Optimisation Strategies for Power Management of Autonomous Systems

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Abstract

Power requirements on autonomous systems are increasing due to rapid technology growth. Today's methods for controlling these resources use expensive and conservative strategies, or, employ pre-defined power schedules that heighten the risk of mission failure in a dynamic environment. An intelligent Power Management System (PMS) is required to improve, or maintain, system capability.

The strategies proposed here aim to contribute towards an intelligent PMS. Using optimisation methods, an adaptive PMS, capable of constructing the *best executable* power schedules while satisfying real-time requirements, is presented. A three-level optimisation strategy is introduced. Due to the feasibility requirement of the solutions produced, the first level uses a constraint satisfaction approach. Then, the solution is improved using a local search algorithm. Next, a global search algorithm is used in the remaining execution time to explore the possibility of further improvement in the solution. The efficiency of the optimisation process is enhanced by use of convex programming techniques. Other complementary modules are incorporated to form a complete optimisation framework, enabling autonomous operation of the vehicle.

Using an unmanned aircraft system as a case study, with the objective of minimising fuel consumption, the proposed PMS is demonstrated to be capable of adapting to its dynamic environment, coping with any change in problem description and constraints. *Best executable* solutions are constructed, while satisfying real-time requirements. When compared to existing approaches, the strategies proposed here show improvement in terms of the objective of the optimisation process.

In summary, a certifiable framework that autonomously optimises the power management for a complex system is presented. Key features of this framework include simultaneous control of multiple types of power, complete operation cycle power scheduling, special adaptations to handle increased problem complexity (flexible components/features and soft constraints), construction and delivery of intelligent advice, and *best executable* solution selection, in real-time and on-board.

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Nomenclature

Roman Symbols

B	Matrix containing the lower and upper bounds for the decision variables
$c2$	A parameter for the PSO algorithm
$c1$	A parameter for the PSO algorithm
C_{max}	Maximum energy capacity of power store
C_t	Energy level of power store at time interval t
D	Total number of electrical power sinks
d	Electrical power demand
$E(x_{ijt})$	Function that relates the electrical machine efficiency to x_{ijt}
$\mathcal{F}_{ekt}(x_{kt})$	The fuel consumption rate by the engines, specifically when propulsor, k, is set to x at time interval t
$\mathcal{F}_{git}(x_{ijt})$	The fuel consumption rate by the generators, specifically when generator i is set to x at time interval t
$\mathcal{F}_{e^*}(x_{kt})$	The fuel consumed for one in-flight engine shutdown and restart
F_{max}	Total fuel available
$\mathcal{F}_{total}(x_{kt}, x_{ijt})$	Total fuel used
γ	Desired power output for a power source based on the soft constraint
$h(x_{ijt}, x_{kt})$	Function describing event-specific constraints
i	Electrical power source
j	Electrical power sink
K	Total number of propulsive power sources
k	Propulsive power source
m	Number of constraints
N	Number of decision variables

n	Number of separable, high impact soft constraints
N_T	Total number of time intervals
p	Propulsive power demand
$P(x_{ijt})$	Function that relates the power electronics efficiency to x_{ijt}
ϕ	Penalty weight for the violation of the soft constraints
q	Penalty weight for the violation of the asymmetry constraint
$Q(x_{kt})$	Function describing the relationship between fuel consumption and the propulsor setting.
S	Total number of electrical power sources
s	Electrical power source supply
T	Entire remaining mission time
t	Time interval
δ^a_{kt}	Asymmetry tolerance between propulsive power sources
δ^l_{jt}	Lower tolerance for electrical power demand
δ^u_{jt}	Upper tolerance for electrical power demand
δ^l_{kt}	Lower tolerance for propulsive power demand
δ^u_{kt}	Upper tolerance for propulsive power demand
$V(x_{kt}, x_{ijt})$	Evaluation function for the heuristic optimisers
φ	Number of maximum iterations for the PSO algorithm
ς	The current iteration for the PSO algorithm
w_n	Temporary decision variables, where $n = 1, 2, ..., 2N$
$\boldsymbol{x_t}$	A vector of decision variables describing the power supply and delivery plans for a given time interval t
x_{ijt}	Electrical power delivery from power source i to power sink j for time interval t
x_{kt}	Propulsive power delivery from power source k for time interval t
y_t	Unit time of the time interval t
z	Instances of engine IFSD

Acronyms

ACO	Ant colony optimisation

AIS	Artificial immune system
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural networks
ASTRAEA	Autonomous Systems Technology Related Airborne Evaluation and Assessment
CAA	Civil Aviation Authority
CBA	Centroid-based adaptation
CEPC	Component for electric power control
COP	Constrained optimisation problem
CP	Constraint programming
CSP	Constraint satisfaction problem
DE	Differential evolution
DM	Decision maker
DMP	Decision-Making Platform
DOP	Dynamic optimisation problem
DP	Dynamic programming
DPM	Dynamic power management
DVS	Dynamic voltage scaling
EA	Evolutionary algorithm
EHM	Equipment Health Management
EM	Electrical machine
EMS	Energy management system
EP	Evolutionary programming
GA	Genetic algorithm
GCS	Ground control system
GP	Genetic programming
GUI	Graphical user interface
HESS	Hybrid Energy Storage System
HEV	Hybrid electric vehicles
HP	High pressure

ICAO	International Civil Aviation Organization
IFSD	In-flight shutdown
IPMS	Intelligent Power Management System
KKT	Karush-Kuhn-Tucker
LP	Lower pressure
LR	Lagrangian relaxation
MALE	Medium altitude long endurance
MCDM	Multi-criteria decision-making
MMS	Mission Management System
MOO	Multi-objective optimisation
MOP	Multi-objective optimisation problem
MPC	Model predictive control
NLP	Nonlinear programming
NM	Nelder-Mead
PACT	Pilot Authority and Control of Tasks
PEI	Power electronic interface
PE	Power electronics
PM	Power Manager
PMS	Power Management System
PSO	Particle swarm optimisation
PSP	Power supply plan
PS	Power System
QP	Quadratic programming
RCPS	Resource-constrained project scheduling
RO	Robust optimisation
RTO	Real-time optimisation
SA	Simulated annealing
SC	Supercapacitor
TRL	Technology readiness level

TS	Tabu search
UAS	Unmanned Aircraft System
UAV	Unmanned aircraft vehicle
UGV	Unmanned ground vehicle
USV	Unmanned surface vehicle
UUV	Unmanned underwater vehicles
VMS	Vehicle Management System

Chapter 1

Introduction

1.1 Motivation

Autonomous systems, such as autonomous vehicles, have become a key area of research. These systems are often deployed to execute tasks which are deemed too dangerous, dull, or dirty for humans to perform. Examples of applications of autonomous systems include: remote sensing, surveillance, search and rescue, transportation, and payload delivery (Siciliano and Khatib, 2008). In recent years, the work done in this area has grown significantly, introducing more complex and advanced technologies. As a result, these systems are facing both limited energy resources and increased power demands. Optimal management of available resources is essential to support advancements on autonomous systems and to improve overall system capability. Optimal power management is also necessary to achieve reduced operational risks and costs, while simultaneously increasing endurance and flexibility (Graham et al., 2014).

Today's typical Power Management System (PMS) for autonomous systems regulates the power supply and delivery of the vehicle based on a conservative pre-defined power schedule, or by reactive control, which ensures power is available for the worst-case sustained peak power requirement (Morley and Wall, 2010). This approach is robust in the event of unprecedented changes within an expected range. However, the power inefficiency and equipment costs are high. Additionally, unnecessary pollutant emissions arise as a result of excess power generated. The power inefficiency implies that the operational capability of the system could be extended if the power usage is improved. Increasingly, longer operation times are a key product feature for autonomous systems. Improved power management is a key enabling technology that offers an efficient way of achieving these requirements (Karunarathne et al., 2011). Note that power management in this context includes electrical, propulsive, hydraulic, pneumatic, and thermal power.

The system environment, equipment health, and operation objectives are subject to dynamic change throughout operation. These factors increase the potential risk of operation failure. A human controller may communicate an updated power schedule. However, this often requires a significant amount of time and a reliable communication network, both of which are not always available. An update of the power schedules based on real-time dynamical changes is required. Recent technology strategies by industries and governments also aim to encourage development of systems with a higher level of autonomy. These factors necessitate an on-board PMS with autonomous operation capability. As a result, an improved integrated PMS capable of constructing optimal, or *good quality*, power supply and delivery plans, on-board and in-operation, is required as part of the technology growth in autonomous systems. Thus, an intelligent PMS, as proposed in Morley and Wall (2010), aims to meet these goals.

1.2 Aims and objectives

This research aims to contribute to the advancement of an intelligent PMS by developing optimisation strategies, capable of addressing prescribed criteria, for use in an autonomous energy and power management system.

The realisation of this aim resolves into the following objectives:

1. to deliver the best possible power plans describing the power supply and delivery for the vehicle system for a given operation;

2. to develop a framework that is suitable for embedding within the vehicle's Integrated Power System, and ultimately be suitable for a wide variety of multi-source, multi-sink power systems;

3. to be implementable in real-time[1] using limited computing resources;

[1]For the application used for this research, the computation is limited to four minutes.

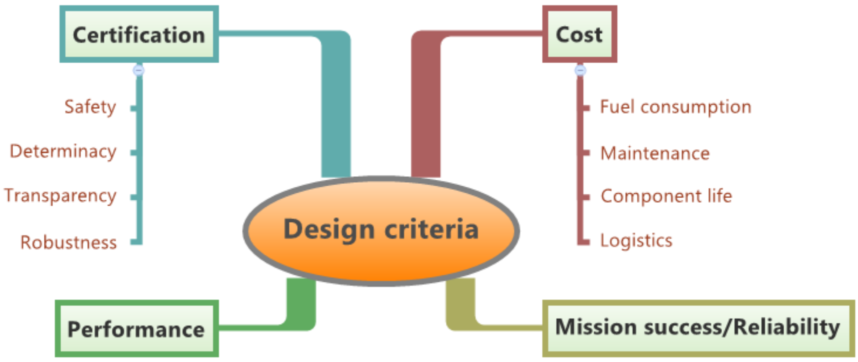


Figure 1.1: Design criteria for IPMS development.

4. to include considerations of implications on costs (maintenance, component life, fuel consumption, support, and logistics), performance and reliability, and certification requirements, using a systems approach (Figure 1.1); and

5. to enable the autonomous operation of the power management of the vehicle.

This research was part of the Autonomous Systems Technology Related Airborne Evaluation and Assessment (ASTRAEA) II programme, where it serves as the advanced thread research (ASTRAEA, 2012; Wall and Mansor, 2012).

1.3 Outline of the thesis

This thesis is divided into seven chapters. A brief description of the chapters follows.

Chapter 2 highlights the requirement of an intelligent PMS. This chapter reviews the existing approaches and presents the remaining research gaps based on the literature. This chapter also provides the necessary material describing optimisation concepts and discusses relevant methods and applications that have been, or would be, beneficial for improving today's PMSs.

Chapter 3 describes the problem formulation for the research and proposes a solution architecture. The requirements of the improved PMS are discussed. Based on a target application, a power system architecture is established. Then, a complete Integrated PMS framework is presented. Chapter 3 provides a basis for the development of the work presented in Chapters 4 to 6. Outline of Chapters 3 to 6 is illustrated in Figure 1.2.

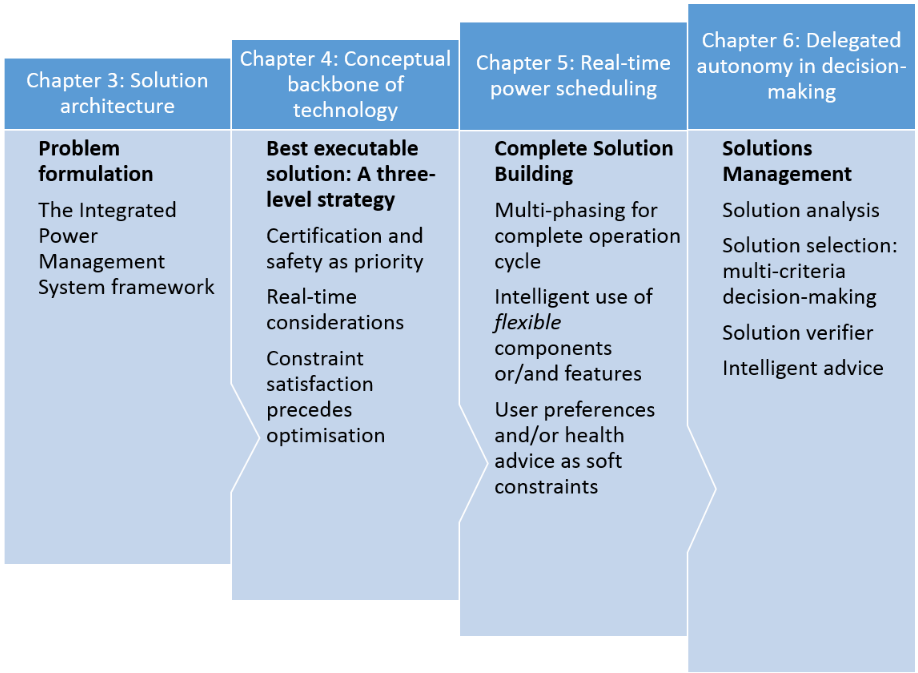


Figure 1.2: Structure of the thesis.

Chapter 4 presents the main strategy behind the Integrated Power Management System. Adopting a three-level strategy, the safety of the system is guaranteed while optimisation of solutions is sought within the real-time requirements of the system. A case study is included to demonstrate the capability of the strategy.

Chapter 5 develops the ideas presented in Chapter 3 and 4 to form a complete solution building process within the optimisation framework. This involves solving for a complex problem. *Flexible* components or/and features are introduced along with integration of soft constraints. The incorporation of these elements introduces complementary modules within the Integrated PMS framework. Comparison between the proposed technology and existing approaches is presented, along with several case studies to illustrate the capabilities of the proposed PMS. The performance of the Integrated PMS with different problem sets is shown, exploring the impact of different conditions to the capabilities of the PMS.

Chapter 6 describes the solutions management, which highlights the autonomous decision-making feature of the Integrated PMS. This chapter explores multi-criteria decision-making approaches and discusses the development of an autonomous decision-making scheme. The strategies developed for autonomous decision-making and construction of intelligent advice as a product of solutions exploitation form a good stepping stone for future research in this area.

Chapter 7 is the concluding chapter. This chapter summarises the research undertaken and outlines recommended future directions of Intelligent Power Management Systems for autonomous systems.

1.4 Contributions

This PhD research has fulfilled its goals and aims, initially set up at project start (Mansor et al., 2012b). In this thesis, a certifiable framework of a Power Manager that demonstrates the capability to satisfy the requirements as one of the key enabling technologies in the development of intelligent autonomous systems is introduced. The developed strategies improve operational costs and capability through certifiable intelligent re-planning. The main contributions arising from the research undertaken are detailed below.

- **A systems-based approach optimisation framework suitable for power management on-board multi-source, multi-sink power systems.** To complement today's approaches that tend to focus on component-level power management, an adaptive and flexible system-level planning framework is proposed. Considering the dependency between the power components, optimisation was sought, not only favouring the efficiency or performance of one particular component, but also other components. For example, as opposed to today's approaches, power sources of multiple types are simultaneously optimised. The framework allows information exchange between the PMS and other control systems within the vehicle, optimising vehicle operation. To the author's knowledge, this is the first time that a power management framework has been proposed that incorporates system-level optimisation. This power management framework is described in Chapter 3 and its contents described in Chapters 4 to 6.

- **A three-level optimisation strategy to produce the *best executable* solutions.** To comply with certification requirements and satisfy the real-time requirement of the problem solution, a three-level optimisation strategy within the power management framework has been proposed. At the initiation of the PMS, a feasible solution is sought first, guaranteeing a solution to be executable in the first instance. This is important for the safety requirement of the autonomous system. Then, exploiting the initial feasible solution, an improved solution is sought using local search techniques. The solution attained becomes the new best solution. Using the remaining execution time and computing resources, the *best executable* solution is sought using a global search technique. The efficiency of the three-level strategy is enhanced, enabling real-time implementation, by representation of the feasible search space using convex programming and convex combinations.

This novel contribution is described in detail in Chapter 4 and has been published in Mansor et al. (2014a).

- **A real-time *complete* power supply and delivery planning.** The proposed approach allows the entire power supply and delivery plans of the vehicle to be constructed in real-time i.e. *complete* power planning. This includes its capability to handle non-separable features of the problem, by converting the complex problem to be more tractable and solvable in real-time and on-board.

  This approach also handles soft constraints describing user preferences and/or health advice. This results in alternative solutions to the problem, and flexibility in the power management strategy.

  The capability of this approach to do the above while optimising user objectives, in real-time with computation restrictions, is new and is discussed in Chapter 5, where complementary features are proposed to enable the autonomous operation of the power management.

- **An autonomous multi-criteria decision-making framework.** Proposals on how to handle autonomous multi-criteria decision-making in the context of alternative solutions of soft constraints integration, can be found in Chapter 6. The PMS autonomously analyses and selects the *best executable* solution from a set of alternative solutions based on user preferences. This corresponds to the requirements of the PMS to act independently based on the delegated autonomy of the PMS. By exploiting system information and available *good* alternative solutions, intelligent advice is constructed to be returned to the user.

- **Technology development support.** The optimisation framework proposed supports the new smart switching technology used in industry; specifically, the network reconfiguration planning included in the solutions constructed (Wall and Mansor, 2014). The work presented here is planned to be developed further by Rolls-Royce plc to a higher technology readiness level (TRL), from TRL 3 to TRL 4 and above. This complements the company's vision to develop future integrated power systems.

- **Dissemination of research to industrial sponsors.** Other contributions of this research include dissemination of technology developed in two company-wide sessions, four written reports (Mansor, 2012a,b, 2014; Mansor et al., 2012a), and four live demonstrations of the approach to Rolls-Royce plc.

Additional related research that is not covered elsewhere in this thesis includes:

- **A review of hybrid evolutionary multiple criteria decision making methods.** This paper reviews the techniques that have been developed to improve multi-criteria optimisation problems, specifically techniques that combine concepts from two fields: evolutionary multi-objective optimisation and multiple criteria decision making. The importance of decision-maker preferences and the approaches used to model them are discussed. Based on the shortcomings of the current state-of-the-art, a commentary is provided where key issues that should be addressed by fellow researchers within the field are suggested.

  This contribution has been published in Purshouse et al. (2014). An extension to this work, a journal publication, is in preparation.

- **Risk-based Bayesian Sequential Decision Making for Autonomous Fault Management.** This work focusses on developing approaches that promote reliability at the lowest life cycle cost for complex engineering systems. To improve the existing health management approaches, a change detection approach followed by an action selection scheme are proposed. First, a probabilistic change detection using Bayesian sequential analysis is introduced to identify system faults. Then, a risk-based decision-making scheme is developed which selects the best control action to mitigate faults detected suitable for a health monitoring and management system.

This contribution is documented in Mansor et al. (2014b).

- **Decision Making Technologies Evaluation and Roadmap.** In-line with Vision 20 timelines for Rolls-Royce plc and the University Technology Centre within the University of Sheffield, review and evaluation of existing approaches for decision-making have been presented in Mills and Mansor (2014). The technological requirements for more autonomous decision-making in aerospace, marine and civil nuclear are elicited through discussion with stakeholders. This resulted in research plans for an autonomous decision-making architecture to overcome the limitations of today's control strategies.

Chapter 2

Literature Review

2.1 Power Management for Autonomous Systems

2.1.1 Introduction

As explained in Chapter 1, autonomous systems are often deployed to execute tasks that are deemed too dangerous, dull, or dirty for humans to perform. Applications of autonomous systems include remote sensing, surveillance, search and rescue, transportation, and payload delivery (Siciliano and Khatib, 2008; Tan et al., 2007). Examples of autonomous systems include unmanned aircraft vehicles (UAVs), unmanned surface vehicles (USVs) and unmanned ground vehicles (UGVs). UXVs[1] may not necessarily be autonomous, but remotely piloted vehicles that have low levels of autonomy, if any. Some sources differentiate between UXVs and Unmanned X Systems. For example, complex UAVs with delegated autonomy may be referred to as Unmanned Aircraft Systems (UASs) (UAVS, 2014). *Systems* for this case may not only represent the vehicle itself, but all supporting systems. UXVs or UXSs, these systems aim to gain higher levels of autonomy and to fulfil their missions safely. This research study focuses on complex autonomous systems, specifically large autonomous unmanned systems with advanced power and control systems and delegated autonomy. Figure 2.1 is an example system of this research[2]. Note that the intended future applications may be more complex than the system shown in Figure 2.1.

There are different levels of autonomy and *autonomy* should not be confused with

[1] X may be appropriately represented according to vehicle type, e.g. aircraft or aerial vehicles may be represented by UAVs.

[2] This photo is taken by SCDBob (2007) during *Giornata Azzurra* 2007 (Italian Air Force airshow) at Pratica di Mare AFB, Italy.

Figure 2.1: Predator: An example target system of this research.

automation. Automation does not involve independent decision-making whereas autonomy involves decision-making and enactment of the choice of actions (Hill et al., 2007). Automation uses pre-determined arrangements. The level of autonomy of a system depends on the decisions that the system is authorised to make. Based on the modified Pilot Authority and Control of Tasks (PACT) levels found in Hill et al. (2007), the autonomy referred to, in the interest of this research, is PACT level 4b and/or 5a. Future UXSs should be capable of deciding and enacting a set of actions, while reporting to ground control (PACT level 5a). However, there may be incidences that enable the ground control to intervene (e.g. disagreement) and the UXSs will act based on this intervention (PACT level 4b).

The surge of interest in autonomous systems in recent years has resulted in various developments of the subsystems on-board these vehicles, and is expected to continue to rise. These developments enabled these vehicles to have increased capability and wider applicability. Worthiness and legal requirements are key impeding factors for some systems. For example, certification and safety remains an issue for civil applications of UASs. However, programmes such as the Autonomous Systems Technology Related Airborne Evaluation and Assessment (ASTRAEA) programme are working towards opening up the civil airspace for UASs by deriving suitable certification and safety regulations (Adgar, 2012; ASTRAEA, 2012; Dopping-Hepenstal, 2012; Insaurralde and Petillot, 2013; Siciliano and Khatib, 2008).

As a result of work towards achieving a higher level of *autonomy* for unmanned vehicles, they are equipped with complex architectures (for example, automated sense and avoid and autonomous operation of mission management) (Diaz et al., 2013; Siciliano and Khatib, 2008; Tan et al., 2007). These result in larger power demands across the unmanned system (Morley and Wall, 2010). Longer missions (endurance missions) are one of the requirements of modern missions and improved power management may increase the probability of mission success (Karunarathne et al., 2011).

Typically, an unmanned system is deployed on missions with limited resources and a pre-defined conservative power schedule to be enacted (or use of a reactive control scheme) by the Power Management System (PMS). Often, not only is the system likely to produce more power than required, the extra costs that come with the supply of the extra power (due for example, to larger power sources and, therefore, a heavier vehicle) are also significant. Power inefficiency leads to unnecessary operation costs. Furthermore, recent requirements to reduce pollutant emissions enforces the need to improve existing PMSs (UKGov, 2012). If power usage is improved, reduction in costs and pollutant emissions, and improvement in vehicle capability may be achieved. It is worth noting that power management in this context includes electrical, propulsive, hydraulic, pneumatic, and thermal power.

Upon deployment, an unmanned system is subject to dynamic changes due to environmental factors (e.g. weather), system health (e.g. component failures), and mission changes. These often raise issues in terms of new power requirements and power plans since the pre-defined power schedule may no longer be the best schedule, with the attendant risk of mission failure. The capability of the system may severely deteriorate with events (Figure 2.2).

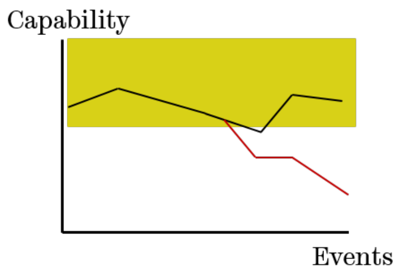


Figure 2.2: Future PMS aims to encourage capability of the vehicle to remain within desired range (shaded region) despite deterioration introduced by events.

A human controller may communicate with the unmanned system to override and supply the unmanned system with an updated power schedule. However, the communication network between the human controller and the unmanned system may be severed. There are attempts to reduce the incidence of severed communication between the unmanned system and the ground control, e.g. Bhattacharya and Basar (2010), however this is outside the scope of work of this research. Communication disruption between human controller and unmanned system may continuously occur throughout the operation cycle, increasing the risk of mission failure (due to power shortage, for example). Continuous updating of power schedules based on the dynamical changes experienced by the vehicle is required. This necessitates on-board power management capability with autonomous operation.

Often, a high level of mission logistic support is required (with associated cost) for the deployment of unmanned systems. Hence, the autonomous operation of power management also enables the logistics to be reduced. Furthermore, some unmanned systems may require additional criteria. For example, certification for UASs requires that an autonomous decision-making scheme is available on-board to demonstrate that the UAS is fit for its purpose.

Autonomous systems may be equipped with various components, depending on the type and purpose of the power system. These multi-source, multi-sink power systems may operate using different types of power simultaneously. Power sources may be gas turbine engines, internal combustion engines, electric generators, power stores (such as batteries and supercapacitors), or combinations of these, while power sinks may be electrical load sinks or power stores. The PMS controls the power supply and delivery for power systems. A PMS capable of maximising all resources, exploiting component features and characteristics, while minimising overall costs, or any other objectives, is required.

Based on the points made above, an Intelligent Power Management System (IPMS), as proposed in Morley and Wall (2010), is required. The IPMS aims to regulate the power system by constructing the best power supply and delivery plans based on available information which is updated regularly based on the vehicle's dynamic environment.

2.1.2 Intelligent Power Management Systems

The envisioned Intelligent Power Management System (IPMS) should be capable of optimally managing power on-board autonomous unmanned systems in real-time. The on-board IPMS will accommodate events that occur during missions, ensuring safety and performance of the unmanned system. The impact of decisions made would be considered for other complementary systems such as impact on mission success (mission management) and component life (equipment health management). In summary, the intended impact of the IPMS, based on Morley and Wall (2010) and discussions with industrial partner, is to:

- improve the applicability and capability of the vehicles, e.g. endurance missions;
- improve operational flexibility, e.g. contingency planning;
- improve the probability of mission capability, reliability, and success;
- improve the efficiency and performance of the vehicles;
- reduce costs (both manufacturing, e.g. vehicle mass, and deployment, e.g. fuel usage and logistics); and
- reducing pollutant emissions, e.g. CO_2.

As highlighted in Chapter 1, this research aims to contribute to the development of the IPMS. In the remainder of this Chapter, a brief overview of today's power management of complex autonomous systems is first provided (Section 2.2). Since the field of optimisation is a recurrent feature for a number of power management solutions, optimisation is introduced and relevant optimisation techniques follow (Section 2.3). Then, a review of advancements in PMSs is presented (Section 2.4). Finally, a commentary is presented at the end of this Chapter, highlighting pertinent concepts, techniques, and methods (Section 2.5).

2.2 Power management: a brief overview

Traditional power management in industry, for vehicles such as aircraft, often uses a manual manipulator (human controller) (Wall et al., 2013). Load sharing methods, such as droop control, may be used to manage power independent of human controllers. Often, the methods employed today tend to reduce overloading the power components to improve efficiency, but not (strictly) optimising the power management. This may be achieved by load shedding, if the power sources are overloaded (Breit, 2012).

There are available approaches that seek to improve the power management on board vehicles. Based on the literature, it is noted that most power management development within this area of research encompasses low-level administration of power planning, or single-type power control. For example, the components may be controlled optimally at component-level without considering the impact of the control actions on other components or sub-systems within the vehicle. Many in-use approaches focus on one type of power optimisation despite the vehicle's dependence on multiple types of power (Wall et al., 2013). In Calvignac and Pons Perez (2010), the inventors propose exploitation of power stores to improve the power efficiency of the system. However, only the electrical components of the system were considered.

The power management of these systems is also not optimised based on in-operation events. There is research attempting to improve the use of power. For example, the use of intelligent agents to manage power distribution on board these vehicles have been explored. However, this approach has been proven to have limited success (Wall et al., 2013). It is acknowledged however, that some information on the improved use of power management may not be widely available due to commercial sensitivity.

Level of autonomy of research found in literature varies. The techniques or methods proposed for improved power management on-board may not necessarily be suitable for autonomous systems despite being targeted for UXVs. Unmanned systems for this case may only indicate remotely controlled systems or systems with a low level of autonomy, instead of fully autonomous systems. The work presented here focuses on systems that operate with a high level of autonomy as mentioned above.

Although optimal solutions are sought where possible, this is an unrealistic goal for real-world problems. *Good* solutions are sought. In order to achieve this, optimisation techniques are often applied to achieve optimised solutions.

As mentioned before, the literature on improving the power management of unmanned systems utilise a number of optimisation techniques. To improve readability, this thesis introduces optimisation and key information of selected optimisation techniques (in Section 2.3) prior to presenting a review of the literature for power management (in Section 2.4).

2.3 Optimisation methods

2.3.1 Introduction to optimisation

Optimisation is a field of research where many developments and applications of its techniques onto real-world problems have been reported. Optimisation techniques allow the user to search for the best, or best attainable, solutions for a problem. In this section, optimisation is first introduced briefly and then followed by the characteristics of the power management problem. Then, a review of relevant optimisation techniques is presented.

Optimisation methods aim to find the best possible feasible solution while satisfying a set of constraints (if any). In order to do so, mathematical representations of the objective, constraints, and candidate solutions must be determined. The classical components of a scalar optimisation problem, without loss of generality, can be reduced to a general mathematical form:
Minimise

$$f(\boldsymbol{x})$$

with respect to $\boldsymbol{x}$, subject to:

$$\boldsymbol{g}(\boldsymbol{x}) \geq 0$$

$$\boldsymbol{h}(\boldsymbol{x}) = 0$$

where $f(\boldsymbol{x})$ is the objective function, $\boldsymbol{x}$ is a vector of decision variables, $\boldsymbol{g}(\boldsymbol{x}) \geq 0$ is a vector of inequality constraints, and $\boldsymbol{h}(\boldsymbol{x}) = 0$ is a vector of equality constraints. The characteristics of these core components of optimisation influence the classification of the problem that in turn, determine the choice of optimisation methods used. The features that often determine the methods used include the characteristics of the objective function(s), the nature of the constraints, the size of the search space, and the nature of the decision variables (Burke and Kendall, 2005; Edgar and Himmelblau, 1988).

There are many readily available optimisation methods as an outcome of much research and efforts that have been invested into the field of optimisation. However, there is no single best method that can be used to solve all types of optimisation problems. In fact, each optimisation method has its own set of advantages and disadvantages. Depending on the class of optimisation problem, different approaches may be more suitable than others.

For example, if the problem has a linear objective function and linear equality constraints, this problem falls under the class of linear programs. This class of problems can be solved efficiently using simplex or interior point methods (Burke and Kendall, 2005). A variation of linear programs is when the decision variables are required to be integers or binary, in which case this problem becomes an integer programming problem. Inequality constraints may also be converted to obey the standard form of linear programming problems by introducing slack variables. Many books and reviews are available which further discuss typical methods used for solving different classes of optimisation problems (Burke and Kendall, 2005; Edgar and Himmelblau, 1988; Hillier and Lieberman, 1995). Note that some problems may be classified into several classes of optimisation problems. Additionally, a specific class of optimisation problem may be solved using a number of optimisation methods.

Basic concepts and terminology within optimisation are listed below.

Components of an optimisation problem:

Decision variables

Decision variables form the possible solutions to an optimisation problem (Burke and Kendall, 2005; Edgar and Himmelblau, 1988). The domain where these variables lie are referred to as the decision, or search, space.

Objective functions

An objective function represents the criterion, attribute or value that a user wishes to optimise. A set of decision variables that optimises an objective function is sought. Geometrically, optimisation may be viewed as searching for the point in an n-dimensional space where the objective function has an extremum (Edgar and Himmelblau, 1988). In some cases, this function may also be termed a cost or evaluation function.

Constraints

The feasibility of a decision variable, or a set of decision variables, is determined by the set of constraints imposed on the problem (Burke and Kendall, 2005). Equality constraints limit the feasible points to hyperplanes, curves, or a single point. On the other hand, inequality constraints limit the decision space by defining a feasible region (Edgar and Himmelblau, 1988). If the optimisation solution is found at an inequality constraint boundary, that constraint is said to be an active constraint. The differences between an unconstrained problem, a constrained problem (inactive constraint) and an actively constrained problem are illustrated in Figure 2.3. The infeasible regions defined by the constraints are represented by the shaded regions. In Figure 2.3(c), the active constraint alters the optimal solution, indicated by a star.

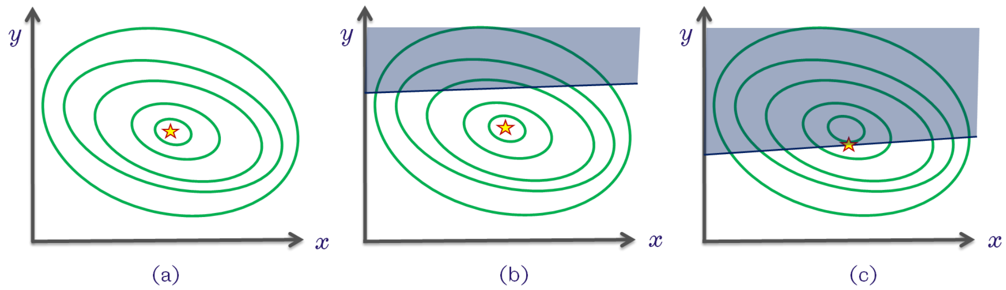


Figure 2.3: Example problems: (a) an unconstrained problem; (b) a constrained problem (inactive); (c) an actively constrained problem. Stars indicate global maxima.

Single- and multi-objective optimisation

The basic representation of the optimisation problem is a single-objective, or scalar, optimisation problem, where only one objective function is considered. In multi-objective problems (MOPs), more than one objective is considered. Usually, MOPs do not produce a unique solution to the problem.

Global and local minima

A local extremum (maximum or minimum) is the best point within a neighbourhood of solutions within the search space. A unimodal function has a single extremum. For unimodal objective functions, a local minimum (or maximum) is the global minimum (or maximum). However, for multi-modal functions, both local and global extrema exist. Figure 2.4 demonstrates the differences between unimodal and multi-modal functions. In Figure 2.4(b), the red dashed lines indicate the location of the two local maxima. The global maximum is indicated by a star. This characteristic of the objective function affects the nature of the search region and consequently the optimisation result (Edgar and Himmelblau, 1988). For example, the results of a numerical optimisation of a multi-modal function are sensitive to the starting point of the optimisation process.

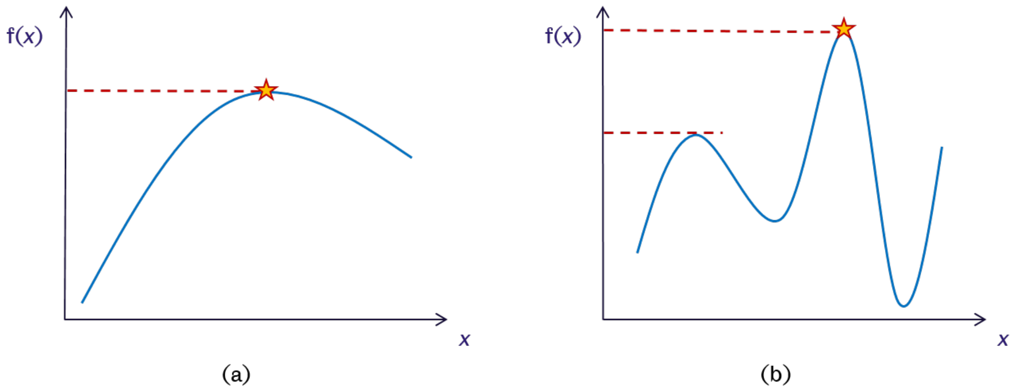


Figure 2.4: Example objective functions: (a) a unimodal function; (b) a multi-modal function. Stars indicate global maxima.

Convexity

A set Y is said to be convex if and only if for any two points $x, y \in Y$, $z = \alpha x + (1 - \alpha)y \in S$, where $\alpha \in [0, 1]$, $\forall x, y \in Y$ (Edgar and Himmelblau, 1988; Hua-Liang, 2011). The convexity of the problem reflects the nature of the problem. Convex objective functions are unimodal functions. Their local solution is also the global solution.

Types of optimisation methods:

Analytical methods

Analytical methods are used when objective functions are well-behaved. These methods tend to calculate the potential extremum by using necessary conditions and the analytical derivatives of the objective functions (Edgar and

Himmelblau, 1988). The performance of these methods is dependent on the characteristics of the objective function. For example, analytical methods perform well for smooth, continuous, unimodal objective functions. For these cases, these methods are computationally efficient.

Heuristic methods

Heuristic methods need not be posed with well-behaving objective functions. Optimality of the solutions constructed cannot be guaranteed unless all other possible solutions are examined (e.g. by using exhaustive search). However, these methods are designed to search for good quality solutions (Burke and Kendall, 2005), thereby enhancing the likelihood of finding a global solution. The computational efficiency of these methods vary depending on the specific methods used.

Evolutionary methods

Evolutionary methods are population-based heuristic methods. Originally inspired by Darwin's theory of survival of the fittest and evolution, the search strategies adopted by these methods involve concepts of mutation, recombination, and selection. These evolutionary algorithms (EAs) exploit good solutions and explore other possible solutions using elements of randomisation (Burke and Kendall, 2005). Evolutionary methods, however, tend to be more compute-intensive.

Types of search strategies:

Direct search

Direct methods search for an extremum by direct comparison of objective function values at a sequence of trial points without involving analytical derivatives of the objective function (Edgar and Himmelblau, 1988). Intrinsic features of these methods are their normally faster convergence, and ability to handle functions with discontinuities and points of inflections. For example, it has been proven that direct methods are superior compared with indirect methods when solving nonlinear, multi-variable optimisation problems (Edgar and Himmelblau, 1988). This type of search is adopted by some heuristic methods.

Deterministic search

Methods which adopt a deterministic search produce the same solutions for every experiment, when repeated with the same initial conditions (Burke and Kendall, 2005). These methods may be trapped in a local minimum, depending on the starting point of the optimisation process. Analytical methods and some heuristic methods deterministically search for solutions.

Stochastic search

Stochastic search includes a stochastic element to the search process, where every run of the search is likely to produce a different solution. These methods have the ability to escape local minima, producing solutions that are more likely to be the global minima (for multi-modal objective functions). The explorative nature of these methods forms one of the attractive features of stochastic methods. Some heuristic methods utilise stochastic search, e.g. evolutionary methods.

Global and local search

Global search methods are methods that explore the entire search space of the optimisation problem. Global search methods tend to adopt a stochastic search process and have the tendency to find globally optimal solutions[1] for multi-modal problems. Conversely, local search methods search only a region, or neighbourhood, of the search space. These methods specialise in improving an initial solution by moving the search towards a minimum or maximum. These methods rely on exploiting an initial solution to find the nearest extremum. The final solution may be optimal, depending on the starting point (i.e. initial solution) (see Figure 2.5).

Hybrid methods

In some cases, the optimisation methods used to solve a problem combine more than one optimisation technique. This is a useful way to combine the advantages of different types of optimisation methods, enhancing the final problem solution.

[1]This is with the exception of exhaustive search, which is a deterministic search process. The exhaustive search method methodologically searches for every possible solution, i.e. the entire search space, for the optimal solution.

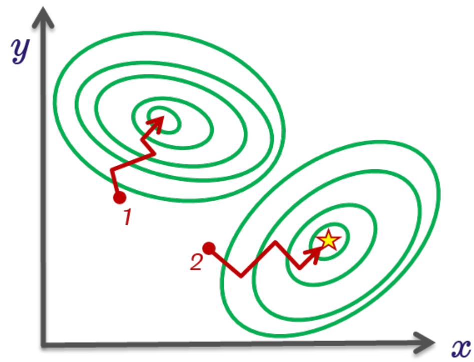


Figure 2.5: A local search strategy example with two different starting points leading to two different extrema. The star indicates the global maximum.

2.3.2 The power management optimisation problem

The power management problem addressed in this research study can be formulated as an optimisation problem. Before reviewing available methods and advancements found in the literature, the areas of optimisation relevant to the power management problem are identified. Identified classes of optimisation problems dictate the directions of the review.

Nature of the decision variables and the corresponding search space

The decision variables of this problem are continuous. These decision variables describe the state of each component (e.g. a power source s is generating x amount of power) at given times for the entire system operation. A large set of variables may be required to represent this.

Characteristics of the objective function

Typical objectives of the power management problem include fuel consumption reduction, component life and performance maximisation, among others. These objectives may be considered independently or simultaneously, and may be conflicting. Although some components of these objective functions may be convex or linear (which allows for easier optimisation), these functions are likely to be nonlinear and multi-modal as a whole. These functions are also likely to change depending on the system state. Power management problems require techniques that are suitable for solving nonlinear and possibly time-varying objective functions. This research study mainly focuses on single objective optimisation and considerations which deal with multiple objectives are briefly highlighted.

Nature of the constraints

Management of the power components on board complex autonomous systems must satisfy a set of constraints determined by the system state, operating conditions, etc. These constraints may comprise multiple types such as equality, inequality, linear, nonlinear, or dependent, constraints. There may also be hard and soft constraints. Violation of hard constraints leads to infeasible solutions. On the other hand, soft constraints need not be satisfied. It is preferable that these constraints are satisfied. However, violation of these constraints do not produce infeasible solutions.

Other considerations

The optimisation strategies for the PMS must be implementable in real-time. Construction of optimal solutions within a short period of time, e.g. four minutes, and limited computing resources is sought. The PMS may be triggered on several occasions during mission depending on mission changes (if any), component health warnings, and the environment (such as weather). Additionally, the solutions and strategies taken to find these solution must be safe, and comply with legal requirements, since the intended type of application for this research is for safety-related systems.

Short summary

The optimisation of the power supply and delivery plans do not fall under only one class of optimisation problem, but several classes:

- real-time optimisation (RTO) problems;
- constrained optimisation problems (COPs) and constraint satisfaction problems[1] (CSPs);
- scheduling problems;
- robust optimisation (RO) problems;

[1]Strictly, constraint satisfaction problems are not optimisation problems. However, special cases of constraint satisfaction problems can be optimisation problems.

- dynamic optimisation problems (DOPs);
- and potentially multi-objective problems (MOPs).

An overview and the implications of these classes or features of problems are discussed below.

2.3.3 Classes of optimisation for Power Management Systems

Real-time optimisation problems

Executable solutions must be found within a short period of time with limited computation resources, to fulfil the real-time requirement of the PMS on-board autonomous systems. Compute-intensive methods must be avoided. With this in mind, some general comments can be made on the choice of algorithms to be used for the optimisation of power management.

In general, there are two strategies for optimisation algorithms to evaluate and search for optimal solutions (Michalewicz and Fogel, 2000). The algorithms may evaluate complete solutions (e.g. hill-climbing techniques), or partial solutions (e.g. branch and bound, A* algorithm). Algorithms which construct complete solutions are capable of providing a solution at any time. If the search process is limited by time, or for an unprecedented reason the algorithm needs to be stopped, the algorithm is still capable of producing a solution. However, algorithms which solve partial solutions may not be capable of producing any feasible solution, if the search process is stopped midway. Hence, the optimisation strategies for PMS should construct and evaluate complete solutions, instead of partial solutions.

Due to these real-time constraints, the performance from the computation costs[1] perspective of the methods used for the problem solution must be reasonable. Algorithms with efficient use of computation resources are sought. A compromise between the quality of solutions produced and the computation costs may be inevitable (Chu and Wah, 1991). Although it is also an optimisation problem with limited processing and memory resources, computation time is of higher priority. However, the former should still be considered during method selection.

For real-time optimisation, it is clear that the choice of algorithm is crucial. Ideally, the algorithm selected should be capable of:

[1]Computational time or memory.

- producing feasible, robust and complete solutions,
- producing the solutions in a reasonable amount of time, and,
- using the available computing resources efficiently.

Hierarchical- and decomposition-based optimisation

In most real-world problems, especially real-time applications, the problems often become NP-hard[1] and finding optimal solutions for these problems prove to be challenging. An approach to help ease the complexity in solving these problems is the concept of hierarchical optimisation.

A problem can be simplified by constructing a coarser search space, thereby achieving a crude solution which is then refined. The coarsening process may be initiated by forcing a set of candidate solutions to meet a set of constraints which are easily satisfiable followed by expansion of these solutions to satisfy the remaining constraints. For example, the *on* or *off* state of a power component can be determined first before the exact operating setting (see Figure 2.6(a)). In hierarchical problems that involve finding solutions for divisions of a finite time horizon, such as a power plan for a PMS, the power setting for the current operation phase can be solved first before solving the power settings for the following operation phases (see Figure 2.6(b)). Depending on the intended hierarchical approach, the problem may be handled differently.

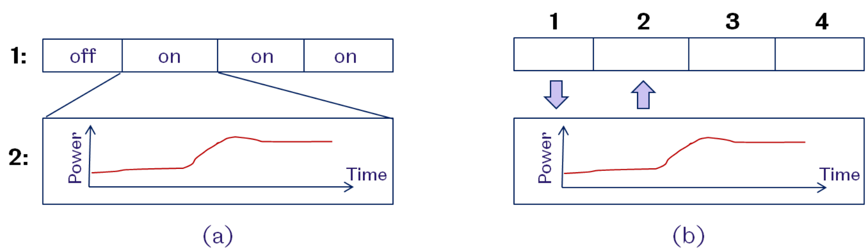


Figure 2.6: Examples of hierarchical optimisation: (a) the power source is determined to be switched on or off prior to determining the exact power setting; (b) the power setting for a power source is determined in detail for a given time interval before analysing the next time interval.

[1] NP-hard problems may be intractable, i.e. may not be solved in polynomial time, and still remain an open question in the field of complexity in optimisation (Burke and Kendall, 2005; Leung, 2004).

In the literature, hierarchical optimisation problems are also termed multi-level optimisation (bi-level optimisation if only two levels of optimisation are involved). Anandalingam and Friesz (1992) define hierarchical optimisation as solving a series of optimisation problems in a predetermined sequence, where the concept of players was introduced. This is illustrated simply by taking bi-level programming as an example: the first player (first decision variable) anticipates the response of the subsequent player (second decision variable). The final solutions formed are influenced by the coupling of decisions at each level. This approach may be viewed as a nested optimisation model where a leader and follower exist (Lai, 1996). Vicente and Calamai (1994) provide a review on bi-level and multilevel programming.

Haubelt et al. (2003) implement a hierarchical decomposition of the search and objective space as an approach to reduce computational time for a MOP. They achieve this by introducing a hierarchical representation of their decision variables in their method. Although the solutions are represented in a hierarchical configuration, partial hierarchical representation may also be used within the decision vector. In their hierarchical optimisation strategy, the problem is decomposed first, followed by exploration of the decision space. This allowed the size of the search space to be reduced, minimising the evaluation costs. This was also highlighted by Yamin (2004) on decomposition of problems. The non-monotonicity feature of the decomposed objective function led Haubelt et al. (2003) to utilise heuristic techniques over exact methods. Blum et al. (2011) also express the advantages of utilising hierarchical optimisation techniques with heuristic methods.

Consistent with the idea of converting complex problems to more tractable problems, decomposition of problems is one of the techniques that could be implemented. As with hierarchical and CSP-based methods[1], this approach reduces the size of the search space and the computation time. Decomposition of a problem into subproblems has shown improved algorithm performance in some cases (e.g. in Yamin (2004)). Decomposition of problems may be achieved using Benders' decomposition (Benders, 1962) or Dantzig-Wolfe decomposition (Dantzig and Wolfe, 1960). Although some of these methods may be limited to linear problems (or any other restrictions), the concepts used in each method may be transferable.

[1]CSP-based methods are discussed below.

The concept of divide and conquer of a problem was recalled by Casbeer and Holsapple (2011) in their multi-target, multi-task assignment problem with precedence constraints for a UAS. The problem is converted into a restricted master problem and an original sub-problem, with the objective to minimise the distance travelled by the UAS. The authors applied column generation (based on Dantzig-Wolfe decomposition) with branch and price optimisation to construct optimal solutions for the task assignment problem. It was reported that column generation alone could not provide an optimal solution. However, a feasible optimal solution was achieved when the branch and price method was used subsequent to column generation. Hence, Casbeer and Holsapple (2011) suggest that although column generation has the potential to increase the tractability of a problem, it should be used alongside other techniques.

Constraint satisfaction problems and constraint-handling

It is critical that feasible solutions are constructed for the power management problem. Hard constraints must be met, producing feasible solutions. CSPs are discussed first due to its speciality in finding solutions that satisfy the defined set of constraints. Then, techniques for constraint-handling in optimisation problems is discussed.

A CSP comprises (Brailsford et al., 1999; Ghallab et al., 2004; Liu et al., 2002):

1. A finite set of variables, $\mathcal{X} = \{x_1, \cdots ..., x_n\}$, where n is the number of variables.

2. A domain set that describes the finite and discrete domain for each variable, $\mathcal{D} = \{D_1, ..., D_n\}$.

3. A constraint set that describes the restrictions on the values of the variables, $\mathcal{C} = \{c_1, ..., c_m\}$, where m is the number of constraints.

A solution set, $\sigma = \{x_1, ..., x_n\}$, to the CSP is such that the solutions are within the defined domain of the variable set by $\mathcal{D}$ and satisfies all the constraints in $\mathcal{C}$. A CSP is *consistent* if σ is non-empty.

CSP-based approaches are targeted for combinatorial problems (Brailsford et al., 1999). Although this research is interested in solving a continuous problem, CSPs are reviewed to provide any lessons learnt, albeit at a conceptual level. CSPs are strictly decision problems, they only search for feasible solutions. However, a CSP is converted into a constrained optimisation problem (COP) if solution quality is taken into account (Burke and Kendall, 2005; Leung, 2004).

In general, techniques for CSPs first eliminate all infeasible solutions, i.e. solutions which do not meet all the constraints, before analysing the quality of the solutions. Using techniques for CSPs, the feasibility of the problem is first evaluated. If found to be infeasible, some constraints may be relaxed to enable feasibility. This will reduce unnecessary computing effort. Of course, the practicality of the approach is dependent on the system of interest.

The methods used to solve CSPs depend on the tractability of the problem (Burke and Kendall, 2005). Techniques for CSPs include a depth-first backtrack search algorithm and inference methods (e.g. consistency methods) (Salido et al., 2008).

A general algorithm for CSPs begins by initialising a variable domain and a constraint store which defines the variables. Next, the domain is reduced by propagation (filtering) which may produce a solution. If a solution is not found, consistency of the problem is investigated. If inconsistency is not proven, the problem is branched by adding a temporary new constraint and the process is repeated. The temporary constraint divides the problem into sub-problems which are mutually exclusive but collectively exhaustive. However, if the inconsistency is proven, other branches are evaluated. For cases where the CSP is also a COP, the objective value is calculated, recorded, and compared with other solutions (if any) (Leung, 2004).

Search methods for CSPs consist of two forms: extension and repair. One form of search constructs solutions by extending a set of consistent (feasible) decision variables (one decision variable at a time) until a complete solution is formed. The other form of search, repair, alters a complete solution (one decision variable at a time) until all the decision variables in the solution are consistent. There is often a trade-off between efficiency and completeness between these two approaches (Burke and Kendall, 2005).

CSP-based methods have been used with heuristic methods to improve the performance of an algorithm in search of optimal solutions (Blum et al., 2011). Blum et al. (2011) report the use of constraint programming (CP), also known as constraint logic programming, to eliminate all infeasible solutions from the search space. Then, a heuristic method is applied to search for the best solution in the remaining search space. CP works similarly to branch and bound[1], however for problems such as job scheduling, CP is more favourable (Leung, 2004).

A CSP-based method, the divide and concur (sic) method, was proposed by Gravel and Elser (2008). Alongside the idea of problem decomposition, the authors proposed decomposing complex problems into smaller, more tractable sub-problems. The problem is divided into sub-problems based on constraints and solved separately. Then, an overall solution is selected by resolving conflicts by consensus (ignoring complete constraint satisfaction). The general concept of the technique is to convert the CSP to a geometrical problem where each constraint produces a set in a given space. The objective of the method is to search for the point of intersection of all the sets formed by the constraints. This is done by minimising the distance of the projections formed by each set. It was unclear whether a single solution or a set of solutions will be produced using this method. This method is claimed to be suitable for both discrete and continuous problems.

Many other research were found. For example, algorithms and applications for CSPs can be found in Brailsford et al. (1999). Barták et al. (2010) provide a survey for CSP, planning and scheduling from an artificial intelligence perspective. Liu et al. (2002) propose a multi-agent approach for CSPs. Verfaillie and Jussien (2005) discuss constraint solving in an uncertain and dynamic environment. The authors provide an interesting outlook in solving real-world problems in the presence of constraints.

Generally, there are several approaches that can be adopted to handle constraints in optimisers. The search space may be restricted depending on the constraint definitions; only feasible solutions are sought. When both feasible and infeasible solutions may be analysed by the optimiser, penalties may be imposed. When infeasible solutions are found, some optimisers may be designed to alter these solutions to force feasibility or simply eliminating these solutions from a set of possible solutions.

The constraint-handling procedures for analytical methods may comprise find-

[1]Branch and bound method repeatedly partitions the problem into a set of sub-problems and eliminates those that are shown to be sub-optimal based on the bounds on these sub-problems (Burke and Kendall, 2005).

ing active constraints first before searching along the boundary of these active constraints for an optimal solution, for example. In evolutionary algorithms (EAs), additional schemes must be incorporated into these otherwise unconstrained optimisers. Examples of constraint-handling approaches include special representations of the decision variables and penalty functions (Burke and Kendall, 2005; Coello, 1999; Michalewicz and Fogel, 2000). Coello (2002) provides a survey for theoretical and numerical constraint-handling techniques used in EAs. Many research may be found in the literature (Chen et al., 2013; Fletcher, 1973; Fonseca and Fleming, 1998; Han and Mangasarian, 1979; Lawrence and Tits, 1996; Michalewicz, 1995).

Scheduling problems

Scheduling is discussed here since some elements of the power management problem involve scheduling of tasks, i.e. temporal power sink control.

> *Scheduling is concerned with the allocation of limited resources to activities over time (Robert and Vivien, 2010).*

Scheduling theory was introduced in the 1950s (T'kindt and Billaut, 1999). Since then, scheduling methods have been implemented in many applications. Typically, a scheduling problem involves constructing a plan which determines the allocation of resources to tasks while fulfilling a set of constraints and objectives. Prior to the search of problem solution, the type of scheduling (e.g. job-shop scheduling and resource-constrained project scheduling (RCPS) problem) is often determined first, as well as the scheduling objectives (e.g. makespan and tardiness). This problem may be solved using exact methods, heuristic methods, or hybrid techniques.

Scheduling problems are a type of combinatorial problem. Common examples of readily available scheduling algorithms include: Hu's algorithm; largest-processing-time rule; smallest-processing-time rule; and the Hodgson-Moore algorithm (Leung, 2004). There are also recent research which describe heuristic methods for scheduling: ant colony optimisation (ACO) (Dorigo and Blum, 2005); artificial immune system (AIS) (Darmoul et al., 2006); and particle swarm optimisation (PSO) (Shi, 2001). Other than that, constraint programming (CP) has also been used to solve scheduling problems (Leung, 2004). T'kindt and Billaut (2001) provide a survey for multi-criteria scheduling.

Energy-efficient scheduling is an example of an online scheduling problem. Energy-efficient scheduling introduces two mechanisms: power-down mechanism, and dynamic speed scaling (Robert and Vivien, 2010). These approaches have been applied to embedded systems (Shin et al., 2000) and small robots (Mei et al., 2005). Although the mechanisms alone are insufficient to address the complete power management problem, they may be integrated into the final problem solution. Note that online scheduling problems slightly differ from the real-time scheduling referred to in this thesis. Online scheduling refers to scheduling problems where any future information (e.g. tasks) are unknown whilst in the real-time scheduling proposed in this thesis, some information is known although uncertainties are involved (Robert and Vivien, 2010).

Robust and dynamic optimisation problems

Real-time power management on-board autonomous systems requires robust solutions. Uncertainties (which motivate the need for robust solutions) may be introduced in a number of different ways (Jin and Branke, 2005):

- perturbation of decision variables;
- noise in objective function, either by modelling errors or noisy models;
- dynamic nature of objective function.

Depending on the types and number of uncertainties involved, including their relationships to one another, different strategies can be implemented. Jin and Branke (2005) provide a review on handling uncertainties in evolutionary computation. The importance of robust optimisation is also expressed by Beyer and Sendhoff (2007) in their survey. In this survey, the potential of EAs and direct search methods when dealing with robust optimisation problems is highlighted.

Bui et al. (2012) express the considerations involved for dynamic optimisation problems where the conditions of the problem are changed mid-evaluation. This scenario is likely to occur for the power management problem. Bui et al. (2012) have emphasized the requirement of the solutions to adapt to the new conditions and have proposed a method as a problem solution. In their method, solutions obtained before a change in problem description, problem constraints, or problem objective, are integrated into the search process for new solutions. This accelerates the search process. Their method applies the idea of exploiting known solutions for future evaluations.

In their paper, Bui et al. (2012) also provide a brief review in adaptation to dynamic environments and suggested a technique to handle a type of dynamic optimisation problems. The research focusses on scheduling and planning, specifically resource-constrained project scheduling (RCPS), which falls under the NP-hard class of problems. Bui et al. (2012) list several methods that have been applied to solve RCPS problems which include:

- branch and bound
- Lagrangian relaxation (LR)
- dynamic programming (DP)
- priority-based methods
- truncated branch and bound
- local search techniques
- tabu search (TS)
- simulated annealing (SA)
- evolutionary algorithms (EAs).

In most practical cases, a suboptimal solution is accepted to ensure the feasibility of the selected solution is maintained. Bertsimas and Sim (2004) seek to improve this conservative approach by experimenting with the probabilistic bounds of constraint violations to reduce the price of robustness. Using a chance-constrained optimisation program, Campi and Calafiore (2004) incorporate uncertainty during decision-making. They exploit the convex properties of the problem to minimise the computational burden of the decision process. This of course is only applicable for convex problems. More information on recent advances in robust optimisation may be found in Gabrel et al. (2014). Beyer and Sendhoff (2007) also provide a robust optimisation survey. Many other relevant studies are found (Bertsimas and Brown, 2009; Bertsimas et al., 2011; Cicerone et al., 2012; Dubois et al., 1996; Guo and Li, 2014; Karimi et al., 2012; Montes et al., 2014; Natarajan et al., 2009; Vayanos et al., 2012; Vilkkumaa et al., 2014).

Multi-objective optimisation problems

Multi-objective optimisation is an optimisation problem which involves two or more objectives to be optimised simultaneously (Fleming et al., 2005). If more than three objectives are required to be optimised simultaneously, the problem is also known as many-objective optimisation.

This research focusses on single objective optimisation. However, this research may be extended to include multi-objective optimisation. Hence, this thesis briefly discusses the implications and techniques used to handle MOPs. The complexity involved when considering multiple objectives is at least as difficult as the single objective problem and may convert the problem to NP-hard. The multi-objective nature of the problem introduces a need to handle the problem differently. In most cases, it is infeasible to construct a solution that optimises all objectives. Thus, the concept of Pareto optimality is introduced (Robert and Vivien, 2010; T'kindt and Billaut, 1999).

Often, multi-objective optimisation problems involve simultaneously minimising several, often competing, objectives. This vector optimisation problem usually has no unique solution, but a set of non-dominated solutions known as the Pareto optimal set (Fonseca and Fleming, 1998). An improvement in one objective of a solution in the Pareto set often results in the degradation in another objective.

Depending on the formulation of the problem, the MOP may be handled using several approaches:

- aggregation of objective functions: linear (weighted) combination of all the objectives into a single objective thus, treating the problem as a single objective optimisation problem;
- bounded constraints: conversion of objectives into constraints, treating the problem as a scalar optimisation problem;
- lexicographical order: ranking of objectives by importance;
- minimising the distance between the optimal solution and the ideal solution (Utopian point);

- integrated approach: multi-objective optimisation using *a posteriori* information (a decision-maker is required).

Each of these approaches has its own advantages and disadvantages. Depending on the nature of the problem, different approaches may be more suitable. Note that not all of these approaches utilise the concept of Pareto optimality. For example, since aggregation of objective functions treats the problem as a single objective optimisation, the solution(s) produced will not involve Pareto optimality. An interesting study found in the literature related to this topic is by Bui et al. (2012). Their method uses the second objective of their problem to help the selection of an updated schedule. The down-selected solutions help the human user to select one final solution. This idea of exploiting the multi-objective nature of the problem is a possible strategy for the power management problem addressed in this thesis, particularly to support a scheme to autonomously select one final solution.

Multi-objective optimisation introduces additional issues into the complex real-time power management problem. For cases where a set of solutions is produced, a decision-maker is often required to select the best solution, based on his/her expert opinion. However, this raises a question of how a satisfactory solution can be obtained in the absence of a decision-maker. The problem solution for improving PMSs should include an automated mechanism where a satisfactory power schedule is selected, if more than one solution exists.

2.3.4 Optimisation search strategies

In general, optimisation methods may be separated into three main groups: analytic (traditional), deterministic-heuristic, and stochastic-heuristic methods. Deterministic search is desirable for systems that require legislation approval or certification. Analytic and deterministic-heuristic methods are deterministic. For well-posed problems, this search strategy may be very efficient and capable of producing the optimal solutions. Example analytical methods include the steepest descent method, the conjugate gradient method, the Newton method, and the quasi-Newton method (e.g. the Davidon-Fletcher-Powell method). However, these methods often suffer when the objective function is non-differentiable, or multi-modal. Most analytical methods also suffer from the curse of dimensionality. There are heuristic methods that are deterministic[1]. For example, the Nelder-Mead (NM) method is a direct method that does not require any derivatives of the objective function to be calculated (Nelder and Mead, 1964). This method is a direct local search method; it is still susceptible to problems with multi-modal objective functions. Other examples include grid search and pattern search.

On the other hand, stochastic methods tend to be capable of escaping local minima and do not require function derivatives. These methods tend to exploit intensification and diversification of solutions. While good solutions are exploited, an explorative search is also performed to enable a wider search in the decision space. Examples include SA, genetic algorithm (GA), PSO, differential evolution (DE), AIS, and ACO. However, these methods tend to be unconstrained optimisers and special schemes must be adopted when addressing constrained optimisation problems.

Another drawback of these types of methods are, of course, their difficulty in gaining approval in terms of legislation and certification for safety-related systems due to lack of transparency and determinacy. Although heuristic methods cannot guarantee optimality, they tend to be more successful in finding global minima (Bianchi et al., 2008; Burke and Kendall, 2005).

Hybridisation of methods is a popular strategy among researchers who wish to combine desirable properties of different approaches and reduce some of the drawbacks of the individual approaches (Banks et al., 2007b). Combinations of heuristic methods, and analytical methods with heuristic methods have been explored. For example, population-based methods have been used to initially identify promising areas within the search space rapidly and local search is then used to find the optimal solution. In general, hybrid metaheuristic techniques combine the use of two or more methods by either:

- integrating one method into the other,
- applying methods sequentially,
- integration of concepts from different methods into a new algorithm.

[1]These methods are referred to as deterministic-heuristic methods in this thesis.

Although in practice these methods show promising results, they tend to be problem specific.

The performance (e.g. accuracy and speed) of optimisation methods is dependent on the problem formulation and also the choice of methods used. Consider Figure 2.7. Formulation of models that describe the problem with low fidelity (Model$_a$) can often be easily solved using analytic methods. Although these may provide exact, deterministic solutions, these solutions may be sub-optimal since the models do not represent the problem accurately.

On the other hand, models that describe the problem with high fidelity (Model$_p$) to the true system may not be tractable to solution using analytic methods. Instead, heuristic (both deterministic- and stochastic heuristic) methods are more suitable. Although optimality cannot be guaranteed, the solutions obtained using these methods tend to generate solutions that are closer to the true optimal solution. The quality of the solutions obtained from these models is dependent on how the models are formed. Precise solutions are obtained using approximate models whilst approximate solutions are obtained using precise models (Figure 2.7).

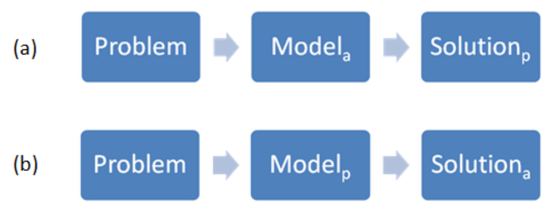


Figure 2.7: A real system can be represented (a) approximately or (b) precisely. The solutions obtained from these models are (a) precise or (b) approximate (a = approximate and p = precise) (Michalewicz and Fogel, 2000).

For a problem such as the one addressed in this thesis, the model representation fidelity must be sufficiently high to ensure that the solutions produced by the optimisation processes will be beneficial for the application. This implies that analytic approaches may not be suitable; heuristic approaches may prove to be more reliable. However, safety-related systems, which are the main interest of this research, are required to demonstrate determinacy, transparency, and tractability due to certification and safety requirements. It is desired that the algorithms involved must be *safe*.

Additionally, since the intended application is for real-time systems, the solutions produced must be robust (taking uncertainties into account). Analytic methods may suit the criteria for certification and safety requirements better compared to heuristic methods. However, the solutions produced are unlikely to be close to the best executable solution for the problem. The solutions obtained by using heuristic methods may be closer to the true optimal solution, albeit at the cost of transparency of these algorithms. It is worth noting that some stochastic-heuristic methods can be modified to be deterministic, albeit losing some of the strengths of the approach. A compromise may be required to satisfy the problem requirements.

Figure 2.8 depicts the typical attributes of the three main types of optimisation methods in terms of computational efficiency, flexibility, fidelity of the real system representation, and determinacy. Heuristic (both deterministic- and stochastic-heuristic) methods have a wider coverage of possible attributes, depending on the specific algorithm selected. However, analytic methods tend to dominate specific areas of the attribute distribution (see Figure 2.8). Analytic methods tend to have low flexibility and fidelity but high determinacy and computational efficiency. Flexibility here refers to the ability of the algorithms to solve a range of problems. Stochastic-heuristic methods tend to be less efficient computationally and not deterministic. However, stochastic-heuristic methods may be flexible, depending on the selected algorithm implemented. Deterministic-heuristic methods have lower flexibility but higher determinacy.

In the power management problem, strategies that have high computational efficiency, flexibility, determinacy, and high fidelity of the real system are sought. However, there are often trade-offs between these attributes. Heuristic methods are favoured for their flexibility and ability to use high-fidelity models. Deterministic-heuristic methods are especially preferred due to their deterministic nature. However, some stochastic (stochastic-heuristic) methods can be altered to ensure determinacy.

2.3.5 Optimisation prospects for power management

Based on the concepts and techniques presented above, heuristic and hybrid methods are the most promising for application to the power management problem. Com-

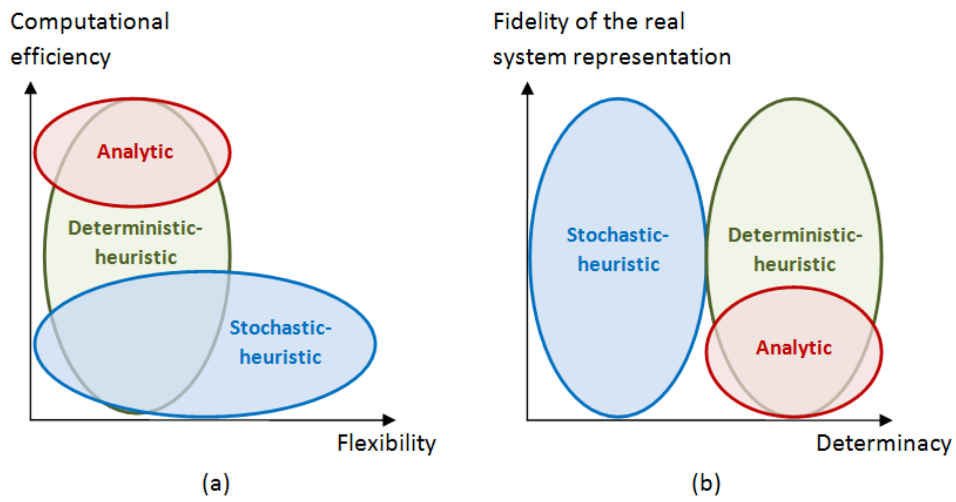


Figure 2.8: Typical regions for the three groups of optimisation methods for specific attributes: (a) computational efficiency against flexibility and (b) fidelity of the real system representation and determinacy.

plementary techniques that could be integrated into the problem solution include: concepts from hierarchical optimisation and constraint-satisfaction-based methods. Some of these methods may increase the tractability of the problem, reduce the size of the search space, as well as reduce the computation time. However, hybridisation of methods and decomposition of the problem should be implemented with caution since only algorithms that examine complete solutions are of interest. The solutions produced by the selected algorithms must be robust, feasible, and obtained within time and computing resource limitations. An automated decision mechanism must also be developed if a set of solutions is produced instead of a single solution. Optimisation techniques have been applied onto some PMSs, and are discussed in the next section.

2.4 Advancements in Power Management Systems

In this Section, today's state of the art in power management for unmanned systems is first discussed. Then, useful approaches that have been explored on other systems that may be transferable to unmanned systems are highlighted. For example, power management for hybrid vehicles has gained much attention and exploration over recent years. Lessons learnt from other power systems, such as the mature field of electric distribution networks, are also briefly outlined. Autonomy, not limited to power management, is also reviewed. Mission Management Systems (MMSs), for example, share similar requirements and characteristics to PMSs. Approaches adopted for these systems may be applicable to the target system of this research. A summary is then provided, capturing pertinent approaches available today.

2.4.1 Power management for unmanned systems

Various studies are reported to improve the power management on-board unmanned vehicles. From individual task scheduling to power generation control, many of these reports focus on a particular component or aspect of the problem. In most cases, the power management strategies are focussed on component-level optimisation, power balancing, and power system architecture optimisation. The type of application varies from small robots with simple control mechanisms to much larger systems with complex architectures. The former tends to be the focus of many studies.

Task or power sink scheduling and control

The importance of power on mobile robots (or similar) has been expressed in various studies. A number of these studies rely on improving the power efficiency on-board the unmanned systems by manipulating the load demands of the system (Brateman et al., 2006; Mei et al., 2005; Ogawa et al., 2006; Zhang et al., 2009). Although some of these research showed potential in their examples, the real benefit of these approaches to the entire vehicle system (or more complex systems) and applicability to more complex problems is unclear.

Two methods are proposed by Mei et al. (2005) to be utilised along with motion planning in order to enable better power management: dynamic power management (DPM) and real-time scheduling. In motion planning, the vehicle speed and route are optimised. DPM dynamically adjusts power states of system to favour power reduction, if possible. The DPM manipulates the voltage differential and frequency of the processor, and the power consumption setting (power state) of components on-board the vehicles, while still achieving system performance. For example, DPM shuts down a component if the component is inactive for a prolonged duration, or is predicted to be redundant during the mission. This can be achieved using time-out or dynamic voltage scaling (DVS). Meanwhile, the real-time scheduler ensures mission attainment by scheduling tasks to meet all the deadlines, optimising power management where possible. Two of the suggested methods to do so are the rate monotonic and earliest deadline first scheduling methods, for simultaneous use with DPM.

Mei et al. (2005) also constructed a power model for each component on-board the vehicle, providing insight into the power consumption of each of the components. The authors did not test these real-time techniques on their robot(s). It was also unclear what were the specific rules or conditions that were used for the decision-making algorithm. For example, there was no clear rule made to indicate when the shutdown of a component was necessary (e.g. how long a component must be inactive before it is switched off?).

An energy-efficient scheduling approach is proposed by Brateman et al. (2006) to improve the power usage for autonomous mobile robots by formulating the problem as nonlinear optimisation problem. They present cases where energy could be reduced while avoiding collisions simply by manipulating the processor frequency and motor speed. This is an example of a component-level power control of the system.

Ogawa et al. (2006) propose a component for electric power control (CEPC) to minimise the power consumption of a small robot architecture in real-time. The CEPC controls the resource distribution, task priorities, predicted power consumption, and state monitoring of the system after receiving user commands. The underlying strategy leads to efficient use of batteries and executing alternative tasks which consume less power, where possible. However, this raises a question of how well the strategy will work if there is no alternative set of tasks; the potential of this strategy is limited.

Zhang et al. (2009) suggest that the power consumption on-board small mobile robots could be reduced by controlling the robot speed and processor frequencies. These two power sinks consume power differently depending on their state (i.e. speed and frequency setting). The problem was formulated as a discrete-time problem with random terminal time and probabilistic state constraints. However, the authors converted the coupled optimisation problem (joint speed control and power scheduling) into a deterministic nonlinear optimisation problem and proposed an exact optimisation method to solve the problem. Power functions, specific for their application, were derived and Lagrange multipliers were utilised alongside Karush-Kuhn-Tucker (KKT) conditions to obtain optimal solutions. In cases where the KKT conditions were not met, further analysis is suggested to obtain optimal solutions. Nonetheless, Zhang et al. (2009) guarantee optimality if the conditions are met and claim that the proposed method outperforms heuristic methods. However, the exact comparison between the two methods was unclear. This is an example of how a precise solution may be obtained using an approximate model.

Power generation control

Several studies attempt to improve power management by manipulating the power generation (power source control). Lesperance et al. (2005) designed a power management unit that functions both as a power supply and also as a pressure monitor on small robots powered by compressed air. The power management unit uses information from the battery monitoring board. Kottas et al. (2009) also applied a similar strategy for small robots. Both studies monitor or estimate the remaining charge in batteries and recharge as necessary. Kottas et al. (2009) also estimate the battery discharge and work towards achieving a more efficient use of power delivery. However, the power supply is supported externally. Not only is there an on-board power supply, but a separate mobile recharging platform is made available for use of the robots. These studies focus on specific batteries for a specific type of small robots; the wider applicability is unclear.

Another report on work done to improve power management for small robots is by Xie et al. (2008). They suggest that the PMS should control the charging and monitoring of the batteries to avoid battery damage. In this case, the objective of the PMS is to deliver power to the power sinks while maximising life of the power source. This optimises the power management only at the component level. The ideas and concepts introduced (Kottas et al., 2009; Lesperance et al., 2005; Xie et al., 2008) may be useful when considering part of the problem solution of the problem statement. However, some of the methods used are unclear and ambiguous.

Khare and Singh (2011) propose a method to manage and optimise the power generation on-board hybrid unmanned surface vehicles (USVs). Following complete modelling and analysis of the power sources on-board the USV of interest, Khare and Singh approach the problem differently compared to other studies listed in their review. Previous studies attempted to optimise power generation by implementing a hierarchical-based controller, stochastic optimisation (stochastic dynamic programming), and energy hub strategy. The authors claim that these methods do not fully utilise more economical power sources (solar and wave power sources) and propose an optimisation strategy based on priority and cost optimisation, where the objective is to minimise the cost/energy ratio. Instead, they model this problem as a discrete time optimisation problem with an objective function that minimises the error between energy demand and energy supply.

Khare and Singh (2011) acknowledge the difficulty in optimising hybrid power systems due to nonlinear models involved in the problem formulation and the large number of control variables. In their problem solution, the renewable power sources have the first priority during power generation whilst fuel cell, batteries, and diesel generators are only utilised when the former fails to meet the mission power demands. The authors model the total power demand as the sum of static load demands and random mission power demands. However, they only consider 7% of the typical mission duration of the USV of interest. The constrained nonlinear optimisation problem is solved using an interior point algorithm. It is implied that their solution may not be globally optimal, confirming the earlier discussion; analytical methods are likely to produce local solutions. The results of this study are also used to indicate suitable component sizing for the system.

Karunarathne et al. (2011) propose a power and energy management system for a small fuel cell UAS which comprises three subsystems: a PMS, a power electronic interface (PEI), and an energy management system (EMS). This power and energy management system controls the power generation on-board to optimise the fuel cell system performance while meeting the propulsive power demanded by the power system to achieve its mission (assuming constant payload). Since the performance of the fuel cell is dependent on the air supply, EMS tries to maximise the net power output of the fuel cell via control of the compressor. The EMS forms decisions to satisfy long-term objectives (to improve fuel cell performance) (Karunarathne et al., 2010). The PMS uses these decisions to construct short-term policies to control the PEI. The PMS determines the operating state of the power sources (fuel cell and battery) based on the demands across the system and battery state of charge. Meanwhile, PEI manages the power delivery, determining whether the power is used for charging or for propulsion. The hierarchical optimisation approach depends on the cooperation of the EMS to set the best setting for the fuel cell, and the PMS and PEI to support the implementation of this decision (in milliseconds).

Three operation states are utilised by Karunarathne et al. (2011): (1) start-up (battery only), (2) charging (fuel cell is on and charging battery), and (3) high power (both fuel cell and battery are supplying power). These states are determined by the PMS using a rule-based power sharing algorithm. The PEI also operates based on a rule-based algorithm. The rules used to form decisions are based on the load power demands. The proposed method utilises an adaptive neuro-fuzzy inference system (ANFIS), which relies on training the compressor power to attain optimal compressor power to reduce the difference between the actual compressor power produced and the optimal compressor power. Although the approach only considers air supply as the main variable to improve fuel cell performance, its power control architecture concept and approach used to construct control rules are interesting. However, due to its lack of transparency, this strategy may not be suitable for applications that requires certification.

Other forms of power management

In order to optimise the energy consumption on small hybrid-electric UAS, Harmon et al. (2005) propose an online controller to approximate the engine torque setting that would minimise power consumption. The online controller interpolates from nonlinear efficiency maps for the engine, motor and battery produced offline using available information (battery state of charge, demanded torque, and rotational speed). Harmon et al. (2005) claim that the proposed method has low computational cost, generalises, uses less memory, and outperforms rule-based controllers by 6.3–6.5%. However, this approach may be limited by the pre-loaded efficiency maps that would not consider real-time changes to the system, and for more complex systems, this strategy may require more memory. This strategy may be limited to small systems.

A neuro-endocrine controller is proposed by Sauze and Neal (2010) to meet large power demands of a small sailing robot despite environmental factors and limited heterogeneous set of power supply. However, the technique appears to be somewhat esoteric and later studies showed conflicting results (Sauze and Neal, 2011). Huang and Wu (2011) mainly present strategies for a predictive maintenance system on-board a small robot. Although the strategies involve PMS and dynamic power scheduling (which involves re-planning), their research lacked clarity on the specific method utilised for power scheduling.

Summary

Research on power management for unmanned systems are varied. Most of the research have small systems as their target applications, focus on design of the power system architecture, or limited to component level control that may be suitable for autonomous or remotely controlled vehicles. The highlights of intelligent power management are research that investigated the power demands alterations (power or task scheduling), and power generation (power source control e.g. Karunarathne et al. (2011)), both of which could improve the power efficiency of the system. To further explore approaches or strategies that may beneficial to improve the power management on-board complex autonomous systems, we briefly review the power management for other (manned) power systems below. This includes hybrid electric vehicles, among others.

2.4.2 Power management for other power systems

Manned vehicles

There is increasing interest in improving the power management on board systems such as more-electric aircraft (e.g. Husband (2014)), more-electric ships (e.g. Doerry et al. (1996)), and especially in hybrid electric vehicles (HEVs) (e.g. Lin et al. (2003)). These systems are complex and require efficient power management. Advancements of power management in these areas contribute to the wider research of power management and may provide lessons learnt for improving power management on board autonomous systems. Compared to autonomous systems that are of interest in the autonomous power management research, these systems share a future long-term goal of reducing costs, emissions, and improving performance.

Feng et al. (2012) propose the use of multi-agent system-based real-time load (power sink) management for all-electric ship power systems. In their approach, the agent system determines the switch status of the loads depending on the system constraints. The approach exploits load priorities. Load shedding of non-vital loads is performed as needed. As a consequence of certification restrictions, however, agent systems may not be appropriate for the type of application addressed in this thesis.

As a power store, a supercapacitor may act as a power source or a power sink. Styler et al. (2011) suggest a predictive and active PMS for power stores on electric vehicles where the power demands are predicted and the power levels in storage are manipulated to improve supercapacitor efficiency. Their strategy is to fully charge the supercapacitor before a predicted demand spike and usage of all stored power prior to excessive power generation. For example, if the vehicle is about to reach an idle state (where there is a supply of unused generated power), any power stored is discharged (used) to enable recharge in the subsequent stage. The study focusses more on the design for the hybrid system such the sizing required and also the capabilities of the proposed systems. The energy management system itself constructs the power demand profiles using models and driver history. The power stores are used as simple buffers. The performance of the PMS, however, is limited to the prediction capabilities of the algorithms.

In order to reduce fuel consumption and pollutant emissions by hybrid vehicles, Kermani et al. (2012) suggest an energy management system based on Pontryagin's minimum principle[1]. Model predictive control (MPC) was suggested where an offline optimisation algorithm is combined with a real-time predictive algorithm. Optimal powertrain operating points (engine torque, engine state, and gear number) are determined, based on the prediction of future driving conditions. To attain good predictions on long-term future states, Kermani et al. (2012) propose a method that uses a predicted distribution of the states. In order to reduce the computational cost, an offline computed mapping is integrated into their method. The proposed method could be separated into three cascading controllers: (1) the battery state of

[1]Pontryagin's minimum principle provides a necessary condition for optimal control based on the Hamiltonian.

charge correction, which compensates for prediction errors; (2) the prediction and optimisation algorithm, which determines the Hamiltonian costate variable which is piecewise constant; and (3) the powertrain control, which provides the solution to the problem (decision variables). These controllers utilise variables determined by the predecessor controller. Kermani et al. (2012) acknowledge the risk of sub-optimality of the solutions; this is not surprising due to the real-time execution of the strategy. However, based on their comparison study and available methods, the solutions produced may be sufficient, or at least prove to be the best that are attainable.

Lin et al. (2003) sought to improve fuel economy and reduce emissions of future ground vehicles. The authors suggest a two-level power management strategy. A top-, or vehicle-, level control algorithm determines the power levels to be generated and the loading of the two power sources. Meanwhile, a low-, or component-, level controller that operates at a higher rate would then execute these decisions. The authors identify three general approaches for power management in HEVs: (1) heuristic control (rules, fuzzy logic, for example, for estimation and control); (2) static optimisation e.g. exploiting steady-state efficiency maps; and (3) dynamic optimisation. The authors argue that dynamic optimisation is more accurate under transient conditions but is more compute-intensive. Using dynamic programming (DP), the gear shift sequence and power split are determined. However, the way the authors use the solutions from the DP differs from other research. Instead of using the DP solutions directly, the authors extract useful information to form an improved rule-based algorithm[1]. This an interesting approach to construct control rules.

There are other research which seek to improve the energy management on-board hybrid vehicles (Faggioli et al., 1999; Koot et al., 2005; Moreno et al., 2006; Rodatz et al., 2005; Won and Langari, 2005). Faggioli et al. (1999) explore the use and management of supercapacitors on-board electric vehicles and present the potential benefits of this power store for these types of systems. Won and Langari (2005) propose an intelligent energy management agent system for use on-board parallel hybrid

[1]The initial rule-based algorithm is based around expert intuition and efficiency maps. For example, recharge of the battery is determined based on maintaining the state of charge at an efficient range (55–60%).

vehicles. The fuzzy rules used to determine the power split between the components exploit the knowledge of the driving environment. Koot et al. (2005) explore prediction and non-prediction methods to improve energy management. These smarter energy management strategies show noticeable benefits in terms of fuel savings and emissions reduction compared with traditional power control approaches. Rodatz et al. (2005) discuss the use of real-time methods to encourage optimal power flow management for a fuel cell and supercapacitor hybrid vehicle. Moreno et al. (2006) discuss a component-level energy management system for a HEV using supercapacitors and neural networks. Chau and Wong (2002) provide a more in-depth analysis and review of HEV research, discussing the driving force behind the research, such as emissions requirements and strategies used to improve the power management, e.g. alterations of system configurations and design, and power flow management.

More recent studies utilising optimisation techniques to improve the energy and power management systems were found (Guanetti et al., 2014; Heppeler et al., 2014; Murgovski et al., 2014; Yang et al., 2014). Using a predictive control strategy, Heppeler et al. (2014) seek to optimise the vehicle velocity, torque split, and gear shifting by applying a discrete DP approach. Murgovski et al. (2014) decompose the energy management problem into two sub-problems: static and dynamic optimisation problems. While some elements of the optimisation process are designed to be implemented offline, they apply convex optimisation to improve the efficiency of the optimisation process. Yang et al. (2014) provide an interesting review on the optimisation methods that have been explored for the integration of plug-in vehicles into the electrical power grid. This includes both analytical and heuristic methods.

The majority of the research seek improvement in the design of the power system or component-level power control. Although component-level optimisation, such as battery lifing is beneficial, further optimisation of power management may be achieved. In many cases, power efficiency was gained by exploiting prediction methods to improve vehicle operation. This approach may be limited as the ability of the proposed methods to perform well with unprecedented events occurring mid-operation is unclear. Very little research work in this area utilises integrated system-level control. The literature lacks system- or vehicle-level planning with the exception of Lin et al. (2003). An observation that should be noted is the amount of research investigating the benefits of power stores and strategies to fully exploit these components. Of course, as power store technology is on the rise, interests in investigating their potential is not surprising.

Electric power distribution system

Another area of research that shares similar characteristics and requirements with PMSs on board autonomous systems are electric power distribution networks. These power systems must satisfy the load demands, which vary depending on the time horizon. While doing so, the power system should be operated economically to avoid unnecessary costs. The objective during power generation and distribution planning is minimisation of operating costs, or maximisation of profit. The constraints of the system may include fuel constraints, demand fulfilment, power ramp rate limits, transmission flow limits, and generation limits. Electric power distribution networks may need to regulate the power generation between many power sources, which may have different capabilities (e.g. different generation limits) and characteristics (e.g. wind or fuel powered sources). The purpose of including this section in this thesis is to provide a brief, but not exhaustive, overview. Instead, it is to present the ideas and possible approaches that might influence the improvement of power management for autonomous systems.

Prior to the application of optimisation in electric power systems, an operator, knowledgeable in the system's characteristics and operating costs, assigned the unit commitment of the power sources (generators) (Yamin, 2004). Over the years, subsequent to the introduction of the use of optimisation methods to produce power schedules, both deterministicand metaheuristic methods have been exploited.

Deterministic methods that have been implemented for electric power distribution network scheduling include (Yamin, 2004):

- integer and mixed integer programming
- branch and bound method
- dynamic programming (DP)
- Lagrangian relaxation (LR).

Metaheuristic methods that have been used to produce power schedules for electric power distribution network include (Yamin, 2004):

- expert systems
- fuzzy logic
- artificial neural network (ANN)
- genetic algorithm (GA)
- evolutionary programming (EP)
- simulated annealing (SA)
- tabu search (TS).

Yamin (2004) reviews only methods used up to 2004. However, this provides an overview of the application of optimisation techniques for power distribution networks, including the advantages and shortcomings of these techniques. Different methods are used depending on the formulation and the objective of the problem. Some studies are only interested in the power state *on* or *off* for a power source, while some extended the problem to determine the exact power setting of the power sources. The constraints of the problem also varied across the field of research. The constraints include resource constraints and the coupling between multiple types of power sources. Some types of constraints result in an increase in the problem complexity.

Yamin (2004) also highlights the difficulty faced by past studies when integrating multiple types of power sources into the optimisation problem. One method to overcome this is to use decomposition methods. Decomposition of the problem into a set of small sub-problems proves to be an interesting and plausible approach for an improved PMS because it allows reduction of the problem complexity (improving the tractability of the problem), enabling the problem to be solved in reasonable time. This may be a suitable approach for use in real-time optimisation.

Often, there is a trade-off between the tractability of the models and the true representation of the system during problem formulation. Equivalently, a trade-off between optimality and computation time of problem solutions may also be unavoidable. There is no available *best* method for solving the power scheduling problem; most strategies implemented are problem-specific. However, more recent studies which apply hybrid techniques seem to be promising. Some techniques appear to have been applied to industrial power systems (e.g. PG&E power systems) (Yamin, 2004). However, it was unclear whether most of the techniques discussed were applied to real power systems.

Since Yamin (2004), there have been further research that explore new strategies to improve power management (AlRashidi and El-Hawary, 2009; Asghari and Sharma, 2014; Lopes et al., 2007; Lujano-Rojas et al., 2012). For example, AlRashidi and El-Hawary (2009) discuss the use of particle swarm optimisation (PSO) in electric power systems. An attractive feature of PSO is its simplicity, and as a result, it has gained much attention as a general purpose optimiser. Hybridisation of this algorithm with other methods also seems promising. Some of these optimisers have been successfully tested in real-world applications.

Although optimisation problems found in electric power distribution networks are different to those found in autonomous systems, they provide an additional perspective on how power management problems may be handled. The techniques presented may still be transferable to our system of interest.

2.4.3 Autonomy in system management

Mission management systems (MMSs) are briefly discussed due to their mutual dependencies with PMSs. These two management systems share similar characteristics and often work in synergy in autonomous systems. A MMS ensures mission goals are met by constructing and enacting plans describing the future tasks of a vehicle based on system information, system requirements, mission goals, and ground control commands. The plans constructed by MMSs are often constructed offline (pre-mission) and updated when necessary by communication with ground control. Ground control plays a significant role in the mitigation of unexpected events that occur mid-operation. This may involve optimisation and decision-making by the ground control. However, in recent years, autonomous operation of MMSs has gained much interest and is in development. Selected recent developments in MMSs are presented below to contribute key ideas and concepts that are pertinent to the improvement of autonomous power management.

On board an unmanned vehicle, the MMS has access to information describing the state of the vehicle. This information may include system health diagnostics and prognostics, mission goals, and available resources. Subject to real-time changes involving the vehicle, the MMS has to mitigate faults and optimise mission plans based on available resources to enable the mission goals to be met. In Tang et al.

(2010), the mission re-planning problem is formulated as a multi-objective optimisation problem where the objectives include the percentage of mission accomplished and the time taken for the mission completion. However, due to prognostic information of the system health, Tang et al. (2010) also consider uncertainties within the optimisation formulation. The methods used to solve this problem are dependent on the choice of an *insurance policy*. For example, a conservative policy ensures that critical tasks are executed by re-planning using robust optimisation methods that uses more computational power. On the other hand, a moderate policy would utilise methods that are (computationally) cheaper but are likely to be sub-optimal.

Autonomous and partially-autonomous MMSs for UASs have also been introduced are intelligent agents were used to update mission plans (Tan et al., 2007). This MMS applies rule-based strategies, reactive rules, and ground control commands depending on the event that arises. The MMS is designed in a hierarchical structure, with different groups of agents (with different tasks and capabilities) in each layer. Depending on the layers and type of task (e.g. navigation, route re-planner), the autonomy of the UAS varies, as illustrated in the case studies. Several others have reported agent-based MMSs (Gunetti, 2011; Karim et al., 2004). Note that although these MMSs are agent-based, it is still necessary for an optimiser to be embedded within the agent-based system architecture. Information from the optimisation processes is used by the agents.

Bui et al. (2012) formulated a military MMS planning problem as a resource constrained project scheduling (RCPS) problem with multiple objectives. The authors exploit these problem objectives to solve their dynamic scheduling and planning problem. Their method focussed on meeting the problem objectives while minimising the costs from re-planning. Re-planning costs include the cost that is incurred when a resource has to be relocated. For example, if the cable connection between a power source and sink is changed, there is a corresponding cost towards the change. One of the features of the method is that it does not alter or re-plan, executed or in-execution, tasks. As a result, this reduces the overall operating costs.

Their proposed method, centroid-based adaptation (CBA), uses information from a previous set of non-dominated solutions (their area of attraction within the search space) to create a new population for the re-planning stage; this speeds up the search process (Bui et al., 2012). Note that CBA is intended for use with EAs such as GA. This real-time method was applied on a military MMS where different scenarios were given and the performance of CBA was analysed (and compared with other methods used to initialise populations). CBA showed promising results by exploiting the multi-objectivity of the problem, which was not employed in other works. Several possible solutions are produced. To assist the decision-making process, the authors introduced a second objective to help selection of the final solution. Although the methodology proposed in this work is interesting, a decision-maker is required to make the final decision (i.e. not autonomously).

To support the increasing autonomy in unmanned marine vehicles, Insaurralde and Petillot (2013) propose an intelligent control architecture to organise the tasks of multiple collaborating marine vehicles. In their case study, their strategy enables a marine surface vehicle and an underwater vehicle to co-operate autonomously. The control architecture uses a knowledge-based database that stores human expert information and high-level reasoning agents to adjust the mission plans accordingly.

Diaz et al. (2013) propose a strategy that combines elements of both a PMS and a MMS for the autonomous control of rover missions. Their strategy focuses on path planning initially, followed by resource management that is based around a constraint-based solving algorithm.

Other approaches used to contribute to autonomous planning include: constraint satisfaction techniques (Ghallab et al., 2004); genetic programming (Oh and Barlow, 2004); normal boundary intersection numerical method (Jilkov et al., 2007); Bayesian framework (Tisdale et al., 2009); genetic algorithms (Edison and Shima, 2011; Ellefsen, 2011; Shima et al., 2006); and agents (Karim et al., 2004).

2.4.4 A brief summary of today's power management

In recent years, many studies have contributed towards improving PMSs. The strategies and applications are varied. Literature on the power management of the target system of this research, i.e. complex autonomous systems, however, may be limited due to commercial sensitivity. A number of research have focussed on improving power management for small robots and some of the suggested methods and ideas presented show promising results. However, due to the greater complexity of the intended application, it raises questions on the reliability and scalability of the proposed methods.

A number of the problems and problem solutions (not limited to small robots, but also other applications) may prove to be too problem-specific. Nonetheless, examples of some pertinent methods include analytical methods such as Langragian relaxation with KKT conditions (Zhang et al., 2009) and heuristic or hybrid methods (Bui et al., 2012; Khare and Singh, 2011; Yamin, 2004). These methods may be incorporated as part of the problem solution. Model predictive control (MPC) (e.g. in Kermani et al. (2012)) performs well in handling transients and dynamic systems. However, system-level (static, or steady-state) optimisation[1] is of particular interest of this research, and MPC is more suited for middle-level optimisation.

There are also studies that illustrate the ideas behind the methodology rather than their implementation on real applications (Tang et al., 2010). This perhaps is due to the lack of maturity and absence of certification of these proposed technologies, as mentioned by Morley and Wall (2010) in their proposal for an intelligent PMS. It is also worth noting that perhaps the generality of the studies was aimed to increase the applicability of the concepts and ideas onto other platforms.

A key observation from the literature is the potential for optimisation techniques to improve PMSs.

2.5 Towards Intelligent Power Management Systems: a summary

Optimisation strategies for a flexible PMS are required. These strategies aim to improve today's PMSs and contribute to the development of IPMSs as highlighted in Section 2.1. These optimisation strategies will enable the PMS to construct optimal power plans while satisfying system constraints in-operation and on-board autonomous systems. Since the PMS is intended for real-time application, the construction of the power plans are constrained to the time available for computation and the use of a limited computing resource, i.e. those suitable for the on-board computing environment. It is essential that solutions (new plans) are constructed in

[1]System- and component-level optimisation in power management is discussed further in Chapter 3

sufficient time to be relevant to the on-going dynamic situation. The PMS will be capable of dynamically updating optimal schedules to adapt to change of problem description, problem constraints, and problem objective.

Evidence of research to improve current PMSs can be found in the literature and have been discussed in Section 2.4. However, the applications and outcomes are insufficient to meet the goals of an IPMS. Although a complete, more holistic PMS is required, there were lack of reported research on this topic. Most studies focus on the control of only part of the PMS platform. The strategies for problem solutions found in the literature are varied and not all researchers formally formulated their problem as an optimisation problem.

Based on the review of relevant optimisation methods in Section 2.3, hybrid methods and decomposition techniques are found to be two promising optimisation strategies that could be integrated into improving future power management strategies. Desirable features from different methods may be combined to encourage good quality solutions to be found. Decomposition of the problem into a set of more tractable problems may enable solutions to be found in real-time and with limited computing resources.

The selected algorithms must examine complete solutions. This guarantees that a solution exists even if the optimisation process is stopped prematurely. The selected algorithms should also be capable of computing a satisfactory solution in a reasonable amount of time, while making efficient use of computing resources. The solutions produced should also include some measure of robustness.

The absence of a decision-maker raises several issues. If there are desirable traits in the solutions, how can these preferences be expressed and forced onto the solutions produced? In cases where feasible solutions cannot be found, how should priorities of the constraints be handled to enable the best executable power schedule to be constructed? Further, if more than one solution exists, which solution should be selected for enactment? The solutions produced for the proposed PMS must be executable by the autonomous system, without assistance from a decision maker. This also implies that if the solution is infeasible, appropriate actions should be taken to enable an executable solution to be constructed.

Accuracy, speed, and determinacy are some of the attributes that are required by the PMS. The accuracy of the solutions may be increased by representing the problem with high fidelity models (representing the real system). Due to the application of the strategies produced, the algorithms selected must also show determinacy and speed. While deterministic and traditional approaches show determinacy, they are not always suited to be used for high fidelity models due to problem tractability and speed. Heuristic or stochastic approaches tend to be better suited for high fidelity models, producing good solutions within an acceptable time interval. In order to still achieve the three attributes of accuracy, speed, and determinacy, a compromise and hybridisation of methods may be necessary.

In summary, from the problem requirements and the range of optimisation methods that are discussed in Sections 2.3.2 to 2.3.4, those that are of interest are:

- algorithms which are capable of solving problems involving continuous and discrete decision variables
- algorithms which execute complete solutions and store a feasible solution at all times
- algorithms which are capable of handling nonlinear discontinuous objective functions
- algorithms which are efficient and suitable for real-time computation
- methods for handling uncertainties
- algorithms which combine desirable features from different methods (i.e. hybrid methods)
- methods that produce one best executable solution at the end of the evaluation.

These requirements will be studied in the succeeding Chapters.

Chapter 3

Problem Formulation and Solution Architecture

A strategy to solve a problem is to first form an in-depth understanding of the problem and identify the key components and goals. Next, problem characteristics should be fully captured. Then, methods that are suitable for solving the problem may be selected based on the identification and classification of the problem type. This enables a set of candidate methods or techniques suitable to form the problem solution to be identified and down-selected. Implementation and testing of these methods introduce opportunities for reiteration and fine tuning the overall approach to find the best possible problem solution (Figure 3.1).

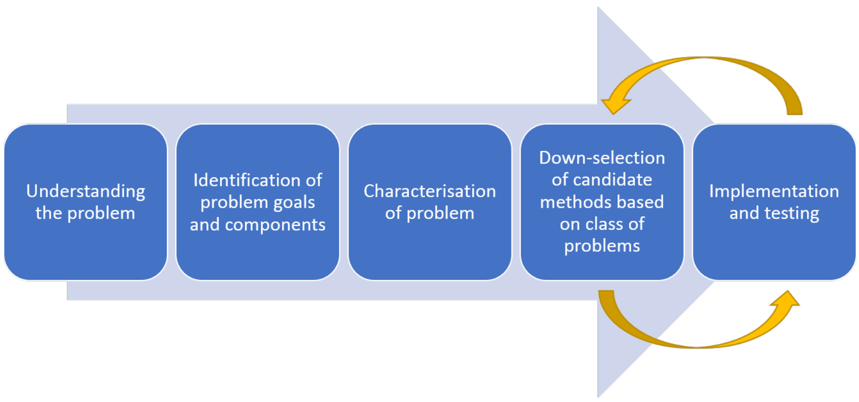


Figure 3.1: Problem solving strategy.

In the previous Chapter, the challenges in the optimal management of power on-board autonomous systems have been discussed. Autonomous systems have varying features and capabilities; however, they may share a number of problem characteristics. For example, both marine and aerospace systems are equipped with multiple power sources and power sinks, albeit marine systems are likely to have a larger number of components to manage compared with aerospace systems. Both systems are subject to restrictions based on certification and worthiness. Of course, certification requirements change depending on the system of interest. These features, or requirements, highlight a set of characteristics that describes the problem, enabling the identification of the classes of problems that need to be solved. This subsequently led to a set of criteria of the problem solution.

To address the challenges of developing optimisation strategies suited for the optimal control of power on-board future more-intelligent autonomous systems, a particular case study is used as a starting point to develop an Integrated Power Management System. These strategies are envisaged to be transferable and applicable to different systems that belong to the same classes of problems.

This Chapter describes the particular case study, detailing the problem setting, system information, and system model. Key issues from the literature are highlighted. The representative system is also used to illustrate the mechanism behind the entire power management framework, from input demand to power schedule output – the complete framework of an Integrated Power Management System.

3.1 Managing power on board Unmanned Aircraft Systems

Unmanned Aircraft Systems (UASs) are example autonomous systems that have gained much interest in the last few decades. This has resulted in various developments of the subsystems on-board the UASs, and this is expected to continue. Larger power requirements impose a heavier burden on these systems that are already limited in terms of power.

Upon deployment, a UAS is subject to dynamic changes due to environmental factors (e.g. weather), system health (e.g. component failures), and mission changes. These often raise issues in terms of new power requirements and power plans since the pre-defined power plan may no longer be the best power schedule, with the attendant risk of mission failure (Figure 3.2). An optimised Power Management System (PMS) capable of constructing these updated power plans in real-time, and in-mission is required. The PMS should consider other requirements such as certification; UASs are example systems which are heavily regulated by organisations such as the UK Civil Aviation Authority (CAA).

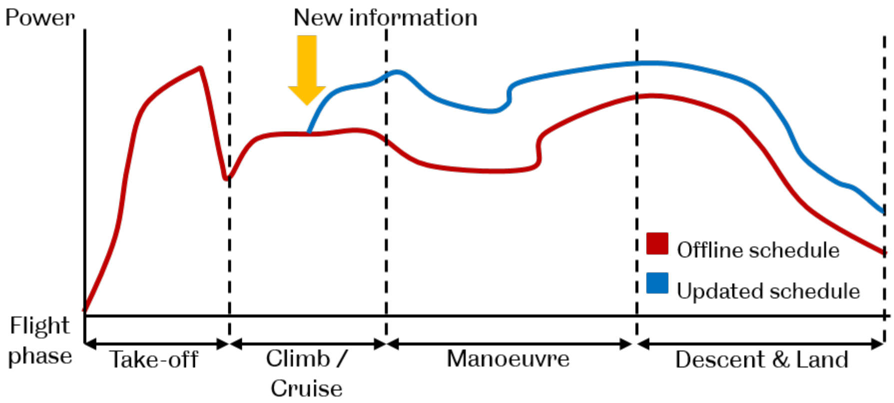


Figure 3.2: Flight profile: PMS is required to re-construct power schedules in response to new events.

3.2 Problem definition and scope

This research aims to contribute to the development of an intelligent PMS and to demonstrate the capability of optimisation strategies in power systems. The strategies formed are aimed to fit into any multi-source, multi-sink power system: a plug-and-play capability. The envisioned optimised PMS will be capable of constructing optimal power schedules while satisfying system constraints in-mission and on-board UASs. Therefore, the schedules computed are constrained to the time available for computation and the use of a limited computing resource, i.e. those suitable for the on-board computing environment. It is essential that the solutions (new schedules) are constructed in sufficient time to be relevant to the on-going dynamic situation. The PMS must be capable of dynamically updating optimal schedules to adapt to change of problem description, problem constraints, and problem objective.

The key challenges to construct such adaptable and responsive PMS are to ensure that the *autonomous* system performs better than existing technologies in terms of solution quality (*optimal* solution) and *responsiveness*, whilst restricted to *real-time* requirements (Figure 3.3). Of course, the overall solution to the problem posed must be *certifiable*.

As an autonomous system operating at a relatively high Pilot Authority and

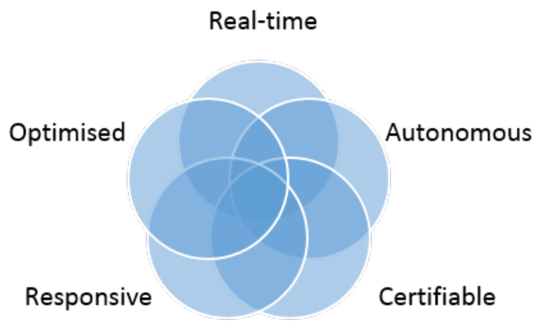


Figure 3.3: Challenges in developing an Intelligent Power Management System.

Control of Tasks (PACT) level, the PMS must be capable of intelligently selecting the best solution and be responsive to new scenarios and events such as a mission change. The decision-making process relies on analysing the impact of possible actions based on a specified objective, without a complete knowledge of the environment. The selected action affects other control systems within the vehicle and the PMS is required to consider these effects during action selection. Although the PMS is allowed several minutes to construct a power schedule, it is expected that this solution is constructed within the computing restrictions and has a useful level of accuracy.

The typical computing resources are those that are typically available on an airframe. Memory and processor bandwidth restriction limit the choices of approaches used in the PMS; for example, numerically intensive approaches or approaches with large memory requirements are deemed unsuitable. The use of supercomputers is inappropriate for this study. The timeliness requirement of the solution construction poses a challenge for the optimisation problem. An optimal solution is sought. However, optimality of solution relies on the time to search for the best solution. Time is a luxury for this application and it is accepted that the solution may be sub-optimal due to these computing constraints. The models representing the problem and the objective of the problem are not always easily available. For example, although fuel consumption and operational costs may be estimated using available resources, modelling life of vehicle components and maintenance outages are non-trivial. The absence of some of these models and complexity of the system itself introduce uncertainty and risks. The improved PMS should be capable of capturing these uncertainties.

Lack of regulations for unmanned systems generates a problem for the design for a problem solution; regulators require example systems to certify and industry requires standards to specify product requirements. However, guidelines by regulatory authorities have highlighted the requirements for on-board systems to be transparent, safe (at least as safe as manned aviation), and deterministic.

Today's control strategy does not utilise system management that optimises multiple sub-systems of the power system simultaneously. Consider the monitoring and control layer in Figure 3.4 for example, the control measures are often restricted to a particular sub-system. In future control strategies, it is envisaged that this control strategy is altered to deliver a more integrated vehicle management system, where all the sub-systems are managed at the same time (Figure 3.4). This forms a more hollistic view of the problem and the subsequent problem solution.

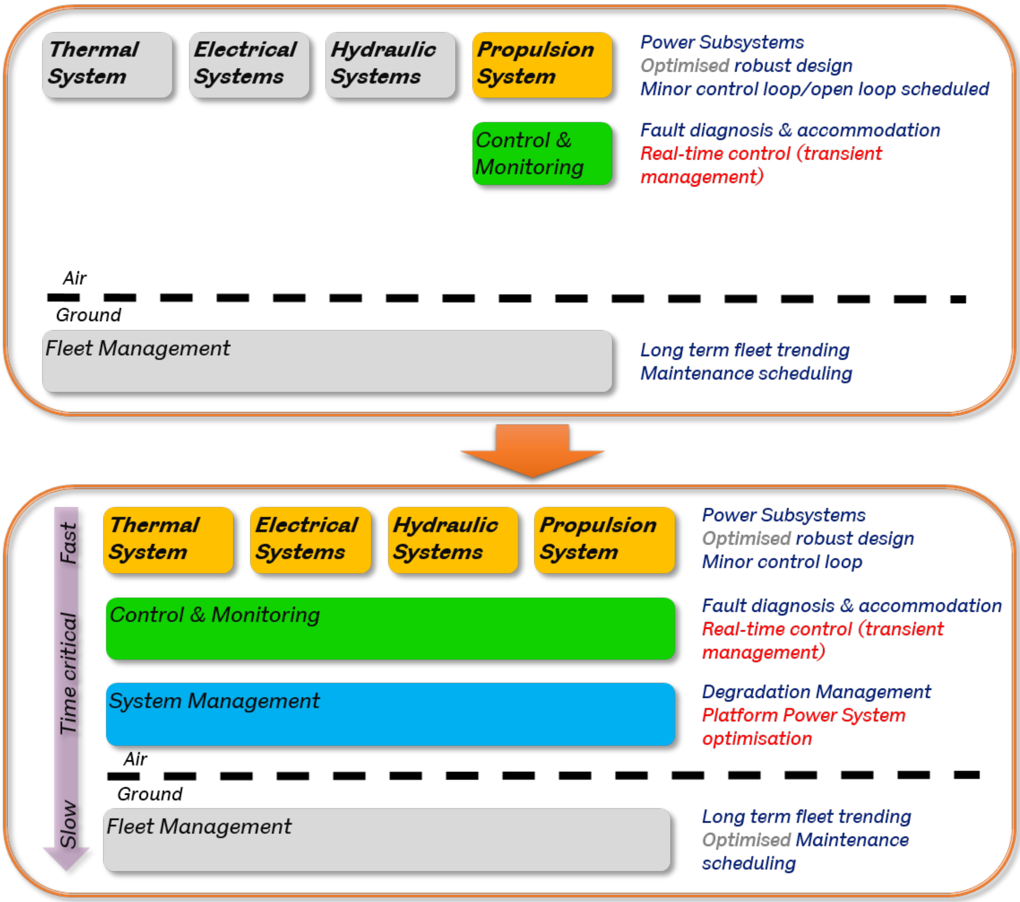


Figure 3.4: Example change from existing control strategy to a more integrated vehicle management system (Wall and Mansor, 2014).

This research study focusses on developing the top-level control strategies i.e. the systems management level (Figure 3.5). For control at the system- or top-level, static (steady-state) optimisation is considered. This control layer would complement the middle-level controller, which manages the system transients, and the low-level controller, which handles the individual component optimisation.

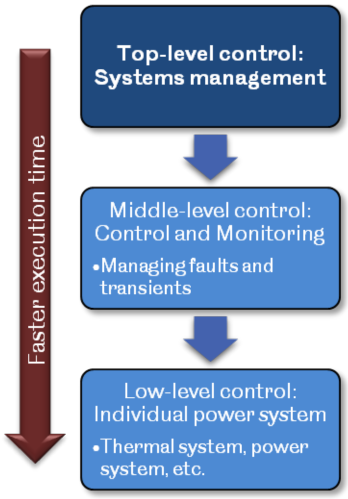


Figure 3.5: This research study focuses on developing a top-level control strategy for PMSs (dark blue).

3.3 System architecture

The optimisation strategies developed are designed to be part of the top-level control for power management on board UASs. Figure 3.6 illustrates an example architecture for a power system and its control. The top-level control comprise Vehicle Management System (VMS) and the PMS. Within the PMS, complementary sub-systems exist; e.g. Equipment Health Management (EHM), Power Manager (PM), Hybrid Energy Storage System (HESS) Feasibility Determination. The VMS supplies the PMS with mission plans and the PMS returns reports on the power management of the system. The focus of the research is to develop optimal control strategies for the Power Manager (PM) highlighted in bright blue in Figure 3.6. The top-level control layer interfaces with the middle-level control layer by providing the power schedule to be enacted. Example information are: the state of charge of energy stores, power setting for power sources, and network configuration information for load management. The PMS also passes information from the VMS to the middle-level controller e.g. load forecast. The middle-layer control accepts top-level steady-state commands and provides required reference signals for the low-level controllers, allowing the top-level demands to be satisfied. This level also handles transients and ensures system stability.

Figure 3.7 shows the simplified top-level architecture of the system and the relationship between the systems and sub-systems. The current state of the UAS, Ground Control System (GCS) commands, mission power demands, health status, and other relevant information are available to the PMS via the VMS. Health advisories, which are constructed by the EHM using diagnostic and prognostic information, are also provided to the PM. Using the information supplied, the Optimisation Platform within the PM constructs optimal power supply plans (PSPs). These PSPs are the power schedules that describe the power supply and delivery for the entire mission. These plans, or schedules, are subject to the approval of the Decision-Making Platform (DMP), which also lies within the PM. If approved, the PSP will be enacted by the PM. If rejected, the Optimisation Platform will re-evaluate the problem based on the information provided by the DMP and propose an alternative solution. Infeasibility warnings and advisories suggesting improvements to the solutions or alternatives are sent to the VMS.

3.3.1 Power system architecture

With Autonomous Systems Technology Related Airborne Evaluation and Assessment (ASTRAEA) II programme as reference, a Medium Altitude Long Endurance (MALE) UAS has been used as a starting point for this research (Wall, 2012a). Details of the power system architecture is discussed in Appendix A. The UAS of interest comprises two Model 250 Turboprop Gas Turbine Engines, with a high pressure (HP) starter generator and a low pressure (LP) generator attached to each engine (Rolls-Royce, 2014; Wall and Mansor, 2012). A power store/energy storage device is considered, specifically a supercapacitor (SC) with $500kJ$ energy capacity. Energy stores may be a power source or power sink depending on the power state. A $270V$ DC electrical bus is connected to the power sources and power sinks. Figure 3.8 depicts the schematic diagram of the power system architecture. An additional feature of the system is a set of smart switches that equips the PMS with the capability

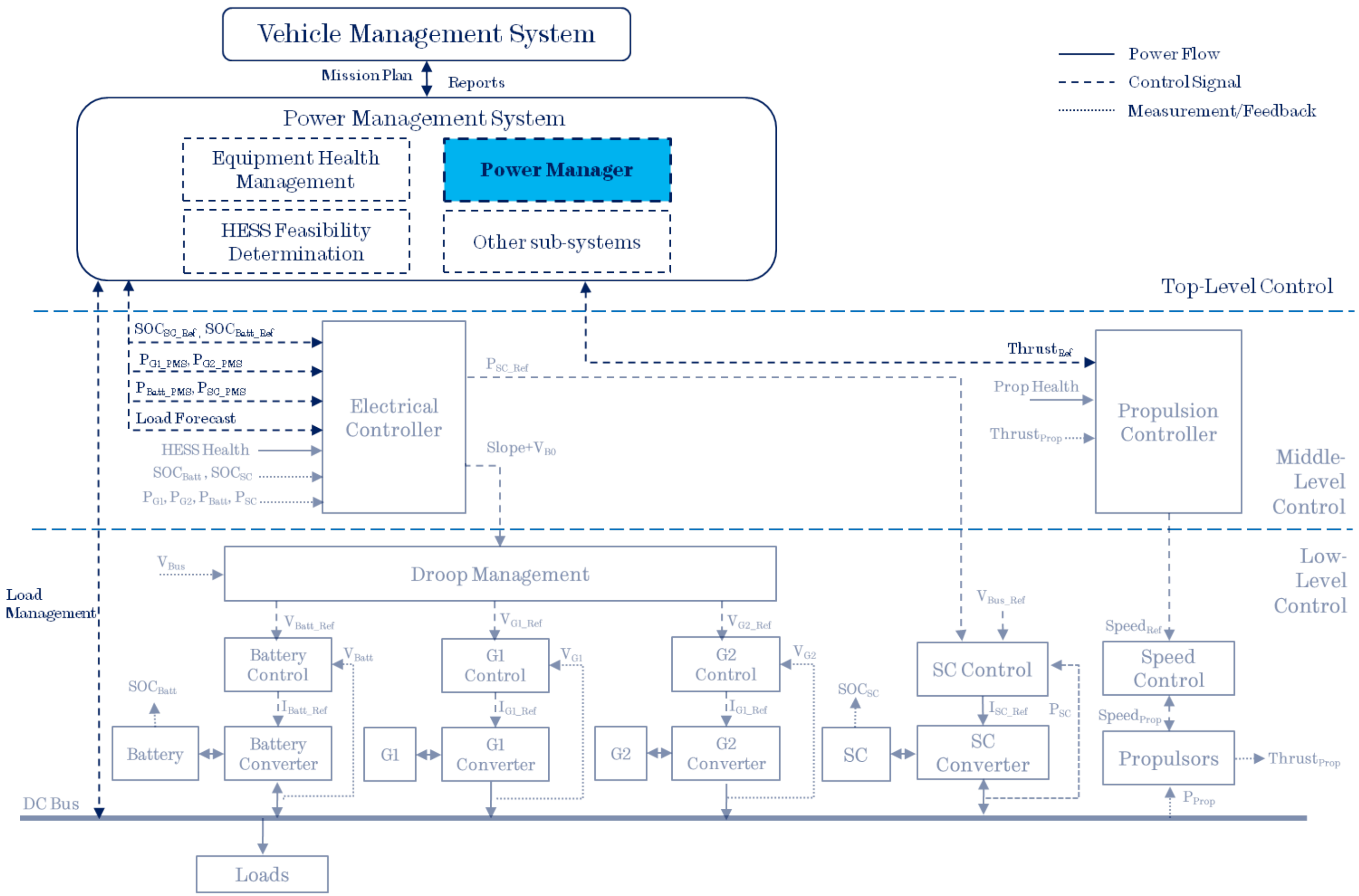


Figure 3.6: Example power system architecture. Faded components indicate that they are out of the scope of this research study (Cano and Mansor, 2014).

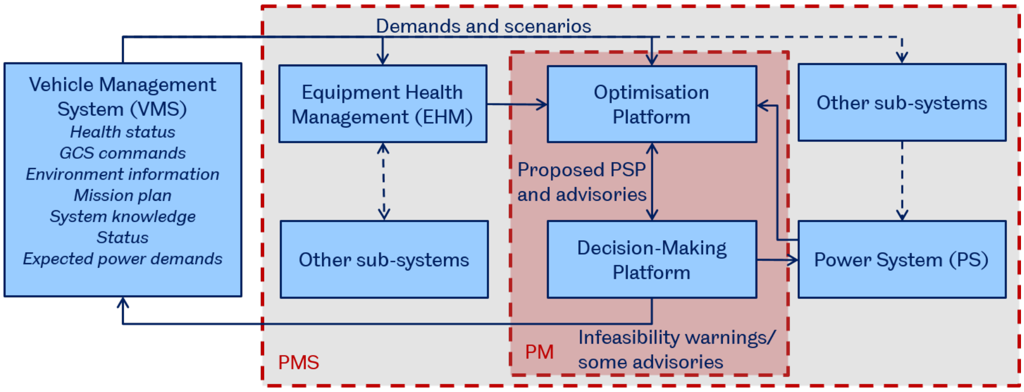


Figure 3.7: The PMS and VMS interact with each other, enabling the PMS to be informed of mission requirements and inform the VMS of warnings or relevant report. The PMS itself comprises of multiple complementary sub-systems.

of directly controlling the electrical power supply and delivery between the power sources and the power sinks. In other words, the PMS is responsible for allocating specific amounts of power from power source (generator or SC in discharge mode) i to power sink (or SC in recharge mode) j. The possible power delivery (network configuration) is shown in Figure 3.9, where the optimisation process would search and optimise the values represented by the red arrows.

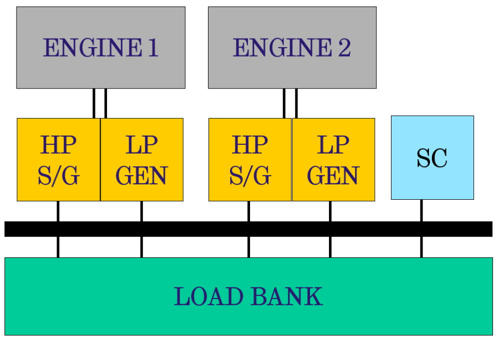


Figure 3.8: Power system architecture adopted for this research study (S/G = starter generator, GEN = generator).

3.4 Existing Power Management Systems

3.4.1 Power management within industry/Rolls-Royce plc

Existing technologies within the company utilise rule-based schemes to manage the power on board these systems. These control schemes are application-dependent and are listed below (Wall and Mansor, 2014):

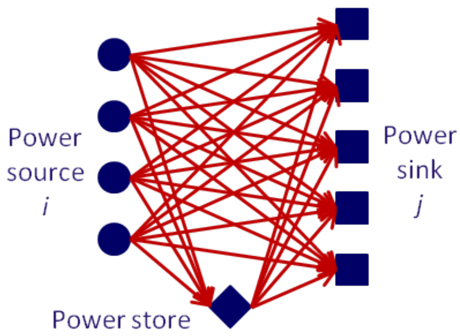


Figure 3.9: Network configuration.

1. Equal load share on propulsors, equal proportions of load share for electrical generators.
2. Equal load share on propulsors, equal real-valued load share for electrical generators.
3. Equal load share on propulsors, LP-first loading for electrical generators.
4. Equal load share on propulsors, HP-first loading for electrical generators.

Load shedding (load prioritisation) may be enabled if the problem is infeasible. These schemes do not incorporate network configuration, power store control, or planned in-flight engine shutdown/restart control in the power scheduling.

3.4.2 Optimisation strategies for power management systems

Existing technologies used by industry may be improved by not relying entirely on rule-based control. A control approach that adapts to events and optimises the control based on system health has the potential to improve system performance, components life, and overall costs. As seen in the academic literature (Chapter 2), some research has sought to incorporate new ideas to improve future control measures of existing PMSs. However, a complete framework that satisfies the design criteria and capable of meeting all the future IPMS goals is still lacking. Most studies focus on the control of only part of the power management problem. Many researchers also propose strategies for improved power management limited to smaller systems which are not easily transferable to larger, more complex autonomous systems, with multiple power sources and multiple power sinks.

The envisaged PMS is conferred delegated autonomy during flight. When there is no, or reduced communication, with the decision-maker (human controller), selection and enactment of the best solution becomes more challenging. The stand-alone integrated PMS should be able to function independently while ensuring safety of the system (including worthiness and certification requirements of target applications) and satisfying criteria set if the PMS is to be embedded into future applications of autonomous systems. A transition from functional autonomous operations to economic autonomous operations for a given system is sought. In other words, instead of focussing only on producing feasible solutions, this research aims to improve, or *optimise*, the actions of autonomous systems.

3.5 Optimisation techniques as tools

Optimisation techniques seek the best solution with regard to a particular objective, or criterion, for a given problem. In this thesis, the aim is to improve how the power on board an unmanned vehicle is managed using optimisation techniques. Akin to other real-world problems, the problem posed in this research combines elements from several types of optimisation problems. A single solver may not be the best fit for use on an integrated PMS due to this mixture of characteristics. A hybrid approach[1] may be more suitable for the improved PMS.

In the context of PMS, optimisation can be used to exploit the characteristics and capability of each power system component in favour of the specified objective. Consider a case where the improvement of generator efficiency is sought. Figure 3.10 (a) displays a demand of a particular mission load on the generators. Existing power control would satisfy this requirement by reactive control as shown in Figure 3.10 (b), albeit at the cost of the generators operating outside their optimal operating zone. However, using optimisation techniques, intelligent use of a supercapacitor to support the optimisation of the generator efficiency can be deployed (Figure 3.10 (c)).

Other features of the system may also be exploited to further optimise the power management on board these systems. For example, planned engine in-flight shutdowns (IFSDs) are possible for this UAS, subject to airspace regulations. An IFSD may contribute to fuel savings depending on the mission requirements. EHM ad-

[1] A hybrid approach combines different techniques into one single approach.

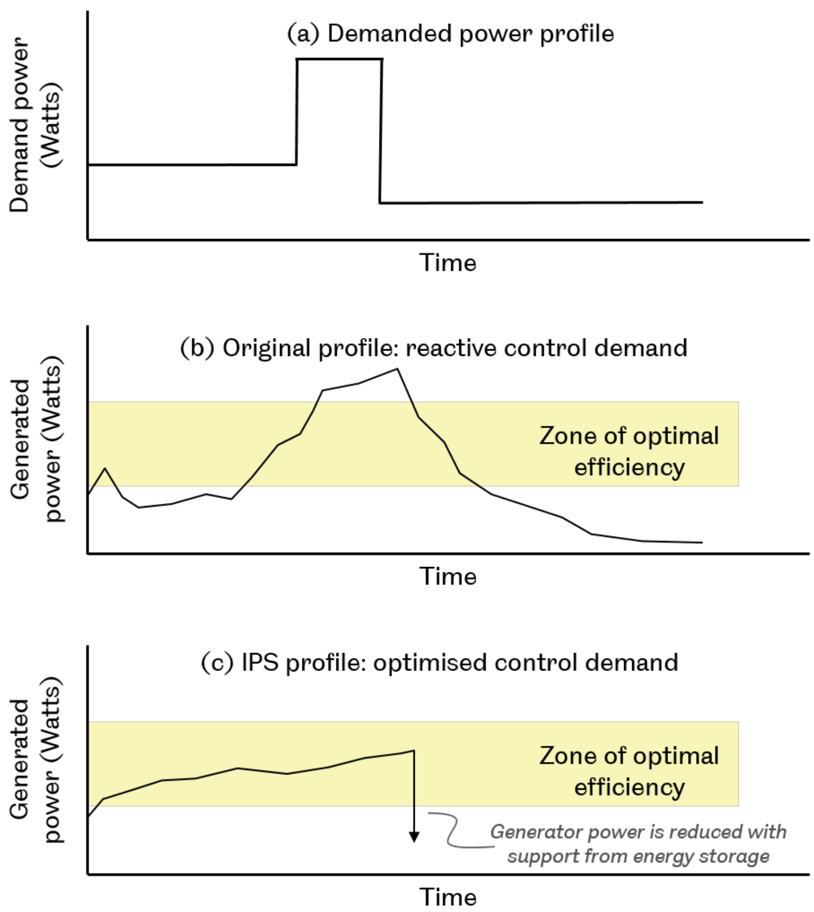


Figure 3.10: Power demand and delivery: (a) Power demand. (b) Generator response to power demand. (c) Co-operative power delivery by generator and supercapacitor for improved generator efficiency.

vice may also form soft constraints that would indirectly contribute towards longer term fuel savings. These features of the problem may be exploited by optimisation techniques to produce the best solution.

Although optimisation provides a promising strategy for improving power management, there are several challenges to address. An abundance of optimisation solvers may be found in the literature. However, they are often problem-specific (applied optimisation techniques), or too restrictive for use for power management problem of this research (theoretical optimisation techniques). Optimisation techniques that are adaptive to changes in problem description, constraints, and objectives are required. Since the strategies developed here are envisaged to be applicable to other power systems, the problem solution must be sufficiently generic to allow use by other applications. Additionally, they must be executable in real-time and satisfy certification requirements. To summarise, the techniques applied must be:

1. Capable of supporting complete solution building and storing a feasible solution at all times.

2. Adaptive to change in problem objective, constraints, and description, i.e. flexible for multiple classes of optimisation problems.

3. Computationally efficient, i.e. solvable in four minutes using a standard computer.

4. Capable of supporting the autonomous feature of the PMS.

3.6 Proposed Integrated Power Management System framework

The main output of the Integrated PMS[1] describes an executable power schedule for the vehicle. A typical power schedule constructed by the improved PMS describes the power setting of each power source, the total power delivered to each power sink, the network (switch) configuration and the power supplied by each of these connections, for each time interval for the entire mission. Advisories may

[1]The Integrated PMS is an optimised PMS, however, it does not fully meet all the criteria for an IPMS. Thus, it is not referred to as an IPMS. For example, this Integrated PMS does not guarantee robust solutions, which is a requirement for IPMS.

be included along with the power schedule. Minimisation of fuel consumption is adopted as the optimisation problem objective. The constraints of the problem are system constraints (e.g. maximum capability of power sources), equipment health constraints (e.g. degradation of components), and task constraints (e.g. required power to be supplied to ensure task completion). The mathematical representation of the problem, including a list of constraints, is presented in Chapter 4.

Before introducing the optimisation strategies developed, the complete process for solution attainment is described in this section. First, upon receiving new information from the VMS, EHM, and PS, the PMS, or specifically the PM, formulates all the information into an optimisation problem. For example, the cost function (fuel consumption minimisation for this case) is selected. Then, the problem feasibility is verified by analysing all the constraints of the system (constraint management). If the problem is infeasible, it is forcefully converted to a feasible problem (infeasibility management), using load prioritisation, for example. Once feasibility is found, or if the problem is feasible in the first place, the problem is passed on to the optimisation platform where possible solutions to the problem are constructed (solution building). Next, the quality and feasibility of the solutions are analysed. Finally, the best executable solution is verified and selected for enactment (decision-making platform). The solutions management is also responsible for providing the VMS with intelligent advice (Figure 3.11).

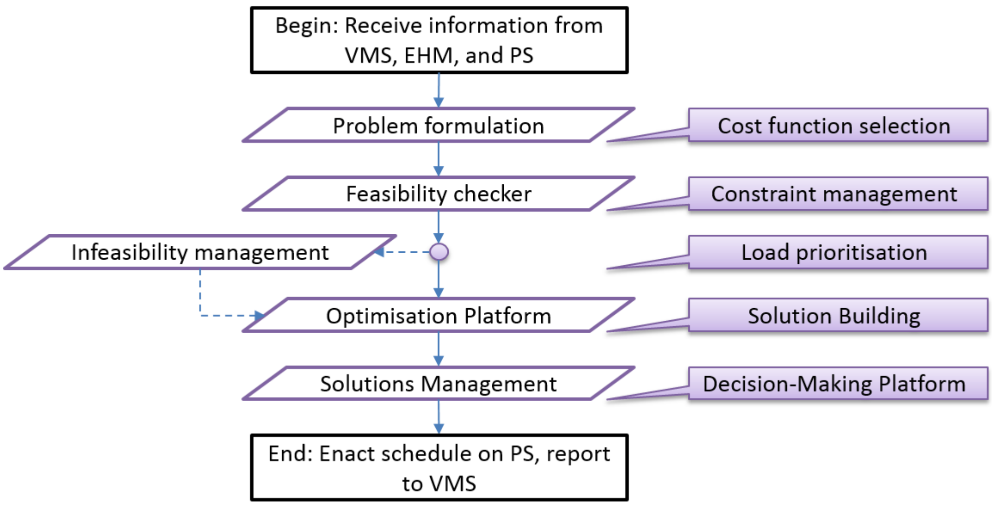


Figure 3.11: The Integrated Power Management System framework (input to output).

3.6.1 *Problem formulation* module

The information received by the PMS is assumed to have been validated and electrical load demands smoothed (Mansor et al., 2012a). Validation ensures all the information provided are relevant and within expectations, guaranteeing that the data processed post-validation are within the capability of the PM. Load smoothing ensures the power settings of the power source(s) are not altered unnecessarily, which may be more costly and inefficient. Load smoothing determines the load demand for a particular time interval.

The time intervals are defined based on the flight phases or sub-phases. The phasing of the flight profile is not performed by the PM but included in the input data provided. The factor that differentiates the boundary of these time intervals may be large changes of load demands or altitude (altitude of the vehicle affects many variables and behaviour of the system). This segmentation improves the accuracy and efficacy of the power schedule constructed at the end of the optimisation process.

Based on the mission and user preferences, the objective of the problem is selected. This study has focussed only on one objective: fuel consumption minimisation. Other objectives were not considered due to the absence of appropriate models.

The *problem formulation* module within the PM constructs the optimisation problem based on the input data provided. The optimisation problem can be described by:
Minimise

$$f(\boldsymbol{x_t})$$

with respect to $\boldsymbol{x_t}$, subject to:

$$\boldsymbol{g}(\boldsymbol{x_t}) \geq 0$$

where $f(\boldsymbol{x_t})$ is the objective function describing the fuel consumption for a particular set of decision variables, $\boldsymbol{x_t} \in \mathbb{R}^N$ is a vector of N decision variables describing the power supply and delivery for each time interval, t, and $\boldsymbol{g}(\boldsymbol{x_t}) \geq 0$ is the set of m constraints. Examples of these constraints include predicted electrical demand constraints, fuel availability constraint, and available power supply constraints. These components are updated accordingly in the following modules: *feasibility checker* and *infeasibility management.*

3.6.2 *Feasibility checker* module

In order to warrant efficient use of available time and computing resources, the feasibility of the problem presented is promptly analysed. If the problem is found to be infeasible, appropriate actions are immediately taken (infeasibility management). Redundant constraints are eliminated. The constraints analysed here are *hard* constraints. This type of constraint represents statements or conditions that must be satisfied. If violated, the solution becomes infeasible. These constraints typically describe mission demands, fault protection systems, regulatory requirements, and capability of the system components.

Hard constraint in this context may be categorised into two types: separable (e.g. predicted electrical demands for a particular time interval) and non-separable constraints (e.g. fuel constraint). Satisfaction of separable constraints can be analysed at one (time) interval at a time and need not be considered at full flight profile. This type of constraints tend to change with each time interval. Feasibility of the electrical supply and demand can be verified by ensuring the total power demand is at least equal or smaller than the amount of electrical power available for every time interval.

In contrast, satisfaction of non-separable constraints can only be determined when analysing the problem solution as a whole. Fuel constraint is an example of a non-separable constraint; the sufficiency of the fuel can only be determined once an estimate of the total fuel used for the entire remaining flight has been obtained. The total fuel used can be estimated by using a simple rule-scheme that assigns equal proportions of power from each power source and estimating the fuel consumed based on this power setting (similar to the approach used to manage power described in Section 3.4.1). If predicted fuel consumption is equal or less than the available fuel, the problem is considered feasible.

Soft constraints are described as constraints that are statements or conditions where a degree of relaxation or slackening is allowed. These constraints are often the result of EHM advice or requests to the PM, or user preferences. For example, Component A may only be capable of producing $50kW$ of power, however, the component may experience severe wear and degradation above $45kW$. The hard constraint here would be the maximum power produced by Component A, i.e. $50kW$, whilst the soft constraint here is $45kW$. If the system is in high power demand, the soft constraint may be slackened in order to complete the mission. Soft constraints do not affect the feasibility of the problem and are handled differently compared with hard constraints. See Section 5.3 for soft constraints handling.

3.6.3 *Infeasibility management* module

A series of actions are taken if infeasibility is found, depending on the type of infeasibility. For this study, there are two sources of infeasibility: (1) electrical load demand infeasibility; and (2) fuel consumption infeasibility. The former occurs when the expected mission electrical load requirements cannot be met by the system capacity for the given time interval. This may be due to a sudden change in mission plans or perhaps the health state of the power sources. The latter, the second source of infeasibility, occurs when the expected fuel consumption of the flight is predicted to be insufficient, i.e. it exceeds the amount of fuel available on flight. Other factors such as thrust constraint may also be considered. However, it is assumed that the system will not be requested to perform at thrust loads other than those designed for the vehicle.

These two types of infeasibility present the PM with two similar issues. In the first instance, the infeasibility may be resolved at time interval level, i.e. not necessarily affecting the power scheduling for the entire flight. On the other hand, the second type of infeasibility must be handled by considering the scheduling problem as a whole. The example below illustrates this difference.

Case 1: Infeasibility in electrical load satisfaction for time interval t. To resolve this infeasibility, support from the power store is sought first. If infeasibility is not resolved for time interval t using power store support, the *infeasibility management* module drops the load demands one at a time based on priorities provided by the VMS until problem feasibility is achieved, i.e. load prioritisation[1]. Time intervals $\neq t$ are not affected unless they require

[1] This may also be referred to as load shedding.

power store support, e.g. for cases where there are multiple instances of electrical load infeasibility.

Case 2: Infeasibility in fuel consumption. This instance of infeasibility does not indicate the time interval(s) that causes the violation of the fuel constraint. Power store support is not sought but instead load prioritisation is conducted. All the loads for every time interval have a corresponding priority ranking provided by the VMS and the *infeasibility management* module sheds loads one at a time until feasibility is found. Note that the load prioritisation here is performed based on the rankings of the loads for the whole mission instead of considering the load priorities one time interval at a time.

Notice that these two cases stem from violation of separable and non-separable hard constraints, respectively.

Any shedding of the loads are recorded and returned to the VMS at the end of the optimisation process. Once feasibility is found, the problem is passed on to the optimisation platform. Example cases demonstrating the capability of the *feasibility checker* and *infeasible management* modules are illustrated in Chapter 5.

3.6.4 *Optimisation platform* module

In the *optimisation platform* module, all the information has been prepared and processed to fit onto classical optimisation components i.e. objective (or cost) function, constraints, and decision variables. This enables the solver of the *optimisation platform* to produce an optimal power plan and advisories. The power plan for the entire flight cycle is the main output for the solver; advisories, or intelligent advice, constitute a secondary output.

The optimisation solver forms the core of the optimisation platform, forming the best executable power schedule. For applications where the optimisation process is performed in real-time, as the target application is, it is generally accepted that the solutions constructed are sub-optimal. Global solutions can be difficult to obtain in noise-free multi-modal[1] models and even more difficult in the presence of noise, limited resources, and limited information on the true state of the system and environment. These challenges faced by the optimisation platform influence the type

[1]Multi-modal functions are functions that have more than one local optima.

of solvers used, as outlined in Section 3.2. The details of the optimisation solvers selected are discussed later in Chapter 4.

3.6.5 *Solutions management* module

The solutions constructed by the solver are checked to ensure that the solutions are within expectations and to determine whether the solutions produced are acceptable and suitable to be enacted by the PM. For cases where the solver produces more than one power plan[1], the PM is required to select one solution. This decision-making process lies within the *solutions management* module of the PM. Feasible and accepted solutions are passed on for enactment and/or as warnings to the VMS (advisories). Details of the scheme implemented in this module can be found in Chapter 6.

3.7 System model

The aim of this research is to demonstrate a proof of concept for an integrated PMS that contributes towards the development of an IPMS. Although the envisaged PMS would improve the power scheduling on-board the UAS based on any specified objective, this research focuses on improving the fuel consumption. Similar to the ASTRAEA II programme, the models used to estimate the fuel consumption of an aircraft are constructed by decomposing fuel consumption into two main components: (1) thrust-based fuel consumption, and (2) electrical-based fuel consumption (see Figure 3.12).

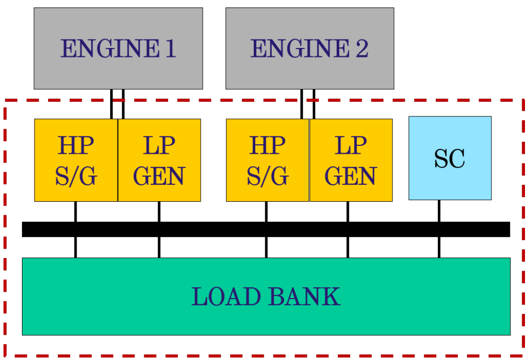


Figure 3.12: Schematic diagram of the power system. Red dashed box indicates the set of power components that contributes to the electrical-based fuel consumption.

[1]More than one solution may be produced when soft constraints are incorporated.

The models developed for this study extend the models used in ASTRAEA II by incorporating nonlinearities, efficiencies, losses, component dynamics, and dependencies of components that form a sufficient estimate of the total fuel consumption. The system model was based on a White Paper provided by Wall (2012a) and other supporting documents (Wall, 2012c, 2013a,b,c). A detailed description of the system modelling is elaborated in Appendix A. A summary of the models used is provided below.

The predicted mission demands are assumed to be piecewise-constant. The full problem, i.e. the entire flight profile, may be segmented into N_T time intervals, t. This segmentation is determined in the most part by significant change in thrust or load demands, flight phases based on the International Civil Aviation Organization (ICAO) definitions, and altitude, among others.

Thrust load fuel consumption

The fuel consumed by the propulsive components of the system is a linear approximation represented by:

$$\mathcal{F}_{ekt} = Q(x_{kt}) \tag{3.1}$$

where $\mathcal{F}_{ekt}$ denotes the fuel consumption rate when propulsor, k, is set to x at time interval t, and $Q(x_{kt})$ is the function describing the relationship between the fuel consumption and the propulsor setting.

Electrical (generator) load fuel consumption

The fuel consumed by the electrical components (electric generators and indirectly SC) is modelled by:

$$\mathcal{F}_{git} = \frac{x_{ijt}}{E(x_{ijt})}\left(1 + P\left(x_{ijt}\right)\right) \tag{3.2}$$

where $\mathcal{F}_{git}$ denotes the fuel consumption rate when generator i is set to x at time interval t, where ij describes delivery of power from generator i to power sink j, $E(x_{ijt})$ and $P(x_{ijt})$ denote the functions describing the electrical machine efficiency and the power electronics efficiency, with respect to x_{ijt}, respectively. These functions sufficiently capture the behaviour of the system that includes the dependencies between the propulsive and electrical power components.

Total fuel consumption estimation

The total fuel consumption is represented by:

$$\mathcal{F}_{\text{total}} = \sum_{t=1}^{N_T} \left(\sum_{k=1}^{2} y_t \, \mathcal{F}_{ekt} \left(x_{kt} \right) + \sum_{i=1}^{4} y_t \, \mathcal{F}_{git} \left(x_{ijt} \right) \right) + z\mathcal{F}_{e^*} \left(x_{kt} \right) \tag{3.3}$$

where $\mathcal{F}_{\text{total}}$ denotes total fuel consumption based on $\mathcal{F}_{ekt}$ and $\mathcal{F}_{git}$. y_t is the unit time of the time interval t, z is the number of instances when/if an engine is shut down during flight, and $\mathcal{F}_{e^*}$ denotes the fuel cost for one in-flight engine shutdown and restart.

Dependencies between components, SC losses (set to 1%), SC recharge lag, and in-flight engine shutdown/restart lag are incorporated into the system models (see Appendix A for details.) Network connections losses are considered negligible.

3.8 Summary

In this Chapter, the requirements of an improved PMS are highlighted. Based on the target application and design criteria, a new Integrated Power Management System framework is proposed. This framework illustrates how information is exploited to form an executable power schedule and an advisory report at the end of the optimisation process. A brief summary of the models developed for the optimisation problem is also highlighted. This Chapter provides a structure for the work to be described in Chapters 4–6.

Chapter 4

Constructing Best Executable Solutions

A generic framework of the Integrated Power Management System that describes the construction of the best executable power schedule based on available information has been presented in the previous Chapter. The core strategy behind the architecture of the problem solution developed in this research project is presented in this Chapter. Parts of this Chapter have been published in Mansor et al. (2014a).

4.1 Optimisation problem formulation

The power supply and demands across the system change, based on mission tasks, and due to internal and external factors; this may result in infeasibility of the existing power schedule. The integrated PMS aims to update the infeasible power schedule by searching for the *best executable* power schedule based on pre-defined and updated information using optimisation techniques. This is executed during operation while adhering to time and computational constraints. The problem formulation is as follows:

Minimise

$$\underbrace{\mathcal{F}_{\text{total}}(x_{ijt}, x_{kt})}_{\text{Total fuel}} = \sum_{t=1}^{N_T} \left(\underbrace{\sum_{k=1}^{2} y_t\, \mathcal{F}_{ekt}\,(x_{kt})}_{f(\text{propulsive load})} + \underbrace{\sum_{i=1}^{4} y_t\, \mathcal{F}_{git}\,(x_{ijt})}_{f(\text{electrical load})} \right) + \underbrace{z\mathcal{F}_{e^*}(x_{kt})}_{\text{engine IFSD costs}} \tag{4.1}$$

with respect to x_{ijt} and x_{kt}, subject to a set of constraints that are described below (Equations 4.2–4.11), where x_{ijt} is the electrical power from power source i to power sink j at time interval t and x_{kt} is the propulsive power from power source k at time interval t. This objective function calculates the predicted total fuel consumed for the remaining flight based on the power settings described by the decision variables.

The power setting for each electrical power source, i, must be non-zero and below the power source's maximum capacity, s (see Equation 4.2). The number of electrical power sources is denoted by S and the number of electrical power sinks is denoted by D. If the power store is discharging, $S = 5$, otherwise, $S = 4$, for the example system.

$$0 \leq \sum_{j=1}^{D} x_{ijt} \leq s_{it}, \text{ for } i = 1, 2, ..S \tag{4.2}$$

The propulsive power requirement is represented by Equation 4.3, where K denotes the number of engines ($K = 2$ for the given UAS example) and p is the required thrust with lower and upper tolerances of δ^l_{kt} and δ^u_{kt}, respectively. The electrical power requirement is represented by Equation 4.4, where the electrical power demands are denoted by d with lower and upper tolerances, δ^l_{jt} and δ^u_{jt}, respectively. If the power store is recharging, $D = 6$, otherwise, $D = 5$, for the example system.

$$p_{kt} - \delta^l_{kt} \leq \sum_{k=1}^{K} x_{kt} \leq p_{kt} + \delta^u_{kt} \tag{4.3}$$

$$d_{jt} - \delta^l_{jt} \leq \sum_{i=1}^{S} x_{ijt} \leq d_{jt} + \delta^u_{jt}, \text{ for } j = 1, 2, ..D \tag{4.4}$$

The set of engines of the example system for this research is bounded by symmetry requirements. The difference in propulsive power generated by the two engines, $|x_{kt|k=1} - x_{kt|k=2}|$, must not exceed the allowable tolerance, δ^a_{kt} (see Equation 4.5). This tolerance changes depending on the system, or vehicle, state. The UAS of interest also allows one of the engines to be shut down during flight[1], if it proves beneficial. If an engine is shut down, the two corresponding generators that are powered by said engine will also be shut down (see Equations 4.6a and 4.6b).

$$|x_{kt|k=1} - x_{kt|k=2}| \leq \delta^a_{kt} \tag{4.5}$$

$$\text{If } x_{kt|k=1} = 0, \text{ then } s_{1t} = s_{3t} = 0. \tag{4.6a}$$

[1]This capability is of course dependent on airspace requirements, mission requirements, etc.

$$\text{If } x_{kt|k=2} = 0, \text{ then } s_{2t} = s_{4t} = 0. \tag{4.6b}$$

Since the constraints describing the electrical power supply and demands (Equations 4.2 and 4.4) incorporate power store information, Equation 4.7 must hold, where $S = 5$ and $D = 6$. The power store cannot deliver power to itself; it can be a power store, a power sink, or remain inactive.

$$x_{SDt} = 0 \tag{4.7}$$

Equations 4.8a–4.9 express the constraints involving the power store. The state of charge of the power store for a given time interval, C_t, directly influences the amount of available electrical power, x_{Sjt}, and is described by Equation 4.8a, where α is a constant that takes account of the power store energy transfer losses when the SC is discharging or recharging. If the power store is discharging, it is acting as a power source and cannot be a power sink (Equation 4.8b). If the power store is recharging, the maximum recharge power is limited by the state of charge of the power store and the maximum[1] energy the power store is capable of storing, $C_{\max}$ (Equation 4.8c). Equation 4.8c incorporates the SC recharge lag and the energy transfer losses, where β is a constant relating to the SC recharge lag. Again, if the power store is recharging, it cannot be a power source (Equation 4.8d). The amount of energy discharged or recharged for time interval t must be updated to ensure the power store state of charge is represented accurately for the next time interval, $t + 1$ (Equation 4.9).

$$\sum_{j=1}^{D} x_{Sjt} \leq \frac{\alpha C_t}{y_t} \tag{4.8a}$$

$$\text{If } \sum_{j=1}^{D} x_{Sjt} > 0, \text{ then } \sum_{i=1}^{S} x_{iDt} = 0. \tag{4.8b}$$

$$\sum_{i=1}^{S} x_{iDt} \left(1 - \beta \sum_{i=1}^{S} x_{iDt}\right) \leq \frac{\alpha}{y_t} \left(C_{\max} - C_t\right) \tag{4.8c}$$

$$\text{If } \sum_{i=1}^{S} x_{iDt} > 0, \text{ then } \sum_{j=1}^{D} x_{Sjt} = 0. \tag{4.8d}$$

[1]This maximum value does not include reserve requirements imposed on the power store.

$$C_{t+1} = C_t - \frac{y_t}{\alpha}\sum_{j=1}^{D} x_{Sjt} + \frac{y_t}{\alpha}\sum_{i=1}^{S} x_{iDt}\left(1 - \beta\sum_{i=1}^{S} x_{iDt}\right) \tag{4.9}$$

The (predicted) fuel consumed based on the power settings described by the decision variables must be less or equal to the available amount of fuel, $F_{\max}$ (Equation 4.10). Finally, Equation 4.11 represents any event-specific hard constraint(s) that may be applied. Note that the constraints listed above are *hard* constraints; *soft* constraints are discussed later in Chapter 5.

$$\mathcal{F}_{\text{total}}(x_{ijt}, x_{kt}) \leq F_{\max} \tag{4.10}$$

$$h(x_{ijt}, x_{kt}) \geq 0 \tag{4.11}$$

A power schedule for the entire remaining mission time, T, is required. However, this causes the problem dimension to expand considerably if solved simultaneously. For each t, there are 27 decision variables (for this problem). Taking a 20-hour flight with $N_T = 32$ time intervals as an example, the optimisation problem now has 864 decision variables. These optimisation problem must also be solved with respect to interdependent constraints, which are more difficult to solve compared with independent constraints. Solving for the entire mission, i.e. solving for all the time intervals simultaneously, is expensive in terms of execution time and computation resources. The search space becomes very large and infeasible regions arise depending on the sequence of values assigned for the decision variables. This search process is not sufficiently efficient to be solved in four minutes.

A divide-and-conquer approach is proposed in which the problem is decomposed into a set of sub-problems defined by the time intervals, representing y_t unit time. Each optimisation sub-problem is then solved independently. At the end of the analyses, the solutions to every sub-problem are combined to form one solution. This solution is verified to ensure the overall feasibility of the system.

There are shortcomings in the sense that, since this non-separable problem is converted to a set of separable problems, the estimated optimal solution may be sub-optimal overall. Arguably, the sub-optimality of the problem is already inevitable due to the real-time requirements of the PMS and the non-convexity of the overall problem. The optimisation when the search space is unrestricted[1] resulted in an inefficient search. Feasible solutions were more difficult to find and more time is required to find *good* solutions, a luxury that is not afforded for real-time optimisation problems. Rapid construction of complete feasible solutions are sought. The advantage of this approach is that it limits the number of decision variables per run, rendering the problem more tractable and allowing for an accelerated search for solutions. The decomposition of the problem into a set of sub-problems also allows the objective function to be modified at each flight phase according to the system's dynamic environment, thereby increasing the fidelity of the models and system utility. An example of a phase-dependent change in the objective function is when the vehicle significantly changes its flying altitude between two phases.

In-flight events introduce the requirement to update the default problem setting. In other words, the constraints of the problem (Equations 4.2–4.10) may change, and additional constraints may be introduced (Equation 4.11). For example, for cases where there is a severed connection between the i_{th} electrical power source and the j_{th} power sink at the t_{th} time interval, the following additional constraint must be satisfied:

$$x_{ijt} = 0.$$

4.2 Optimisation strategy

Based on the problem description above, the optimisation problem may be categorised as a single-objective nonlinear constrained optimisation problem with continuous decision variables (e.g. the power settings of the generators). Another key feature of the problem due to the safety-related nature of the application is the requirement to guarantee feasible solutions within a short time frame, e.g. four minutes. Also, the methods selected are required to demonstrate determinacy, transparency, and tractability, due to certification requirements.

Analytical methods search for precise solutions for an approximate model. Although the search process is deterministic and transparent, the solutions produced

[1]Restriction, or representation, of the search space allows for more efficient search. However, when dealing with interdependent constraints, this representation do not perform as well and exceed the real-time requirements of the problem.

may not be close to the true optimal solution. On the other hand, heuristic methods search for approximate solutions for a precise model. These methods often produce *good* solutions, albeit (in most cases) at the cost of transparency and determinacy. Analytical methods may suit the criteria for safety requirements better than heuristic methods. Nonetheless, the solutions obtained using heuristic methods may be closer to the true optimal solution. In order to achieve the desired attributes of the improved PMS (e.g. accuracy, speed and determinacy), it is argued that a compromise of these attributes and hybridisation of methods is necessary.

4.2.1 Optimisation solver: a three-level optimisation approach

A three-level approach within the Solver is proposed to construct the *best executable* power schedules (Figure 4.1). *Best executable* solutions here refer to the best solutions, in terms of pre-determined objective(s) and feasibility, found within the allocated time and resources. The core idea behind the strategy proposed here is to guarantee that a feasible solution is available in the first instance. This is particularly useful if the PMS execution time is reduced during execution, where a solution must be available and ready to be enacted. Then, using the remaining time, resourcefully improve and update the solution to the *best executable* solution.

First, in Level 1, a constraint satisfaction approach is used to rapidly find a feasible solution based on the available information. Then, in Level 2, the proposed PMS optimises this solution using a local search algorithm that improves the feasible solution in a relatively short amount of time, providing an intermediate solution. This local search algorithm seeks for the best solution within the neighbourhood of the feasible solution. Finally, in Level 3, the remaining time is invested in a global search algorithm that explores the search space for the *best executable* power schedule for the specified problem. The methods used for each level of the adaptive PMS are described below and summarised in Figure 4.2.

4.2.1.1 Level 1 – Constraint satisfaction: guaranteeing feasibility

Constraint satisfaction techniques focus on finding a solution satisficing all constraints while ignoring any objectives. These techniques are often used in decision problems rather than optimisation problems. However, the idea behind constraint

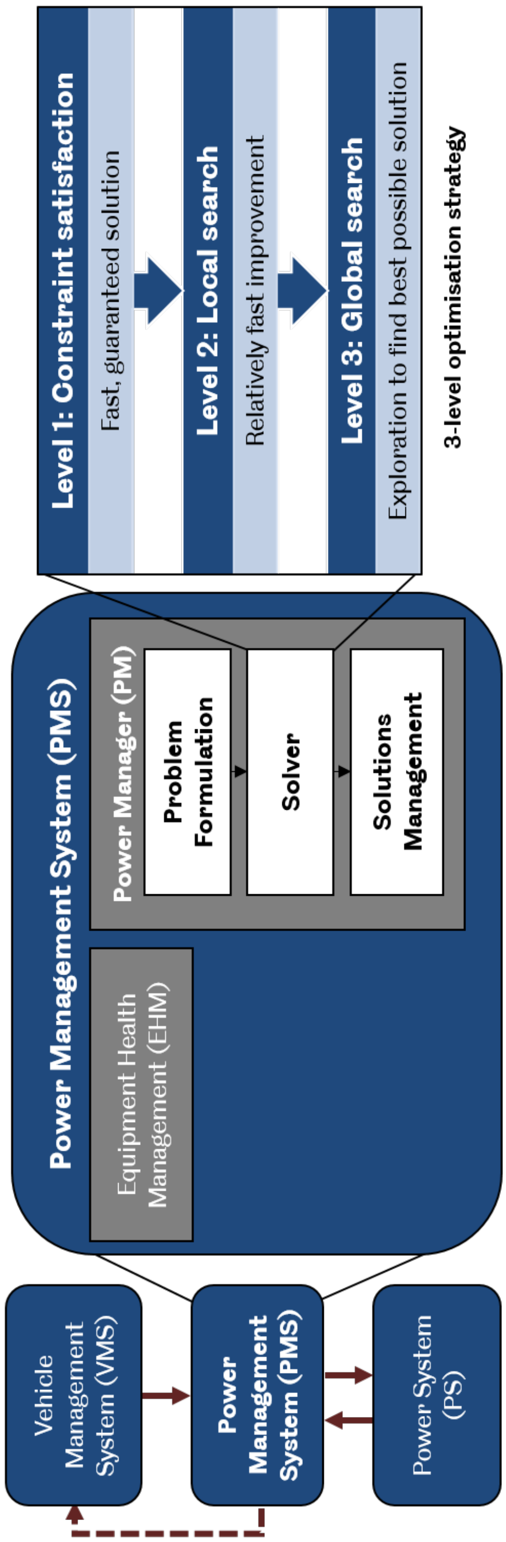


Figure 4.1: PMS overview.

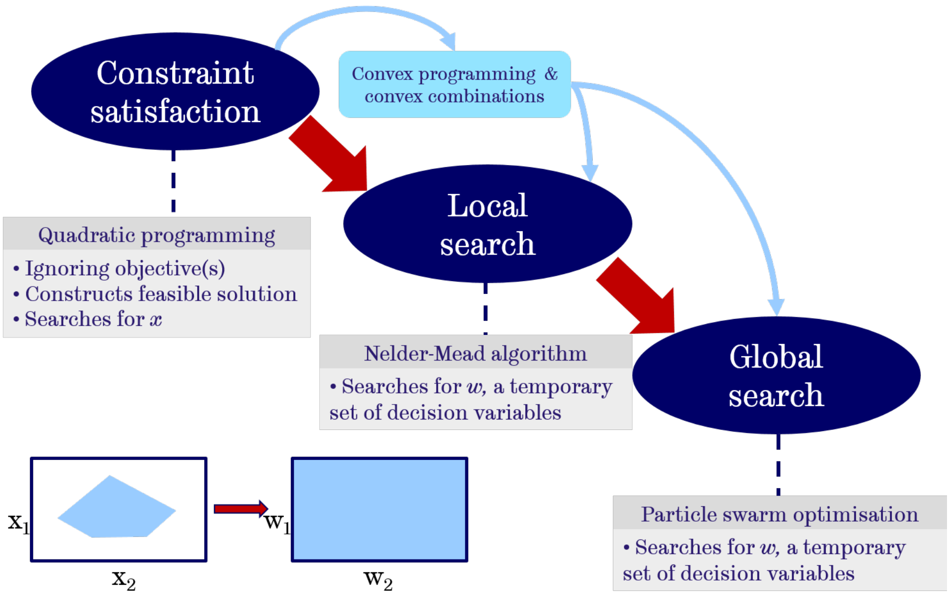


Figure 4.2: Three-level optimisation strategy.

satisfaction is very useful for the intended application since safety is a high priority and guaranteeing feasibility of a solution at the beginning of the optimisation strategy enables the overall control approach to be more likely to be certified.

In Level 1, power demand constraints (Equation 4.4) are assumed to exclude tolerances and these constraints are converted to equality constraints. It is argued that demand tolerances are best applied in the optimisation levels (only) to obtain benefits from manipulating the power generated. The objective function is also temporarily ignored, applying a strict constraint satisfaction approach. Thrust demands for Level 1 are met by providing equal loading for each of the propulsor. The power store is excluded temporarily since the use of supercapacitor is not required. Optimisation involving the control of the power store is discussed in Chapter 5. The problem is reformulated as:

Minimise

$$\sum_{j=1}^{5}\left(\left(d_{jt}-\sum_{i=1}^{4}x_{ijt}\right)^2\right) \tag{4.12}$$

with respect to x_{ijt}, subject to:

$$0 \leq \sum_{j=1}^{5} x_{ijt} \leq s_{it}. \tag{4.13}$$

In the above formulation, minimising (Equation 4.12) seeks to ensure that the power demand equality constraints (Equation 4.4) are satisfied. The resulting solution will be feasible assuming the solution converges and is zero. It is also assumed that Equations 4.14 and 4.15 (below) hold; these equations represent the feasibility of the problem. An analytical method (quadratic programming (QP) (Frank and Wolfe, 1956)) is used to solve the above problem. This solver is deterministic and is capable of rapidly finding a solution.

$$\sum_{j=1}^{5} d_{ijt} \leq \sum_{i=1}^{4} s_{it} \tag{4.14}$$

$$\mathcal{F}_{\text{total}}(x_{ijt}, x_{kt}) \leq F_{\text{max}} \tag{4.15}$$

4.2.1.2 Efficiency booster: CVX solver

The search space of the optimisation problem is very large and includes both feasible and infeasible solutions if the decision variables are bounded to the non-negativity of the decision variables and the maximum capability of the power sources. However, exploring a large decision space with a high probability of finding infeasible solutions is not desirable. These bounds cannot be directly reduced due to the coupling between the decision variables. To resolve this issue, the hard linear supply and demand constraints are exploited to construct a feasible search space for the optimisation process.

Since the constraints (Equations 4.2–4.4) are affine, the decision variables, $\boldsymbol{x}$, can be redefined to another set that is, by definition, within the convex hull[1] of the constraints (assuming the problem is well posed), producing only feasible solutions. The minimum (or maximum) value for each decision variable, while satisfying Equations 4.2–4.4, are determined to form the lower (or upper) bounds using a CVX solver, see Grant and Boyd (2013), a software package for specifying and solving convex programs. Using the concept of convex combinations,

$$\boldsymbol{x} = B\tilde{\boldsymbol{w}}$$

where

$$\tilde{\boldsymbol{w}} = \frac{w_b}{\sum_{b=1}^{2N} w_b}$$

[1]Convex hull is the intersection of all convex sets (constraints), containing all the feasible points of $\boldsymbol{x}$.

and B represents a matrix containing the bounds for the decision variables, $\boldsymbol{x}$ is a vector of the original decision variables, $\tilde{\boldsymbol{w}} \in [0,1]^{2N}$, $w_b \in [0\ 1]$ are the *temporary* decision variables, and N is the number of the original decision variables, $\boldsymbol{x}$. This representation of the problem is used in both Level 2 and Level 3 Solvers.

4.2.1.3 Level 2 – Local search: an improvement

Subsequent to finding a feasible solution, an improvement to the obtained solution in a short amount of time is sought. Using a local search, a local minimum may be rapidly found. A local search explores the neighbourhood of a starting point, which for this case is a known feasible solution. A global minimum is only found if the starting point is sufficiently near the global minimum, i.e. in the global minimum's basin of attraction, or if the problem is unimodal. Although this level often finds only a local minimum (for multi-modal functions), it is obtained within a reasonable time and provides an improved solution compared with the solution obtained from Level 1.

A deterministic-heuristic search method is proposed for Level 2. Using this class of methods, the determinacy of Level 2 of the PMS is guaranteed; this is desirable for autonomous systems. Heuristic search methods produce solutions that are closer to the true optimal solution compared with solutions constructed using analytical methods. Heuristic methods search for approximate solutions using precise models (Michalewicz and Fogel, 2000). It is also more likely that this type of method copes well with different objective functions, a function that estimates vehicle performance, for example.

The main task of this level is to improve the Level 1 solution, not to search for the global minimum. Global search is often the reason that stochastic search is introduced into heuristic techniques. The Nelder-Mead (NM) algorithm (Nelder and Mead, 1964) is selected for Level 2 and performs well in finding the nearest minimum while optimising a nonlinear function. This technique discards the worst point out of an $N+1$ point simplex (N is the number of decision variables) and use its reflection to move towards the nearest minimum using a set of rules. This technique solves unconstrained or box-constrained nonlinear problems.

Before the introduction of the CVX Solver, solving Equations 4.2–4.4 and using penalty terms to handle the constraints was found to be inefficient. The optimiser spent a considerable amount of time in the infeasible regions of the search space. The representation of the decision variables allows an efficient use of the NM algorithm while directly satisfying the constraints at all times. The local search algorithm can now solve the problem as a box-constrained optimisation problem. The NM algorithm for the reformulated problem now searches for $\boldsymbol{w}$ (with much smaller bounds), while optimising Equation 4.1 subject to only the symmetry requirement (Equation 4.5) and event-specific constraints (Equation 4.11). Using convex combinations in the reformulated problem also guarantees that only feasible solutions (with respect to Equations 4.2–4.4) are explored and Equations 4.2–4.4 may be omitted from the optimisation process. The efficiency of the Level 2 algorithm is significantly improved by exploiting the convex components of the problem to shrink the search space.

To handle constraints that are not solved by the CVX Solver, penalty terms are added to the objective function to help the algorithms to find solutions satisfying the remaining constraints. The following is an example of penalty imposed on the objective function when the symmetry requirement constraint is not met:

$$V(x_{ijt}, x_{kt}) = \mathcal{F}_{\text{total}}(x_{ijt}, x_{kt}) + q\left|\delta_{\text{at}} - \left|x_{kt|k=1} - x_{kt|k=2}\right|\right| \tag{4.16}$$

where

$$q = \begin{cases} > 0 & \text{if symmetry constraint is violated} \\ 0 & \text{otherwise.} \end{cases}$$

Equation 4.16 is the evaluation function utilised for the optimisation process and q is the penalty weight for the violation of the symmetry constraint.

4.2.1.4 Level 3 – Global search: best executable solution

A global solution is sought. Solution from the Level 1 Solver has been improved by initiating a local (neighbourhood) search, forming the Level 2 Solver solution. This improved solution has a high probability of being a local minimum. Using the remaining allocated execution time, a global solution may be attained by exploring the search space. To escape from the local minimum, global optimisers often introduce stochastic elements to the search process. This increases their chance to escape from the basin of attraction of local minimum, and find the global minimum, or at least an improvement to the initial local minimum.

A stochastic global search is proposed as the Level 3 algorithm. This level runs for the remaining allowed execution time for the PMS, and explores the search space to find the *best executable* power schedule. An algorithm that searches for complete solutions is sought. Particle swarm optimisation (PSO) (Kennedy and Eberhart, 1995) was selected as the global search algorithm for Level 3 due to its speed and its ease of application (e.g. small number of algorithm parameters to set).

Particle swarm optimisation solves an optimisation problem by updating a swarm of particles (solutions) at every iteration, based on each particle's best solution and the swarm's best solution. This is a stochastic search algorithm where random perturbations are enforced to explore the search space, while exploiting the best solutions found so far.

The algorithm, which is also an unconstrained optimisation solver, solves for $\boldsymbol{w}$. To ensure the solutions are within the feasible bounds, $w \in [0\ 1]$, alterations to the solutions are performed as needed; for $w > 1$, $w \leftarrow 1$, and for $w < 0$, $w \leftarrow 0$. The algorithm uses penalty terms in the evaluation function to manage the symmetry requirement constraint and event-specific constraints (as for the Level 2 algorithm).

To summarise, the constraint-handling scheme used comprise representation of the problem using the CVX Solver, adjustments to the decision variables based on their lower and upper bounds ($w \in [0\ 1]$), and penalty methods (e.g. Equation 4.16). This scheme allows for efficient search for feasible solutions and an easy approach to handle constraints that are not handled by the CVX Solver; good feasible solutions are found with few algorithm parameters. Other constraint-handling schemes are available in the literature (Banks et al., 2007b; Coello, 1999, 2002; Fuentes Cabrera and Coello, 2007; Pulido and Coello, 2004). However, some of these schemes may not necessarily be suitable for real-time optimisation. Perhaps future research could explore methods to further improve the constraint-handling scheme employed if this scheme proves to be insufficient for the application of interest.

4.2.2 Overall optimisation strategy

The overall structure of the proposed integrated PMS is to:

1. Update the *default* problem formulation (Equations 4.1–4.10) and any additional constraints (as required), according to the information provided to the PMS.

2. Find a feasible solution using a constraint satisfaction technique.

3. Construct the upper and lower bounds of the decision variables using convex programming based on the default constraints; this enables an efficient representation of the problem.

4. Improve the feasible solution using convex combinations and a local search algorithm.

5. Invest the remaining execution time in a global search algorithm to find the best attainable solution for the problem.

6. Select the best executable solution for enactment.

4.3 Case study

A three-level optimisation strategy: a proof-of-principle example

- Single-type power control: electrical power optimisation only.
- Optimisation of propulsive power source and power store settings optimisation is excluded for this example.
- Partial power scheduling. Specifically, only three time intervals of the entire flight profile is considered for this example.

Consider a case where an UAS is on a surveillance mission[1] and, mid-flight, a health-related event occurs[2]. In order to ensure the success and optimal operation of the mission, the PMS is triggered to re-plan the power schedule for the flight.

A *normal*, or *default*, scenario indicates full component health and maximum rated power rating for the power sources. The system is planned to operate over three time intervals, in this *toy* example, and is pre-loaded with an offline power schedule. A new event is introduced in *Interval 2* (while the system is in *Interval 1*)

[1]See Appendix B for construction of representative flight input data set used for this research study.

[2]Mission descriptions and events that have been used for this project were adaptations from Edgar (2011) and Asare (2012).

that leads to infeasibility of the power schedule for the remaining operation time. Thus, a new schedule is required. The integrated PMS is activated as a result of this new event, and a revised best attainable power schedule is constructed. For this case study, only the electrical power supply and delivery is optimised and both propulsors are set to equal loading to satisfy the propulsive power requirement. Power stores are not included. The purpose of this case study is to demonstrate a proof-of-principle of the proposed strategy; additional features and capabilities are discussed in coming Chapters.

For this event, Generator 4 experiences a health issue that decreases the maximum power rating to $42kW$ from $50kW$ while the allowable power demand tolerances remain at $\pm 15\%$. This causes the previous solution to become infeasible. The PMS is notified of this change and a new power schedule is constructed within the allocated four minutes on a representative processing architecture. Table 4.1 shows the power distribution for *Interval 2* based on the infeasible solution, and the feasible solutions constructed by Levels 1 to 3 of the PMS. The rows represent each power source while each column represents each power sink. For example, Generator 1 is to supply Sink A with $0.78kW$ based on the previous (infeasible) solution. Table 4.2 depicts the fuel consumption in kg/s for each phase and algorithm. Implementation was in MATLAB vR2011a on Intel Core $3.20GHz$ processor with $4GB$ RAM; the computational constraints were not exceeded for this demonstration.

4.4 Discussion

Updated solutions for *Interval 2* (Table 4.1) show that although some components of the new solution were similar to the infeasible solution, others were altered, especially the power setting for the affected power source. In most cases, the small differences are likely to be due to the algorithms optimising the solutions according to the equipment efficiencies, exploiting allowable demand tolerances. Larger differences, for example, occur in Generators 3 and 4 for both cases. This is likely to be due to wider efficient operating regions for larger power sources compared with the smaller power sources. Recall that the fuel minimisation function incorporates equipment efficiencies and is reflected in the avoidance of maximum loading of the power sources. This is also beneficial to maintaining the life of the equip-

Interval 2		Sink A (kW)	Sink B (kW)	Sink C (kW)	Sink D (kW)	Sink E (kW)	Power generated (kW)
Generator 1 (kW)	P	0.78	1.19	1.20	1.18	0.71	5.06 *(6)*
	L1	1.10	0	0	0	0	1.10 *(6)*
	L2	0.92	1.12	1.13	1.11	0.88	5.15 *(6)*
	L3	0.96	1.12	1.12	1.12	0.92	5.25 *(6)*
Generator 2 (kW)	P	1.83	2.92	3.52	2.72	1.61	12.58 *(15)*
	L1	0	0	14.00	0	0	14.00 *(15)*
	L2	1.97	3.22	3.24	3.01	1.79	13.23 *(15)*
	L3	1.91	3.22	3.22	2.95	1.67	12.96 *(15)*
Generator 3 (kW)	P	3.76	13.41	13.12	9.97	3.53	43.78 *(50)*
	L1	0	32.00	18.00	0	0	50.00 *(50)*
	L2	3.74	14.44	14.56	10.42	3.23	46.39 *(50)*
	L3	3.67	14.12	14.12	10.76	3.44	46.12 *(50)*
Generator 4 (kW)	P	3.75	13.57	13.28	10.05	3.13	43.77 *(42)*
	L1	8.90	0	0	24.30	8.80	42.00 *(42)*
	L2	3.47	11.67	11.49	8.96	3.02	38.61 *(42)*
	L3	3.49	11.72	11.72	8.51	2.89	38.31 *(42)*
Power supplied (kW)	P	10.12 *(10)*	31.08 *(32)*	31.11 *(32)*	23.91 *(24.3)*	8.98 *(8.8)*	-
	L1	10.00 *(10)*	32.00 *(32)*	32.00 *(32)*	24.30 *(24.3)*	8.80 *(8.8)*	
	L2	10.10 *(10)*	30.45 *(32)*	30.41 *(32)*	23.50 *(24.3)*	8.92 *(8.8)*	
	L3	10.02 *(10)*	30.18 *(32)*	30.18 *(32)*	23.34 *(24.3)*	8.91 *(8.8)*	

Table 4.1: Power grid: power distribution for *Interval 2*. *P*, *L1*, *L2*, and *L3* represent previous solution, Level 1 solution, Level 2 solution, and Level 3 solution, respectively. The numbers in brackets indicate the maximum power available from each power source (in the *Power generated* column) or the power requirement of each power sink (in the *Power supplied* row). Text in red indicates source of infeasibility.

Objective value	Interval 2	Interval 3
Level 1 (kg/s)	0.0140	0.0144
Level 2 (kg/s)	0.0134	0.0143
Level 3 (kg/s)	0.0133	0.0143

Table 4.2: Objective values for *Intervals 2 and 3*.

ment since maximum usage will cause additional equipment wear and subsequently reduce equipment life. Only in Level 1 does the PMS ignore these inefficiencies, seeking only to satisfy the constraints, while temporarily ignoring the fuel consumption optimisation.

The fuel consumption is reduced as the PMS progresses from Level 1 to Level 3 (Table 4.2). The changes may seem small, however, in large applications, this improvement is capable of significantly reducing the costs of operation. For example, comparing solutions of Level 1 and Level 3 in the case study presented here, which has a 40 hour total operation time, the Level 3 solution may save up to $100kg$ of fuel, equivalent to 3% of the total fuel available. In *Interval 3*, there is no improvement from Level 2 to Level 3 at the precision shown here. This may be because the PMS may have reached a global minimum or is sufficiently close in value to the global minimum at Level 2.

4.5 Algorithms, complexity, and limitations

Although specific algorithms are used in the Integrated PMS proposed here, future users are, of course, not restricted to only using these algorithms.

Level 1 Solver

In Level 1, QP forms an efficient approach to solve linear constraints (Edgar and Himmelblau, 1988). Depending on the problem posed, the QP method may use interior point or active set algorithms for solving the optimisation problem. Using an interior point algorithm, solutions are sought based on Karush-Kuhn-Tucker (KKT) conditions. The optimal solutions are obtained through search from within the feasible region to the boundary of the feasible region (Burke and Kendall, 2005; Edgar and Himmelblau, 1988; Hillier and Lieberman, 1995; MathWorks, 2014). An active set algorithm directs the search by exploiting the set of active constraints to find the optimal solution. Although these methods are proved to be efficient for most problems (Burke and Kendall, 2005), this may not hold for all problems (e.g. very large and complex problems). For the case presented above, the QP method is used to solve for a set of linear constraints and only the constraint satisfaction problem is solved. This approach performs well for this purpose.

Level 2 Solver

Other greedy, or direct, search methods may be adopted for the Level 2 Solver. Of course, the algorithms selected must be able to efficiently solve for a large number of decision variables. Grid search is one of the simplest approaches as a deterministic-heuristic method. However, for a problem dimension such as the problem addressed here, grid search was found to be unsuitable. The Nelder-Mead algorithm was used instead. It is recommended that a heuristic method that does not require derivatives of the objective function to be calculated is best for this strategy, i.e. a direct search method. In the NM algorithm, there are several parameters that may influence the performance of the Solver: the number of maximum iterations, the tolerance of objective function improvement, and the procedure-specific coefficients (i.e. the reflection coefficient, the contraction coefficient, and the expansion coefficient). These parameters are not fine-tuned for this application and are set with real-time considerations in mind and based on the recommendations found in Nelder and Mead (1964)[1]:

Number of maximum iterations: $10N$

Tolerance of objective function improvement: 10^{-6}

Reflection coefficient: 1

Contraction coefficient: 0.5

Expansion coefficient: 2.

[1] Of course, these parameter settings may not be optimal for the power management problem. However, as mentioned above, fine-tuning of the parameters is not part of the aims of this research.

Level 3 Solver

Particle swarm optimisation was selected as the Level 3 algorithm. Any global search method may be used. PSO was selected for this study due to its ease of implementation and ability to adapt to dynamic changes and provide *good* solutions (Banks et al., 2007a; Shi, 2001). Of course, PSO is also known to suffer from stagnation, as highlighted by Banks et al. (2007a). This perhaps could be improved by fine-tuning parameters when addressing specific applications. Excessive restriction of the movement of the swarms may inhibit exploration and, thus, reducing the probability of finding the global optimal solution. However, restriction may be advantageous in a sense that it maintains stability. The settings are described below for each parameter (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998a,b):

Population size: $4N$

Number of maximum iterations, φ: $20N$

Inertia weight: $\frac{1.4(\varphi+2-\varsigma)}{\varphi}$ where ς is the current iteration

$c1$ **coefficient:** 2

$c2$ **coefficient:** 2.

The PSO algorithm is seeded with the two previous feasible solutions arising from Levels 1 and 2, and perturbations of these two solutions.

4.6 Other considerations

Scalability

Three time intervals are presented here, representing only part of the full flight profile of the mission. In Chapter 5, the scalability of this PMS framework is presented, where the full flight profile is included in the solution building process.

Sensitivity

The case study above illustrates the ability of the Integrated PMS for one particular scenario. To investigate the true capability and limitations of the this power management strategy, a sensitivity analysis must be performed using different sets of flight profiles; this is presented in Chapter 5.

Alternative objectives and impact

There are a few additional costs that may be incorporated into the objective value of the optimisation problem. For example, the costs of altering the power settings of the generators are assumed negligible. This assumption may hold from the perspective of minimising fuel consumption, where *cost* is defined as *fuel*. However, for maximisation of life of components for example, this assumption may not hold. For this case, it would be *costly*, in terms of component life, to assume that such frequent (and in some cases, unnecessary) changes are negligible. Care should be taken when selecting a different cost function to be optimised. Although the Integrated PMS is designed to be applicable to any power system or any objective, some adaptations may inevitable.

Similar situations arise when there are additional preferences set by the system operator that do not directly affect the main objective, but do affect the quality of the solutions produced from the operator's perspective. An example of this is an operator preference to reduce the number of generators switched on, if possible. In Chapter 5, approaches to accommodate these preferences are highlighted.

Transferability

The optimisation strategy presented here is suited for scheduling power for a multi-source, multi-sink power system. While this control strategy is aimed for real-time optimisation, it could also be used to solve for off-line optimisation problems. It is not suited for low-level control where it is a requirement to construct a control action in a fraction of a second, but provides a good strategy to optimise a full operation schedule with look-ahead capability. Example applications that may benefit from such an optimisation strategy are marine applications and hybrid propulsion aircraft (Doerry and Davis, 1994; Doerry et al., 1996; Gohardani et al., 2011; Husband, 2014; Jayabalan and Fahimi, 2005; Logan, 2007; Malkin, 2014; Moreno and Pigazo, 2007).

4.7 Summary

The Integrated Power Management System framework described in Chapter 3 allows information to be accepted and processed by the PM into meaningful variables. These variables and embedded systems models are then used to search for the *best executable* solutions using a three-level optimisation strategy. The core idea behind this control strategy is to combine concepts from constraint satisfaction, convex programming and heuristic (optimisation) techniques. Although specific algorithms are recommended here, future applications need not be restricted to these choices of Solvers. The backbone of the control strategy is to first seek a feasible solution as fast as possible (the Level 1 Solver), followed by optimisation (the Levels 2 and 3 Solvers). Future users of the strategy may adopt alternatives to the algorithms used here, viz. QP, NM, and PSO.

The optimisation strategies in this cross-platform PMS are aimed to suit any real-time power management of complex systems. In the case study presented, the proposed PMS demonstrates the capability to solve and provide the *best executable* solution for an UAS within real-time requirements. In Chapter 5 and subsequent chapters, methods to handle different scenarios are presented, providing extensions to the core three-level approach.

Chapter 5

Real-Time Power Management: Complete Solution Building

Construction of a power supply plan for a sample set of time intervals has been described in Chapter 4. In this Chapter, construction of complete[1] power schedules with simultaneous electrical and propulsive control is discussed in more detail. Strategies to handle complexity introduced by *flexible* components and/or features are also discussed. To accommodate user preferences, soft constraints are introduced and mechanisms to handle these preferences are outlined. Case studies are presented to demonstrate the capability of the proposed PMS, as well as comparisons between the performance of the optimised PMS and existing technologies. A description of the sequence of actions as part of the Infeasibility Management is included. Finally, a demonstration of the Integrated PMS is presented at the end of the Chapter. The approaches described in this Chapter form the complete solution building process within the Integrated PMS.

5.1 Multi-phase power scheduling: a separable problem

Due to the real-time operational requirements of the PMS, the strategy used to construct the complete power schedule must be efficient during the search process. However, long flight times, as expected from MALE UASs, and finer granularity of phasing[2] that improves the usefulness of the power scheduling, will introduce more time intervals (i.e. sub-problems) causing computational power and processing

[1]Solutions that describe the power management of the system for the entire remaining flight are considered *complete* solutions.

[2]*Phasing* influences how the problem is decomposed into a set of sub-problems or time intervals.

time to increase significantly. For example, constructing a power schedule for a 20-hour flight with 32 time intervals equates to solving an optimisation problem with decision variables of size[1] $NN_T = 704$. This has the potential to create a very large search space for the optimiser and consume considerable time and computing power. The integrated PMS solves this problem by solving each sub-problem individually (Figure 5.1). Then, at the end of the optimisation process, these solutions are combined to form a complete solution before passing on to the next component of the PM framework. Of course, this increases the probability of attaining a sub-optimal solution instead of an optimal solution. However, it is possibly an inevitable trade-off against the real-time requirements of the system. The feasibility of the problem is still maintained by the support of feasibility checker, infeasibility management, and solutions management modules.

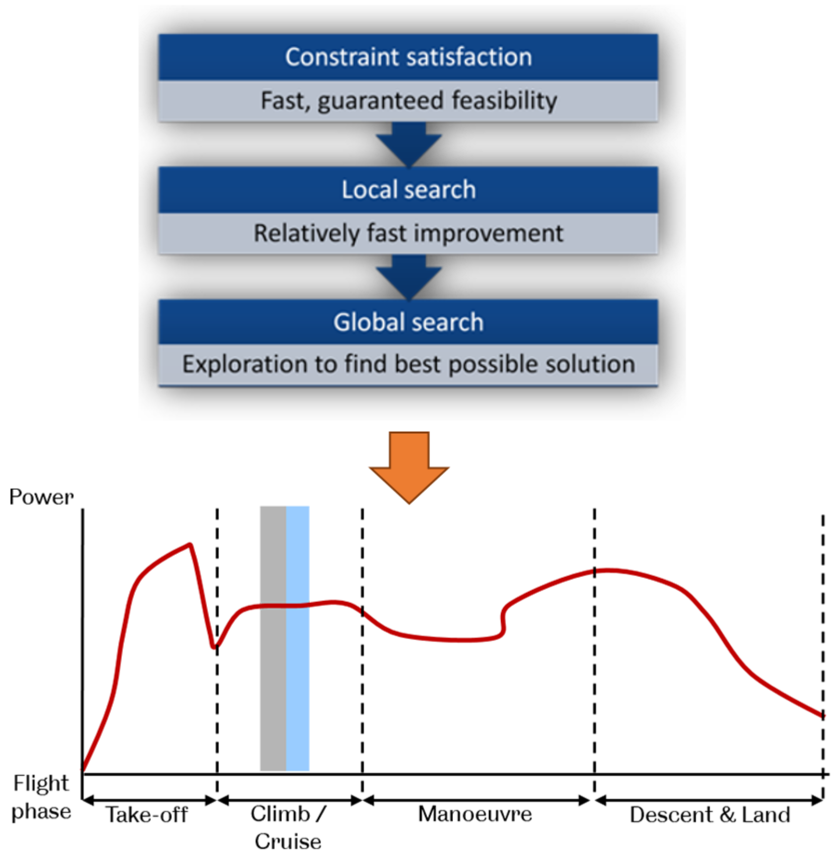


Figure 5.1: The three-level optimiser solves the problem one time interval at a time. Example time intervals are depicted in blue and grey.

[1]The number of decision variables per phase (with power store setting excluded), $N = 22$, and the number of time intervals, $N_T = 32$.

As opposed to the strategy described in Chapter 4, propulsive power settings are now optimised along with electrical power settings. The simultaneous scheduling of these components is also determined for the entire flight, i.e. complete flight scheduling. Complete flight schedule refers to the current point of flight to the end of flight. A case study describing the construction of a complete power schedule is provided below.

5.1.1 Case study I

Case study I: Multi-phase (separable) power scheduling

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability disabled.
- Complete flight profile power scheduling.

Consider a case where the UAS[1] is about to commence a 20-hour surveillance mission. A power schedule describing the power supply plan for the entire flight is required. The PMS is initiated to perform this task. The optimiser within the PMS seek to minimise the fuel consumption of the vehicle with respect to the electric and propulsive power settings for the entire flight. For this example, use of power store and engine IFSD are disabled. Table 5.1 lists selected information of the input data provided to the PMS.

Parameter	Value
Electric power source supply, s_i	$s_1 = 6$
	$s_2 = 15$
	$s_3 = s_4 = 50$
Total propulsive power source supply	8000
Number of time intervals, N_T	32
Number of decision variables, N	$22N_T = 704$
Electric power demand tolerances	3.5–15%
Propulsive power demand tolerances	5–20%
Propulsor asymmetry tolerance	10^{-6}–15%

Table 5.1: Information provided by the input data. For brevity, only selected input data is presented here. See Appendix B for detailed example of the PMS input data.

The generator supply (capacity) and total electrical sink demands are shown in

[1]The case studies in this thesis employ the power system architecture described in Chapter 3.

Figure 5.2. Figures 5.3–5.5 describes the power schedules for the planned flight. The power schedules were constructed within four minutes. The solution improves as the optimisation process progresses from the Level 1 Solver to the Level 3 Solver. The Level 3 Solver solution is the *best executable* power schedule with expected total fuel consumption of $1138kg$. Table 5.2 lists the total fuel consumption for all three feasible solutions (see Figure 5.6 for the fuel trend over the entire flight).

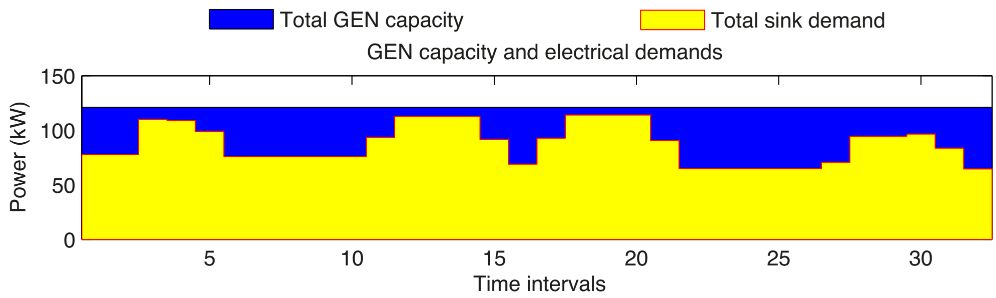


Figure 5.2: Available generator supply (capacity) overlaid with the total electrical power sink demands for the mission.

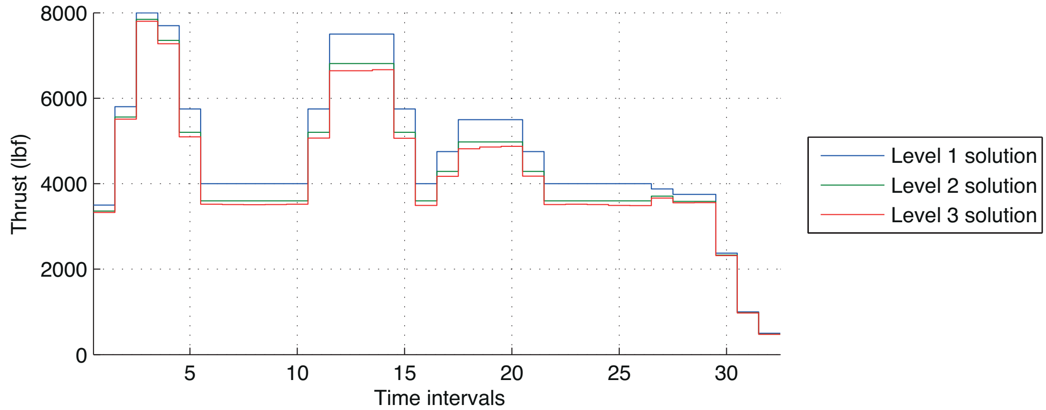


Figure 5.3: Thrust settings.

No optimisation takes place in the Level 1 Solver; this solver is only responsible for providing a fast, feasible solution. Since the Level 1 Solver does not optimise fuel consumption, the Level 1 solution may assign high operating settings to the generators, despite reduced efficiency (see Figure 5.4). The propulsor settings are also determined without exploiting the thrust tolerances (see Figure 5.3). This scheme produces a feasible but a far from optimal solution.

The Levels 2 and 3 Solvers explicitly optimise the fuel consumption of the power

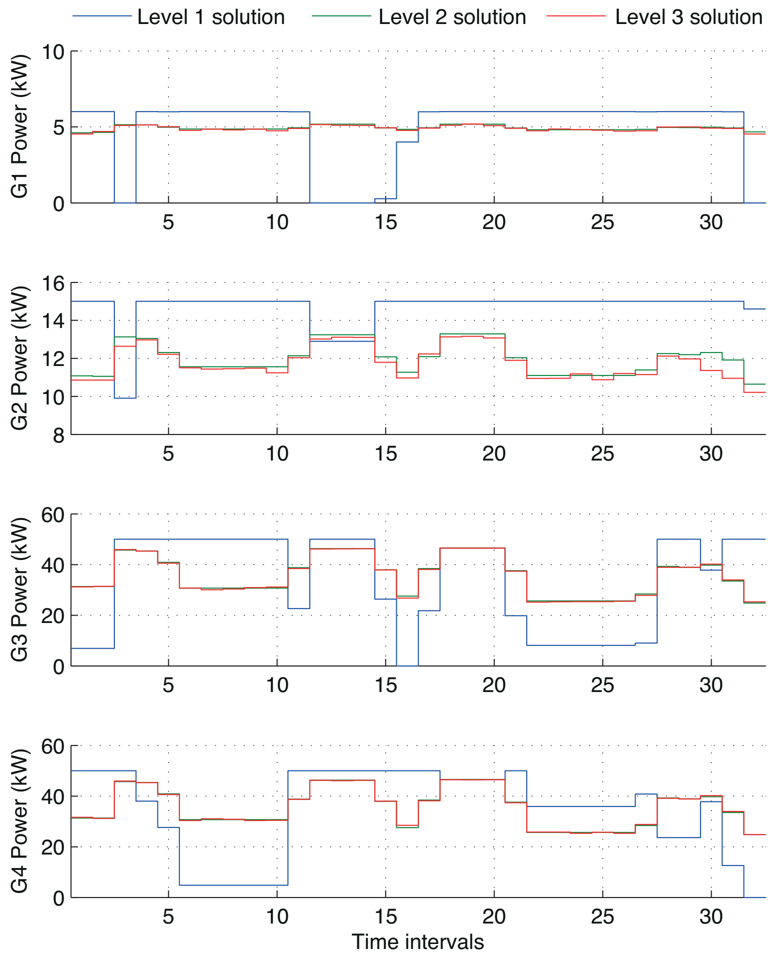


Figure 5.4: Generator settings.

Solver	Level 1	Level 2	Level 3
Total fuel consumption (kg)	1188.9	1149.9	1137.7±0.6

Table 5.2: Total fuel consumption for the three feasible solutions constructed by the PMS. The mean and standard deviation for the fuel consumed by the solution of the Level 3 Solver are obtained from 30 experiments.

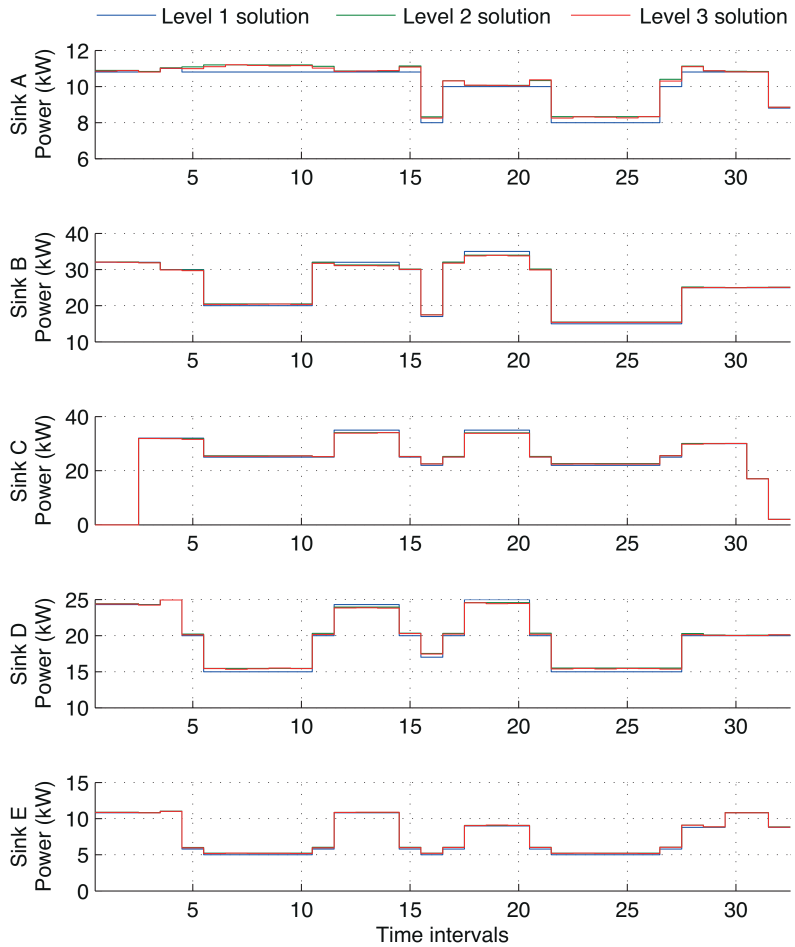


Figure 5.5: Electrical power delivery to power sinks.

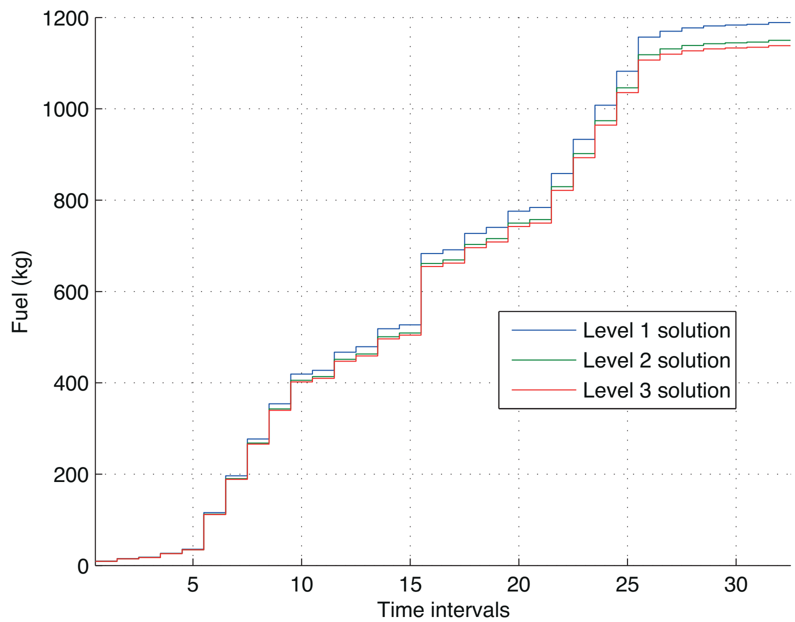


Figure 5.6: Fuel consumption.

schedules constructed. For example, these solvers take into account the efficiency regions of the power sources and exploit the tolerances on the power demands, resulting in better solutions compared to the Level 1 solution (Figures 5.3–5.4). The improvements of the fuel consumption of the Levels 2 and 3 solutions are 3.3% and 4.3%, respectively, when compared to the Level 1 solution. The Level 2 Solver seeks improvement within the neighbourhood of the feasible solution. On the other hand, the Level 3 Solver explores the entire (global) search space for the best solution.

5.1.2 Assumptions and limitations of the control strategy

While the assumptions listed in Section 4.5 hold, there are several other comments that should be made concerning the optimisation strategy. Extensions from Chapters 3 and 4 to accommodate simultaneous control of propulsive and electrical power settings for a complete flight profile are straightforward. The main challenges of achieving this lie within the modelling and representation of the system (see Section 4.1 and Appendix A), and ensuring the problem is solvable within the allocated time and computational resources.

The introduction of the CVX Solver in Chapter 4 that enhances the efficiency of the search process enables the real-time restrictions to be met. The trade-off between search efficiency and optimality is acknowledged and the strategy of treating the problem as a set of separable problems forms an acceptable pragmatic way of solving the problem. Since the hard constraints are also managed by the feasibility checker and solutions management components (Chapters 3 and 6) within the PM, treating the problem as a set of separable problems do not pose a problem during the solution building process.

A primary impediment to this strategy arises from the real-time requirements of the system. The case study presented above comprises 32 sub-problems, or time intervals, and satisfied the real-time restrictions. However, for longer flights, or larger number of sub-problems, the optimisation process may exceed the time and computational resources provided. The upper limit on N_T is dependent on the computing power available. Using the input data in the case study above, the relationship between the execution time and number of sub-problems to be solved for is investigated.

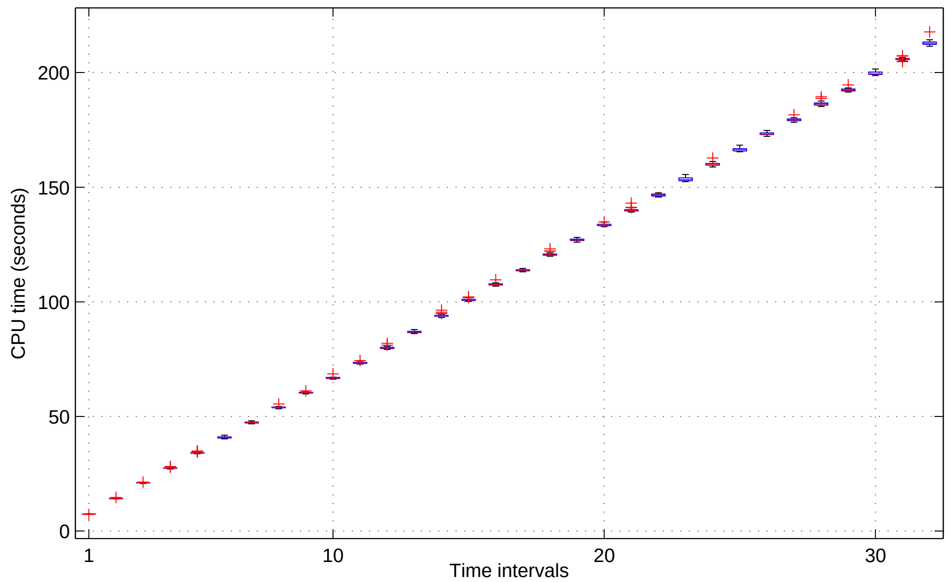


Figure 5.7: Boxplot of the computation time (in seconds) for Case Study I with increasing number of sub-problems.

At the start of the experiment, the PMS was initiated to construct the power schedule for the entire flight, i.e. $N_T = 32$. The execution time was observed. Next, the PMS was again initiated albeit with $N_T = 31$ to solve for; the PMS solved for $t = 2, 3, ..., 32$. The execution time was then observed. This procedure was repeated until $N_T = 1$. Figure 5.7 shows the performance of the Integrated PMS for an increasing the number of sub-problems using MATLAB vR2011a on an Intel Core 3.20GHz processor with 4GB RAM. The linear relationship between the number of sub-problems may enable the user to estimate the maximum number sub-problems that is solvable for the Integrated PMS for this power system set-up, given an execution time. (The execution time and computational power consumption may be improved by implementing the system on a real-time embedded system, optimising the codes used for the Integrated PMS, and use of C++ for example.)

5.1.3 A comparison of Integrated PMS with existing technologies

There are four rule-based schemes used in today's UASs within Rolls-Royce plc (Wall and Mansor, 2014):

- Rule 1: Equal load share on propulsors, equal proportions[1] of load share for electrical generators.
- Rule 2: Equal load share on propulsors, equal real-valued[2] load share for electrical generators.
- Rule 3: Equal load share on propulsors, LP-first loading for electrical generators.
- Rule 4: Equal load share on propulsors, HP-first loading for electrical generators.

These approaches do not incorporate network reconfiguration. Load prioritisation may be enabled. When the proposed PMS is compared to these existing technologies, the following results are obtained.

Scenario 1

Employing an input data that comprises 32 time intervals to represent a 20-hour surveillance mission, seven power schedules were constructed using existing technologies (i.e. the four rule schemes above) and the Integrated PMS. Four of these power schedules are obtained from the rule schemes and the remaining three power schedules from the three-level optimisation strategy within the PM.

Scenario 1	Rule 1	Rule 2	Rule 3	Rule 4	Integrated PMS		
					Level 1	Level 2	Level 3
Feasibility	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Costs (time, s)	0.0131	0.0131	0.0131	0.0131	212.8±0.9		
Total fuel use (kg)	1169	1189	1158	1189	1189	1150	1138

Table 5.3: Scenario 1: 20-hour flight with 32 time intervals. Engine IFSD and SC use are disabled. The mean and standard deviation for the time taken by the Integrated PMS to construct the best executable solution are based on 30 experiments.

Based on the results obtained (see Table 5.3), Rule 3, i.e. LP-first loading for the generators, is the best *rule scheme* for this platform and input data, with Rules 2

[1] For example, all generators are loaded at 50% of their capacity.
[2] For example, all generators are set to produce $5kW$.

and 4 performing the worst. The Level 1 solution does not perform better against existing technologies. However, it is acknowledged that during solution attainment in Level 1, no optimisation takes place. The Level 1 solution still supports network reconfiguration, which the rule based schemes do not. Solutions from Levels 2 and 3 show improvement when compared with the rule-based schemes. The Levels 2 and 3 solutions are predicted to consume 0.7% and 1.7% less fuel, respectively, when compared with the Rule 3 solution.

5.2 Multi-phase scheduling: a non-separable problem

The multi-phase scheduling strategy described in Section 5.1 treats the problem as a separable problem. This is reasonable for power scheduling involving only electrical and propulsive power sources, with no power store within the system architecture. The target application of this technology however, is equipped with electrical and propulsive power sources, and a power store. Additionally, the target system also has the capability of planned engine in-flight shutdown (IFSD) and restart control. These two *flexible* components or features compound the non-separability of the optimisation problem[1]. The capability of the PM to manage these components is important not only for this application, but also other applications. Although specific components are addressed here, other power systems, especially future power systems, would be equipped with *flexible* components or features with similar characteristics and impact to the system. For example, the use of batteries and supercapacitors (single or multiples) in UASs has been suggested in Bossard (2014) and propulsor shutdown may be an element of future more electric aircraft (Husband, 2014).

5.2.1 *Flexible* components or features

The integration of *flexible* components or features into the PM scheduling capability introduces complexity to the problem; these components impose dependent or conditional constraints. For example, a decision describing the power settings at phase t may affect the constraints at phase $t+1$. Details on these *flexible* components or

[1]Strictly, the problem presented earlier in this thesis is a non-separable problem. However, strategies up to this point have decomposed the problem and treated the problem as a separable problem with suitable components to ensure feasibility.

features are expanded below.

Power store: Supercapacitor

The use of a supercapacitor (SC) aims to support the peak power demands of the system, improve the efficiency of the power generation by sharing loads with the generators, enable possible reduction in generator size, and in some cases support planned engine in-flight shutdown (see below). The SC may act as a power source or a power sink. Introduction of the SC into the system, however, increases the problem complexity, not only in terms of the number of decision variables but also in dependency between the sub-problems. For solving the separable problem described in Section 5.1, it is assumed that the configuration[1] of the problem does not change, and that the use of power in a particular time interval does not affect subsequent or preceding time intervals. The energy stored in the SC may change with every time interval, depending on its use. For example, if the SC is to be discharged at time interval $t+1$, the SC must have sufficient power to meet this requirement and if not, the SC must be charged at time interval t to comply with the requirement at time interval $t+1$. If the SC is not charged at time interval t and the SC does not have sufficient energy left in storage, SC cannot be used at time interval $t+1$. A pre-specified amount of energy reserve must also be maintained within the SC as part of the system requirements. The proportion of energy reserve depends on the flight phase.

Engine shutdown/restart capability

The benefits (i.e. fuel savings) of a planned engine in-flight shutdown (IFSD) may be attained if the engine IFSD is performed for a significant amount of time during flight since this action has an overhead cost (as described in Section 3.7). The option to perform engine IFSD affects the configuration of the problem. An engine IFSD would automatically exclude two generators from use. To fully explore the impact and potential fuel savings of IFSD, the

[1] *Configuration* here refers to the power system component set-up that is modelled by the optimisation problem. For the SC case, the electrical power component of the system is particularly of interest. For example, if the SC is discharging for phase t, then the configuration is five electrical power sources and five electrical power sinks. In Section 5.1, since the SC is not active, the configuration always comprises four electrical power sources and five electrical power sinks.

optimisation problem must be considered as a whole. Optimisation of one sub-problem at a time cannot investigate the benefits and costs of engine IFSD sufficiently.

5.2.2 Complexity introduced by the *flexible* components or features

The *flexible* components or features described above cannot be integrated directly into the optimisation strategies presented earlier in this thesis. These components or features introduce constraints that transform the converted separable problems to a non-separable problem. A decision to discharge the SC or decision to perform an IFSD on an engine for a particular time interval would affect the constraints on other time intervals. A decision made for a given time interval may affect the capacities or performance of the power components in future time intervals. This necessitates the requirement of the PM to adopt a more holistic approach for solving the problem, and to consider n-step-ahead dependencies, for example.

The models describing the problem, including the system model, are updated accordingly to sufficiently represent the *flexible* components or features (see Section 4.1 and Appendix A). This includes the requirement to maintain a pre-specified amount of reserved energy in the SC. The exact amount of energy changes depending on flight phase and mission. This causes difficulties in determining the amount of energy that should be charged or discharged. Consider a case where the required SC energy reserves for two phases are 5% and 10%. If the SC energy is used up to the remaining 5% for the first phase, the decision is feasible for the first phase. However, this does not hold for the second phase, where at least 10% energy should be reserved within the SC. Discharging the SC to energy levels below the reserve requirement renders the power schedule infeasible. In the proposed PMS, the energy reserve requirements defined by the input data are accommodated by setting the maximum reserve requirement for all the phases as the reserve requirement for all these phases. For example, using the previous example, the SC energy reserve for both phases would be defined as 10%.

The inclusion of SC management also introduces not one, but four (or five, depending on whether the SC is acting as a power source or a power sink) additional decision variables for each sub-problem to support network reconfiguration, thereby imposing a heavier burden on the computational costs for optimisation. CVX is applied to guarantee feasibility of solutions by converting the search space into a feasible search space, improving the feasible search efficiency, as before. However, CVX implementation requires the configuration to be specified prior to its execution to enable the feasible search space to be defined. If the configuration changes after the CVX analysis, the space defined by the CVX Solver will no longer be guaranteed to be feasible. The configuration of the system must be determined before the CVX analysis is performed.

To generate the optimal power schedule, the problem should be solved as a whole. However, this is expensive (both in terms of computation and time). There exists a trade-off between the two desirable traits, the search efficiency within the optimisation solvers and optimality of solutions (Figure 5.8). As a compromise, the problem is decomposed into the same set of sub-problems as before, but with a slight alteration to the PM framework to accommodate these flexible components or features and their roles in optimisation of the power schedules.

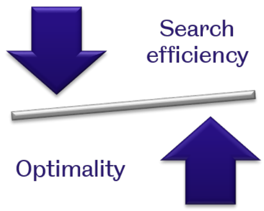


Figure 5.8: Trade-off between optimality of solutions and search efficiency of the optimiser.

5.2.3 Intelligent control of *flexible* components or features within the Integrated PMS

After a feasible solution is found at Level 1, the PM seeks the improved solution based on a given configuration. The configuration describes the state of the engine (on or off), and the SC state (inactive, discharging, or recharging). The strategy that enables the non-separable problem to be solved using a separable approach, is to determine this configuration prior to optimisation of the power schedule i.e. before the CVX Solver is executed. A *configuration stage* is introduced within the PM framework (Figure 5.9) for this purpose. At this configuration stage, the flexibility of the components or features is explored and the best configuration of the system is estimated.

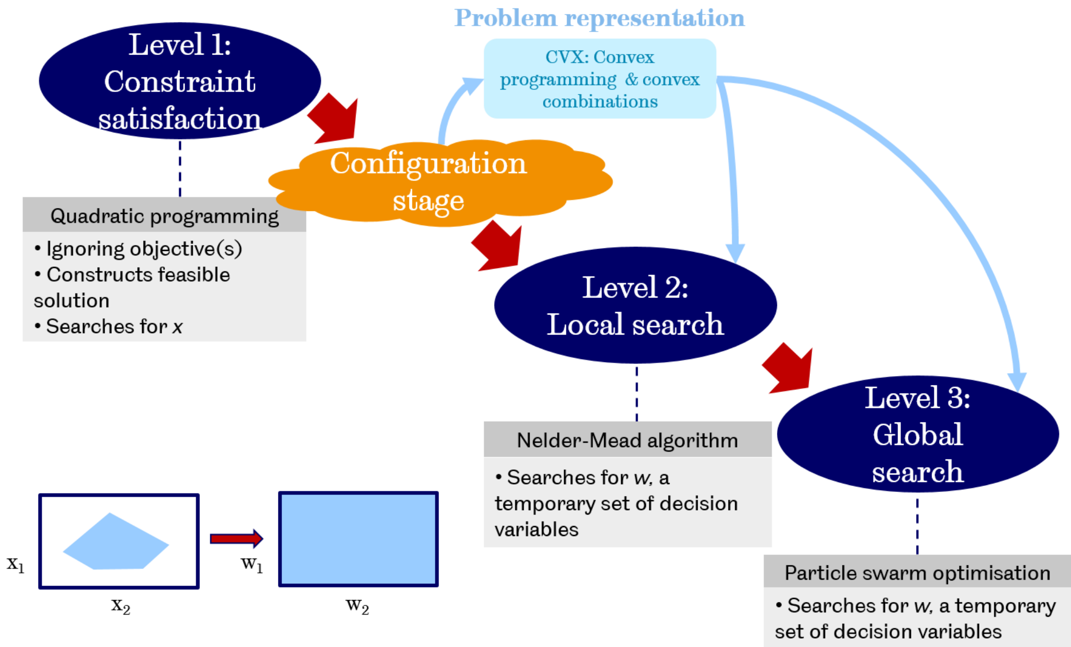


Figure 5.9: An updated scheme for the optimisation process. Level 1 seeks for a feasible solution. The configuration stage analyses the flexibility and determine the best expected configuration. Level 2 solves for the selected configuration and Level 3 refines this solution.

A rule-based greedy approach is adopted to rapidly find the best configuration for each sub-problem. In this approach, the fuel consumption for different configurations is estimated. Then, these configurations are ranked based on these estimates, where the most promising configurations are highly ranked. These rankings form the sequence of actions to determine the configuration for each sub-problem. The sequence of actions taken by this rule scheme is explained by an example below (Figure 5.10):

1. Estimate fuel consumption for each sub-problem if engine IFSD is permitted according to airspace regulations and mission demands (i.e. *survey*). Employ SC to support generators, enabling improved efficiency of the generators. The fuel consumption is estimated by setting the power output of the active generators to be of equal proportions and equal thrust loads on the engines (if both engines are on). *Rank* each sub-problem, based on the expected fuel consumption (where a rank of 1 indicates the least fuel consumption).

2. Set the configuration for sub-problem with rank 1 to the preferred configuration (i.e. Sub-problem 2 in the example shown in Figure 5.10). Update the constraints that are affected by this for sub-problems preceding and succeeding Sub-problem 2, and *freeze* Sub-problem 2. Sub-problems whose configuration cannot be modified are also frozen. For example, if Sub-problem 2 requires all the energy stored in the SC, the energy of the SC will no longer be available for the phase immediately preceding Sub-problem 2. *Freezing* here indicates that the configuration of the phase cannot be further modified (identified by the green sub-problems in Figure 5.10).

3. Go to the next best-ranked sub-problem (rank 2) i.e. Sub-problem 5. Set the configuration of Sub-problem 5 to favour reduction of fuel use. Again, the constraints for remaining (non-frozen) sub-problems are updated accordingly. Sub-problem 5 is then frozen along with any other sub-problems with no flexibility.

4. Step 3 is repeated until all sub-problems have been frozen.

5. Steps 1–4 are repeated for cases where engine IFSD is disabled and for cases where engine IFSD and SC use are disabled. Engine IFSD costs (if any) are incorporated. The configuration set with the least total fuel consumed, when compared with the fuel consumption estimate when engine IFSD and SC use are disabled, is selected for optimisation. The optimisation problem, i.e. the configuration set-up, is updated based on this information.

The rule-scheme explained above forms the survey, rank, and freeze approach embedded within the *configuration stage*. This approach is only applied from the incident[1] interval to the end of flight. Other schemes may be adopted to predict the best configuration settings. For example, a forward (or backward) approach may be employed, which forms a special case from the survey, rank, and freeze approach. In the forward approach, the ranks of the phases based on Figure 5.10 would be $\{1, 2, 3, 4, 5\}$ (or the opposite for backward approach). From the experiments conducted, the survey, rank, and freeze approach produces the best, or comparable, fuel consumption predictions compared with the forward or backward approaches.

[1]Incident interval is the time interval where an event that triggers the PM activation occurs.

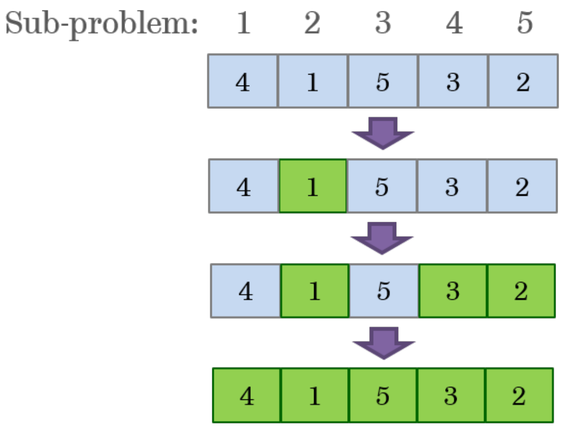


Figure 5.10: Survey, rank, and freeze approach. (Numbers depicts the rank of the sub-problems.)

Subsequent to finding an optimised solution based on the best predicted configuration set from the survey, rank, and freeze approach, an iterative feature may be incorporated into the PM to explore other configurations. This applies for applications or instances where the PM have additional exploration time. The alternative configuration set may be the next best configuration set obtained from the survey, rank, and freeze approach, or other approaches that may be pre-defined.

The survey, rank, and freeze approach allows a fast technique to determine the configuration set. This allows the CVX Solver to shrink the search space accordingly, promoting solver efficiency. This approach, however, does not consider all possible configurations set in its evaluation. The risk of suboptimality of solutions is higher but efficiency of the search process is gained. Additional rules may be incorporated to reduce bias and conduct more exploration of other possible configuration sets. The configuration stage could also benefit from better fuel consumption estimation. These improvements may form part of future research.

This strategy performs an estimation in real-time and optimises the use of the power store for system-level power control. It does not focus on simply power store efficiency but also other components within the system. This is in contrast to other work found in the literature. For example, Faggioli et al. (1999) exploited power stores as power buffers in an electric vehicle and used to only maintain constant and smooth delivery of power. This strategy is well suited for middle and low (component) levels power control, however, it is argued that the approach does not fully consider the efficiency of other components in the system. Other similar work may be found in the literature (Bernard et al., 2010; Kallel et al., 2014; Karunarathne et al., 2008; Kermani et al., 2012; Mahmood et al., 2014; Rodatz et al., 2005; Serrao et al., 2011; Styler et al., 2011).

5.2.4 Case study II

Case study II: Multi-phase (non-separable) power scheduling

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability enabled.
- Complete flight profile power scheduling.

Consider the example in Section 5.1.1 but now with SC use and planned IFSD enabled. The PMS is initiated to construct the *best executable* power schedule based on these conditions. Table 5.4 lists additional information provided in the input data.

Parameter	Value
Number of decision variables, N	$26N_T = 832$ (SC recharging) $27N_T = 864$ (SC discharging)
Energy storage capacity, s_5 or d_6	$500kJ$
Energy storage reserve requirements	5–20%

Table 5.4: Information provided by the input data, in addition to the information provided in Table 5.1.

Figures 5.11–5.14 describe the power schedules constructed for the planned flight. Figure 5.15 displays the total fuel consumption for the schedules constructed. Total fuel consumption of the solutions produced, when the different *flexible* components or features are enabled, are also listed in Table 5.5.

The *best executable* power schedule constructed by the Integrated PMS includes an instance of planned IFSD during the second half of this mission (see Figure 5.11), with the SC supporting the generators to supply power on-board (see Figure 5.14). No power is supplied by Generators 1 and 3 when Engine 1 is shut-down (see Figure 5.12).

The total fuel consumed by the power schedules when both SC use and engine IFSD are enabled is reduced, progressing from Levels 2 to 3: 5.5% and 6.2%, re-

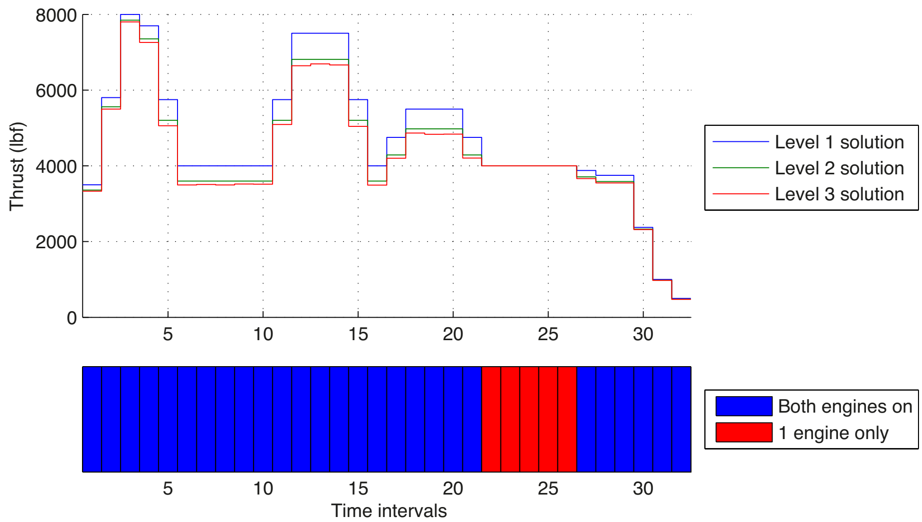


Figure 5.11: Thrust settings.

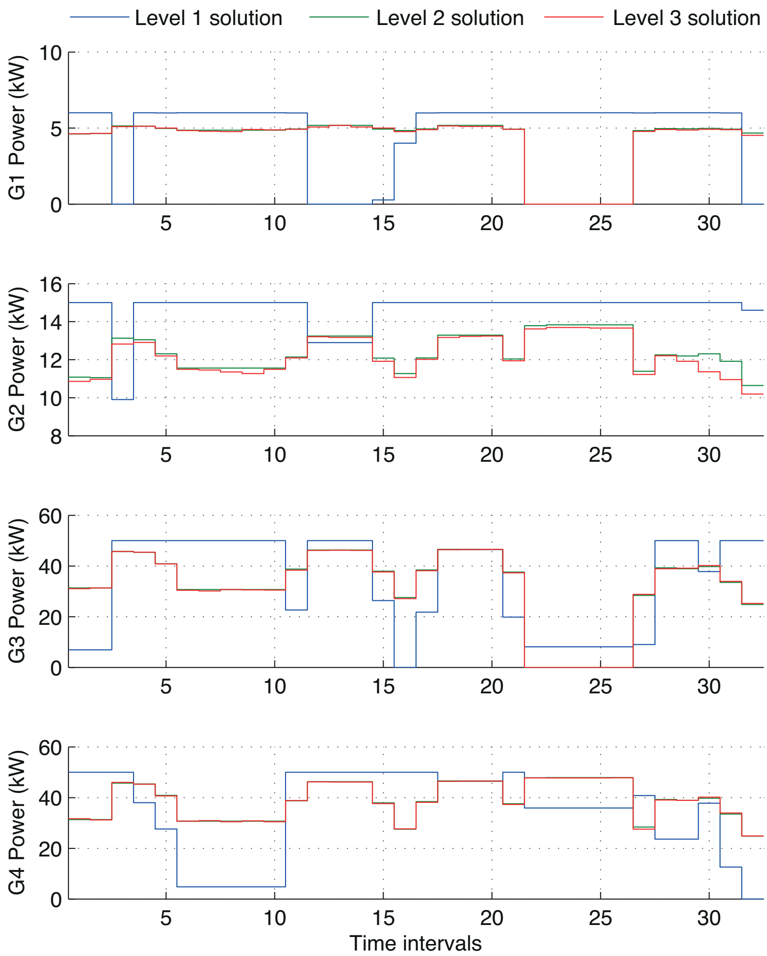


Figure 5.12: Generator settings.

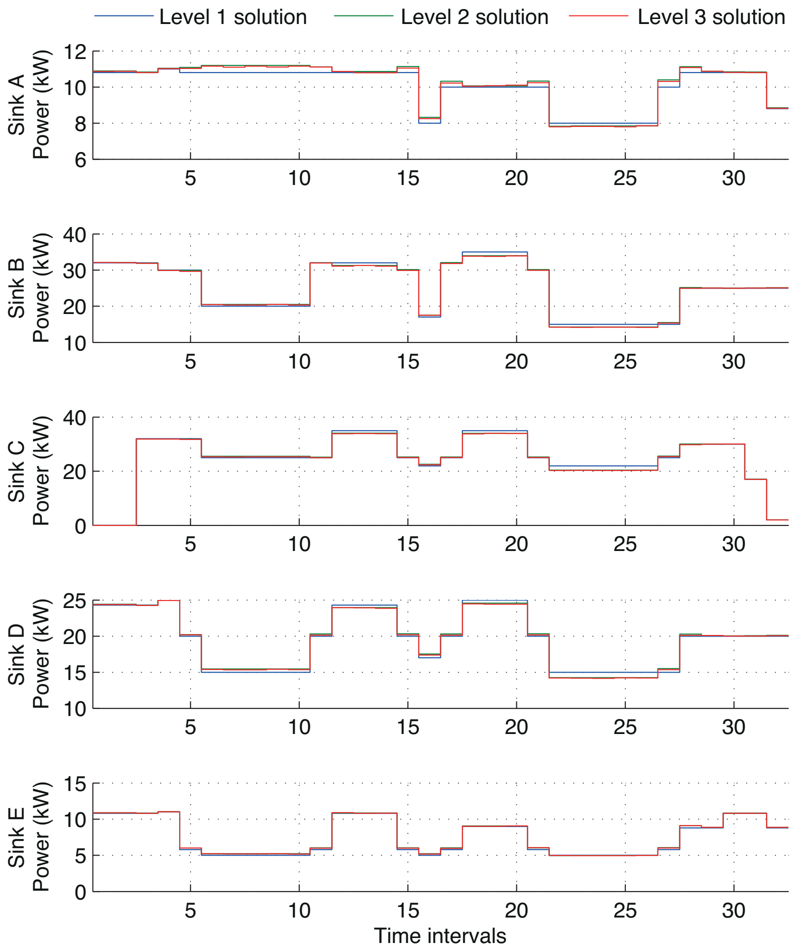


Figure 5.13: Electrical power delivery to power sinks.

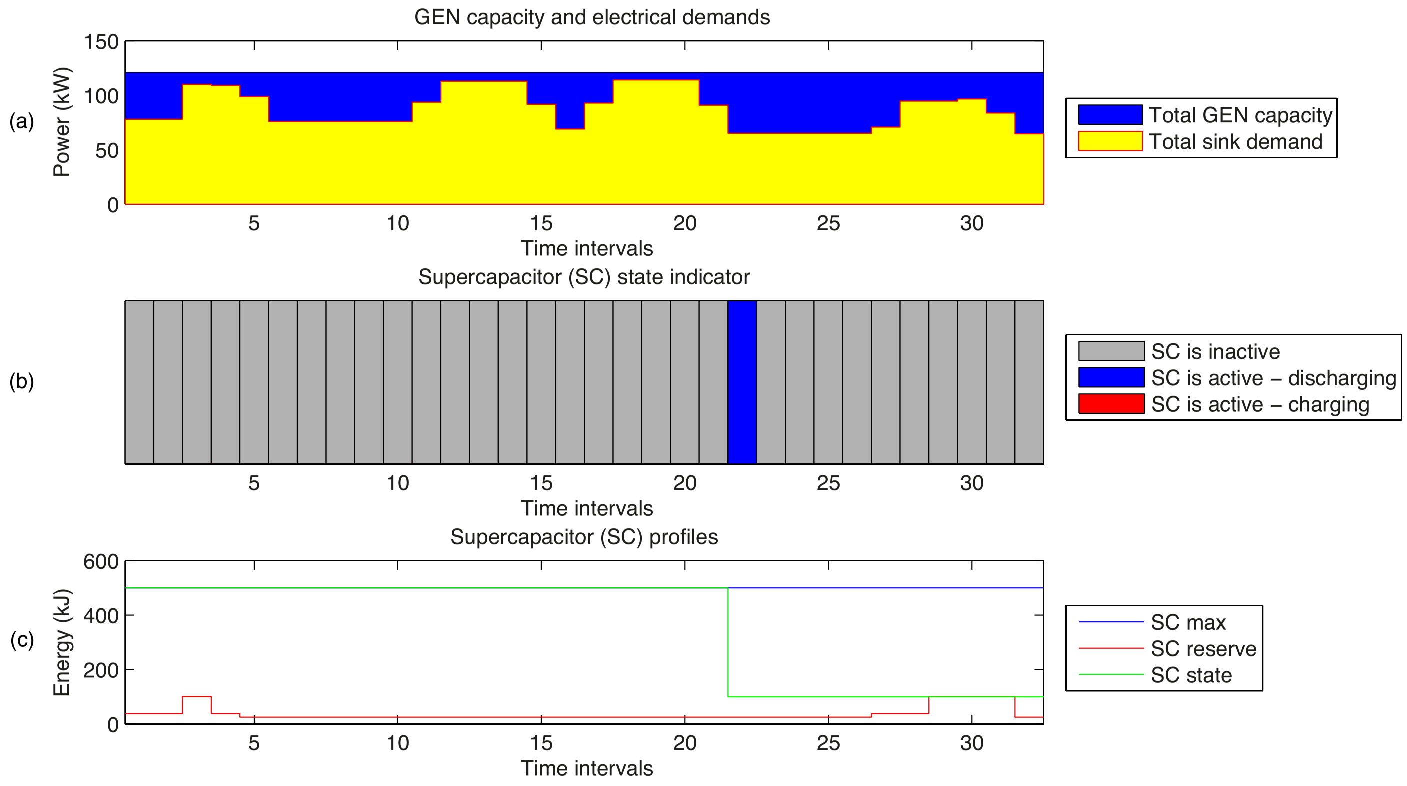


Figure 5.14: (a) Available generator supply (capacity) overlaid with the total electrical power sink demands for the mission. (b) Supercapacitor state indicator for the entire flight. (c) Energy levels of the SC for the mission.

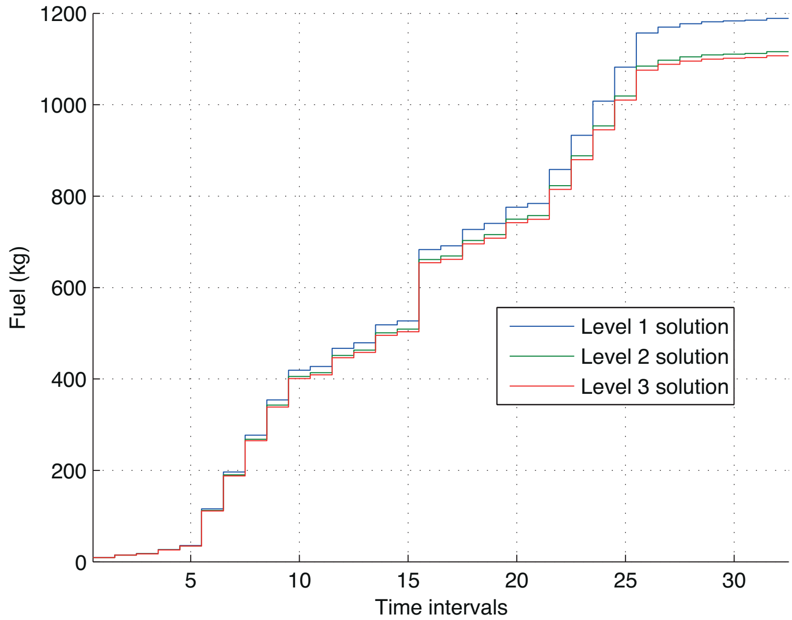


Figure 5.15: Fuel consumption.

spectively, when compared with the Level 1 solution. The differences when SC use and engine IFSD are enabled or disabled are highlighted in Table 5.5. For the SC use only enabled scenario, fuel savings may be gained, albeit not as much savings when both SC use and IFSD are enabled. Fuel savings are not noticeable for the engine IFSD only scenario. This is because for this mission, no engine IFSD takes place. For this particular input data, the SC is required to support engine IFSD. The 2.0% improvement in fuel consumption between the Level 3 solutions represents the potential benefits that may be gained from exploiting SC and engine IFSD.

Total fuel consumption	Level 1	Level 2	Level 3
SC use and IFSD enabled (kg)	1188.9	1124.1	1115.1±0.4
Only IFSD enabled (kg)	1188.9	1149.9	1137.6±0.4
Only SC use enabled (kg)	1188.9	1149.8	1137.6±0.5

Table 5.5: Total fuel consumption for the feasible solutions constructed by the PMS with different flexible components or features enabled. The mean and standard deviation for the fuel consumed by the Level 3 Solver solutions are obtained from 30 experiments.

5.2.5 Assumptions and limitations of the control strategy

A risk of employing the configuration stage to handle the *flexible* components or features is that the rules used may be too restrictive to enable the optimiser to construct an optimal solution. The approach may also suffer from premature freezing or produce inaccurate ranking due to the coarseness of the fuel consumption estimates. Additional rules may be added to enable an improved survey. However, this would require additional rules and may be costly in terms of computation costs. The complexity of the rules implementation may increase significantly and cause delay in quickly attaining a best predicted configuration set. Perhaps methods such as linear temporal logic (Ozay et al., 2011) could be explored in further work.

The SC may not be utilised to its maximum capability due to the coarseness of the time intervals. A middle-level control that complements the top-level control of this research (as discussed in Section 3.2) may improve this by fine tuning the charge and discharge of the SC for one or two time intervals at a time but with greater granularity.

The execution time to compute the improved PMS strategy increases linearly with the number of time intervals (similar to the performance analysis for Case study I). This may provide a guide to future users on the limitations of the Integrated PMS. However, the execution code may be optimised, improving the real-time performance of the PMS strategy.

The key feature of the configuration stage is that it supports the optimisation strategy; the integration of the *flexible* components or features in the problem becomes manageable. Potential drawbacks are acknowledged.

5.2.6 A comparison of Integrated PMS with existing technologies

The performance of the Integrated PMS is compared with the performance of the existing power management approach (as described in Section 5.1.3) below.

Scenario 2

Employing the same input data as Scenario 1 (Section 5.1.3), but with SC use and engine IFSD now enabled, another set of power schedules were obtained using existing technologies and the integrated PMS (see Table 5.6). Enabling these features

Scenario 2	Rule 1	Rule 2	Rule 3	Rule 4	Integrated PMS Level 1	Integrated PMS Level 2	Integrated PMS Level 3
Feasibility	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Engine	Both on	Both on	Both on	Both on	Both on	Intelligent control	
Super-capacitor	Unused	Unused	Unused	Unused	Unused	Intelligent control	
Costs (time, s)	0.0131	0.0131	0.0131	0.0131	210.0±0.9		
Total fuel use (kg)	1169	1189	1158	1189	1189	1124	1115

Table 5.6: Scenario 2: 20-hour flight with 32 time intervals. Engine IFSD and SC use are enabled. The mean and standard deviation for the time taken by the Integrated PMS to construct the best executable solution are obtained from 30 experiments.

does not influence the solutions produced by the four *existing* schemes, as they do not incorporate SC or IFSD control in their rule-based schemes.

As before, the expected fuel consumed from Levels 1 to 3 improves; there is an improvement of 2.9% and 3.7% when comparing Rule 3 against Level 2 and Level 3 solutions, respectively. These results illustrate the additional features of the power system that the integrated PMS is capable of handling, and the benefits of optimisation within the power scheduling for power systems.

5.3 Scheduling with soft constraints

The construction of complete multi-phase solutions has been described in Sections 5.1–5.2, addressing the handling of separable and non-separable hard constraints. In this section, soft constraints are introduced and an approach for handling them is presented.

5.3.1 Soft constraints: definition, impact, and integration

Soft constraints are constraints that need not be satisfied. Their satisfaction is desirable but not essential in an optimisation problem[1] (Brailsford et al., 1999). In some cases, violation of soft constraints is unavoidable to ensure feasibility of the optimisation solution (Burke et al., 2008, 2002).

[1] Violation of these constraints does not influence the feasibility of the problem. Feasibility is determined by hard constraints satisfaction only.

The PM is expected to handle EHM advice or requests that may be soft constraints, e.g. health recommendations. Other than that, additional user preferences may be introduced as soft constraints. Depending on the type of mission, there may also be discrepancies between how some components of the system are managed. For example, it may be desirable that the SC energy level is depleted by the end of the flight, if the UAS is expected to return to base. However, if the UAS is expected to land in an area where energy supply is limited, the SC energy storage may be conserved to support engine restart for the flight return.

There are several types of soft constraints that may be introduced for the power management problem. Some types of soft constraints are specific. For example, due to health analyses of the power components, it is preferable that Generator 1 is loaded below 80% of its capacity. On the other hand, a non-specific soft constraint may be the request to simply reduce the load on a particular power source, for example. The impact of the soft constraints may also differ in terms their affect on the primary objective and hard constraint satisfaction.

The incorporation of soft constraints into an optimisation problem may result in the selection of a global optimal solution to be less obvious (Michalewicz, 2012). Satisfaction of soft constraints based on EHM advice may reduce maintenance costs, or reduce risk of mission failure. However, the satisfaction of these constraints may not necessarily be in favour of minimising fuel consumption. To ensure that the integrated PMS is sufficiently adaptable and flexible to user preferences, soft constraint management is introduced.

The soft constraint management is based on the characteristic and impact of the constraints on the objective of the optimisation problem. Figure 5.16 provides an overview of the soft constraint integration. The prime objective of the PM is to minimise fuel consumption. These soft constraints may be complementary to this objective, or conflicting. With this in mind, the overall strategy to handle soft constraints within the PM is to first identify the set of active soft constraints, ensuring that the soft constraints are satisfiable and do not violate any hard constraints. Then, the characteristic or impact of these soft constraints is analysed. Non-separable constraints are incorporated into the configuration stage, while separable constraints are handled by the Level 3 Solver. Soft constraints that do not effect the primary objective may be incorporated directly in to the CVX Solver.

Figure 5.17 illustrates the different examples of soft constraints introduced in this study, their classification and impact (colour coded), and subsequent integration into the PM framework.

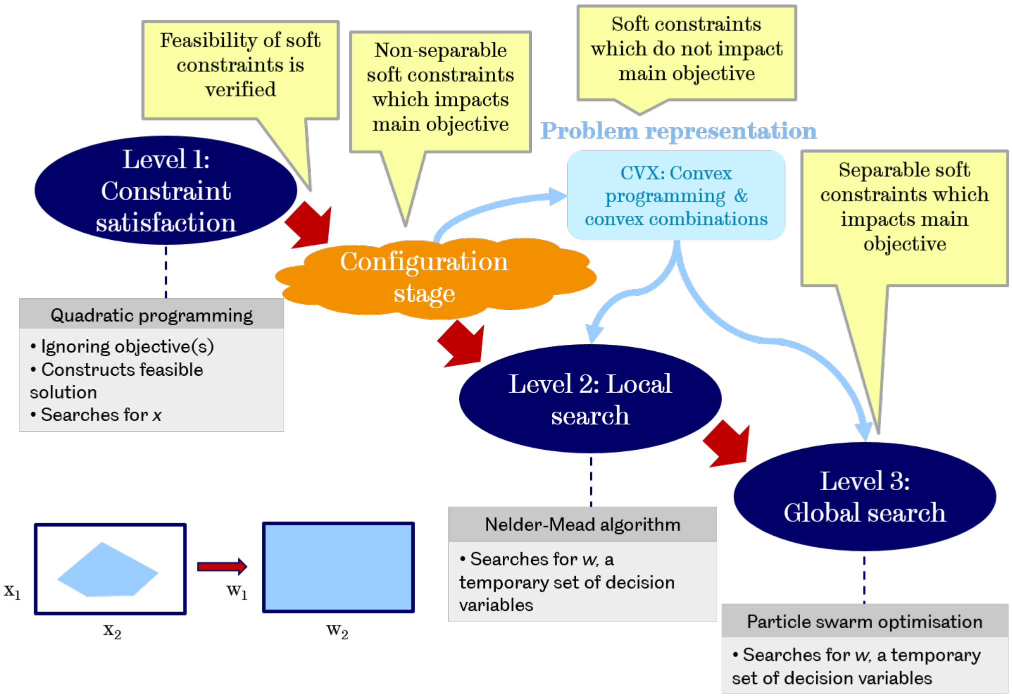


Figure 5.16: The effect of soft constraints integration into the overall three-level strategy.

If the soft constraints cannot be satisfied without the violation of hard constraints, these soft constraints are considered unsatisfiable and are omitted from the optimisation process. If the soft constraints are satisfiable, they may be introduced into the configuration stage or into the Level 3 Solver, depending on the nature of the constraints (separable or non-separable), similar to the strategy to handle hard constraints of the problem.

Soft constraints that manipulate the engine IFSD or the SC use are incorporated in the configuration stage. Soft constraints that do not contribute towards minimisation of fuel consumption tend not to be satisfied in the configuration since the configuration stage is designed to select configurations that correspond to the best estimated fuel savings. These soft constraints, however, do provide additional information that the configuration stage may find useful. For example, if an engine

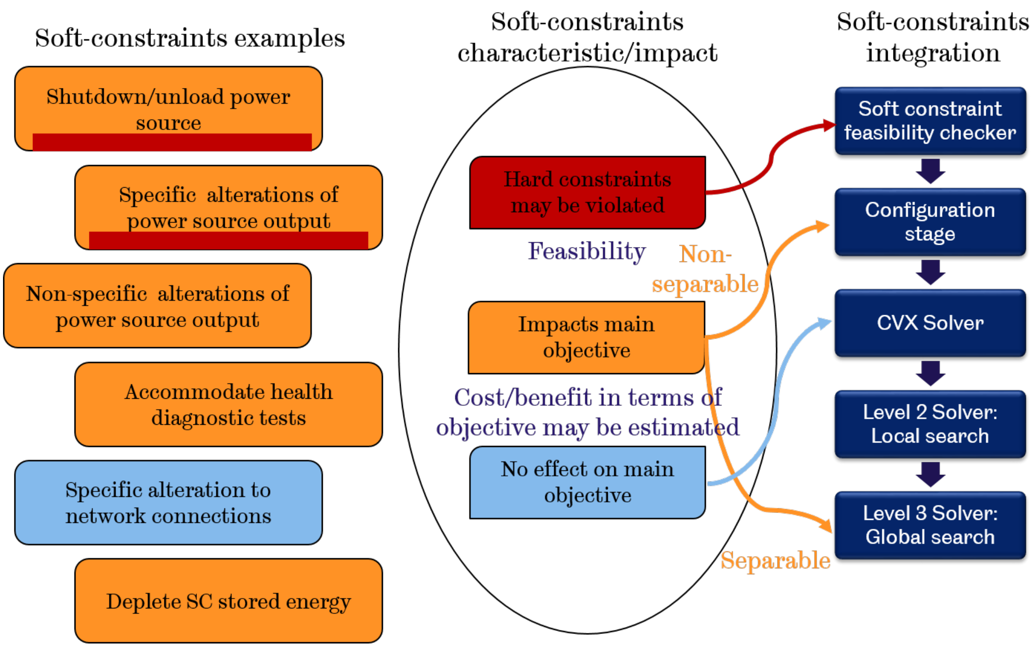


Figure 5.17: Soft constraints handling.

IFSD is found to be the best action for a given flight, soft constraints that indicate which engine or which generators should be turned off based on health analyses may provide a decision aid in configuration stage. The soft constraints may also be indirectly satisfied if the keep-out zone described overlaps with the non-efficient zones of the generators. These redundant soft constraints will not be explicitly handled by the PM but eliminated.

Special cases exist where specific alterations of network connections are requested by the EHM. This soft constraint does not affect the main objective (for this problem[1]) as the usage of the connections used in this system is assumed to be negligible and does not affect the fuel consumption of the vehicle. Of course, if a large number of network connections is requested to be switched off, the fuel consumption is likely to be affected. This scenario is not considered in this research study and is a candidate for future investigation. The Level 3 Solver handles any remaining feasible separable soft constraints and is discussed next.

[1]Other objectives functions may be used in future. These network connections are likely to be directly handled if the main objective is maximisation of life of the components, for example.

5.3.2 Level 3 Solver handling of separable, high impact soft constraints

Penalty terms are used in the Level 3 Solver to seek solutions that satisfy separable, high impact soft constraints. For example, when an EHM recommendation that introduces a soft constraint for a generator to operate within a specified threshold, the objective function that addresses this particular soft constraint is:

$$V(x_{ijt}, x_{kt}) = \mathcal{F}_{\text{total}}(x_{ijt}, x_{kt}) + q\left|\delta_{\text{at}} - \left|x_{kt|k=1} - x_{kt|k=2}\right|\right| + \phi\left|\gamma_{\text{it}} - x_{it}\right| \tag{5.1}$$

where

$$\phi = \begin{cases} > 0 & \text{if soft constraint is violated} \\ 0 & \text{otherwise.} \end{cases}$$

ϕ denotes the penalty weight for the violation of the soft constraint, and γ denotes the desired power output for the generator based on the soft constraint. ϕ is set to zero unless the generator is generating power outside the specified threshold, i.e. the penalty is only incurred when the soft constraint is not satisfied.

Equation 5.1 is constructed for each separable, high impact active soft constraint. For example, if the soft constraint describes the desired engine operating zone instead of the generator operating zone, the term $\phi\left|\gamma_{\text{it}} - x_{it}\right|$ is replaced with $\phi\left|\gamma_{\text{kt}} - x_{kt}\right|$, where γ_{kt} is the desired power output of the engine defined by the soft constraint. As before, this term only penalises the objective function if the specified engine is operating outside the specified threshold. If EHM recommendations comprise both soft constraints, two objective functions are used. One objective function is as described by Equation 5.1, and the other objective function is an alteration of Equation 5.1: $\phi\left|\gamma_{\text{it}} - x_{it}\right|$ replaced with $\phi\left|\gamma_{\text{kt}} - x_{kt}\right|$.

The PSO algorithm is used to solve for each of these objectives including one without any penalty terms resulting from soft constraint violation (i.e. fuel consumption minimisation alone). In other words, the PSO algorithm solves for $(n+1)$-swarms, where n represents the number of high impact soft constraints, and each of these swarms is solved for a different objective function. The introduction of soft constraints at Level 3 Solver introduces the possibility of more than one solution to be proposed to the Solutions Management.

The overall impact of soft constraints integration into the three-level optimisation strategy is illustrated in Figure 5.16. Note that unsatisfiable soft constraints may still be addressed; the PM attempts to reduce the violation of the soft constraint, where possible. If the generator power output cannot be reduced to 80% of its capacity due to mission requirements, for example, the PM, specifically the Level 3 Solver, would encourage the soft constraint violation to be reduced by incorporating a penalty term (as described above), which minimises the power output of the generator as much as possible while satisfying the mission requirements (hard constraints).

The real-time requirements of the optimisation process are maintained by introducing rules or adjustments to the parameters used for optimisation. For example, redundant constraints are removed using rules to determine whether they are satisfiable. Soft constraints that are used as decision aids in the configuration stage form part of the rules that are used to select which engine is to be shutdown, for example. In the absence of a soft constraint of this nature, the default setting within the configuration stage would be set up beforehand based on user preferences, e.g. shut down the engine that supports the set of generators with the least total capacity. For cases where the soft constraints are incorporated into the Level 3 Solver, multiple swarms are introduced. The number of iterations and particles in a swarm is autonomously set to be the same for each swarm and that the total number of particles and iterations remain the same when compared with the case when no soft constraints are involved. Although the optimisation process and end result may be affected by this, the real-time capability of the system may be maintained.

The problem addressed in this research focusses on solving a single-objective optimisation problem, viz. fuel consumption minimisation. Real-time changes to the system health and preferences introduce soft constraints. As a result, the best solution to the power management problem becomes less clear. Satisfaction of the soft constraints may be conflicting with fuel consumption minimisation. The strategy introduced here is an extension to a single-objective optimisation problem, with elements of an additional objective to consider (i.e. satisfaction of the soft constraints). A key feature of this strategy is its capability to be flexible to change in the conditions of the system and produce a set of *good* solutions, autonomously in real-time. It is acknowledged that this strategy has its limitations, however, future research will investigate better strategies to handle these soft constraints for a real-time optimisation problem (see Section 5.3.4).

There have been some research found in the literature addressing optimisation problems with soft constraints. It is acknowledged by the community that introduction of soft constraints may result in the global optimal solution to be less clear. Michalewicz (2012) affirms this and alludes that for real-world problems, it may be acceptable to produce similar solutions to that of experts. Handling of soft constraints have been investigated by several studies for various applications e.g. rostering and timetabling problems, and pipe network optimisation. Introduction of penalty terms was adopted by several studies (Burke et al., 2008; Savie and Waiters, 1995). Some studies also treated the soft constraints as an objective (Burke et al., 2008, 2002; Chiarandini et al., 2000). None of these studies focuses on real-time optimisation with soft constraints.

5.3.3 Case study III

Case study III: Multi-phase (non-separable) power scheduling with soft constraints

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability enabled.
- Complete flight profile power scheduling.
- Soft constraints introduced.

For the same conditions as presented in Section 5.2.4 but with soft constraints introduced, a case study is presented. Due to health analyses during flight, two soft constraints are introduced. One of the soft constraints requests for reduction in Generator 2 power output to below 80% of its capacity and the other constraints expresses a preference to avoid the 15$^{\text{th}}$ network connection.

Two final solutions from Level 3 are obtained and are listed in Table 5.7. The solution satisfies the soft constraint that reduces the load on Generator 2 and has a slightly larger expected fuel consumption. This information is made available to the user. The constraint that represents the network connection preference to be switched off is satisfied automatically since it is integrated into the CVX Solver directly; it does not affect the total fuel consumption and not handled separately by the Level 3 Solver. When compared with the Level 1 solution, these two final solutions are better by 6.3% and 6.2%, respectively.

Objective	Level 3 solution
Fuel consumption only (kg)	1113.6±0.5
Fuel consumption and soft constraint (kg)	1115.0±0.4

Table 5.7: Total fuel consumption for the feasible solutions constructed by the PMS with soft constraints introduced. The mean and standard deviation for the fuel consumed by the Level 3 Solver solutions are obtained from 30 experiments.

The articulation of soft constraints may result in more than one *good* solution. In this case study, two solutions are produced. The management and final selection of the *best executable* solution (when there is more than one) is handled by the solutions management module. Strategies taken to select the *best executable* solution are described in Chapter 6.

5.3.4 Assumptions and limitations of the control strategy

The integration of soft constraints into the PMS framework is dependent on the main objective. For the optimisation of other objectives instead of fuel consumption, such as life of components, the same strategy may be applied. Using Figure 5.17 as reference, for life of components maximisation, the soft constraint describing the preference on the network connections will be categorised as a soft constraint that would affect the main objective instead of having no effect on the main objective. This soft constraint would be addressed directly in any of the modules, depending on the model used to represent the life of the components.

This strategy to handle soft constraints may be limited by the number of soft constraints introduced. For example, soft constraints that are integrated into the configuration stage may cause more rules to be integrated, increasing the computation burden of this stage. The introduction of high impact soft constraints into the Level 3 Solver may also affect the quality of solutions produced at the end of the optimisation process. The total number of particles, swarms and iterations is dependent on the number of active soft constraints in Level 3. An increasing number of soft constraints would reduce the explorative nature of the stochastic search and may degrade the performance of Level 3 Solver. Limitations on these parameters would reduce the quality of solutions albeit it contributes to ensuring the real-time requirements are met.

Another limitation of the strategy to handle separable high impact soft constraints is that all these constraints are handled individually, with individual objective functions. It is likely that some of these constraints may be complementary and may be grouped together to share the same objective function. This would improve the explorative nature of the Level 3 Solver since effect on the number of particles and iterations for each swarm is reduced.

Fortunately, the number of soft constraints are finite. As the vehicle progresses through the mission, more time will be available to compute a complete power schedule. In other words, the number of soft constraints may limit the performance of the PMS at the beginning of the mission, however, the performance would be improved with time. These points could be further explored in future work. A true multi-objective optimisation problem may be investigated, for example. This perhaps may be a better strategy to handle soft constraints. Depending on the computational requirements, perhaps a combination of strategies may be required.

For the current approach, the expected computation time increases linearly with the number of phases. Since the number of particles and iterations are controlled, this linear relationship is similar to the analyses in Sections 5.1 and 5.2.

Since soft constraints are not incorporated into to the power management systems in today's UASs, this strategy is not compared with existing technologies.

5.4 Infeasibility management

The Infeasibility Management module within the Integrated Power Management framework is activated when infeasible instances of the problem are detected by the feasibility checker module (Section 3.6.3). Using the SC and information arising from priorities of the load demands, the infeasible problem may be converted to a feasible problem.

The strategy within the infeasibility management module is to address any instances of infeasibility based on the type of constraints that is violated, viz. separable or non-separable constraints. For instance, where separable constraints are violated e.g. load demand exceeds generator capability for a particular set of sub-problems, the infeasibility management module resolves the problem by employing SC support and load shedding, as required. The SC is used to meet electrical demands that cannot be met by the generators. If the energy stored within the SC is insufficient, then load prioritisation is initiated. Load prioritisation leads to load shedding based on priority, starting from the lowest priority to the highest priority. The input data provided to the PM by the VMS includes priorities for each load demand to enable this action. Load shedding is only performed while the problem is infeasible. The PM stores the information that describes which loads are shed and the phase index of these loads. This information, as well as information on the required SC setting, is used to update the optimisation problem. For separable constraints violation, the infeasibility management module attempts to ensure feasibility sub-problem by sub-problem.

Algorithm 5.1 Infeasibility management

while Infeasible **do**
    if Infeasibility is caused by separable constraints **then**
        Seek SC support to encourage feasibility
        if Infeasibility persists **then**
            Perform load prioritisation: shed load(s) based on priority for each infeasible sub-problems until problem is feasible
        end if
        Store SC use and/or load shedding information
    end if
    if Infeasibility caused by non-separable constraints **then**
        Perform load prioritisation: shed load(s) of lowest priority among remaining sub-problems until problem is feasible
        Store load shedding information
    end if
    return SC use and/or load shedding information
end while

To handle non-separable constraints violation, e.g. fuel constraint violation, the infeasibility management module performs load prioritisation to reduce system load. In contrast to the way separable constraints violation is handled, the infeasibility management module handles non-separable constraint violation by shedding the lowest priority load demands of all the remaining sub-problems. The entire remaining flight profile is considered, instead of sub-problem by sub-problem load shedding. Supercapacitor support is not sought for this instance of infeasibility. It is argued that the best allocation for SC support cannot be determined. Of course, depending on user preferences and application, this feature could be added. However, the option to use SC support to handle non-separable constraint violation is not employed for the UAS presented in this thesis. Information describing the load demands that are switched off and the affected sub-problems is used to update the (now) feasible optimisation problem. Algorithm 5.1 illustrates the mechanism behind the infeasibility management module.

5.4.1 Case study IV

Case study IV: Multi-phase (non-separable) power scheduling with infeasible requirements

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability enabled.
- Complete flight profile power scheduling.
- Hard constraint violation introduced.

An infeasible scenario where the electrical load demands are larger than the electrical power supply available, specifically at time interval 19, is introduced into the input data used in Section 5.2.4. The PMS is then initiated to construct a *best executable* solution.

The generators are unable to generate sufficient power to meet the mission requirements; SC support is sought. The energy stored in the SC is, however, insufficient to meet the power demands that are not met by the generators. To mitigate this, the PMS performs load shedding based on priority. The PMS then constructs the *best executable* solution based on the updated demands, and returns information on the load shed to the user. This information indicates that one of the power loads is shed, in the 19$^{\text{th}}$ time interval, to force feasibility.

5.4.2 Assumptions and limitations of the control strategy

There may be cases where the capacity of the power system is severely reduced, causing a large number of loads to be switched off. This may affect the safety of the system. For example, due to severe health issues with an engine, two generators may be forced to shut down at a critical flight phase, and the remaining generators are insufficient to support all the loads including flight critical loads. In these cases, the VMS and GCS must intervene; the PMS is not solely responsible for the safety of the system. These cases are expected to be rare and the outcome of the incident will not be worse than if the system was operating without the presence of an optimised PMS. It is likely that authority or autonomy of the UAS is replaced with commands directly from a human operator at this stage. The PMS reports relevant information accordingly, keeping the GCS (human operator) up to date.

5.5 Complete solution

In this Section, a case study is presented where multiple events are introduced and the Integrated PMS is triggered to cope with these in-flight events. This case study is aimed to be more realistic than the introduction of one event at a time, as shown in Case study I to Case study IV.

5.5.1 Case study V

Case study V: Multi-phase (non-separable) power scheduling with a compendium of events

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability enabled.
- Complete flight profile power scheduling.
- Multiple in-flight events are introduced that alter the hard constraints of the problem, and introduce soft constraints to the optimisation process.

During the research study, a graphical user interface (GUI) was developed to demonstrate the capabilities of the optimised PMS to manage events during a simulated flight. Figure 5.18 depicts the GUI that enables the user to interact with the PMS. The *Power Manager* and *System information/update* panels allow the user to trigger the PM and introduce new events. The latter also displays flight information along with the *In-flight system health information* and *Flight phase information* panels. The remaining panels display information relating to the Solvers of the system and the power schedules constructed. Additional pop-up figures, or windows, displaying SC states may be made available by the user, depending on

Total fuel consumed (kg)	Level 1	Level 2	Level 3
Normal	1188.9	1124.1 (-5.5%)	1115.0±0.5 (-0.8%)
Event 1	1153.7	1067.2 (-7.5%)	1061.2±0.3 (-0.6%)
Event 2	1153.7	1067.2 (-7.5%)	1061.2±0.3 (-0.6%)

Table 5.8: Total fuel consumed for normal conditions, event 1, and event 2. The improvement of each l level (against Level $l-1$ solution) is shown in green.

display options.

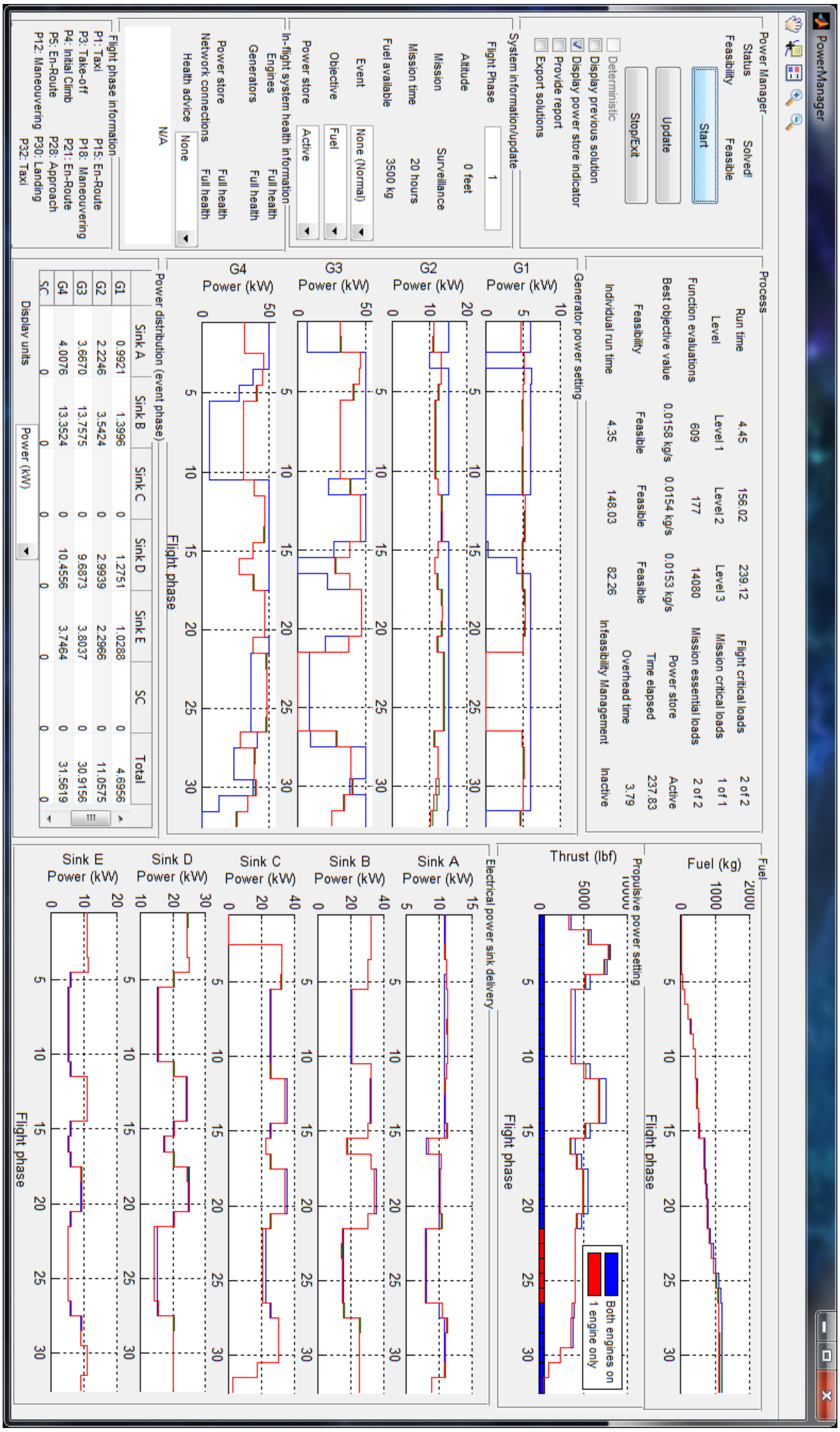
In this final case study, a series of events is introduced during a UAS surveillance mission to investigate the PMS response to multiple events. These events may change mission demands, component capacity, or introduce soft constraints. To accommodate these changes, the PMS is triggered to update the power schedule to the *best executable* power schedule. For this case study, the GUI described above is used.

Consider a 20-hour surveillance mission. At mission start, the vehicle is supplied with a best executable power schedule describing the power supply and delivery for the entire mission (32 time intervals, or sub-problems, in total). Figure 5.18 shows the GUI for the Power Manager at the start of the mission. Figure 5.19 describes the SC state. Figure 5.19(a) figure displays the total available generator power capacity (blue) overlayed with the total electrical power demands (yellow). Figure 5.19(b) indicates that the SC is scheduled to be discharged to support the generators at time interval 22. At this time interval, one of the engines is also scheduled to be shut down (see Figure 5.18 – *Propulsive power setting* panel). Note that when Engine 1 is shutdown, no power is extracted from Generators 1 and 3. Figure 5.19(c) shows that the minimum reserve requirements of the SC charge levels are satisfied. The expected total fuel consumed is listed in Table 5.8. From Level 1 to 3, the total expected fuel reduces from $1188.9kg$ to $1115.0 \pm 0.5kg$, representing 6.2% improvement.

Now, two events are introduced sequentially (see Event 1 and Event 2 below).

Event 1: VMS informs PMS of a change in mission tasks and EHM reports equipment degradation at time interval 6

Effect: Change in electrical power demands with reduced system capability.



	Sink A	Sink B	Sink C	Sink D	Sink E	SC	Total
G1	0.9921	1.3996	0	1.2751	1.0288	0	4.6956
G2	2.2246	3.5424	0	2.9939	2.2966	0	11.0575
G3	3.6670	13.7575	0	9.6873	3.8037	0	30.9156
G4	4.0076	13.3524	0	10.4556	3.7464	0	31.5619
SC	0	0	0	0	0	0	0

Figure 5.18: Normal conditions. Blue, red, and green lines denote a Level 1 solution, Level 2 solution, and Level 3 solution, respectively.

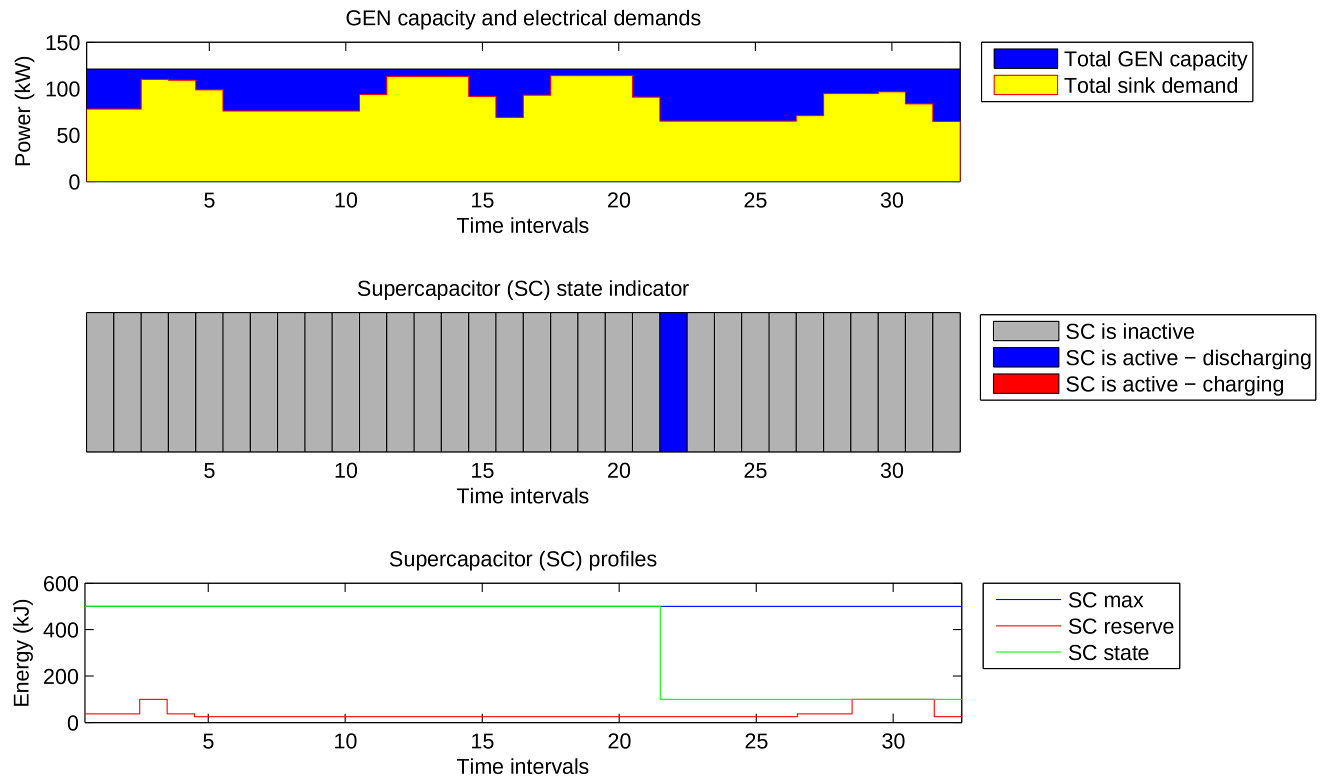


Figure 5.19: Normal conditions: (a) Total available generator power capacity (blue) overlayed with the total electrical power demands (yellow); (b) SC state indicator: inactive, discharging, or charging; (c) Energy levels of SC.

PMS response: The reduction in mission demands and 10% degradation of Generator 3 triggers the PMS to re-plan the power schedule. These alterations result in an updated power schedule with two instances of engine IFSD instead of one initially planned (see Figure 5.20 – *Propulsive power setting* panel). This event also affects the use of SC. As seen in Figure 5.21(b), the SC now discharges at time interval 6 instead of 22. Notice also that Generators 1 and 3 do not supply power to the bus at both engine IFSD instances. Figure 5.21(c) shows that the minimum reserve requirements of the SC charge levels are satisfied. The estimated total fuel consumed is listed in Table 5.8. From Level 1 to 3, the total expected fuel reduces from $1153.7kg$ to $1061.2 \pm 0.3kg$, representing 8.0% improvement.

Event 2: EHM requests for alteration in power schedule at time interval 28

Effect: Soft constraints are introduced.

PMS response: Figure 5.22 displays the result of re-planning. Two solutions are constructed in Level 3 (only one is shown here). The implications of soft constraints are further discussed in Chapter 6. No change is made for SC control.

From the results listed in Table 5.8, improvements in terms of fuel consumption can be observed between the Level 1 and Level 3 solutions. The improvements from the Level 1 to Level 2 solution show the largest improvement. This is expected as Level 1 solution is only a feasible solution and no optimisation in terms of fuel consumption is performed during solution building. Improvements from Level 2 to Level 3 solutions are small. A possible explanation is that the solution found by Level 2 solution may be near to the optimal solution. Another possible explanation may also be that the objective function comprise flat regions (see Figure 5.23). Solutions from Event 2 produce similar results. This may be that the soft constraint introduced does not strongly affect the fuel consumption of the system. The demands of the system and efficiency of the affected generator for this example result in similar solutions with or without the soft constraint imposed.

Note that although the electrical demands are very high for time interval 14 and time intervals 18–20, SC is scheduled to discharge at time interval 6 (or time interval 22 for the normal conditions). However, due to the scheduled engine IFSD,

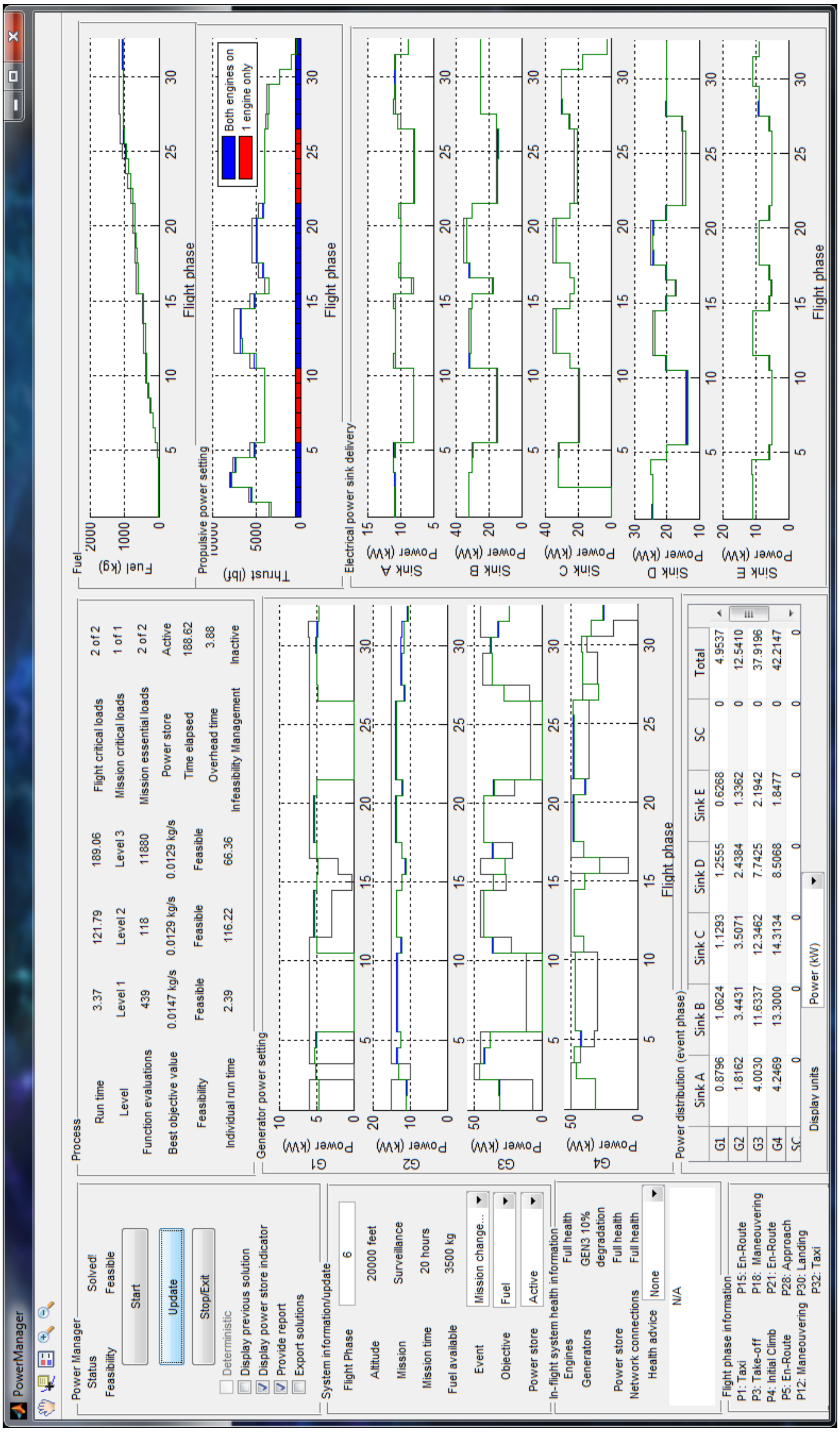


Figure 5.20: Event 1. Black, blue, and green lines denote Level 1 solution, Level 2 solution, and Level 3 solution, respectively.

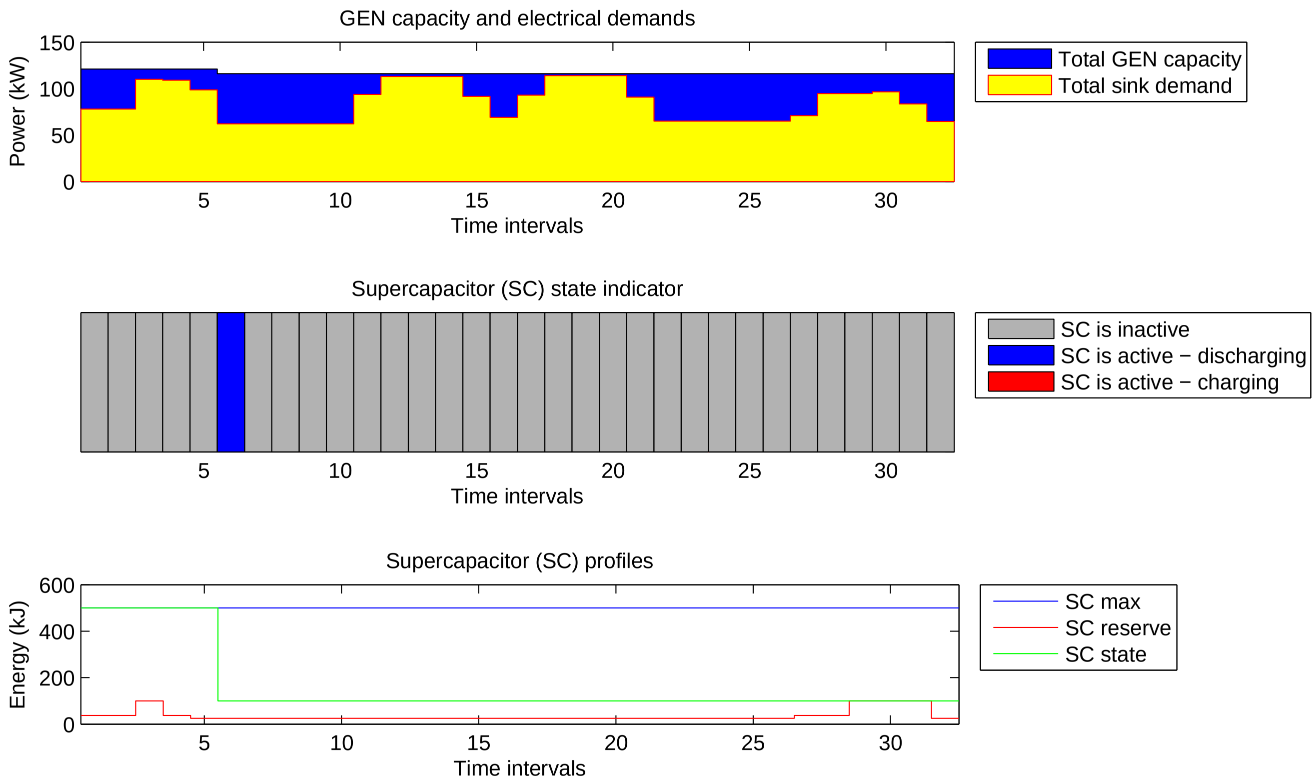


Figure 5.21: Events 1 and 2: (a) Total available generator power capacity (blue) and total electrical power demands (yellow); (b) SC state indicator: inactive, discharging, or charging; (c) Energy levels of SC.

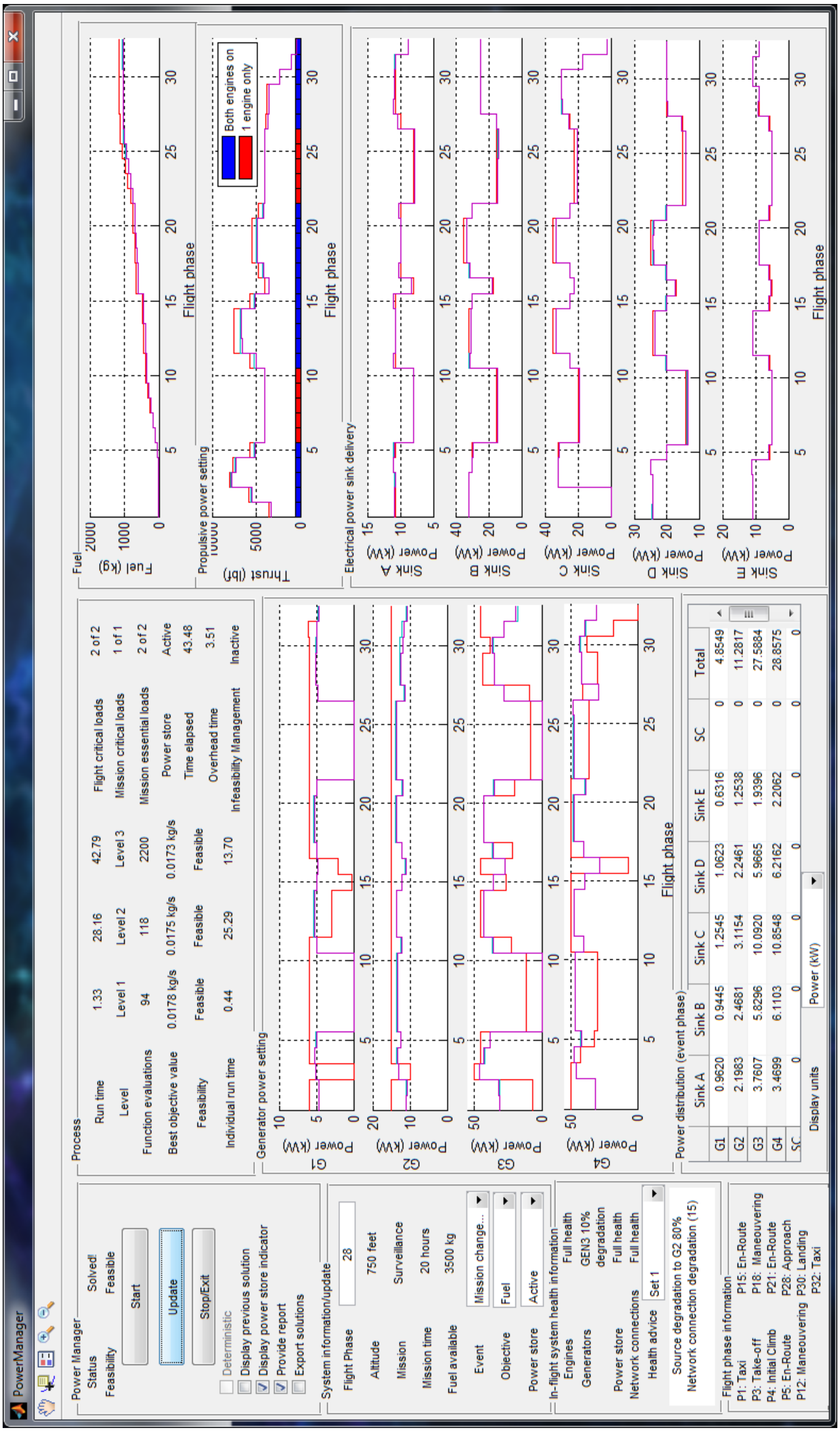


Figure 5.22: Event 2. Red, cyan, and magenta denoting Level 1 solution, Level 2 solution, and Level 3 solution, respectively.

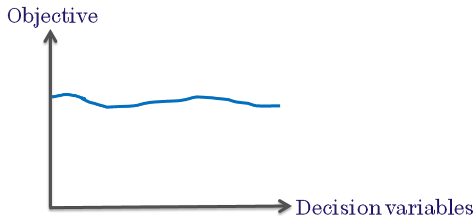


Figure 5.23: Example illustration of an objective function with flat regions.

the PM predicts that the fuel savings are better if SC is used to support engine IFSD rather than support the generators in time interval 14, and time intervals 18–20. SC use is not altered after Event 2 as the SC does not have any remaining energy and the configuration stage is set out to deplete the SC charge by end of flight. (This is the preferred control strategy for SC in this case study).

The flexibility of SC is exploited to support engine IFSD, resulting in improved fuel consumption. Although the implications of soft constraints on solutions management is unclear here, a discussion of this is revisited in Chapter 6.

5.6 Sensitivity analysis for Integrated PMS

The capability of the Integrated PMS has been demonstrated in the above sections. In this Section, the capability of the PMS is further explored using different sets of mission profiles (input data). This experiment is not a thorough sensitivity analysis, rather the capability of the Integrated PMS with different types of missions is investigated.

The size of the experiment was dependent on the number of mission profiles available and the time available to conduct the research. Ideally, randomisation of mission profiles will reduce bias in the analysis (Cox and Reid, 2000). However, this is not practical. The mission requirements must reflect true system demands and constraints of the system components must be satisfied. This study forms an exploratory analysis rather than a statistically significant performance analysis. The effects of change in inputs to solution outcome are investigated, testing the capability and limitations of the Integrated PMS.

Input data may be variable and changes in these mission descriptions may affect the performance of the Integrated PMS. In this study, the effects of the power system architecture (which includes affect of problem size), algorithm parameters (e.g. parameters used in NM), algorithm type, or the objective of the problem are *not* investigated. Instead, the factors describing the decomposition of the problem to a set of sub-problems (e.g. number of sub-problems, flight duration) and loading within the input data are investigated.

To analyse the sensitivity of the PMS, a local or global method may be adopted (Tang et al., 2007). Local methods are easy to implement and tend to not demand excessive computation power. However, they are incapable of capturing the interactions between factors that are likely to cause underestimation of the sensitivity of the target system. Conversely, global methods have a higher probability of capturing the factor interactions, improving the likeliness of capturing the true sensitivity of the target system[1]. In global methods, the full factor space is predefined to feasible ranges before the tests are performed.

Many variables are supplied to the PMS and investigating each input may not be practical. However, this exploratory study investigates the effects of the PMS performance when different types of mission descriptions are applied. The characteristics of the missions are investigated instead of specific factors or variables. To observe the performance of the optimised PMS for different types of missions, the PMS was tested with 30 different sets of input data. These data sets may be categorised into six different mission types:

Type I: Large thrust demands

Type I mission profiles have large thrust demands during flight. For these input data sets, the electrical load demands are not altered.

Type II: Low task demands

The thrust demands for Type II mission profiles are not altered, but the electrical load demands are modified to be in the low task region.

Type III: High task demands

Similar to Type II mission profiles, Type III mission profiles comprise flight missions with the same thrust demands. However, the electrical load demands

[1]Not all global methods capture factor interactions and the techniques used to perform the sensitivity analysis should be selected with care.

are set to high. In some parts of the flight, the system is also expected to operate at full capacity to evaluate the PMS response to tighter constraints.

Type IV: Multiple tasks/destination

Type IV mission profiles describe missions where the UAS is required to perform tasks at two locations. The loads are variable, a mixture of high and low electrical demands.

Type V: Flight only

Type V flight profiles describe missions where the UAS is only required to travel from one location to another. In other words, these mission profiles have long cruise durations and the UAS does not perform any additional tasks.

Type VI: Shorter flights

Flight duration for Type VI missions are shorter. The number of time intervals of this type of missions are less than those in Types I–V (N between 23–27 instead 32).

To reiterate, there are 30 mission profiles in total, which are grouped into six groups denoted by M-T I to M-T VI in Table 5.9. Within each group, there are five different mission profiles labelled I to VI.

For comparison, the Integrated PMS and the existing approaches, the four rule schemes, are employed to construct a power schedule for each mission profile. Due to the stochastic elements of the Level 3 Solver, the experiment is repeated 30 times for the Integrated PMS. Table 5.9 lists the predicted fuel consumption for each of the solutions produced. For the Integrated PMS, only the Level 3 solutions are listed. Improvements in terms of predicted fuel consumption when comparing the best *rule* scheme and the Integrated PMS (both in boldface) are also listed for each mission profile. All solutions constructed are confirmed to be feasible.

The best *rule* scheme for this platform may be Rule 3, which loads the LP generators first. Power schedules for missions with large thrust demands (Type I) consume the most fuel, while missions with shorter flights (Type VI) require the least fuel, as expected. When large amounts of thrust are required to be produced by the propulsors, no engine IFSD may take place and more fuel is required by the engines to meet the thrust demands. Low tasks missions (Type II) require less electrical

	Rule 1	Rule 2	Rule 3	Rule 4	I-PMS	Improvement
M-T I A	1302.4	1319.4	**1290.0**	1319.4	**1260.1**±0.6	2.3%
M-T I B	1313.0	1330.0	**1300.6**	1330.0	**1269.7**±0.7	1.6%
M-T I C	1314.1	1331.1	**1301.7**	1331.1	**1270.5**±0.6	2.4%
M-T I D	1327.4	1344.3	**1315.1**	1344.3	**1282.4**±0.6	2.5%
M-T I E	1343.7	1360.6	**1331.6**	1360.6	**1297.1**±0.7	2.6%
M-T II A	1131.2	1152.0	**1120.7**	1152.1	**1057.1**±0.3	5.7%
M-T II B	1133.6	1154.5	**1123.0**	1154.8	**1059.5**±0.3	5.7%
M-T II C	1146.4	1166.8	**1135.2**	1166.9	**1094.3**±0.4	3.6%
M-T II D	1150.0	1170.4	**1138.6**	1170.7	**1099.1**±0.4	3.5%
M-T II E	1121.6	1142.6	**1111.3**	1142.7	**1066.7**±0.3	4.0%
M-T III A	1232.6	1249.8	**1220.2**	1249.8	**1197.5**±0.4	1.9%
M-T III B	1215.3	1233.2	**1203.4**	1233.2	**1180.4**±0.5	1.9%
M-T III C	1183.0	1202.1	**1171.7**	1202.3	**1150.2**±0.5	1.8%
M-T III D	1170.4	1190.1	**1159.0**	1190.3	**1139.1**±0.5	1.7%
M-T III E	1171.3	1190.9	**1160.0**	1191.1	**1139.6**±0.5	1.8%
M-T IV A	1226.8	1244.2	**1214.5**	1244.2	**1191.9**±0.5	1.9%
M-T IV B	1217.2	1235.0	**1205.7**	1235.0	**1181.8**±0.5	2.0%
M-T IV C	1167.7	1187.4	**1156.9**	1187.6	**1113.9**±0.4	3.7%
M-T IV D	1169.5	1189.2	**1158.3**	1189.4	**1137.4**±0.5	1.8%
M-T IV E	1175.0	1194.4	**1164.5**	1194.6	**1141.8**±0.5	2.0%
M-T V A	1125.5	1146.8	**1113.3**	1146.8	**1102.4**±0.5	1.0%
M-T V B	1104.8	1126.3	**1092.5**	1126.3	**1084.1**±0.4	0.8%
M-T V C	1105.4	1105.4	**1071.2**	1105.4	**1060.9**±0.4	1.0%
M-T V D	1061.7	1084.9	**1050.4**	1084.9	**1042.5**±0.5	0.8%
M-T V E	1211.7	1232.2	**1199.9**	1232.2	**1179.4**±0.5	1.7%
M-T VI A	963.7	977.5	**953.7**	977.5	**937.8**±0.4	1.7%
M-T VI B	931.1	946.8	**922.0**	946.8	**907.3**±0.4	1.6%
M-T VI C	858.6	872.6	**850.3**	872.8	**835.6**±0.5	1.7%
M-T VI D	727.5	741.9	**719.9**	742.2	**712.3**±0.3	1.1%
M-T VI E	920.2	936.3	**911.5**	936.5	**895.9**±0.4	1.7%

Table 5.9: Performance, in terms of total fuel consumed (in kg), of the Integrated PMS for different types of missions, compared with the four rule-based existing approaches (M-T: Mission Type, I-PMS: Integrated PMS). Due to the variability of the solutions produced by the Level 3 Solver of the Integrated PMS, the standard deviations of the total fuel consumed are included. The average improvement (between the *best* rule scheme solution and Level 3 solution (both in boldface)) is displayed in the last column (in %).

power from generators. This enables the PMS to plan engine IFSD, reducing the total fuel consumption for the mission. Depending on the mission, multiple instances of engine IFSD may be planned. This group of mission profiles produced solutions with the best fuel savings. This is likely to be due to the fuel saved by performing planned IFSD during flights.

Missions with high tasks demands (Type III) disable engine IFSD from taking place, as all generators (and both engines) need to be active. The number of rendezvous points in a mission would typically affect the fuel consumption based on the tasks assigned during the manoeuvring phase (Type IV). Typically, manoeuvring phases would consume more power than cruise phases. The fuel consumption is also dependent on the efficiency profiles and energy losses of the components during the mission. Shorter flights would, of course, consume less fuel. However, this depends on thrust and electrical power demands; special cases exist.

Overall, improvements between 0.8% to 5.7% may be observed for this experiment. Improvements are most noticeable for power schedules that employ planned engine IFSD. From this experiment, it is shown that the Integrated PMS is capable of producing good, feasible solutions for multiple types of mission profiles. These solutions perform better than existing approaches used in today's systems.

The capability of the proposed optimiser was also tested with less time restriction imposed on the Level 3 Solver. Using Case Study I, the number of iterations for the solver was increased from 440 to 11000 and was run 30 times with the same conditions as described in Section 5.1.1. There was virtually no change in the mean value of the fuel consumed and there was only a slight decrease in the standard deviation: $1137.7 \pm 0.6kg$ (440 iterations) and $1137.7 \pm 0.5kg$ (11000 iterations).

5.7 Summary

When compared with today's existing technologies, the Integrated PMS performs well in terms of the expected fuel consumption of the power schedules constructed. The execution time for the proposed PMS is longer than the rule-based schemes used on today's systems. However, significant benefits in terms of fuels costs may be observed. As opposed to existing approaches, the Integrated PMS is capable of:

- handling multiple in-flight events, or scenarios,

- accommodating additional features such as flexible components and/or features, and
- handling soft constraints.

There are limitations on the proposed PMS. Significant limitations are the number of time intervals that could be solved by the PMS within the real time requirements i.e. four minutes, and the explorative nature of the Level 3 Solver, especially when soft constraints are introduced. As seen in the analyses shown in earlier sections, for example, the execution time linearly increases with number of time intervals. The soft constraints that are handled directly by the Level 3 Solver alters the algorithm's parameters to ensure solutions are constructed within the real-time requirements. This effects the explorative nature of the Level 3 Solver and may result in construction of lower quality solutions. Since these soft constraints are handled individually, the number of soft constraints that may be handled is limited, and future work should seek to improve this aspect of the PMS.

The key impediment to the Integrated PMS performance are the real-time requirements imposed on the system. This takes priority over finding the optimal solution. Sub-optimal solutions are accepted as the end product of the optimisation process. However, benefits of optimisation during power scheduling have been illustrated. Additionally, it is acknowledged that with time, especially for the application of this strategy onto the real vehicle system, the available computation on-board is likely to improve. Additional computation power would further improve the performance of the PMS.

The Integrated PMS is able to perform consistently well over different types of input data used or more restricted search region as a result of tighter constraints. However, the PMS and the sensitivity analysis performed did not consider uncertainties of the system. This should be addressed in future work.

A framework that constructs the *best executable* power schedules for a complex system has been presented. Approaches suitable for handling various features and components are described. The complexity introduced by the non-separability of the problem, flexible components/features and soft constraints is demonstrated to be manageable in the proposed framework; the core of the Integrated PMS does not need to be changed for solution building. Instead, complementary options in the Integrated PMS have been introduced. Although specific components have been considered, the key ideas of approaches for handling these complexities have been illustrated and are expected to be transferable to other applications. The optimisation approach also outperforms the existing approaches used on today's equivalent systems. Of course, further testing and verification is required to gain a complete comparison. In Chapter 6, the final element to the Integrated PMS is presented – Solutions Management. The Solutions Management module selects the *best executable* solution when there is more than one *good* solution.

Chapter 6

Real-Time Power Management: Solutions Management

In this Chapter, the final element of the Integrated PMS framework is presented. The Integrated PMS is expected to enact the re-planned power schedule independently, i.e. utilising the delegated autonomy awarded to the PMS. In other words, the Power Manager is required to select the *best executable* solution for enactment and return any advice that may be of interest to the user (human controller). To achieve this, the Solution Management module performs a final evaluation prior to enactment of the selected power schedule. This decision-making platform forms the final stage of the Integrated PMS.

The Solutions Management module also provides necessary elements to satisfy industrial contingency planning requirements, e.g. a solutions verifier. Even though feasibility has been guaranteed, for certification purposes, a solutions verifier is included within the Solutions Management module. This final feasibility check ensures that the final solution is feasible prior to enactment.

6.1 Solution analysis

The presence of multiple optimisation solvers and active, high impact soft constraints leads to the generation of more than one solution. The solution building process within the PM framework returns a set of solutions:

1. A feasible solution from the Level 1 Solver (constraint satisfaction);

2. An improved solution from the Level 2 Solver (local search); and

3. $n+1$ optimised solution(s) from the Level 3 Solver (global search), where n is the number of soft constraints handled by the Level 3 Solver. If no soft constraints are active in the Level 3 Solver, then only one solution is constructed in Level 3.

Each of these solutions has a corresponding predicted total fuel consumed for the given mission. The PM must select the *single* best executable solution for enactment. For $n = 0$, the Level 3 Solver solution is selected since only a single best attainable solution is constructed with the resources provided. However, for $n > 0$, more than one solution is produced. The Solutions Management module within the PMS must select the *best* solution.

The main objective of the integrated PMS is to minimise fuel consumption. Therefore, the feasible solution with the lowest predicted fuel consumption should be selected. However, selection of solution strictly in terms of fuel consumption may not be the best control measure for components that have health issues as advised or warned by the Equipment Health Management (EHM), which are expressed as soft constraints.

Soft constraints do not always conform to solutions that favour reduction in fuel consumption. Often, incorporation of EHM advice during solution building results in solutions with larger expected fuel consumption. However, EHM advice serves to improve or maintain the health of equipment and, disregarding the soft constraints, may indirectly affect fuel consumption either in the short term or long term, i.e. not an immediate effect that may be detected by the optimiser. A more holistic view of the problem is required, not only in terms of the immediate impact of actions taken but also the cascaded impact of actions (temporal considerations).

Best executable solution in the context of an integrated PMS refers to solutions that are deemed good quality, and are the best choice of control actions based on the conditions and demands imposed on the vehicle system. Whether these conditions refer to fuel consumption alone, or other factors, is subject to scrutiny. In manned systems, this would be a decision for the pilot or operator (expert knowledge). In an unmanned (autonomous) system, an automated selection mechanism is required. The notion of multi-criteria decision-making (MCDM) is useful in the context of solution selection for the Integrated PM and is introduced next.

6.2 Multi-criteria decision-making

Multi-criteria decision-making arises when a decision must be made that satisfies multiple criteria, or objectives, simultaneously. These objectives are often conflicting and no single solution can be selected as the best solution. An improvement in one objective cannot be achieved without detriment to another objective (Purshouse et al., 2014). In these cases, a set of solutions is constructed. These solutions represent the trade-off between the criteria. Figure 6.1 is an example of the trade-off solutions that may be produced from the optimisation of two objectives (shown here as fuel consumption and lifing costs). The (unachievable) ideal point is marked by the star.

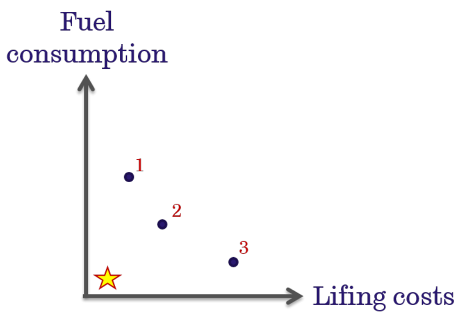


Figure 6.1: Multi-criteria decision-making.

A best single solution may be selected using subjective preferences of a decision maker (DM) to indicate a favourable resolution of the trade-offs. In the context of a vehicle operation, this preference information is expressed by the pilot or operator. The solution building process described in Chapter 5 illustrates how candidate solutions are appraised based on vehicle demands, conditions, and component health reports. The introduction of soft constraints may produce more than one solution, as mentioned in Chapter 5. In this section, the wider process of decision-making is discussed.

> *Decision theory provides a rational framework for choosing between alternative courses of action when the consequences resulting from this choice are imperfectly known (North, 1968).*

Using decision theory, the quality of actions based on expected benefits and costs or risks can be differentiated. This enables users or DMs to decide on the best alternative. Good decisions promote good outcomes. Research over 50 years in MCDM has focussed on incorporating DM preferences to find a single solution (Chankong and Haimes, 1983; Coello et al., 2007; Hillier and Lieberman, 1995; Purshouse et al., 2014). As part of the development of an autonomous multi-criteria decision-making (MCDM) framework within the PM, how DM preferences may be modelled to aid the MCDM process is discussed next.

6.2.1 Preference articulation

Decision-maker preferences may be modelled using three different methods. The first is by *a priori* preference modelling, where information describing DM preferences (DM models) is incorporated at the beginning of the entire process i.e. during problem formulation. The second method to incorporate DM preferences is by *interactive* or *progressive* articulation, where preferences are continuously updated during the search process for finding solutions. The third method, *a posteriori* articulation, is used where the DM is presented with many good solutions and the DM is required to select his/her own preferred solution. Many methods are readily available for each of these types of preference articulation, e.g. outranking approaches, lexicographical approaches, fuzzy logic, utility functions, compromise programming, multi-objective evolutionary algorithms (Coello et al., 2007), each with particular strengths and drawbacks.

For *a priori* preference modelling, DM preferences must be captured completely prior to the search process, which may be complex. Some examples of modelling preferences *a priori* includes reference point or aspiration levels (Fonseca and Fleming, 1998), weighted sum approach (Hwang and Masud, 1979), trade-off information (Branke et al., 2001), lexicographical approach (Ben-Tal, 1980), goal programming (Dinkelbach, 1980), and physical programming (Messac, 1996). These approaches requires the designers or DMs to pre-specify desired objective values and/or provide an accurate and fair representation of the objectives, which may not be possible in practice. For large complex problems, the DM may not be able to accurately express his/her preferences. For example, for multiple events of faults in a critical part of operation with many variables and criteria, the DM may not consistently select the preferred action – some variability may exist – even if the DM manages to maintain problem understanding.

Interactive or *progressive* articulation requires the DM to be present during the search process. Although this forms an interesting approach of preference articulation, it is not viable for the autonomous power management problem. *A posteriori* articulation of preferences presents all possible solutions to the DM. This approach leads to unnecessary expenditure of computation costs and execution time since the optimisers search for solutions outside the DM's region of interest. Description and additional examples of the approaches used in preference articulation can be found (Coello et al., 2007; Marler and Arora, 2004; Purshouse et al., 2014).

Despite a selection of preference articulation methods available, there are still unanswered questions within this area of research i.e. challenges in the elicitation of these preferences. Unification of preference elicitation has been explored in the literature (e.g. Fonseca and Fleming (1998)) and this concept may be practical for the IPMS development. Decision maker information may not always be presented in the same set-up and combinations of this information may be available. Representative measures (weights) of importance of performance and fuel consumption may be provided along with a constraint, such as maximum fuel consumption rate.

6.2.2 Decision-maker(s)

Decision maker preferences may complement or conflict with one another. Multiple experts may be used to model preferences for the power management problem. These experts may be from the same background e.g. maintenance, or may be from different backgrounds e.g. maintenance and pilots. Both types of DM groups may cause variability in the information (expert knowledge/opinion) provided.

For the power management problem presented here, an autonomous decision-making framework capable of handling multiple types of preference, leading to the selection of the best solution(s), is required. Complementary preferences could be handled in such a way that the harmony between them can be exploited. On the other hand, conflicting preferences should be handled with care such that the best solution is selected and unwanted bias towards particular preferences is avoided. The framework must also be able of handling multiple types of preferences. The best solution must be selected autonomously whilst satisfying real-time requirements.

6.2.3 Autonomous decision-making

In MCDM, most decision-making solutions are used as decision support systems instead of a stand-alone framework that functions autonomously. Recommendations are provided to the DM(s) and the final decision is in the hands of the DM. However, some autonomy in decision-making has been introduced in recent years, where the decision-making process selects a solution unsupervised. Although some of these decision-making processes are simple, styled as automated decision-making, more recent research is moving towards autonomous decision-making. It is argued that the latter may incorporate intelligence that is suitable for making decisions in more complex environments, e.g. IPMS in UASs. Whether it is automated or autonomous MCDM, a single best solution to be selected for enactment is required.

A number of research investigations has explored autonomous decision-making (Aissanou and Petrowski, 2013; Furda and Vlacic, 2011; Insaurralde and Petillot, 2013; Kakas and Moraitis, 2003; Xu, 2009). The research by Furda and Vlacic (2011) provides the most interesting starting point for introducing autonomous decision-making in real-world applications. Their proposed method exploits available DM information to autonomously select the best possible solution in real-time. Using a utility function model, a real-time decision-making method to support autonomous driving in city traffic is proposed.

The general framework by Furda and Vlacic (2011) is deconstructed into two stages. First, a feasible solution is sought by using Petri-nets. Second, the driving manoeuvres are optimised to other criteria such as comfort or efficiency. Although the authors highlight the use of MCDM methods, the framework is designed in such way that the framework is solving for one high level objective that is decomposed into several smaller goals, instead of multiple high level objectives. The applicability and performance of the proposed strategy for handling conflicting high level objectives are unclear. In a case study, the authors defined the objective as safely arriving at a destination, instead of comfort and efficiency (that were mentioned earlier in the paper). The MCDM approach used is by modelling utility function constructed using information from traffic system experts i.e. *a priori* preference articulation.

6.2.4 Multi-criteria decision-making within the Power Manager

The power management problem posed in this research study can be viewed as a MCDM problem when the EHM advice is introduced, specifically when soft constraints are introduced into the Level 3 Solver. The main objective of the PM is minimisation of the total fuel consumption. For a given flight mission, a good solution with low fuel consumption may be represented by the blue line in Figure 6.2. However, the introduction of EHM-based soft constraints mid-flight introduce a conflict into the problem. The new information indicates that there may be issues concerned with the system, which, if not acted upon, would affect the life or performance of equipment. This may result in a much higher projected total fuel consumption by the end of flight (orange line in Figure 6.2). However, there is uncertainty with these projections (shaded regions in Figure 6.2). If the EHM advice is ignored, a consequence may be that it increases maintenance costs, or causes a significant drop in the life of equipment and increases the fuel consumption; the initial investment of additional fuel costs to mitigate any health issues may be a good compromise. If these risks are incorporated into the decision-making process of the PM, a compromise solution (green dashed line) may be the best solution.

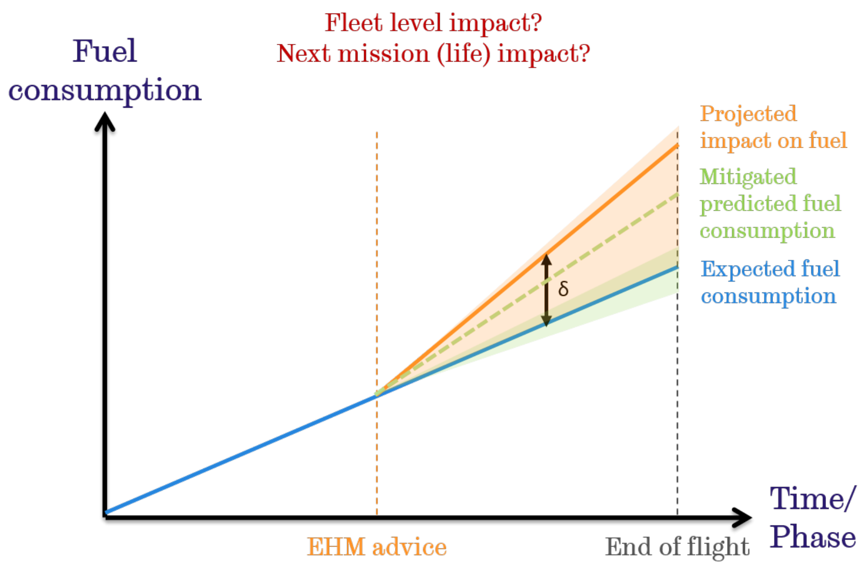


Figure 6.2: Conflicts of interest.

Of course, the PM could incorporate other objectives such as maintenance costs, lifing, and performance into the optimisation problem formulation. However, as mentioned before, models representing these criteria are not yet available. This research study focusses on single-objective optimisation with a systems approach, considering impact on/from other elements other than the fuel and power efficiency of components such as future implications of current decisions.

6.3 Solution selection: decision-making strategy within the PMS

Solution selection is activated when there are n active soft constraints within the Level 3 Solver, producing $n+1$ possible solutions. A *single best executable* solution is required that satisfies DM preferences. These DM preferences are discussed below.

The finite number of high impact soft constraints result in a finite choice of solutions to be constructed by the solution building process within the PMS; the *best* solution is expected to be selected from a relatively small set of solutions. Due to this and from the analysis in Section 6.2.1, this research is confined to the study of *a posteriori* decision-making. Although *a posteriori* decision-making is of interest here, note that the DM model used is constructed by means of *a priori* preference modelling[1]. This preference modelling utilises trade-off information and priority of the soft constraints. The approach is described below.

Trade-off information

> Consider three solutions (Figure 6.3). Solution 1 is the best solution attained when optimising only the fuel consumption (green in Figure 6.3). Solution 2 is the best solution constructed when optimising fuel consumption subject to the Generator 2 power 80% capping request (yellow in Figure 6.3). Solution 3 is optimised with respect to fuel consumption and the Generator 1 90% capping request (blue in Figure 6.3). The overall *quality* of these solutions must be estimated to allow the *best* solution to be selected. Here, trade-off information to aid the decision-making process is introduced. The PM is supplied with information (DM model) describing the allowed trade-off between additional fuel consumption and soft constraint satisfaction (Table 6.1). For example, if the vehicle is in *Approach*, Solutions 2 and 3 (from Figure 6.3) are considered *good* since their expected fuel consumption is 120% or less when compared

[1]Necessary DM preference information is provided to the PMS with other input information.

with Solution 1 (see *Generator degradation (specific)* row in Table 6.1). Based on the proposed scheme and using Figure 6.3 as an example, a few points can be made:

1. Solution 1 (green – fuel only) is considered the best solution if the predicted fuel consumed for solutions 2 and 3 (yellow and blue, where fuel and soft constraints considered) is more than 120% of that predicted for solution 1.

2. Solution 3 could be selected as the best solution if its predicted fuel consumption is within the specified threshold (120%) and solution 2 exceeds the threshold.

3. Solutions 1, 2 or 3 could be selected depending on user setting if predicted fuel consumed based on solutions 2 and 3 are within imposed limits. Figure 6.3 illustrates this case and is discussed next.

This approach may reduce the number of alternative solutions. For cases where the solutions that satisfy the soft constraints are within the specified allowances described by the trade-off information, i.e. good quality, the user is required to establish rules to indicate the solution that is best in his/her interests. For example, the selection rules may be based on the priorities of the soft constraints (see below).

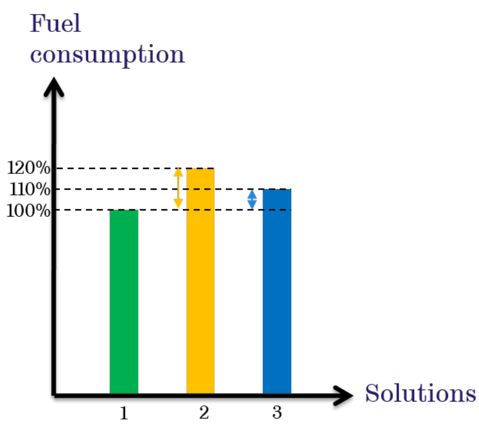


Figure 6.3: Alternative solutions

Soft constraints	Flight phases											
	Taxi		Take-off	Initial Climb	En-Route			Manoeu -vring	Approach		Landing	
	Taxi to runway	Taxi to take-off	Take-off	Initial climb	Climb to cruise	Cruise	Descent	Task/Low flying	Initial approach	Final approach	Flare	Landing roll
Generator degradation (specific)	20	20	5	15	30	30	30	10	20	20	5	5
Generator degradation (non-specific)	20	20	5	15	30	30	30	10	20	20	5	5
Generator keep-out zone	20	20	5	15	30	30	30	10	20	20	5	5
Unload generator (shutdown)	20	20	5	15	30	30	30	10	20	20	5	5
Engine degradation (specific)	20	20	5	15	30	30	30	10	20	20	5	5
Engine degradation (non-specific)	20	20	5	15	30	30	30	10	20	20	5	5
Engine keep-out zone	20	20	5	15	30	30	30	10	20	20	5	5
Unload engine (shutdown)	-	-	-	-	-	20	-	20	-	-	-	-
Reduce number of network switches	-	-	-	-	-	-	-	-	-	-	-	-
Do not use a particular connection	-	-	-	-	-	-	-	-	-	-	-	-
Reduce alterations of generator output	-	-	-	-	-	-	-	-	-	-	-	-
Reduce alterations of engine output	-	-	-	-	-	-	-	-	-	-	-	-
Use SC power by end of flight	-	-	-	-	-	-	-	-	-	-	-	-
EHM advice to perform more tests	20	20	5	15	30	30	30	10	20	20	5	5

Table 6.1: Trade-off information: the allowed additional fuel consumption (in %) for solutions that are optimised subject to soft constraints.

Prioritisation rules

The EHM advises the PMS on the health state of the system. This information forms the soft constraints handled by the Level 3 Solver. Each of these soft constraints has a priority assigned. This prioritisation on the soft constraints may be exploited. It is assumed that the satisfaction of a soft constraint with a higher priority is more valuable compared to satisfaction of a soft constraint with a lower priority. These priority information ranks the soft constraints. If more than one solution is found to be acceptable based on the trade-off information described above, the solution that satisfies the highest priority soft constraint is selected as the *best executable* solution.

Summary of the proposed decision-making strategy

The implications of having more than one solution available at the end of the optimisation process, whose features may be in conflict, have been discussed. Using MCDM approaches, a decision-making strategy has been introduced. The preferred solution is selected by adopting an MCDM approach, forming an autonomous decision-making strategy. These DM preferences are obtained at mission start or at every problem update (PM trigger events). The selection itself is performed at the end of the optimisation search process; *a posteriori* decision-making based on *a priori* preference modelling.

The integrated PMS reports the availability of alternative solutions to the VMS (and consequently GCS). Based on the reports, the DM on the ground may disagree with the choice of solution and request that a different solution is enacted instead. As a result, the integrated PMS enacts the alternative power schedule; the ground control has the power to override any decisions made by the PM.

It is acknowledged that unnecessary computational costs may be incurred by employing *a posteriori* decision-making. Future research may consider incorporating an interactive DM model to detect and eliminate undesirable or impractical solutions during the solution building process (i.e. within the Level 3 Solver). This preference models are expected to be modelled *a priori*, as with the strategy proposed here, due to the autonomous nature of the decision problem.

It is worth noting that real-world problems often comprise multiple objectives, resulting in a multi-objective optimisation problem (MOP). Although this study considers only fuel consumption, it is envisaged that future extensions of this PMS will incorporate other objectives such as robustness, system performance, life of components, and maintenance costs. Solving MOPs also results in a set of solutions for which a decision-making strategy is required to select a single solution most suitable for enactment. This highlights the importance and potential of MCDM approaches in supporting the Integrated PMS framework in terms of autonomous real-time decision-making.

6.4 Solution exploitation: intelligent advice

Useful information may be gained from the optimisation process. Warnings, advice, or recommendations that benefit the system operator may be reported back to the VMS. This enables other sub-systems or ground control to interrupt as necessary, respond to the decision made by the PM, or alter the decision made by the PM. For example, if the infeasibility management module is initiated, information describing the electrical load prioritisation (e.g. load shedding of a particular power sink) is reported back to ground control. This allows an up-to-date capability and performance of the power system to be accessible to the human controller.

Alternative solutions stemming from satisfaction of soft constraints in the Level 3 Solver enable the human controller to be involved. For example the human controller may overrule the decision made by the PMS if the alternative solution is preferred. Other systems within the power system may also be designed to complement the PM. For example, the EHM may utilise the PM output information that describes an estimated (in terms of fuel consumption) cost to determine if a diagnostic test can be performed or otherwise. The VMS may re-plan the mission tasks if the PMS reports insufficient fuel supply for the planned flight.

6.5 Case study

Case study: Multi-phase (non-separable) power scheduling with soft constraints (continued)

- Multiple-type power scheduling: electric and propulsive power settings optimisation.
- Power store and engine in-flight shutdown (IFSD) capability enabled.
- Complete flight profile power scheduling.
- Soft constraints introduced.
- Solutions management module initiated.

Continuing with the examples shown in Case study III and Case study V in Chapter 5, the solutions selected and intelligent advice resulting from the introduction of soft constraints are presented here.

Table 6.2 lists the expected fuel consumed for each of the solutions constructed by the Level 3 Solver for these case studies. The high impact soft constraints are introduced at time interval 28 that corresponds to the *Approach* to *Taxi* flight phases (including *Landing* phases). For these flight phases, the trade-off information indicates that the solutions are deemed good quality if the additional fuel costs incurred are 5%[1].

	CS III-A	CS III-B	CS V-A	CS V-B
Fuel consumption (kg)	1113.6±0.5	1115.0±0.4	1061.2±0.3	1061.2±0.3

Table 6.2: Fuel consumption for each possible solution (CS = Case study, A = solution optimising fuel consumption only, B = solution optimising fuel consumption and soft constraint).

The introduction of soft constraints to the case studies introduces *good* quality solutions. The alternative solutions (CS III-B and CS V-B in Table 6.2) cost an additional fuel cost of 0.1% and $\ll$ 0.1%, respectively, when compared with the solution that only minimises fuel consumption. Either of these solutions could be enacted by the Integrated PMS. For these case studies, the solutions that satisfy the soft constraint with predicted fuel consumption to be within the fuel allowance, are the preferred solutions. The solutions that are optimised only in terms of fuel

[1]According to the trade-off information in Table 6.2, the additional fuel allowed for these phases range between 5%–20%. Here, 5% is considered since it is the lowest allowance.

consumption are reported to the VMS and human controller. Should the alternative solutions be more desirable to the human controller, the Integrated PMS would enact them once instructed to do so.

6.6 Performance, limitations, and other considerations

The Solutions Management module within the Integrated PMS meets the goals of developing future IPMS. The approaches introduced in this Chapter provide a stepping stone for future developments of a real-time autonomous decision-making platform within the PMS. Concepts introduced and applied here may be extended in future work to adapt to more complex situations such as solving for MOPs in the PMS. The quality of the decisions made autonomously by the PMS depends largely on the DM models supplied. This is not a challenge unique to decision-making in PMS, but also in the MCDM community.

Quality of solutions in this research study has been based on fuel consumption and soft constraints satisfaction. Another attribute to determine quality of solutions (not included here) is robustness or reliability of the solutions. There are multiple sources of uncertainty for a problem (Jin and Branke, 2005). An example source of uncertainty lies within the models used. The fuel consumption model used does not consider fuel quality which reflects burn rate, thrust output, etc.; some variability may exist with different types of fuel and engine used. The linear approximation of fuel consumption for the propulsors may not be a sufficiently accurate representation. However, it is acknowledged that the true model may be impossible to obtain in the real-world and an approximation is sufficient, at least until more accurate models are made available. Another example source of uncertainty is from noisy functions or data. For example, the EHM advice is likely to stem from data-driven diagnostic methods, resulting in uncertain health advice (Mills and Mansor, 2014). The dynamic environment of the system is another example source of uncertainty. Although the Integrated PMS is executed in real-time, there is a time lag between when the system state is observed, and when the system is analysed and control measures constructed. During this time lag, the system may have an altered state which would affect the best control measure to be taken. Uncertainty may also lie within the decision space itself. For example, the power schedule may not be executed exactly and this may subsequently affect the quality of solutions. The sensitivity of the system and solutions should be incorporated during solution selection and verification processes and would be addressed in future work.

Future research in the interest of solutions management may also investigate potential application of offline optimisation to complement the real-time optimisation of the Integrated PMS. For example, the recommendations reported back to the VMS may be exploited by ground control.

6.7 Summary

To summarise, a procedure to select a preferred solution, to construct and provide intelligent advice, and to provide additional verification of the solution safety is presented. Although the strategy to handle MCDM problems is not developed in detail, an approach has been proposed. This approach employs *a posteriori* decision-making that is facilitated by use of a DM preference model. Examples of how this may work have been provided. The work presented here provides a good stepping stone for one of the future extensions of the integrated PMS, i.e. solving real-time multi-objective optimisation problems. Further work is required to fully develop this procedure to fully complement problem requirements and the goals of IPMS, and is discussed in the Conclusions and Future Research.

Chapter 7

Conclusions and Further Research

7.1 An Integrated Power Management System

Real-world systems operate in non-ideal conditions, where the systems are exposed to unpredictable conditions. It is critical that the reliability and efficiency of these complex engineering systems are maintained despite these disturbances. Over the years, the improvement of a particular system or product has evolved to include not only component-level optimisation, but also system-level optimisation. A holistic view of the system enables further improvement to the system and may lead to better management of resources.

Recent advancements in the field of autonomous systems include developing intelligent approaches to optimise the power management on board these systems. Autonomous systems equipped with complex and advanced technologies, and often limited supply of resources, require optimised power management to maximise the full potential of these systems. To help maximise the system potential, this research has contributed towards an intelligent Power Management System (PMS) by developing optimisation strategies suitable for an improved, certifiable PMS.

Achievements and impact

In line with the aims of this research, an adaptive, flexible Integrated PMS has been developed. This PMS is capable of constructing the *best executable* system-level power plans for multi-source, multi-sink power systems on-board while satisfying real-time requirements, promoting autonomous operation of autonomous systems.

The Integrated PMS is capable of adapting to its dynamic environment, coping with any change in system state or health, power requirements, environmental conditions, and user preferences. The Integrated PMS may be used prior to operation start, or mid-operation. The PMS reports infeasibility warnings or intelligent advice to the Vehicle Management System (VMS), as required.

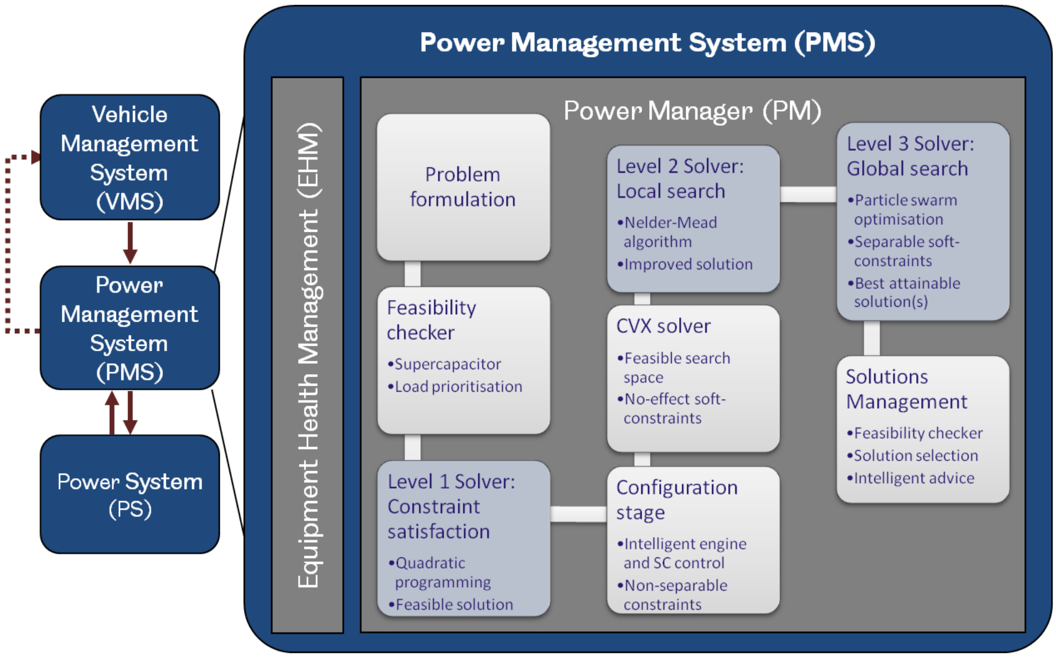


Figure 7.1: Complete PMS overview.

A power management framework was developed, which supports the integration of the system-level power management to the Vehicle Management System (VMS) and the Power System[1] (PS). The Power Manager (PM), which is the main focus of this research, within the PMS receives the information from the VMS, PS, and Equipment Health Management (EHM) and interprets this into meaningful information in terms of power management (optimisation) in the Problem Formulation module (Figure 7.1). Then, the Solver uses this information to re-plan the *best executable* solution. Given that this PM is required to construct the *best executable* power schedule in real-time for a safety-related system, a three-level strategy was adopted within the Solver's architecture (indicated by the three light blue boxes in Figure 7.1). Due to the feasibility (safety) requirement of the solutions produced, the Level 1 Solver adopts a constraint satisfaction approach. Then, this feasible

[1] *Power System* here represents the middle- and low-level control layers and the hardware itself.

solution is improved using the Level 2 Solver to find a better solution in the neighbourhood of the feasible solution. Next, the Level 3 Solver is used in the remaining execution time to search for the *best executable* solution. This strategy guarantees a feasible solution is always at hand and updates the best feasible solution available at each level. Hence, should the execution be halted for any reason, the best (so far) feasible solution could be extracted and subsequently enacted. The Solutions Management module ensures the solutions are suitable for enactment. The other remaining components support the PM in producing the *best executable* power schedule with intelligent advice (if applicable).

From the experiments conducted, the solutions constructed using this approach outperform solutions obtained using existing approaches in terms of the main objective i.e. fuel consumption. Further, the proposed approach has additional features which today's technology does not, for example, intelligent control of flexible components/features and intelligent advice.

This research has shown the potential of using optimisation techniques and systems approaches for improving today's Power Management Systems. The Integrated PMS has been developed to be adaptive and flexible, capable of optimising the power management of multiple types of power simultaneously. The resulting power schedule describes the power supply and delivery of the system for the entire operation. It is capable of supporting various other technologies that have been developing over the years. An example of this is the support provided by the PMS to schedule the power supply and delivery whilst enabling reconfiguration of the network switches; this stems from the smart switching technology that was used in the ASTRAEA II programme. Procedures to handle different types and characteristics of components have been a feature of this work. For example, strategies to handle complexity that arise from multi-phase scheduling have been developed (e.g. handling of power store(s) and engine in-flight shutdown and restart). An approach to exploit soft constraints in producing intelligent advice has also been proposed. The solution selection scheme proposed satisfies the requirement of the PMS to make decisions autonomously; this corresponds to the delegated autonomy awarded to the PMS.

The architecture of the Power Manager has been structured in such a way as to enable certification to be possible and to enable technological transfer to other applications. The core of the technology presented here comprises smaller building blocks and may be altered accordingly to fit into target applications (Figure 7.1). Of course, some modifications may still be required when moving from one application to another, but the base structure remains the same and supports the goal to develop a plug-and-play approach. This research provides a basis for developing future Intelligent Power Management Systems.

Assumptions and implications

The key impediment to the performance of the optimiser is the real-time requirement of the PMS. For example, the scalability of the approach is limited by the available computing power and execution time. The *optimal* solution is unachievable with the resources provided. The information available to the PMS is not complete and the exact environment and states of the system are not fully captured; this research did not include uncertainty handling. Making decisions based on incomplete information cannot guarantee that a good action is selected nor that a good outcome is attained. However, uncertainty handling and a complete sensitivity analysis are outside the scope of this research and are not incorporated into the PMS. The number of soft constraints integration and some of the rules managing the flexible components/features may also restrict the performance of the PMS. Suggestions to improve the PMS are outlined in the next section.

7.2 Recommendations and future research

Robustness and uncertainty incorporation

The power management within the Integrated PMS does not incorporate uncertainties and cannot guarantee that robust solutions are constructed. For autonomous systems, this is an important feature of the approach. The sources of uncertainty may stem from the models used, the dynamic environment, and the power components, among others. A complete sensitivity analysis should be performed that would identify the main sources of uncertainty. Then, suitable approaches to handle these uncertainties should be developed to complement the power management framework. The fields of robust optimisation and dynamic optimisation may be explored in future research to achieve this. To complement this, the Dempster-Shafer theory (Shafer, 1976), possibility theory (Zadeh, 1978), and probability theory (Kolmogorov, 1950) may also be explored.

Soft constraints management

Due to limited computing resources available, the large number of soft constraints that are handled directly in the Level 3 Solver may reduce the explorative nature of the optimisation process, thereby reducing the probability to find the best solution. Future research could explore approaches that may exploit the harmony between the active soft constraints to help maintain or improve the Level 3 Solver explorative behaviour. Further, early identification of unsuitable solutions during the optimisation process would improve the handling of soft constraints.

Exploitation of *flexible* features or components

Some of the rules employed to handle the flexible features or components may be too restrictive. The supercapacitor control, for example, did not produce much benefit to the overall fuel consumption. This may also be due to the granularity of the time intervals and perhaps the benefits of power stores may be maximised using the middle-layer control of the system. Further testing may provide insight to this observation.

Autonomous decision-making

The suggested approach to autonomously select the best solution in the Solutions Management module may be enhanced by incorporation of uncertainties and also addressing some of the challenging issues in the field of multi-criteria decision-making (MCDM). In MCDM, there is continuing research into handling conflicts and harmonies in decision-making, and accurately modelling DM preferences. Research into these areas of interests would improve the autonomous decision-making capability of the PMS. Information such as system risks, system history, and fleet level information may also be exploited to improve the quality of decisions. The MCDM-based research would also contribute towards the PMS capability to handle multiple objectives such as optimising system performance and component life. Treating the problem as a true multi-objective problem may be beneficial.

Other unexplored areas

Future research may also explore other features which are outside the scope of this research. For example, the PMS may be extended to include the temporal scheduling of the power sink demands. Other types of power may also be incorporated such as thermal or hydraulics power management. An offline optimiser may also be developed to complement the PMS off-board.

Real-time embedded platform and experimentation

Industrial interest to develop the Integrated PMS to a higher Technology Readiness Level (TRL) necessitates verification and validation of the approaches. Proving the capability of the PMS via rig testing, for example, may contribute to this. The PMS, which is executed in MATLAB, may be transferred to a real-time embedded platform. An explorative study to learn the limits of the PMS may be conducted. Integration with a middle-layer control may also be investigated (Bossard, 2014).

Other applications

The architecture of the Integrated PMS has been developed to support other applications or systems. Two platforms where the Integrated PMS may be applied have been identified. An example application might be the incorporation of the PMS into marine applications as these vehicles share similar characteristics to the ASTRAEA II platform, albeit more complex. Marine applications comprise multiple types of power source and sink and are expected to have long mission times. Another example platform is *more electric* (or hybrid) aircraft. The Integrated PMS supports engine shutdown and restart control and this may be a candidate approach to manage the propulsor shutdown envisioned in *more electric* aircraft (Husband, 2014). The strategies developed are not exclusively for autonomous systems; manned systems may potentially share the benefits of improved power management.

The work presented here provides a good stepping stone for future research in Intelligent Power Management Systems in autonomous systems. The outcomes of this research have been demonstrated to Rolls-Royce plc and work to develop the strategies presented here to a higher TRL is planned.

Appendix A

Power System Modelling

System architecture

The example platform used for this research is based on the Autonomous Systems Technology Related Airborne Evaluation and Assessment (ASTRAEA) II programme platform that is akin to a small business aircraft such as the Jetstream 31 (see Figure A.1[1]).

Figure A.1: Jetstream 31: An example target system of this research.

As mentioned in Chapter 3, this Unmanned Aircraft System (UAS) platform comprises two Model 250 Turboprop Gas Turbine Engines with a high pressure (HP) starter generator and a low pressure (LP) generator attached to each engine (Rolls-Royce, 2014; Wall, 2012a; Wall and Mansor, 2012). A power store/energy storage device is considered, specifically a supercapacitor (SC) with $500kJ$ energy capacity. A $270V$ DC electrical bus is connected to the power sinks via a set of network switches. These network switches may be controlled to adopt different

[1]This photo is taken by Yummifruitbat (2005) at Filton Airfield, Filton, Bristol. This aircraft (G-BRGN) is operated by the National Flying Laboratory Centre, Cranfield University.

network configurations. Each power sink is prioritised according to the tasks that it is supplying power to. Part of the electrical system architecture of the reference system is shown in Figure A.2.

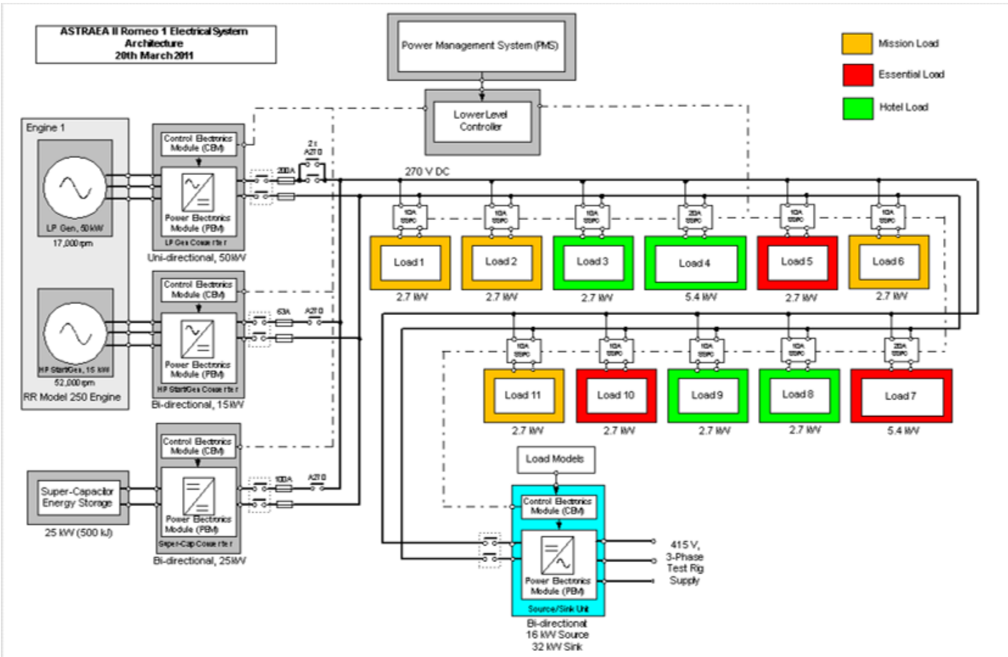


Figure A.2: Part of the ASTRAEA II Romeo I Electrical System (Wall, 2012a).

System model

Power components

It is assumed that the accuracy of the models describing the system is sufficient for the purpose of this research, particularly the relationship between the propulsive and electrical power sources. The change in power source setting for both engines and generators are instantaneous, and no additional costs are incurred for these actions.

Supercapacitor discharge is assumed to be instantaneous. However, there is a lag for SC recharge. Additional power losses when using the SC are also to be considered when optimising the fuel consumption. Similarly, engine in-flight shutdown (IFSD) does not occur instantaneously and delay when shutting down or re-starting must be considered. To manage component dynamics, the models used to describe the problem are updated accordingly. For example, if the SC is recharging with R amount of energy, an additional 1% of energy is included to represent the energy transfer losses.

The electrical efficiencies of the power components are based on Wall (2013a). The power electronics (PE) efficiency improves with loading, however, the PE efficiency drops if the loading is above the peak design load. The electrical machines (EM) efficiency for a power system typically depends on the type of electrical generator employed. For this research, a permanent magnetic design that experiences copper, iron, and friction losses is assumed. For instance, the EM efficiency may be approximated to 92% at 75% load at rated shaft speed. The EM efficiency may be represented by a nonlinear surface map. Variability between machines is expected, however, each machine would typically have a *sweet spot* region wherein a particular combination of shaft speed and load corresponds to the most efficient setting.

Fuel consumption modelling

The fuel consumption is calculated based on the propulsor and generator settings. Figure A.3 illustrates the relationship between the power components and how the total fuel consumption for a given solution is estimated.

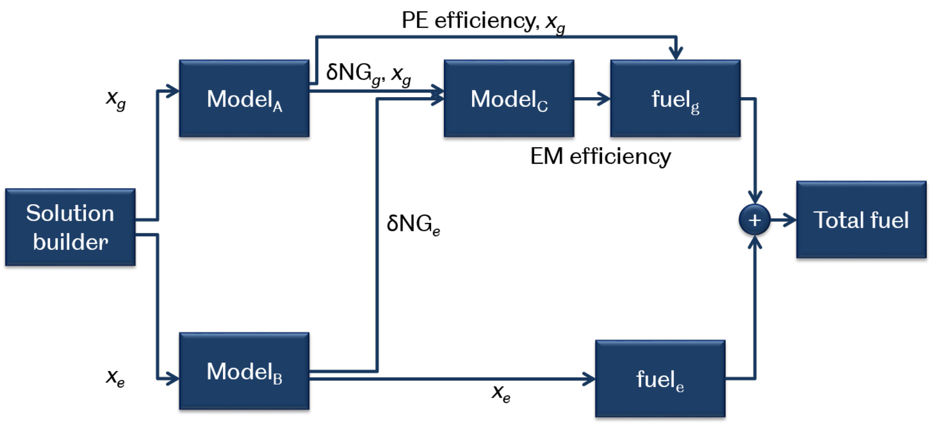


Figure A.3: Fuel consumption model.

The propulsor and generator settings are represented by x_e and x_g, respectively. The changes in NG shaft speeds due to propulsor and generator settings are represented by δNG_e and δNG_g, respectively. Model$_A$ determines the PE efficiency and δNG_g, based on NP and NG loads described by x_g. Model$_C$ determines the EM efficiency based on the change in shaft speeds, δNG_g and δNG_e, as well as the generator settings, x_g. Model$_B$ determines δNG_e based on the propulsor settings,

x_e. NP shaft speed for this system is assumed to be constant. The fuel consumed by the the propulsive and electrical power components are then estimated using the information available (shown as fuel_e and fuel_g). The summation of fuel consumed by the propulsors and generators is equal to the total fuel consumed for a given solution described by x_e and x_g. The fuel model changes with altitude.

For instance, where IFSD is planned, overhead fuel costs to implement this control action are incorporated, based on information provided by Wall (2013b). For this research, it assumed that the Power Manager would only deal with cold starts. For cold restarts, it is assumed that the engine has been turned off for a significant period, i.e. the engine has been cold soaked and requires full de-ice and thermal warm-up cycle to restart. This process requires approximately six minutes. On the other hand, the engine shutdown process would take approximately four minutes. The total fuel consumed to perform one engine IFSD and restart is approximated to be $8kg$.

Using the information provided here, the total fuel consumed for a given power schedule may be estimated. It is worth noting that the power schedule constructed by the Integrated PMS is expressed as a piece-wise constant function.

Appendix B

Input Information

The input data used for this research are based on International Civil Aviation Organization (ICAO) flight phase information and information provided in Wall (2012b). Example input data provided to the Integrated PMS is shown in Tables B.1 and B.2.

Table B.1 lists the phase index, thrust requirements, altitude, health states of the power components, objective, time, and supercapacitor (SC) reserve requirements. All information are provided for each time interval, t, that is represented by the rows of the table. The phase index (*P-Index*) informs the PMS of the state of the aircraft and other relevant information such as airspace regulations. *Thrust1* and *Thrust2* represent the required thrust at the beginning of the time interval and the required thrust at the end of the time interval. The lower tolerance and upper tolerances on the propulsive demands are represented by δ^l_{kt} and δ^u_{kt}, respectively. The allowable asymmetry between the two propulsors are represented by δ^a_{kt}. *Altitude1* and *Altitude2* represent the vehicle altitude at the beginning of the time interval and the vehicle altitude at the end of the time interval. Component health triggers may be represented by *ENG-h*, *GEN-h*, *PS-h*, or *SC-h*, while *d-Mission* represents change in mission demands trigger. Time information for each time interval is represented by *Time* and *Time-p*. The objective of fuel consumption minimisation is represented by 1 for this example. In future research, other objectives may be incorporated.

Table B.2 lists the phase index (as in Table B.1), individual load sink power demands (*Sink A* to *Sink E*) and corresponding tolerances (*A-tol* to *E-tol*) and priorities (*A-pri* to *E-pri*) of these demands. Time tolerances (*t-tol*) are also included for future extensions of the PMS.

P-Index	Thrust1	Thrust2	δ^l_{kt}	δ^u_{kt}	δ^a_{kt}	Altitude1	Altitude2	ENG-h	GEN-h	PS-h	d-Mission	SC-h	Time	Time-p	Obj	SCReserve
3	3500	3500	0.10	0.10	0.03	0	0	0	0	0	0	0	600	600	1	0.07
3	3500	8100	0.10	0.10	0.03	0	0	0	0	0	0	0	900	300	1	0.07
4	8100	7900	0.05	0.05	0.00	0	500	0	0	0	0	0	1020	120	1	0.20
5	7900	7500	0.10	0.10	0.03	500	1000	0	0	0	0	0	1380	360	1	0.07
6	7500	4000	0.20	0.20	0.15	1000	20000	0	0	0	0	0	1800	420	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	6780	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	11760	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	16740	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	21510	4770	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	25530	4020	1	0.05
6	4000	7500	0.20	0.20	0.15	20000	18000	0	0	0	0	0	25950	420	1	0.05
7	7500	7500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	27570	1620	1	0.05
7	7500	7500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	28080	510	1	0.05
7	7500	7500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	29700	1620	1	0.05
6	7500	4000	0.20	0.20	0.15	18000	20000	0	0	0	0	0	30120	420	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	40320	10200	1	0.05
6	4000	5500	0.20	0.20	0.15	20000	18000	0	0	0	0	0	40740	420	1	0.05
7	5500	5500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	42360	1620	1	0.05
7	5500	5500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	42960	600	1	0.05
7	5500	5500	0.20	0.20	0.15	18000	18000	0	0	0	0	0	44580	1620	1	0.05
6	5500	4000	0.20	0.20	0.15	18000	20000	0	0	0	0	0	45000	420	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	49980	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	54960	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	59940	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	64920	4980	1	0.05
6	4000	4000	0.20	0.20	0.15	20000	20000	0	0	0	0	0	69900	4980	1	0.05
6	4000	3750	0.10	0.10	0.03	20000	1000	0	0	0	0	0	70740	840	1	0.07
8	3750	3750	0.10	0.10	0.03	1000	500	0	0	0	0	0	71160	420	1	0.07
8	3750	3750	0.10	0.10	0.03	500	500	0	0	0	0	0	71400	240	1	0.20
9	3750	1000	0.05	0.05	0.00	500	0	0	0	0	0	0	71520	120	1	0.20
9	1000	1000	0.05	0.05	0.00	0	0	0	0	0	0	0	71640	120	1	0.20
11	1000	0	0.10	0.10	0.03	0	0	0	0	0	0	0	72000	360	1	0.05

Table B.1: Input data example (part A).

P-Index	Sink A	Sink B	Sink C	Sink D	Sink E	A-tol	B-tol	C-tol	D-tol	E-tol	A-pri	B-pri	C-pri	D-pri	E-pri	t-tol
3	10.8	32.0	0.0	24.3	10.8	0.05	0.05	0.05	0.05	0.05	1.1	2.1	2.2	3.0	1.2	0
3	10.8	32.0	0.0	24.3	10.8	0.05	0.05	0.05	0.05	0.05	1.1	2.1	2.2	3.0	1.2	0
4	10.8	32.0	32.0	24.3	10.8	0.04	0.04	0.04	0.04	0.04	1.1	2.1	2.2	3.0	1.2	0
5	11.0	30.0	32.0	25.0	11.0	0.04	0.04	0.04	0.04	0.04	1.1	2.1	2.2	3.0	1.2	0
6	10.8	30.0	32.0	20.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	20.0	25.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	20.0	25.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	20.0	25.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	20.0	25.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	20.0	25.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.8	32.0	25.0	20.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
7	10.8	32.0	35.0	24.3	10.8	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
7	10.8	32.0	35.0	24.3	10.8	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
7	10.8	32.0	35.0	24.3	10.8	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
6	10.8	30.0	25.0	20.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	17.0	22.0	17.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.0	32.0	25.0	20.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
7	10.0	35.0	35.0	25.0	9.0	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
7	10.0	35.0	35.0	25.0	9.0	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
7	10.0	35.0	35.0	25.0	9.0	0.10	0.10	0.10	0.10	0.10	1.1	2.1	2.2	3.0	1.2	0
6	10.0	30.0	25.0	20.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	15.0	22.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	15.0	22.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	15.0	22.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	15.0	22.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	8.0	15.0	22.0	15.0	5.0	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
6	10.0	15.0	25.0	15.0	5.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
8	10.8	25.0	30.0	20.0	8.8	0.15	0.15	0.15	0.15	0.15	1.1	2.1	2.2	3.0	1.2	0
8	10.8	25.0	30.0	20.0	8.8	0.05	0.05	0.05	0.05	0.05	1.1	2.1	2.2	3.0	1.2	0
9	10.8	25.0	30.0	20.0	10.8	0.04	0.04	0.04	0.04	0.04	1.1	2.1	2.2	3.0	1.2	0
9	10.8	25.0	17.0	20.0	10.8	0.04	0.04	0.04	0.04	0.04	1.1	2.1	2.2	3.0	1.2	0

Table B.2: Input data example (part B).

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