fuel cell. Additionally, the peak flight time in the newest iteration occurs when the system weighs 11.23 kg which is a significant decrease from the 16 kg that was previously necessary. This improvement comes not only from the



(a) Matrice 200 flight time with new fuel cell (b) Kitty Hawk flight time with new fuel cell

Figure 3.5: New fuel cells

0.78 kg savings from the fuel cell but the fact that only 2.3 kg of battery is necessary to power the system instead of the 6.29 kg. This weight difference can have a large impact on mission logistics. A take off weight of 16 kg is above the DJI's suggested maximum while the new system can easily carry the fuel cell and a small payload. Even with the weight savings the smaller fuel cells still will not increase the flight time on the Matrice 600 and are not useful for the same reasons previously outlined.

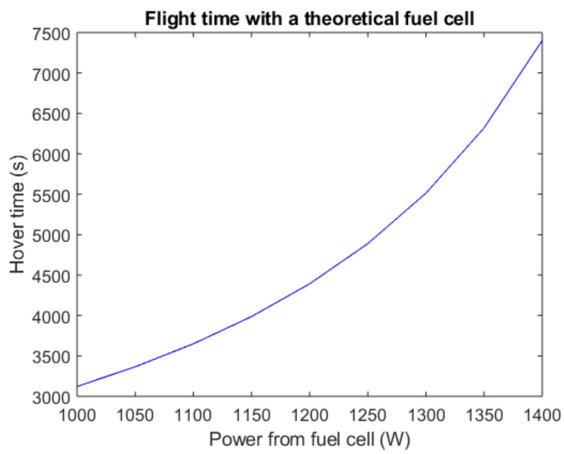
The new fuel cell is not quite viable to be used as a source of energy for the M200. As can be seen in Figure 3.5a, though there is an increase in viability from the previous iteration of fuel cell it is still not enough to be useful for the M200. Small UAV multicopters such as this are still likely far from being able to use hydrogen cells.

The Kitty Hawk also did not show the same potential with the improvements to the fuel cells in large part due to less efficiency as previously outlined. As seen in Figure 3.5b, the battery still outperforms the new advancements. The amount of power needed to power the vehicle, even at the lower weight, is too much for the fuel cell to overcome. This illustrates that higher efficiency multicopters will likely be the first to make use of on board fuel cells, further increasing their capabilities.

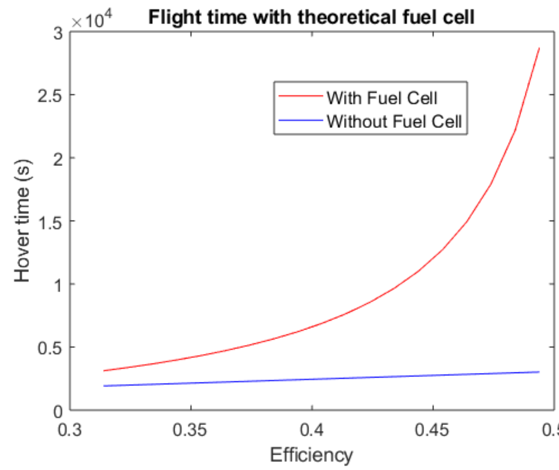
3.3.2.1 Hydrogen Multicopters

Since our first analysis in Spring 2018, a number of hydrogen powered multicopters have been advertised. HES fuel systems has released its HyCopter, a lightweight hydrogen powered multicopter UAV with a 1500 W fuel cell attached [60].Based on advertised specifications, this multicopter can sustain flight for 1.5 h to 3.5 h depending on the tank attached [61]. At the smaller tank the weight is about 11.5 kg and an additional 2.5 kg of payload can be added. MMC has also released a hydrogen powered multicopter called the HyDrone 1550. Based on specifications this multicopter can fly for about 2.5 h at a standard weight of 17 kg with the ability to carry an extra 1.5 kg of weight. This multicopter is equipped with a spare battery though it is not clear whether it is needed for sustained flight or difficult maneuvers.

These new releases show how the effects of new generation of fuel cell technology can have on the multicopter industry. New high efficiency fuel cells have allowed for specially made, high efficiency multicopters to be created that can effectively take advantage of the high energy density in hydrogen fuel. These new multicopters are also consistent with the analysis provided in this paper. A small advancement in fuel cell technology has increased the power density allowing it to completely take the load off of a battery. This allows the limiting factor for flight time to be the amount of fuel that can be carried rather than the battery's energy. As a result they can fly much longer, fully taking advantage of the high energy density of hydrogen. These technologies, though still in their infancy, are exciting and we look forward to seeing how these vehicles will perform in practice.



(a) Theoretical fuel cell



(b) Theoretical efficiency

Figure 3.6: Matrice 600 with theoretical improvements

3.3.3 Future Advancements

Current technology is just now breaking through the barriers previously preventing growth in multicopter flight time using hydrogen fuel cells or solar cells. Presumably minor advancements in fuel cell and multicopter weights and efficiencies are all that is needed for more fuel-cell-powered multicopters. There were two areas we have identified for potential advancement: fuel cell efficiency and aircraft efficiency. Fuel cells need to take the majority, if not all of the load off of the battery to unlock the potential of fuel cells. With either of these advancements the load on the battery quickly approaches zero making the limiting factor of flight time the fuel carried on the multicopter. To illustrate this, two theoretical graphs, Figure 3.6a and Figure 3.6b show how the flight time of the Matrice 600 would be extended if the power output from a fuel cell could be increased while maintaining the 1000 W weight or if increases to how efficiently the Matrice 600 uses energy could be made.

There are two important takeaways from Figure 3.6a. First, a modest increase in power output of just 30%, from 1000 W to 1300 W, increases the flight time by more than 63% compared to the current fuel cell. An advancement allowing this fuel cell to nominally produce its current max power corresponds to a large increase in flight time. Second, as fuel cell technology advances, our ability to traverse long distances with them will rapidly grow, only being limited by fuel storage. Figure 3.6b shows a different, but interesting effect of increasing the efficiency of the system; a hybrid fuel cell system benefits much more than a battery-only system. This happens because the improvement overcomes the issue with power density in the fuel cell. As efficiency increases, more usable power becomes available removing the load on the battery. The relationship seen will hold until the limiting factor becomes the energy in the form of hydrogen the drone is carrying. Once we reach this point, flight time will become linearly proportional to total energy just as it is with the battery. This goes to show that the multicopter efficiency increase has a similar effect as in Figure 3.6a, there is more power available to the multicopter therefore decreasing the load on the battery and extending the life.

3.4 Discussion

Here we discuss key takeaways and limitations we have found during our research that can impact how researchers design, build, and use multicopters. First, using current, commercially available solar cells is a viable path to increase flight time for both single flights and multi-flight missions. $1\,\mathrm{m}^2$ of solar cell can increase the flight time of the multicopters analyzed by around 25%, and can be considered for applications where solar charging is an option. Second, in specific cases, using a 1000W fuel cell on currently available vehicles can increase the flight time. This has the potential to be useful in a number of different applications, but is limited to little or no payload, even on large multicopters. In cases where landing and battery charging is an option, an excess of hydrogen can be carried to supplement the batteries and increase average flight time. Lastly, we are on the cusp of exponentially increasing the flight times and distances of multicopters using fuel cells, and this technology is advancing rapidly as can be seen by the jump from our initial investigation to our analysis of current technology. The industry is starting to break through the barriers to sustained hydrogen-powered multicopter flight, and some companies are releasing their own hydrogen-powered multicopters.

A limitation of note on hydrogen fuel cells that should be noted is the danger of hydrogen gas. Compressed hydrogen can be explosive if sparked, a danger that is very real in multicopters during crashes. Filling the tanks can also be dangerous as a spark can light both the tank on the multicopter and the larger storage tank on fire. The systems required to safely fill these tanks combined with the training necessary is prohibitive to casual multicopter users.

Solar cells have a couple important limitations of their own. Firstly, adding a solar cell must be done very carefully, as many configurations could seriously effect the flight dynamics and stability of the multicopter system. Configurations that closely hug the body of the multicopter without significantly effecting the flight may run into problems by violating one of our key assumptions, that the solar cell is in direct sunlight. The need for direct sunlight makes the multi-flight planner a more likely endeavour as a deployable solar cell can be used to better meet this need.

Chapter 4

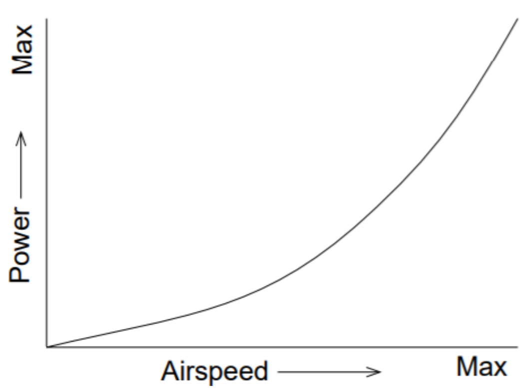
Optimizing Flight Characteristics

4.1 Introduction

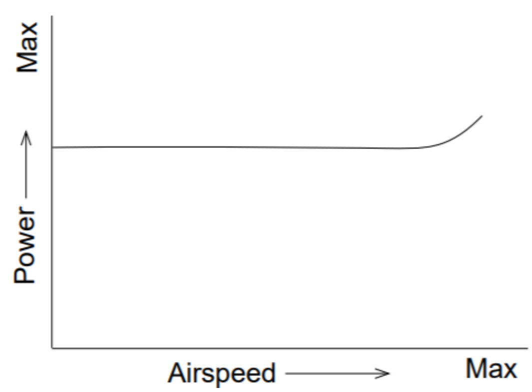
The flight time of a multicopter, or any vehicle for that matter, is based on the relationship between how much energy it uses to run and the amount of energy available. In the previous chapter we discussed ways to increase the amount of energy provided to a multicopter as a way to increase flight times. In this chapter we work to reduce the energy needed to fly. Flight characteristics are a big part of overall efficiency and are an important area of knowledge in all larger aircrafts where the cost of energy is very high.

4.2 Theory

Rotor based aircrafts have three distinct types of drag that affect their efficiency: parasitic drag, profile drag, and induced drag. The authors in [62–64] all describe the effects of these types of drags. Parasitic drag is the drag caused by parts of the aircraft that do not contribute to generating lift or thrust. These parts can be things such as landing gear or any accessories or payloads a multicopter or helicopter is carrying. Parasitic drag, as seen in Figure 4.1a, rapidly increases with speed, meaning the power requirements to overcome it do also. Profile drag, Figure 4.1b, is the frictional resistance of the air as it moves over the profile of the aircraft. Profile drag stays relatively constant for most airspeeds but grows rapidly at very high speeds. This happens because of an effect called retreating blade stall that we will not concern ourselves with in this analysis. The final type of drag is induced drag, shown in Figure 4.2a. This is the drag the multicopter creates to move air through its propellers and create lift. At a hover, all of the airflow through the propellers to create lift must be induced by the multicopter requiring a large amount of power. As airspeeds increase, more air starts moving through the propellers without the induction, lowering the induced drag significantly. This is the driving factor behind translational lift. When all three of these drag factors are considered, a power curve as shown in 4.2b can be created. From this curve, the airspeed that produces the minimum power is deduced and can be used to maximize efficiency.



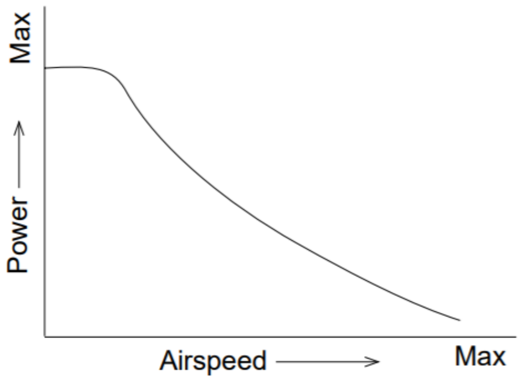
(a) Parasite drag as a function of airspeed



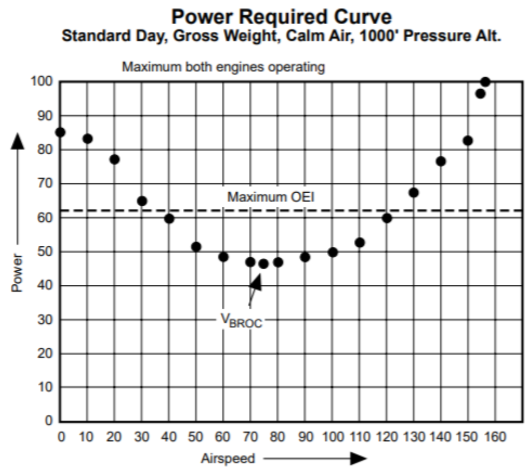
(b) Profile drag as a function of airspeed

Figure 4.1: Figures from [62].

Multicopters, though they have some differences, should be expected to have similar dynamics of a helicopter. They will have drag effects from their features and payloads, they have a similar profile to create friction with the passing air, and they create lift the same way with induced drag. In this chapter we discuss how flight



(a) Induced drag as a function of airspeed



(b) Power curve of a helicopter example

Figure 4.2: Figures from [62].

speed affects the life of a battery in a Matrice 600 multicopter.

The ability to hover with different payloads is also experimentally explored in this section. The theory and math behind the power required to hover is discussed in Chapter 2. Equation 3.4 shows the relationship between the total weight of the multicopter and the power necessary to hover. This equation shows a $M^{\frac{3}{2}}$ relationship we expect do dictate our results.

4.3 Method

The goal of this chapter is to show the effect of payloads on a hover and quantitative evidence that increasing flight speeds can have a positive impact on flight time. For the flight speeds we presume that the main cause of this effect to be translational lift but other effects such as motor and prop efficiency at different speeds can contribute. The contributions of each potential effect are not a concern in this research as we are more focused on the practical application than a deep understanding of the underlying dynamics.

We performed the tests on the Matrice 600 to stay consistent with our simulations of alternate fuel sources. The Matrice 600 is also great for these tests because of its autonomous flight software and the software based battery sets give good and accurate readings, adding to the consistency of our tests. We used the same set of LiPo batteries accross each set of tests as the performance of LiPo batteries change throughout the life of the battery. The differences across different battery sets can cause uncertainty in data.

The metrics we chose to evaluate our performance are average flight duration on a single battery life and average distance traveled on a single battery life. These metrics were chosen because our goal is to improve what can be achieved in a mission. Maximizing mission duration and distance are the primary ways to do this. In testing, not all of the battery levels started at 100% or used the same overall battery percentage. To deal with this, we calculate the time per percent battery which was averaged over each flight and then calculated the flight time that would be achieved going from 100% to 30%, the battery level where the low battery warning appeared. For the distance metric, this time was multiplied by the flight speed to get distance. These tests were done at three ground speeds, a hover, 10mph, and 20mph. Autonomous waypoints and a speed were set at the start of each trial. The Matrice 600 then travelled back and forth at the set speed until the low battery warning was set off. In an ideal situation the UAS would not have to stop and start traveling between waypoints, but we faced limitations. Only 400ft of straight space was available to fly and and the autonomous flight software would cause the multicopter to stop at each waypoint. This We prioritized consistency and relative effect over exactness in these experiments. To get exact results in future work use of a wind tunnel would greatly increase accuracy as the speeds measured would be air speeds instead of ground speeds. The hovering with a payload tests were set up similarly except with attached payloads of $0lbs$, $5.3lbs$, and $10.4lbs$. We conducted experiments on days with similar conditions generally, but small differences in wind speeds, from 5 to 10 mph, were beyond our control and affected the accuracy of our data.

4.4 Results

Our results show a clear increase in efficiency as flight speed goes up across different sets of batteries. Figure 4.3 clearly shows this effect as the time in the air increases with speed for both sets of batteries. In battery set 1, we see a nearly 19% increase in the overall flight time, and about a 7% increase in battery set 2. The cause of the inconsistency is unclear but the trend is not. This result is important because it shows that multicopters share the same power curve characteristics that are experienced by larger aircrafts. Knowing that time of flight increases with speed it is apparent that flight distance will increase dramatically as shown in 4.4. It is unknown from our testing to what speed this trend continues to and more in depth testing is necessary.

Due to the nature of the tests and batteries it is difficult to know the energy contained in each battery set. This prevents us from creating a true power curve representation of our system as we cannot deduce the power necessary without knowledge of the energy the system uses. Instead, in Figure 4.5 we show a relative power curve, where the power to hover is normalized to 100% and the power of different flight speeds is compared to that. In Figure 4.5 we see as little as 87% of the power to hover is necessary to fly on battery set 1, a similar effect to the curve we see in Figure 4.2b. In our tests we do not hit speeds high enough to facilitate the power increase on the right side of the helicopter's power curve and therefore cannot determine the ideal speed to fly. More tests should be conducted to fill in this curve better.

Figure 4.6 shows the effect of different payloads on the hover times. The trend

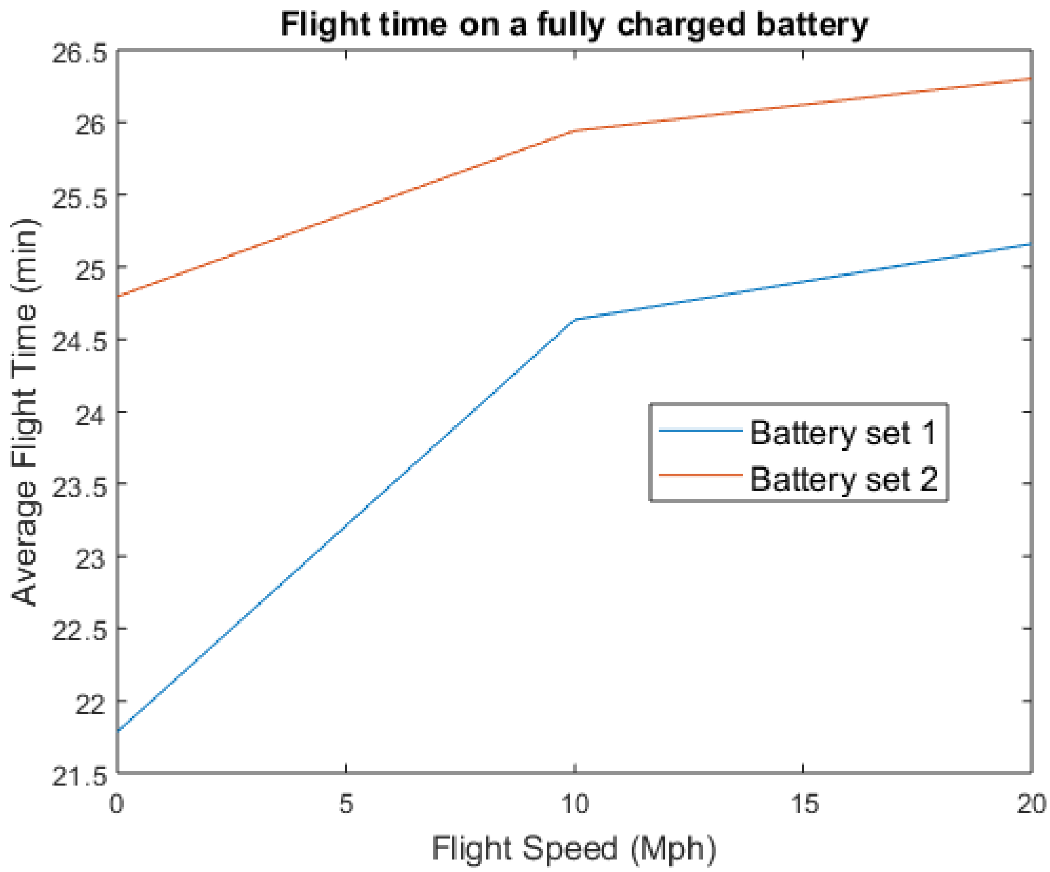


Figure 4.3: Expected flight time over one full battery life

seems to follow the $M^{\frac{3}{2}}$ relationship we expect but more data points would be needed for certainty. The line showing the DJI specifications is just there for reference. DJI only gives the no payload and max payload numbers so only two data points exist. Our number are consistent in comparison, they don't quite meet the expectations but this makes sense as the batteries used have a decent amount of wear on them so aren't expected to perform like the new batteries DJI would be making specifications for.

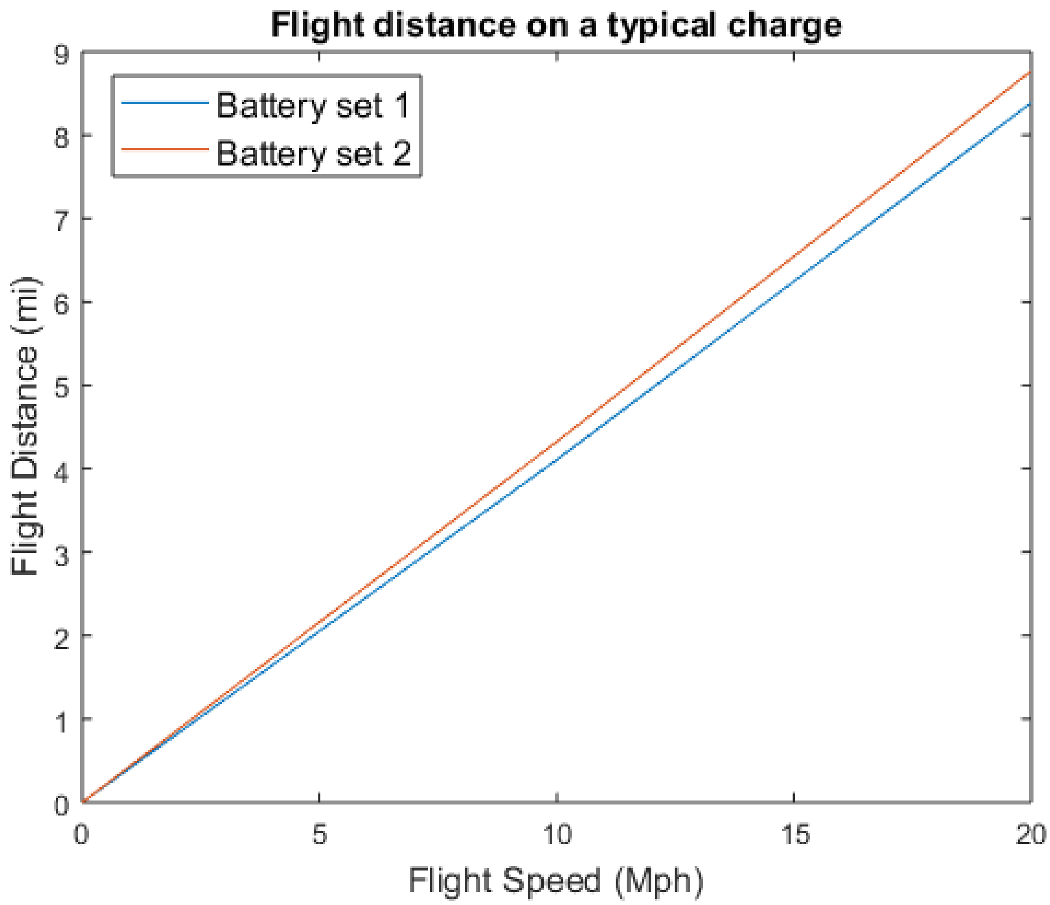


Figure 4.4: Expected flight distance over one full battery life

4.4.1 Discussion

The results show that there is a clear decrease in necessary power to fly as flight speed goes up for the speeds we tested. This is consistent with what has been known about helicopters for years and does not come as a surprise. If this testing was done in consistent conditions and with no stopping and starting necessary, we expect that the effect would be even more prominent and that our results would show a blunted version of the effect of translational lift. To be even more precise more tests, including different speeds and more batteries should be added. Other effects that cause changes in efficiency such as motor efficiency and effectiveness of the propeller blades on different speeds possibly contributed to our overall increase in flight, but we

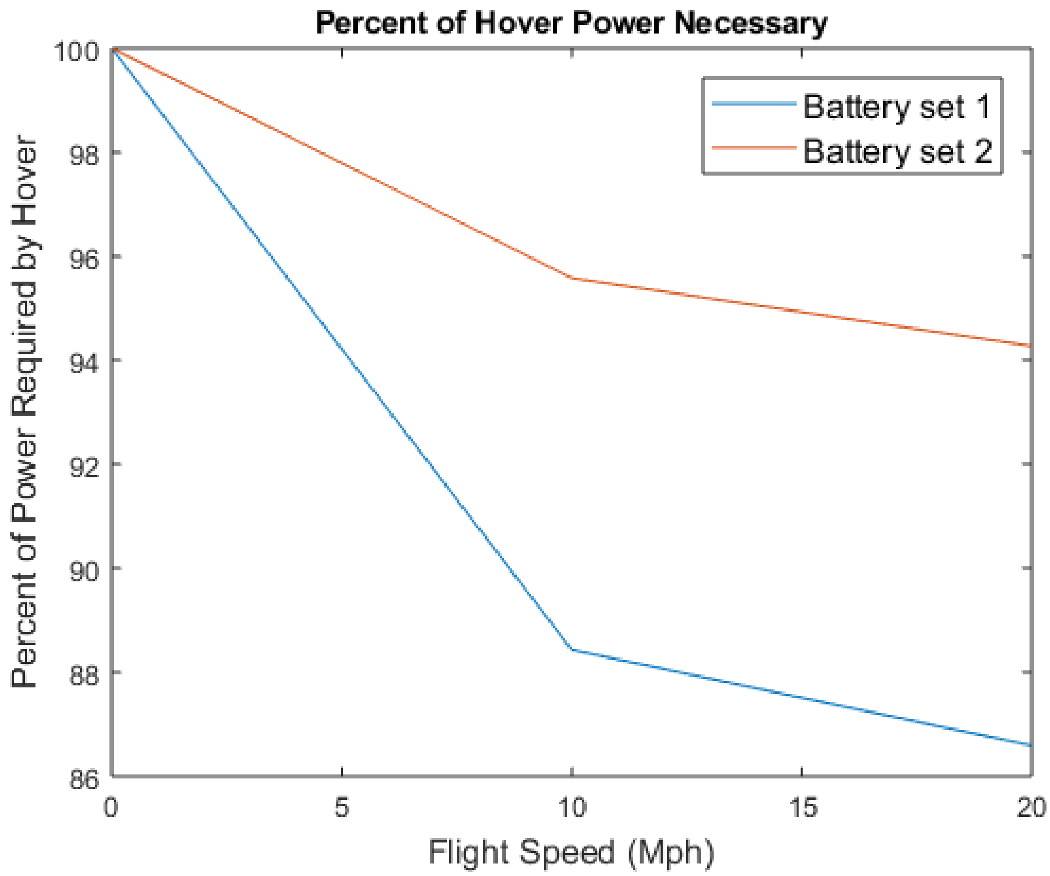


Figure 4.5: Relative power curve compared to a hover

believe they are unlikely to be the primary cause. Experiments such as those done in [36] and [37] show improvements caused by maximizing motor and propeller efficiency, but not on the scale seen in this experiment. Future work to isolate translational lift to more precisely characterize the dynamics would be very useful.

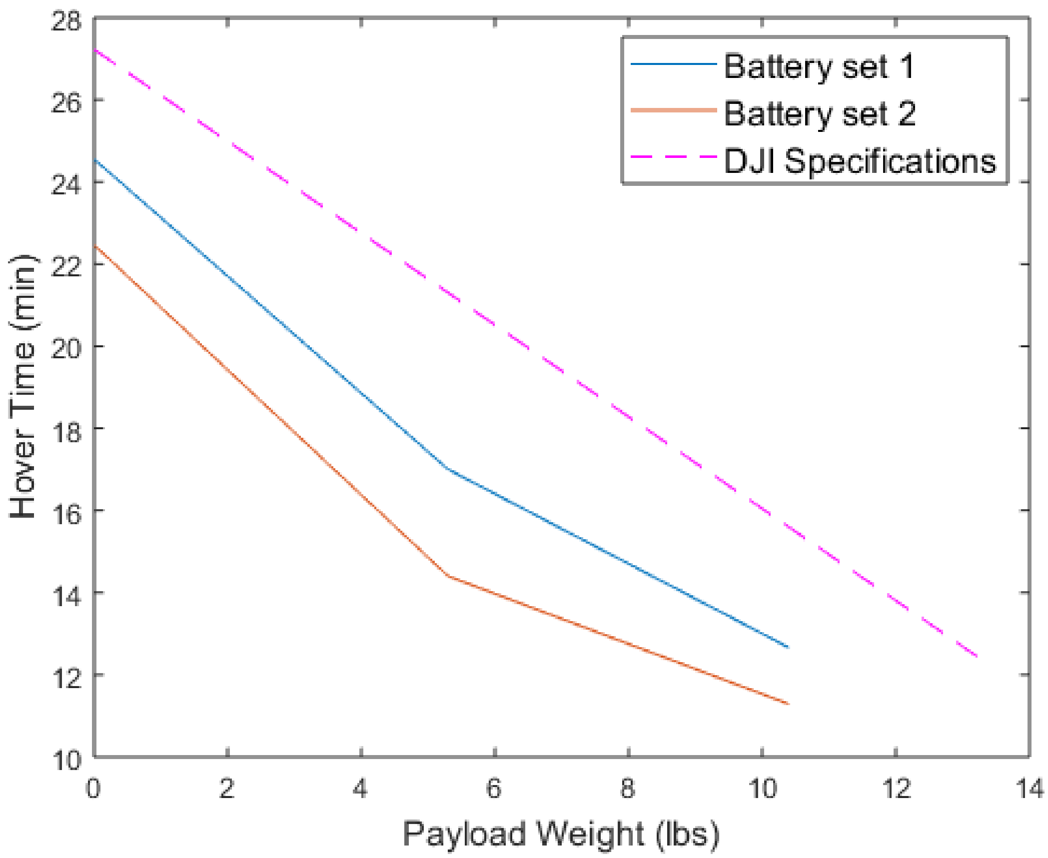


Figure 4.6: Flight times with increasing payload size

Chapter 5

Multi-flight Planner

As the proliferation of UASs increases new techniques to increase automation in all facets including mission planning have become important. In most of these cases, the decisions made are in the face of uncertainty, as conditions and mission objectives can be dynamic. MDPs are a common framework for dealing with these problems. MDPs first appeared in the 60s [65] and have been applied to decision making and planning algorithms successfully [66]. MDPs are powerful because they produce optimal, and easily executable policies in non deterministic environments. MDPs are described as a set of states (S), actions (A), transitions (P), and rewards (R). For each $s \in S$ and $a \in A$ there is a transition probability from one state to another represented by $P(s\prime|s, a)$ where $s\prime$ is the resultant state. For each state, a reward matrix, $R(s)$, is defined which gives value to each state. In most cases there is a small negative reward acting as a cost for non goal states and a positive reward for goals. MDP solvers such as policy or value iteration take this information and converge on the optimal policy by solving the Bellman equation through iteration [65, 67]. The optimal policy, which maps states to actions, is then easily executed as long as the vehicle can observe its current state. In this thesis, we will lay out a plan to build MDPs in a way they can be solved with limited computing power.

Our proposed algorithm, Variable Resolution Horizon (VRH) allows us to accurately and dynamically build an MDP which can be computed online by the UAS using typical MDP solvers because far fewer computing resources are required. We accomplish this by building the state space using a variable resolution approach dictated by a moving horizon. The horizon finds the states that are currently accessible by the system and the variable resolution algorithm determines an appropriate resolution of the state space within that horizon. This allows the next step to be determined with near-optimal accuracy. Outside of the horizon the state space remains at a much lower resolution to reduce space requirements. We can take this approach because precision is only necessary for the next couple of decisions and though future steps are important for computing MDPs the detail is far less useful. By keeping the resolution low outside the horizon we shrink the total size of the state space making computation of the MDP much easier. Making a manageable state space this way then allows us to re-solve the MDP at every step while considering any new information. In our case we apply VRH to a mission planner for a multi-flight mission. In a situation such as this new goals, hazards, and conditions can appear and the ability to adapt to them is imperative.

Another way to lower computational resources when solving MDPs is to use solvers which approximate the optimal policy such as dyamic programming, linear programming, and Monte Carlo simmulation [68–70]. These solvers are powerful and can be used effectively in conjunction with shrinking state spaces to further reduce computational resources necessary. VRH is meant to reduce state space, not as a solver to MDPs though so for the purpose of this paper we ignore differences in solvers and consider reducing state space size as the primary way to reduces computational resources.

Our research is motivated by a multi-flight mission requiring an UAS to land and recharge its battery with a solar cell. We assume <u>possible</u> landing sites are known a priori and each site has an associated cost. At each landing site, the UAS must consider battery charge and time of day to make the next decision of when and where to fly. The state space associated with this complexity is much too large for online solving of the MDP when a fine discretization is used to consider battery charge and time of day. If a more coarse discretization is used, the problem is easily solvable online but is a more suboptimal solution to the planner. We should note that optimal policy in this thesis means something different than in most computer science papers. Typically the optimal policy in terms of MDPs refers to the optimal solution to that specific MDP and is used to evaluate the effectiveness of different MDP solvers. Since we are not developing a solver for an MDP, but rather a way to build the MDP to best solve a problem, we refer to the optimal policy as the policy created by solving the best built MDP. We do this for simplicity as policy iteration, the MDP solver we use, is provably optimal [65] and therefore the effectiveness of the solver does not need to be considered. In either case, typical methods do not allow for dynamic adjustment as the policy is determined before flight and will not change. A new method to determine discretization and deal with dynamic conditions while producing a close to optimal policy is necessary to solve this problem.

5.1 Method

To solve large state space problems we propose a variable resolution approach to the discretization of the physical domain. We theorize that detail in the state space is less advantageous the farther you are from said state. Keeping this in mind we leverage the UASs ability to compute new policies dynamically while it moves through the physical problem, only increasing the resolution of the physical domain that is accessible. The variables that are considered inaccessible are left in a coarse discretization. For

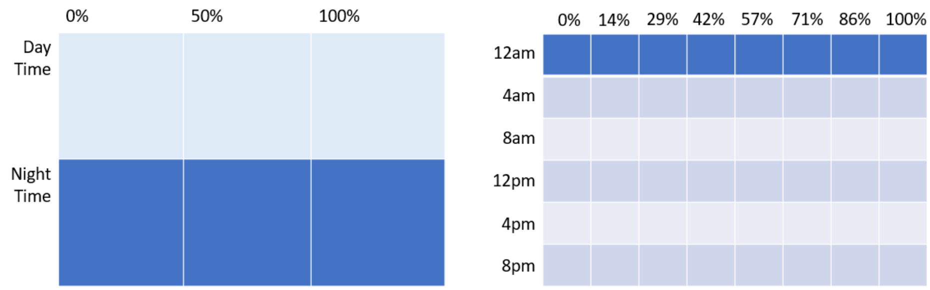


Figure 5.1: Coarse discretization vs. fine discretization of multi-flight example

example, in the multi-flight UAS problem, described further in the experimental setup section, we may start with the discretization bins for charge being 100%, 50%, and 0%, while we create day and night bins for time of day. From here we increase the resolution of the bins according to some sort of criteria that determines more information is necessary. An example of the results of possible discretizations for a landing spot are shown in Figure 5.1. To determine where the resolution should be increased, we create what we call a receding resolution horizon. This horizon finds the states that are immediately accessible to the UAS from its current position and the states accessible from those states, looking as far out as desired for the specific problem. Once a horizon has been determined, a modified value splitting algorithm, similar to that of [55], is used to determine where a finer discretization is useful. A new policy is then computed, the UAS attempts the decided action and the process repeats from the new state.

5.1.1 Discretization of Variables

Creating a viable state space in real world problems is often difficult. This is because there are so many variables in interactions, these variables often are dependent on each other and can be represented by continuous functions. Consider again our motivating example described above. A UAS that needs a multi-flight plan in which it can land

and charge by solar energy. If the UAS has n landing locations available, it will have $n+1$ possible actions; land at each landing spot, represented by l_n, or stop to charge during daytime hours, c. Therefore actions a can be $a = l_n$ or $a = c$. To make these decisions, the UAS must consider what position it should land next, p, what battery life is remaining, b, and what time of day it is, d. All three of these variables can be modeled as continuous, as the UAS could land anywhere between sections at any charge and any time of day. In the case of our motivating example though position is seen as discrete.

To solve this problem the physical domain must be discretized so states can be matched to it and an MDP built. An optimal solution can be obtained for every possible discretization using an MDP solver, though these will all be different as the actual MDP they are solving is different. It follows that the best solution would be the optimal solution that is derived from the MDP with the most information, or the finest discretization. To have true optimality of a solution to this problem, we would need to calculate using the smallest differences in variables the drone could reasonably sense (as mentioned in the introduction the optimal policy refers to the optimal policy of the finest discretization unless otherwise specified). In the case of of the solar charged UAS, if it can land with 1 meter accuracy, sense 1% charge differences, and has a clock counting seconds the state space would contain over 8,000,000 states per square meter. This is obviously unrealistic to attempt. Even in a situation where you break down the charge into 5% increments and day into 15 minute chunks, the average flight time of a UAS on a charge, there would still be 1,920 states for every possible landing spot you choose. For each of these states there are 3 possible actions, meaning the transition matrix will contain S^3 elements. A better solution is necessary for this to be viable.

5.1.2 Receding Resolution Horizon

In stochastic problems receding horizons have been one of the most successful methods for dealing with an infinite horizon or any state space which is too large to compute by building manageable state spaces for MDP solvers. In our case, we use a modification on the receding horizon idea to instead decide where to increase resolution of our discretization. Typical receding horizon approaches could also be applied to the state space as a whole in problems that warrant it, but that will not be explored in this paper.

The chosen horizon can vary on a case by case basis depending on the problem requirements. To calculate the horizon, we consider any $s\prime$ such that transition probability $P(s\prime|a,s) \times \ldots \times P(s^{(n)}|a,s^{(n-1)}) > B$ where n is the number of transitions the horizon should encompass and B is a parameter that can be tuned. Any of these actions or sets of actions which are more likely than the parameter chosen are what we consider reasonable steps. This calculation can then be made easier by evaluating the given system. For example when considering the solar UAS, any landing spot beyond the ones that don't fit the set criteria will also similarly not fit and therefore do not need to be considered. Similarly with the day time, we know that any action can only take at most an hour so we do not increase the resolution of that variable beyond that time. Using the receding revolution horizon with dynamic, real time decision making allows us to completely ignore many states which would otherwise need to be considered.

5.1.3 Value Difference

The discretization of the physical space is what will determine the accuracy of the policy and therefore is adjusted as part of VRH. The higher the resolution of the state space, the closer to optimal the policy is because more data is available to the MDP to consider. The goal of this section is to decide when a physical domain contains useful information that cannot be seen at the current resolution and to expand it. The hope is that we can find a balance in VRH which provides enough detail to produce a near optimal policy while also not overloading the computer with too much information.

Value difference is based on the assumption that any large jump in value between neighboring states likely means important information can be found in the space between them. This tells us that increasing the discretization of the physical domain in this area and rebuilding the state space would be useful. Say there are two neighboring states, s_1 and s_2 where $s_1 = (a_1, b_1)$ and $s_2 = (a_1, b_2)$. In this case variable b is a coarsely discretized continuous variable. If the difference in value of the two states is large, or $|V(s_1) - V(s_2)| > Z$ where Z is the splitting criteria, then we determine that important information is hiding between variable b_1 and b_2. This causes a split in variable b between b_1 and b_2 causing b_2 to shift to b_3. The value assigned to the new b_2 variable is just the average between the immediately surrounding values, or $V(s_2) = (V(s_1) + V(s_3))/2$.

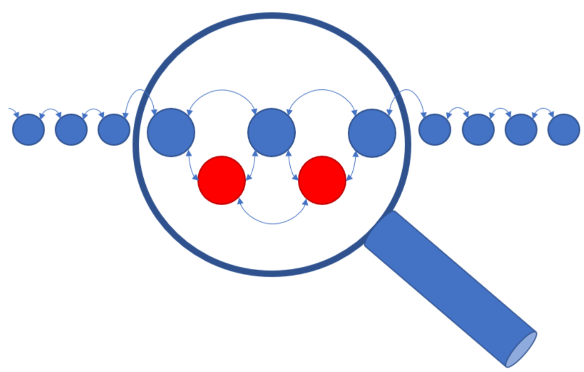


Figure 5.2: Visualization of resolution horizon

5.2 Experimental Setup

We tested the performance of VRH in simulation on a small controlled problem we call our test problem and the much more complicated UAS stop and charge problem, which motivated our research.

5.2.1 Test Problem

To test our solution, we propose a sample problem. The problem consists of a 1 dimensional physical domain in which the "UAS" can move either forwards or backwards with a specified probability as visualized in Figure 5.3. The UAS starts on one end and must reach a goal state that is on the opposite end. For each jump along the physical domain, there are 2 possible probabilities assigned, low ($P(s_i|s_{i+1}) = 0.2$) or high ($P(s_i|s_{i+1}) = 0.8$). When the UAS reaches a low probability transition, the value difference between its current state and the next state is very high compared to when the transition probability is high. Therefore $|V(s_1) - V(s_2)| > Z$ and the value splitting algorithm will split the continuous physical domain to add a new possible state $s\prime_{i+1}$ and shifting $s_{i+1} \rightarrow s\prime_{i+2}$, pushing all future states similarly. This state, which for sake of our problem, has a high transition probability from the current state and the policy will suggest it as the next move. As the UAS moves past this state it will forget the added state and continue on. This problem allows a very controlled environment for us to test the effectiveness of VRH. It splits in predictable places and has an easy to solve "full state space" for comparison.

The full state space, visualized in Figure 5.4 that is used for comparison had a finer discretization throughout it. It contains all of the states seen in the coarse discretization version described above with a high transition probability state in between each of them. This, for comparison gives a very complete state space but with more information than necessary, the condition where VRH should be used. Being able to compute the optimal policy for the full state space allows us to have a performance comparison

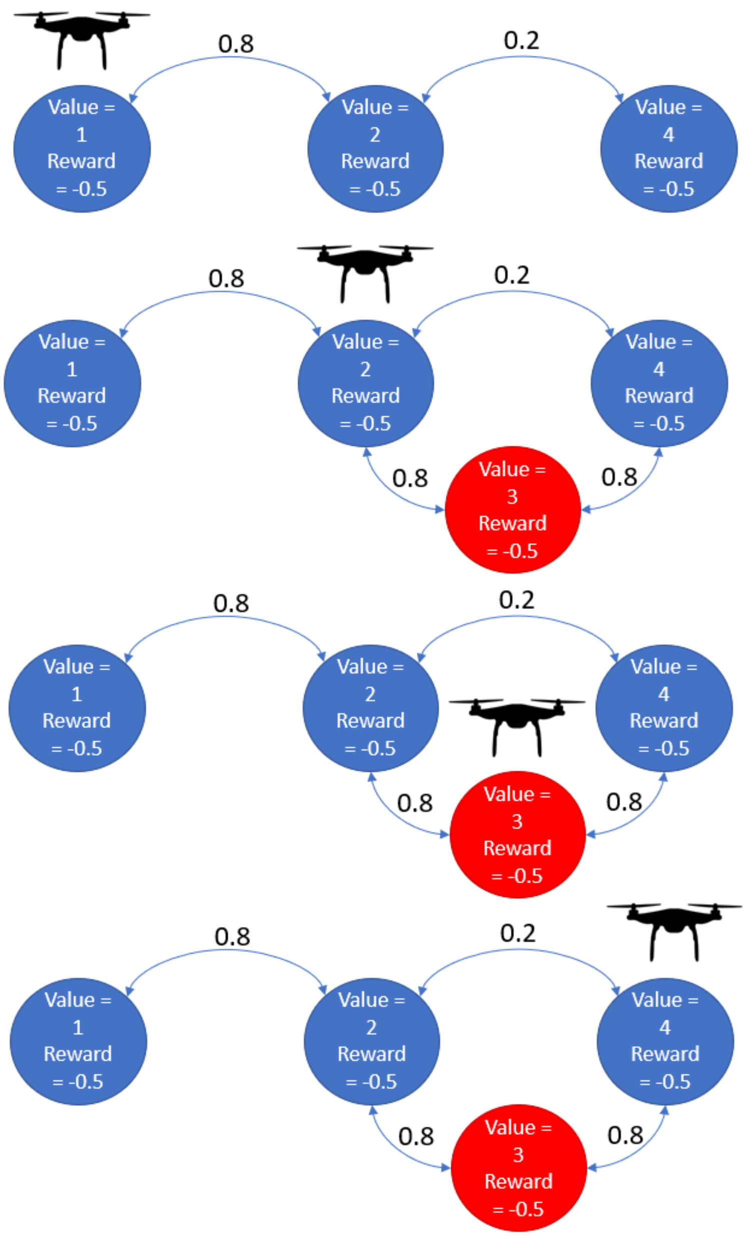


Figure 5.3: Visualization of test problem using VRH to discretize physical space (Z = 1.1)

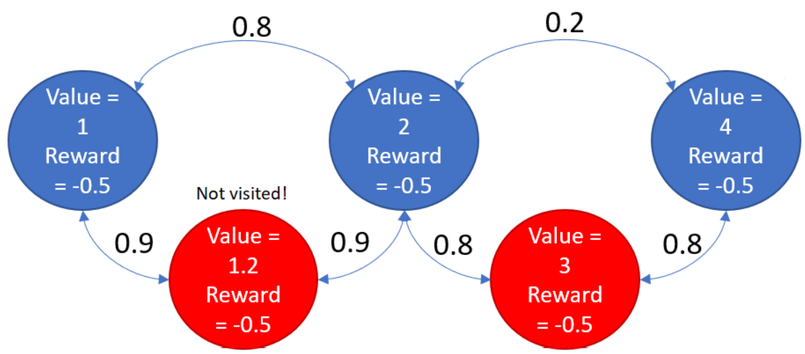


Figure 5.4: Visualization of test problem with maximum discretization

5.2.2 Multi-flight Planning Problem

The motivating problem, as discussed earlier is a simulation of a UAS, which charges using solar power trying to travel from a starting spot to a goal site. On the way the UAS will need to stop and charge to complete the mission. To test this we built a problem space consisting of a rectangular grid with 10 possible landing spots. The start is in one corner and the end is in the far corner. A normal distribution to compute the transition probabilities for flights and charging. Low and high resolution state spaces were made from this grid, with charge being discretized into 3 states for the low and 12 for the high while the time of day was discretized into 2 states for the low and 8 for the high. VRH was initially given the low resolution state space with the ability to change its resolution up to the same discretization as the high resolution when it sees fit. In this problem we want to pick the quickest possible route and therefore the cost function that is to be minimized is a function of time. The only positive reward available is for reaching the goal state.

5.3 Results

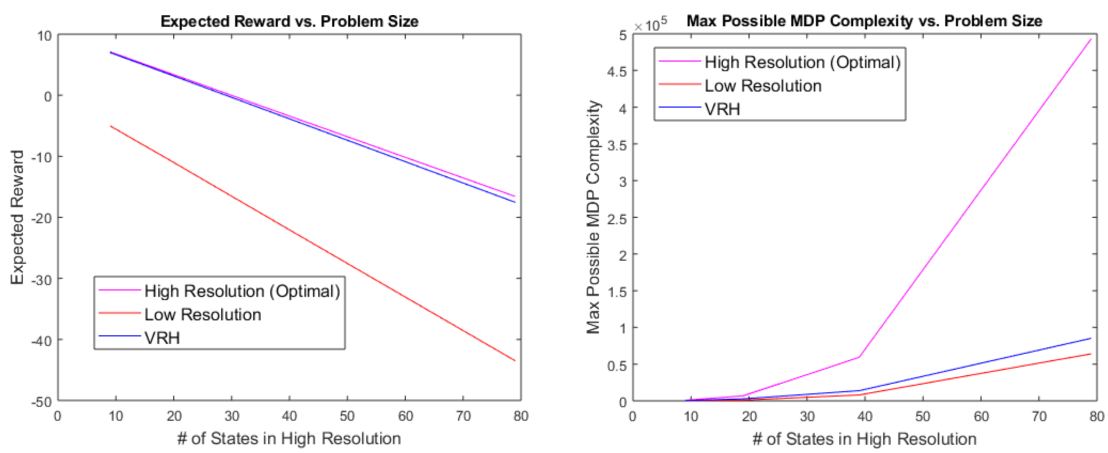
The effectiveness of the algorithm was judged on two different factors, correctness and MDP complexity. Correctness is determined by the average accumulated reward which will correspond to how efficiently the algorithm gets from the start state to the goal state. An optimal algorithm will have the highest average reward, therefore accruing the minimum amount of cost (the negative reward associated with each non-goal state transition). MDP complexity is the metric we use to measure the memory and processing power used by the problem. The MDP complexity is defined as the number of possible states, actions, and rewards all multiplied by each other or $S \times A \times R$. We chose this metric as it is a better indicator of the resources the problem will require and is not dependent on the code implementing it.

Two variables that will have the largest affect on our results, number of states and the minimum optimal path length (MOPL). The MOPL is the number of states that will be visited if the policy could be carried out in a deterministic manner. In Figures 5.2, 5.3, and 5.4 red states show locations that will only be seen when resolution is high while blue states will appear regardless of resolution. The results are split into two sections representing the isolation of each of these variables to show the conditions in which VRH is most effective.

VRH is an algorithm designed to build a MDP state space dynamically and therefore we need to use a typical MDP solver to build a policy. In our case we used Policy Iteration as the solver. The ever changing nature of our state space also means that typical indicators of performance such as expected reward cannot just be computed by the resultant policy, so to test our algorithm we executed it on a simulator up to 10,000 times depending on the conditions and use the averages for our results.

5.3.1 State Space Size

The primary purpose of VRH is to reduce excessively large state spaces to ones manageable by the processor available while not sacrificing significant accuracy, allowing UASs to integrate MDPs into their decision making process more readily. Figure 5.5a shows that even as the size of the state space grows VRH is consistently about 3.5% less efficient than the optimal policy. The savings, as seen in Figure 5.5b rapidly grow as the state space grows, using as little as $\frac{1}{5}$ of the computing resources in the largest case tested. In the optimal case for this test problem, where n is the number of states in high resolution, n states, actions, and rewards must be considered resulting in a complexity of n^3. VRH only sees a high resolution at a maximum of 2 transitions in either direction, while seeing half the states of the high resolution elsewhere. This results in $\frac{n}{2} + 4$ states, actions, and rewards or a MDP complexity of $(\frac{n}{2} + 4)^3$. In other problems the savings are potentially even greater as they depend on the number of states that are hidden to VRH at a time.



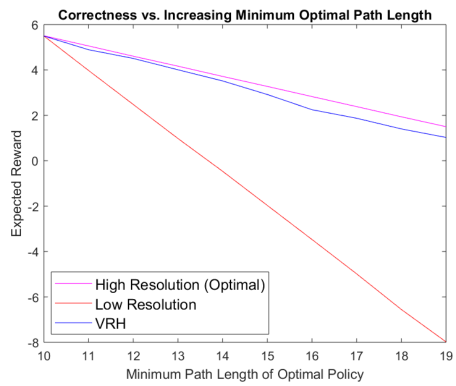
(a) Expected reward as number of base states increases

(b) Complexity as number of base states increases

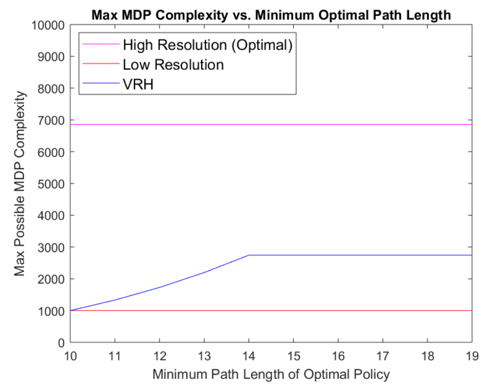
5.3.2 Minimum Optimal Path Length

The MOPL corresponds to the number of states which would be visited if the optimal policy was followed deterministicly. We use this as a control variable because the number of states that the optimal policy visits which are not contained in the low resolution state space, or the red states in Figure 5.3, and Figure 5.4, increase linearly as the MOPL does. For the test problem, there are 10 locations which will be seen by the low resolution and initially by VRH. Nine additional locations appear in the high resolution version. The 10 locations from the low resolution will always appear in the optimal policy, so in a case where the optimal path length is 10, only those 10 locations appear in the optimal path. Every additional stop on the optimal path length will correspond to an additional position from the high resolution version being used on the optimal path. This allows us to test the performance of VRH as the number of times it rediscretizes the state space increases.

Figure 5.6a shows how VRH compares to low and high resolution MDPs. VRH is nearly as effective as the high resolution MDP at solving this problem. When only the initially visible states are visited, VRH and both high and low resolution MDPs preform nearly identically. Even in the other extreme where the minimum optimal path visits every state in the high resolution, meaning VRH will increase to the high resolution at every opportunity, VRH still preforms nearly optimally as seen in Figure 5.6a. Even in the edge case VRH is only 5.6% less efficient than the high resolution MDP. The low resolution on the other hand does not see states that are advantageous to visit and gets stuck attempting low probability transitions rendering it ineffective. The advantage for VRH in this problem comes from the computing resources it saves. Figure 5.6b shows how VRH's max MDP complexity is affected by the minimum path length of the optimal policy. The high resolution MDP has around 7 times the complexity in the low minimum path length of optimal policy edge case and about 2.5 times the complexity as VRH in the high end edge case. This happens as VRH will never need to compute over the entire problem space by limiting high resolution to its horizon. Even in cases where a fine discretization is needed everywhere there is a distinct advantage in VRH's ability to reduce the complexity of the calculations as the high resolution is only seen within the horizon.



(a) Expected reward as MOPL increases



(b) Complexity as MOPL increases

5.3.3 Performance on Motivating Example

Figure 5.7 shows the performance of VRH in terms of expected reward compared to using either the high or low resolution state space. VRH's median performance matched the median performance of the high resolution state space and greatly outpaced that of the low resolution state space. This result is consistent with the sample test problem where VRH's performance nearly matches the optimal case and achieves this while using a fraction of the resources. Figures 5.8b and 5.8a are examples of the changing resources used by VRH in a representative simulation. Even at its peak MDP complexity VRH is about $\frac{1}{3}$ the MDP complexity of the high resolution. The combination of performance and computational savings means that problems too large for high resolution to solve can be solved to a near optimal standard using VRH. The time decisions take can be an issue, at the peak MDP complexity the recalculation can take anywhere between 1 and 3 hours, an issue that depending on the time scale the decision needs to be made on can be prohibitive. In the case of our motivating example the decision's time scale is similar or smaller than the charging time scale and therefore does not slow down the UAS's mission.

The size of problem that can be computed generally by VRH is also greatly increased, opening VRH as a possible solution to any, even non-dynamic problems. In

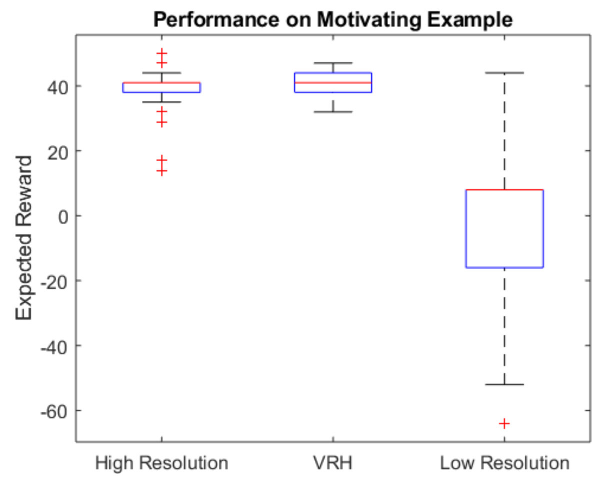
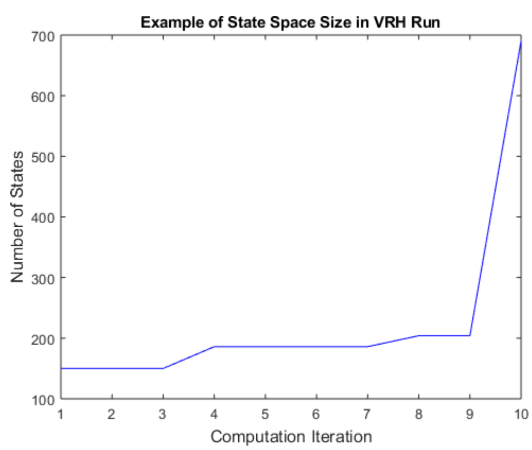
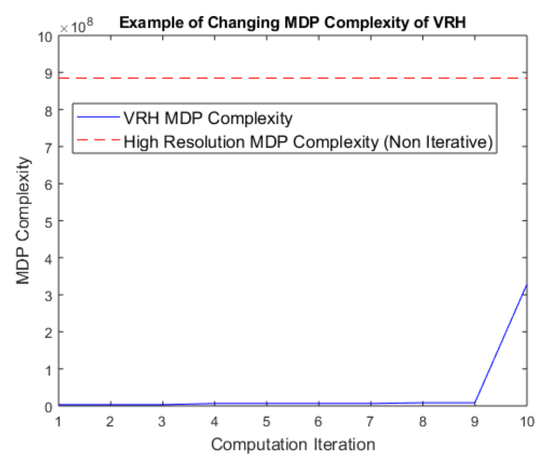


Figure 5.7: Performance of VRH vs. High and Low Resolution

tests the maximum size of problem which could be solved by the high resolution MDP was a 2 by 5 grid, resulting in 10 total states. For VRH we were able to compute solutions to grids as large as 2 by 12, giving 25 states, or 2.5 times the size of a problem. These were run on a lab computer, not a super computer, but this information can be extrapolated to show VRH's usefulness in a variety of situations.



(a) How the state space changes over a run of VRH



(b) Changing MDP complexity of VRH

Figure 5.8: Example of how the state space changes through a run of VRH and how that effects the complexity compared to a high resolution MDP

5.4 Discussion

There are many different conditions under which stochastic problems operate. In environments where changing conditions lend themselves to dynamic responses VRH is an effective method to enable online computing of policy. VRH lowers resource requirements and produces highly accurate policy making it more available to UASs which are typically limited in their computing resources. VRH though is a tool to help build manageable MDPS much like the other techniques discussed in the related work section. Factoring MDPs, receding horizons and alternate MDP solvers all have their utility in making MDPs easier to compute online. In fact they are rarely in conflict with VRH and can be used in conjuncture with it to further reduce the state space, improving solvability.

VRH faces limitations with the run time especially when used on a small processor. Computing online is costly as the new MDP must be solved at each step. There are cases where decisions must be made quickly where VRH will not be able to meet the requirements. VRH though performs better, both in speed and accuracy than recomputing a complete MDP every time making it a more viable solution. In high level mission planning problems though actions often take place on a time scale of minutes instead of seconds. In these cases VRH can compute quick enough to not significantly slow down a mission meaning the run time is less of a concern.

VRH works well in cases where discretization of variables is need and online computing is realistic. This makes it perfect for making decisions regarding surveillance where multiple targets are moving, planning paths where the movement of other objects can be modeled as probabilistic, and in problems such as the travelling sales person where traffic conditions are changing. There are many cases though, where VRH is not useful, practical, or both. These cases happen in tracking controllers where decisions are being made very quickly as recomputing over the state space takes time. They also occur when state spaces are made up of naturally discretized variables where resolution changes are unnecessary. The last case of note is when there isn't a function to calculate or learn the transition probabilities. VRH requires some sort of knowledge of the problems probabilistic dynamics to rebuild a state space.

Chapter 6

Conclusions and Future Work

From our research we believe there is a clear outline for increasing the mission duration of UAS multicopters. The first comes simply from advancements in the fuel sources. Right now we are on the brink of hydrogen fuel cells becoming an incredible asset to the multicopter industry. Companies have begun to release new fuel cell based systems, which at the moment are expensive, often dangerous to use and transport, and lack robustness, but show vast promise in the coming years. As shown in Chapter 2's Future Advancement section an increase to 1400W of power from 1000W could result in 2+ hour flight times. This advancement, or any serious advancement in batteries which can achieve similar results, are poised to be the single biggest breakthrough that will grow this industry. This is because low flight times restricts multicopters mission types severely, and these fuel source improvements can unlock multicopters potential in so many areas.

Understanding flight characteristics, especially how flight speeds can improve efficiency is a great way to make marginal changes. In any case where improving mission duration or distance is important this research should be considered by a flight planner. Our research showed that a 20mph flight speed can improve flight times by up to 19% from a hover on our Matrice 600 airframe. This increase is far from trivial and is important to understand if you need to squeeze every last drop out of a flight.

For the future of this research the flight characteristics should be explored for any flight platform that is used as they will vary from multicopter to multicopter.

The performance of the VRH algorithm in our test situations and its ability to solve the complex problem in our motivating example is very encouraging. VRH performs nearly as well as an optimal policy, topping 5.6% less efficient in our tests, while having a MDP complexity anywhere between 2.5 and 7 times lower than using a typical MDP. This then combines with its ability to adapt to changing conditions makes it ideally suited to increase autonomy and decision making in UASs.

In the future we hope to use VRH's ability to compute online to apply reinforcement learning to path planning. Being able to update online means we can take new information to better build transition probabilities for MDPs. In most mission planners the transition probabilities are based off our best model of the UAS's dynamics. Being able to collect data on the accuracy of the model to improve transition probabilities will lead to a more accurate MDP representation of the physical space we are navigating.

Bibliography

[1] Farris, E., and William, F. M. I., "System and method for controlling drone delivery or pick up during a delivery or pick up phase of drone operation," , Feb. 4 2016. US Patent App. 14/814,501.

[2] Shavarani, S. M., Nejad, M. G., Rismanchian, F., and Izbirak, G., "Application of hierarchical facility location problem for optimization of a drone delivery system: a case study of Amazon prime air in the city of San Francisco," The International Journal of Advanced Manufacturing Technology, Vol. 95, No. 9-12, 2018, pp. 3141–3153.

[3] Hada, Y., Nakao, M., Yamada, M., Kobayashi, H., Sawasaki, N., Yokoji, K., Kanai, S., Tanaka, F., Date, H., Pathak, S., et al., "Development of a Bridge Inspection Support System using Two-Wheeled Multicopter and 3D Modeling Technology," Journal of Disaster Research, Vol. 12, No. 3, 2017, pp. 593–606.

[4] Rossi, G., Tanteri, L., Salvatici, T., and Casagli, N., "The use of multi-copter drones for landslide investigations," 2017.

[5] Scherer, J., Yahyanejad, S., Hayat, S., Yanmaz, E., Andre, T., Khan, A., Vukadinovic, V., Bettstetter, C., Hellwagner, H., and Rinner, B., "An autonomous multi-UAV system for search and rescue," Proceedings of the First Workshop

on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use, ACM, 2015, pp. 33–38.

[6] Doherty, P., and Rudol, P., "A UAV search and rescue scenario with human body detection and geolocalization," Australasian Joint Conference on Artificial Intelligence, Springer, 2007, pp. 1–13.

[7] Beachly, E., Detweiler, C., Elbaum, S., Duncan, B., Hildebrandt, C., Twidwell, D., and Allen, C., "Fire-Aware Planning of Aerial Trajectories and Ignitions," 2018.

[8] Ore, J.-P., Elbaum, S., Burgin, A., and Detweiler, C., "Autonomous aerial water sampling," Journal of Field Robotics, Vol. 32, No. 8, 2015, pp. 1095–1113.

[9] Islam, A., Houston, A. L., Shankar, A., and Detweiler, C., "Design and Evaluation of Sensor Housing for Boundary Layer Profiling Using Multirotors," Sensors, Vol. 19, No. 11, 2019, p. 2481.

[10] Sun, Y., Plowcha, A., Nail, M., Elbaum, S., Terry, B., and Detweiler, C., "Unmanned aerial auger for underground sensor installation," 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2018, pp. 1374–1381.

[11] Krawczyk, J., Mazur, A., Sasin, T., and Stokłosa, A., "FueL cells as alternative power for unmanned aircraft systems–current situation and development trends," Prace Instytutu Lotnictwa, 2014.

[12] Administration, F. A., Helicopter Flying Handbook, US Department of Transportation, P.O. Box 25082, Oklahoma City, OK 73125, 2012.

[13] Padfield, G. D., Helicopter flight dynamics, Wiley Online Library, 2008.

[14] Team, F. S., "Activities, Courses, Seminars Webinars," https://www.faasafety.gov/gslac/ALC/course_content.aspx?cID=104&sID=451&preview=true, ???? Accessed: 2019-10-25.

[15] Khan, M., "Quadcopter flight dynamics," International journal of scientific & technology research, Vol. 3, No. 8, 2014, pp. 130–135.

[16] Roy, N., Gordon, G., and Thrun, S., "Planning under uncertainty for reliable health care robotics," Field and Service Robotics, Springer, 2003, pp. 417–426.

[17] Laroche, P., Charpillet, F., and Schott, R., "Mobile robotics planning using abstract markov decision processes," Proceedings 11th International Conference on Tools with Artificial Intelligence, IEEE, 1999, pp. 299–306.

[18] Meuleau, N., Hauskrecht, M., Kim, K.-E., Peshkin, L., Kaelbling, L. P., Dean, T. L., and Boutilier, C., "Solving very large weakly coupled Markov decision processes," AAAI/IAAI, 1998, pp. 165–172.

[19] Poupart, P., Exploiting structure to efficiently solve large scale partially observable Markov decision processes, Citeseer, 2005.

[20] Dean, T., Givan, R., and Leach, S., "Model reduction techniques for computing approximately optimal solutions for Markov decision processes," Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence, Morgan Kaufmann Publishers Inc., 1997, pp. 124–131.

[21] Aberdeen, D., et al., "Policy-gradient algorithms for partially observable Markov decision processes," 2003.

[22] Tollefson, J., "Hydrogen vehicles: fuel of the future?" Nature News, Vol. 464, No. 7293, 2010, pp. 1262–1264.

[23] Campbell, B., Crase, S., and Sims, B., "Review of Fuel Cell Technologies for Military Land Vehicles," Tech. rep., DEFENCE SCIENCE AND TECHNOLOGY ORGANISATION FISHERMANS BEND (AUSTRALIA) LAND DIV, 2014.

[24] Kim, T., and Kwon, S., "Design and development of a fuel cell-powered small unmanned aircraft," International Journal of Hydrogen Energy, Vol. 37, No. 1, 2012, pp. 615 – 622. doi:https://doi.org/10.1016/j.ijhydene.2011.09.051, URL `http://www.sciencedirect.com/science/article/pii/S0360319911021641`, 11th China Hydrogen Energy Conference.

[25] Himansu, A., Freeh, J. E., Steffen Jr, C. J., Tornabene, R. T., and Wang, X.-Y. J., "Hybrid solid oxide fuel cell/gas turbine system design for high altitude long endurance aerospace missions," 2006.

[26] Ofoma, U., and Wu, C., "Design of a fuel cell powered UAV for environmental research," AIAA 3rd" Unmanned Unlimited" Technical Conference, Workshop and Exhibit, 2004, p. 6384.

[27] Bradley, T. H., Moffitt, B. A., Mavris, D. N., and Parekh, D. E., "Development and experimental characterization of a fuel cell powered aircraft," Journal of Power sources, Vol. 171, No. 2, 2007, pp. 793–801.

[28] Kim, K., Kim, T., Lee, K., and Kwon, S., "Fuel cell system with sodium borohydride as hydrogen source for unmanned aerial vehicles," Journal of power sources, Vol. 196, No. 21, 2011, pp. 9069–9075.

[29] Dudek, M., Tomczyk, P., Wygonik, P., Korkosz, M., Bogusz, P., and Lis, B., "Hybrid fuel cell—battery system as a main power unit for small unmanned aerial vehicles (UAV)," Int. J. Electrochem. Sci, Vol. 8, 2013, pp. 8442–8463.

[30] Gong, A., and Verstraete, D., "Fuel cell propulsion in small fixed-wing unmanned aerial vehicles: Current status and research needs," International Journal of Hydrogen Energy, Vol. 42, No. 33, 2017, pp. 21311–21333.

[31] McConnell, V. P., "Military UAVs claiming the skies with fuel cell power," Fuel Cells Bulletin, Vol. 2007, No. 12, 2007, pp. 12–15.

[32] Reddy, K., and Poondla, A., "Performance analysis of solar powered Unmanned Aerial Vehicle," Renewable Energy, Vol. 104, 2017, pp. 20–29.

[33] Noth, A., "Design of Solar Powered Airplanes for Continous Flight," Ph.D. thesis, ETH Zurich, 2008.

[34] Morton, S., D'Sa, R., and Papanikolopoulos, N., "Solar powered uav: Design and experiments," Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on, IEEE, 2015, pp. 2460–2466.

[35] Shaheed, M. H., Abidali, A., Ahmed, J., Ahmed, S., Burba, I., Fani, P. J., Kwofie, G., Wojewoda, K., and Munjiza, A., "Flying by the Sun only: The Solarcopter prototype," Aerospace Science and Technology, Vol. 45, 2015, pp. 209–214.

[36] Sverdlov, S., "Flight duration, potential and relative efficiency of an electric multicopter," Russian Aeronautics, Vol. 60, No. 2, 2017, pp. 163–168.

[37] Zulkipli, A. H., Raj, T., Hashim, F. H., and Huddin, A. B., "Characterization of DC brushless motor for an efficient multicopter design," Advances in Electrical, Electronic and Systems Engineering (ICAEES), International Conference on, IEEE, 2016, pp. 586–591.

[38] Holda, C., Ghalamchi, B., and Mueller, M. W., "Tilting multicopter rotors for increased power efficiency and yaw authority," 2018 International Conference on Unmanned Aircraft Systems (ICUAS), IEEE, 2018, pp. 143–148.

[39] Huang, H., Hoffmann, G. M., Waslander, S. L., and Tomlin, C. J., "Aerodynamics and control of autonomous quadrotor helicopters in aggressive maneuvering," 2009 IEEE international conference on robotics and automation, IEEE, 2009, pp. 3277–3282.

[40] Gandolfo, D. C., Salinas, L. R., Brandão, A., and Toibero, J. M., "Stable path-following control for a quadrotor helicopter considering energy consumption," IEEE Transactions on Control Systems Technology, Vol. 25, No. 4, 2016, pp. 1423–1430.

[41] Karydis, K., and Kumar, V., "Energetics in robotic flight at small scales," Interface focus, Vol. 7, No. 1, 2017, p. 20160088.

[42] Lazinica, A., New developments in robotics automation and control, BoD–Books on Demand, 2008.

[43] Eaungpulswat, P., and Werner, H., "Area Coverage Algorithms for Multiagent Surveillance Tasks," 2012.

[44] Pohl, A. J., and Lamont, G. B., "Multi-objective UAV mission planning using evolutionary computation," 2008 winter simulation conference, IEEE, 2008, pp. 1268–1279.

[45] Jeong, B.-M., Ha, J.-S., and Choi, H.-L., "MDP-based mission planning for multi-UAV persistent surveillance," 2014 14th International Conference on Control, Automation and Systems (ICCAS 2014), IEEE, 2014, pp. 831–834.

[46] Eubank, R. D., Bradley, J. M., and Atkins, E. M., "Energy-aware multi-flight planning for an unattended seaplane: Flying fish," Journal of Aerospace Information Systems, 2016, pp. 73–91.

[47] Kolobov, A., Weld, D. S., et al., "Discovering hidden structure in factored MDPs," Artificial Intelligence, Vol. 189, 2012, pp. 19–47.

[48] Dean, T. L., Givan, R., and Kim, K.-E., "Solving Stochastic Planning Problems with Large State and Action Spaces." AIPS, 1998, pp. 102–110.

[49] Michalska, H., and Mayne, D. Q., "Receding horizon control of nonlinear systems," Decision and Control, 1989., Proceedings of the 28th IEEE Conference on, IEEE, 1989, pp. 107–108.

[50] Kuwata, Y., and How, J., "Three dimensional receding horizon control for UAVs," AIAA Guidance, Navigation, and Control Conference and Exhibit, 2004, p. 5144.

[51] Chang, H. S., and Marcus, S. I., "Approximate Receding Horizon Approach for Markov Decision Processes: Average Award Case," Tech. rep., MARYLAND UNIV COLLEGE PARK INST FOR SYSTEMS RESEARCH, 2002.

[52] Chang, H. S., and Marcus, S. I., "Two-person zero-sum Markov games: receding horizon approach," IEEE Transactions on Automatic Control, Vol. 48, No. 11, 2003, pp. 1951–1961.

[53] Nash, S. G., "A multigrid approach to discretized optimization problems," Optimization Methods and Software, Vol. 14, No. 1-2, 2000, pp. 99–116.

[54] Grüne, L., and Semmler, W., "Using dynamic programming with adaptive grid scheme for optimal control problems in economics," Journal of Economic Dynamics and Control, Vol. 28, No. 12, 2004, pp. 2427–2456.

[55] Munos, R., and Moore, A., "Variable resolution discretization in optimal control," Machine learning, Vol. 49, No. 2-3, 2002, pp. 291–323.

[56] Bohorquez, F., "Rotor hover performance and system design of an efficient coaxial rotary wing micro air vehicle," Ph.D. thesis, 2007.

[57] Bohorquez, F., and Pines, D., "Hover performance of rotor blades at low reynolds numbers for rotary wing micro air vehicles," 2nd AIAA" Unmanned Unlimited" Conf. and Workshop & Exhibit, 2003, p. 6655.

[58] "Alta Devices Solar cells," `https://www.altadevices.com/a`, Accessed: 2018-12-01.

[59] "HES Aerostak Fuel Cells," `https://www.hes.sg/aerostak`, Accessed: 2018-12-01.

[60] "HES Hycopter," `https://www.hes.sg/hycopter`, Accessed: 2018-12-01.

[61] "MMC UAV," `http://www.mmcuav.com/drones/hydrone1550/`, Accessed: 2018-12-01.

[62] Harris, J., "Implications of the Power Curve on Single-engine Flight in a Twin-engine Helicopter," 1992.

[63] "Profficieny, Behind the Power Curve," `https://www.aopa.org/news-and-media/all-news/2013/november/pilot/proficiency-behind-the-power-curve`, Accessed: 2019-10-21.

[64] "Understanding Helicopter Power Requirements: The Power Struggle," `https://www.rotorandwing.com/2017/10/10/understanding-helicopter-power-requirements-power-struggle/`, Accessed: 2019-10-21.

[65] Howard, R. A., "Dynamic programming and markov processes." 1960.

[66] Alagoz, O., Hsu, H., Schaefer, A. J., and Roberts, M. S., "Markov decision processes: a tool for sequential decision making under uncertainty," Medical Decision Making, Vol. 30, No. 4, 2010, pp. 474–483.

[67] Bellman, R., "A Markovian decision process," Journal of Mathematics and Mechanics, 1957, pp. 679–684.

[68] Silver, D., and Veness, J., "Monte-Carlo planning in large POMDPs," Advances in neural information processing systems, 2010, pp. 2164–2172.

[69] Sanner, S., and Boutilier, C., "Approximate linear programming for first-order MDPs," arXiv preprint arXiv:1207.1415, 2012.

[70] Boutilier, C., Reiter, R., and Price, B., "Symbolic dynamic programming for first-order MDPs," IJCAI, Vol. 1, 2001, pp. 690–700.