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Design of Energy Storage Controls Using Genetic Algorithms for Stochastic Problems

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DESIGN OF ENERGY STORAGE CONTROLS USING GENETIC ALGORITHMS FOR STOCHASTIC PROBLEMS

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering in the College of Engineering at the University of Kentucky

By

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Lexington, Kentucky

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ABSTRACT OF THESIS

DESIGN OF ENERGY STORAGE CONTROLS USING GENETIC ALGORITHMS FOR STOCHASTIC PROBLEMS

A successful power system in military applications (warship, aircraft, armored vehicle etc.) must operate acceptably under a wide range of conditions involving different loading configurations; it must maintain war fighting ability and recover quickly and stably after being damaged. The introduction of energy storage for the power system of an electric warship integrated engineering plant (IEP) may increase the availability and survivability of the electrical power under these conditions. Herein, the problem of energy storage control is addressed in terms of maximizing the average performance. A notional medium-voltage dc system is used as the system model in the study. A linear programming model is used to simulate the power system, and two sets of states, mission states and damage states, are formulated to simulate the stochastic scenarios with which the IEP may be confronted. A genetic algorithm is applied to the design of IEP to find optimized energy storage control parameters. By using this algorithm, the maximum average performance of power system is found.

KEYWORDS: Energy storage, electric warships, genetic algorithm, simulation, stochastic problems.

Si Chen

September 21, 2015

DESIGN OF ENERGY STORAGE CONTROLS USING GENETIC ALGORITHMS
FOR STOCHASTIC PROBLEMS

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Chapter 1. Introduction

1.1 Introduction

In military applications, a successful power system (armored vehicle, warship, aircraft, etc.) must operate acceptably under a wide range of conditions as well as maintain war fighting ability and recover quickly and stably after being damaged. Research in the development of technology for and design of electric warships has increased significantly lately. One method is to apply newly emerging materials, components, and system concepts [1], which includes the wide-scale application of power electronics; another method to improve the performance of electric warships is the introduction of energy storage [2]. Energy storage devices can not only increase the availability by providing short-term electrical power during system faults or battle damage, but also support additional devices, for example, a mission load. Due to the size limitation of the warship, there is a trade-off between the capacity of energy storage device and the space that the energy storage device occupies. Therefore, the performance optimization of the integrated engineering plant (IEP) with restricted installed energy storage capacity becomes an important issue for researchers. The IEP of an electric naval warship contains the infrastructure that provides vital services like electric power and thermal management to mission loads (e.g., sensor and weapon systems) [4], [6], [9], [10].

The main contribution of the study is to develop a method to optimally control the energy storage system of the IEP for stochastic problems. The activity of the IEP, including energy storage devices, is continuous, thus continuous-time optimal dynamic control is required, which is more difficult to solve than static optimization problems.

Secondly, because of the randomness and uncertainties of realistic military applications, the performance of the IEP must be evaluated in a stochastic environment. Although similar conditions apply in deterministic environments [3], it is still more complicated to simulate and verify the cases in a stochastic environment.

Genetic algorithms (GAs) have been widely applied to solve stochastic optimization problems. In this thesis, a GA is used to design the energy storage controls of an electric warship IEP in a stochastic environment. By using this algorithm, the average performance of the IEP is improved.

In previous work, the metric operability is defined as a measure of performance of the IEP [4], [5]. Basically, operability measures how well the IEP provide engineering services to different loads (electric power, communication, thermal management services, etc.) [6], [7]. A similar performance metric is used herein to quantify the performance of the IEP during a given scenario.

Loads on the IEP are categorized in three groups: vital load, non-vital load, and mission load. Each type of load, as well as the generator and energy storage device, is assigned with a particular weight that indicates the significance of that load/device. These weights are event-specific and probably time varying [5]. As the energy storage both charges and discharges, the weight of charging and weight of discharging are assigned to the energy storage device, respectively. These weights are not intrinsically related to the desired performance of the IEP and can be regarded as control parameters; the performance of the IEP is partly determined by the selection of weights for the energy storage devices.

Optimal selection of charging and discharging weights for energy storage would be expected to improve the performance of the warship. Herein, scenarios involving the operation of mission loads or damage to the system are considered. In this thesis, a process using GAs to find the optimal charging and discharging weights of the energy storage is set forth in order to maximize system performance over a stochastic set of operational scenarios.

1.2 Thesis Outline

In this thesis, a GA is applied to the design of an electric warship IEP to find the optimized charging and discharging weights for the energy storage device. The rest of the thesis is organized as follows. The background and previous work in IEP system optimization are discussed in Chapter 2. In Chapter 3, the models of the problem are presented, including the simplified physical model of the IEP, the mathematical model of the power system, and the stochastic engagement model. In Chapter 4, the simulation and optimization of the problem are discussed. Chapter 5 provides conclusions and recommendations for future research.

Chapter 2. Background and Literature Review

2.1 *Integrated Engineering Plant*

Successful power systems in military applications must operate normally under a wide range of conditions, as well as maintain war fighting ability and recover quickly and stably after being damaged by an enemy weapon. The IEP of an electric naval warship is a good example of such power system. The networks of the IEP is illustrated in Fig. 2.1 [8], three major networks are electrical network, fluid network, and control network. The IEP contains the infrastructure which provides vital services like electric power and thermal management to mission loads such as ship propulsion [4], [6], [9], [10].

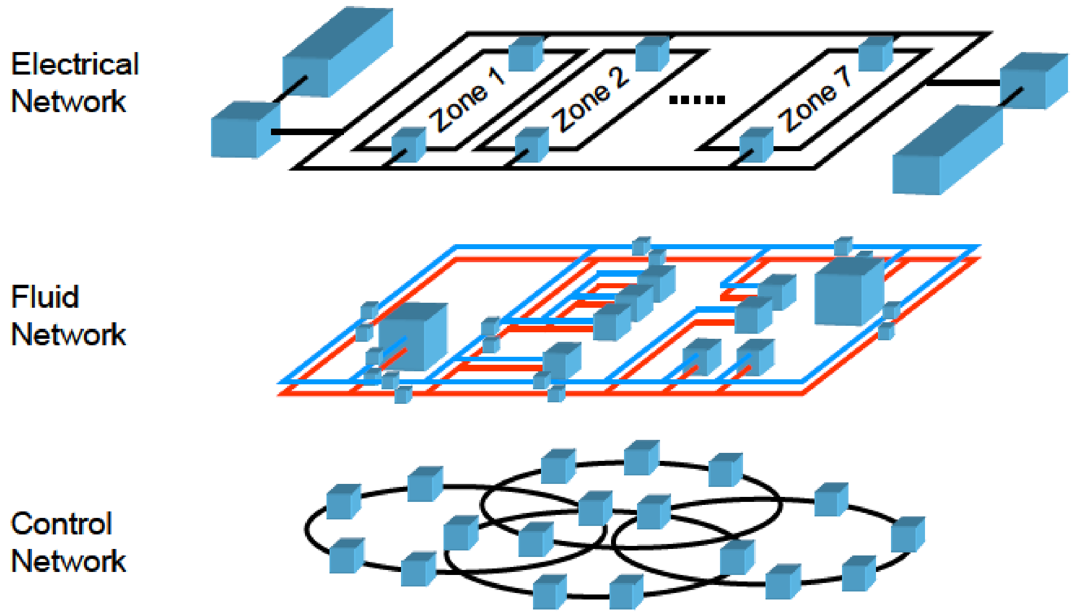

Fig. 2.1 IEP networks [8]

2.2 *Energy Storage*

Although fuel plays the primary storage role on ships, additional energy storage technologies have proven to be of great use for electric power systems [11]. Energy storage system may increase operating efficiency of electric ships and reduce air pollution by consuming less fuel. Furthermore, energy storage systems improve safety and reliability of the electric ship power system due to their operational flexibility [12].

For an electric ship power system, the functions of energy storage devices should perform are described as follows [11]. First, during the loss or damage of power generation, energy storage is required to provide power to some or all of the loads, which is the uninterruptible power supply function. Second, energy storage can provide additional load applications that cannot be provided by the generator alone. Third, energy storage can provide a large pulse of power to a pulsed load without occupying power capability from the power system. For example, in this thesis, energy storage provides electric power to a mission load when a mission starts. Finally, energy storage can be integrated into a hybrid power plant to provide propulsion for the ship [13].

Some major technologies used in energy storage are flywheels, batteries, and ice [11]. Flywheels are applied in power systems by storing rotational energy to stabilize the power system, improve operation, and reduce life-cycle maintenance costs [14]. Batteries can discharge when the peak load exceeds the peak power that can be delivered, then recharge when power demand drops. Also, battery storage is used to smooth load variations and stabilize the system. As a form of thermal storage, large quantities of ice are used for cooling. The battery storage technology is discussed in this thesis.

2.3 Stochastic Optimization and GAs

Stochastic means involving chance or probability. Stochastic optimization problems use random variables with given probability distributions to model some of the inputs to the problem [15] and are widely applied in many industries, including transportation modeling [16], logistics [17], financial instruments [18], network design [19], scheduling [20], energy management [21], and shipboard engineering design [22]. GAs are one of the stochastic optimization techniques that uses random operators to solve optimization problems. Herein, GAs are used to solve stochastic problems involving random disruptions and missions.

The original principles of GAs were first proposed by John Holland in the early 1970's [23]. GAs are the most popular type of evolutionary algorithms [24]. It is a search metaheuristic that mimics natural evolution, using operators such as selection, crossover, and mutation – the principle first proposed by Charles Darwin of "survival of the fittest." GAs generate possible solutions to optimize problems by improving the fitness of the solutions [25]. Fitness is used to measure how well the candidate solutions, called "chromosomes," optimize the objective function, and the value of fitness is the value to be optimized. The basic steps of a typical GA are illustrated in Fig. 2.2: initialization, evaluation, selection, crossover, mutation, and insertion. After each generation, the process repeats with evaluation of the new population. When the stopping criterion is met, the algorithm is terminated.

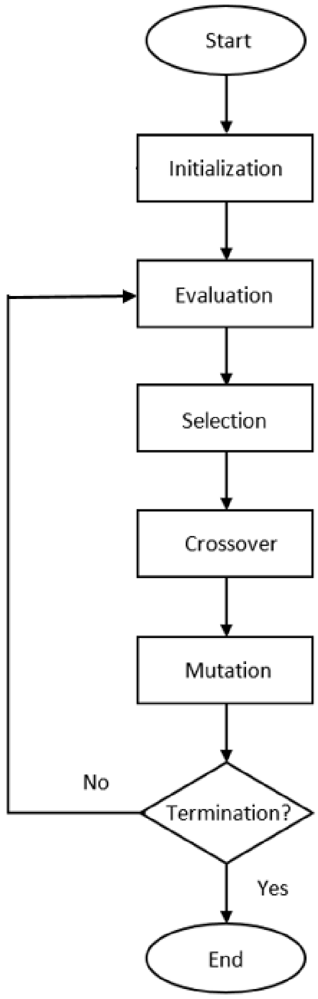

Fig. 2.2. Basic steps of a typical GA

The first step of a GA is initialization, at which the initial population is randomly generated, including the whole search space. The size of the population varies depending on the problem but usually contains hundreds to thousands of potential solutions. During the selection process, part of the population is selected to mate and breed the next generation. The fitter solutions, measured by the fitness function, are more likely to be selected to the next process called crossover (recombination). In this process, every two "parents" solutions are selected to reproduce a new "child" solution, and this "child" solution would inherit characteristics from both its “parent” solutions. However, some studies recommend that more than two “parent” solutions generate fitter “child” solutions [26], [27]. Next, the “child” solutions go through the process of mutation, in which the new solutions change one or more characteristics from the initial states. Mutation is a way to preserve diversity of the population. Since the new solutions may change entirely from the previous ones before mutation, a low mutation probability needs to be set to prevent the search devolving into a random search. The process of crossover and mutation are known as the main genetic operators, some other genetic operators such as regrouping, colonization-extinction, and migration are also used [28]. The process of crossover and mutation continue until a proper size of a new population is generated. By this time, the next generation population is different from the initial generation, and the average fitness is usually increased. Mostly, in order to pass the best characteristics from the current population to the new population, a general process called elitist selection is used to guarantee the solution quality does not decrease [29]. The insertion of new population will start the next generation of the algorithm, which continues until the termination condition is reached. Example termination conditions include a sufficiently optimized solution is found, a fixed number of generations is reached, or an allocated computing budget is reached.

The applications of GAs have been growing significantly, and GAs have been successfully implemented in many areas. Some of the example applications are: economics [30], computer science [31], engineering design [22], manufacturing [32], and many other fields.

2.4 Literature Review

Richards et al. in [7] define survivability as the ability to minimize the impact of a disturbance on value delivery. In [33], the authors identify some limitations of existing survivability engineering: 1) treating survivability as a constraint; 2) considering only static threat environments; 3) considering independent disturbance encounters; 4) considering survivability at a narrow level; and 5) lacking a value-centric perspective. In [34], in order to alleviate limitations presented in [33], two metrics, time-weighted average utility and threshold availability are proposed for the evaluation of the system performance over some interval. In [33], various risk metrics are also considered and discussed.

Cramer, Sudhoff, and Zivi proposed a set of system performance metrics (events, operability, average system dependability, and minimum system dependability) in [4], [5], so the performance of an IEP during a mission or disruption can be quantified and measured. The authors proposed new metrics for the evaluation of the architectures in [37]: average architecture dependability and minimum architecture dependability. By introducing these new metrics, the survivability and performance of the notional IEP are both increased.

Other studies related to performance metrics may include Said in [38], who discussed the concept, methods, and applications of total ship survivability, and Ball and Calvano in [39], who established the fundamentals of a surface ship survivability design discipline.

Related work in shipboard electrical system modeling includes Chan and Sudhoff in [35], who proposed a linear programming approach based on the fundamental power limitations to simplify the modeling. This method disregards the details of electrical dynamics and is mainly used in early ship design problems.

Cramer, Chen, and Zivi [36] found two significant shortcomings in previous linear programming approach [35], one is potential to attempt to solve infeasible linear programs, and the other is problems with load sharing. In their proposed model, the linear program is always feasible and multiple independent load sharing cases are reduced to one linear program solution.

In [22], Cramer, Sudhoff, and Zivi demonstrated a new method by using evolutionary algorithms to solve minimax problems in robust design. This method is more favorable than existing approaches and easier to implement. In [2], Chan, Sudhoff, and Zivi formulated an algorithm to optimally allocate energy storage in electric ships. By implementing this prescribed robustness evolutionary algorithm, the total installed energy storage amount is minimized while reaching a desired level of robustness.

Mashayekh et al. [40] formulated a general deterministic dynamic optimization problem to find the optimum capacity for the energy storage.

In these works, most problems are solved in a static or deterministic dynamic environment, and the problems in [2] and [40] are the optimization of the capacity of the energy storage, given a certain load profile or a preferred level of robustness. In this thesis, the events are simulated in a stochastic environment. The capacity of the energy storage is fixed, and the optimal control weights of the energy storage are sought in order to get the maximum performance of the IEP.

Chapter 3. System Modeling

3.1 Structure of the Proposed Solution

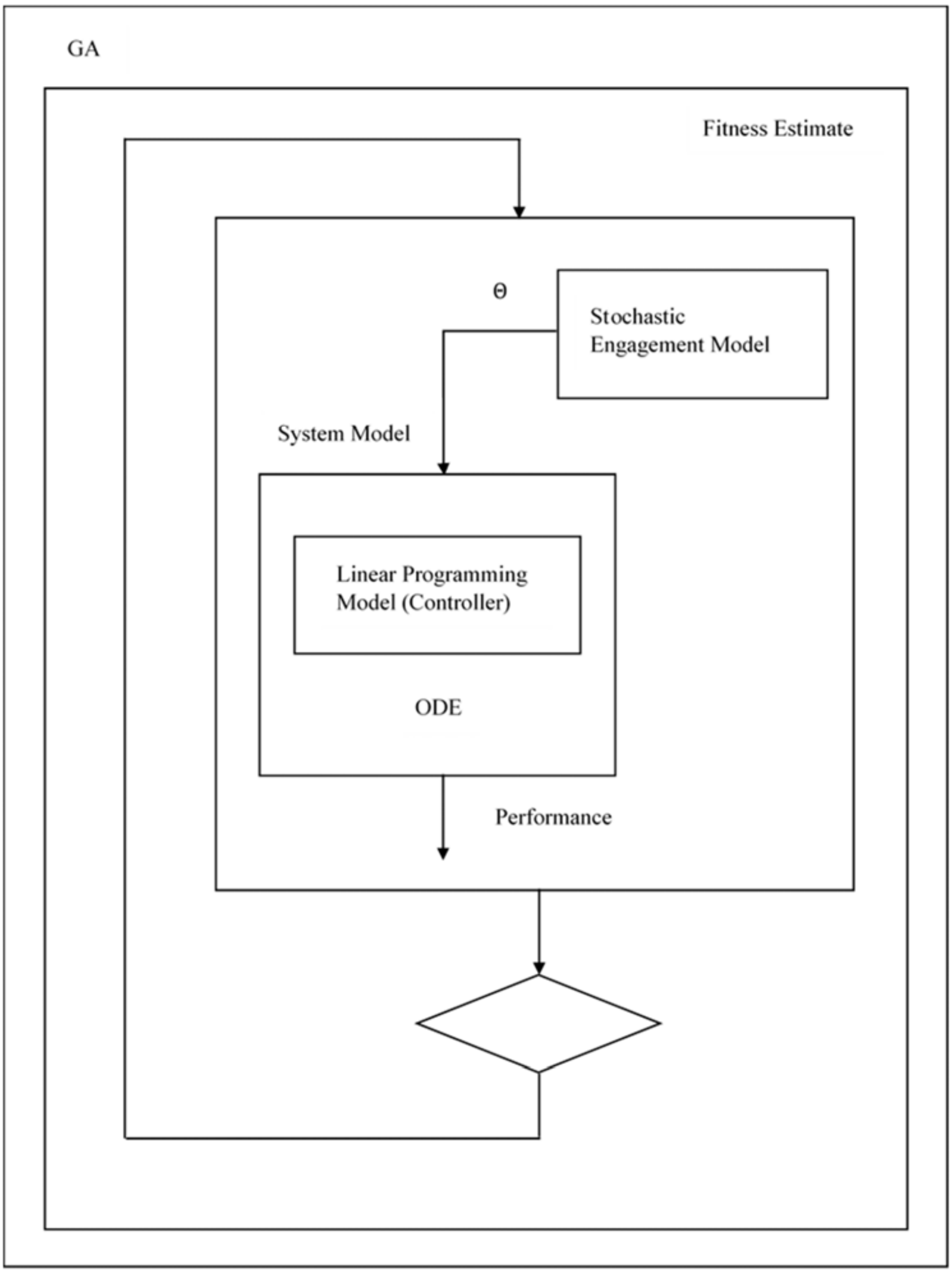

Fig. 3.1. Structure of the Proposed Solution

Fig. 3.1 demonstrates the structure of the proposed solution. The system is represented by an ordinary differential equation (ODE). Within the ODE, a linear programming model is used to represent power conservation and the action of the power controller at each time. The system model is challenged by events drawn from a stochastic engagement model. The mean performance is estimated by averaging a number of sampled performances. This sample mean is used by the GA as a fitness function, which is maximized in order to find the control parameters (i.e., weights in the linear program) that result in the highest expected performance.

3.2 Notional Integrated Engineering Plant

Fig. 3.2 shows a notional medium-voltage dc system (MVDC) [41]. In the four-zone system, there are two main generators (MTG) and two auxiliary generators (ATG). The two propulsion motors (PMD) will operate at different power levels corresponding with the required speed. The radar (R) has two operating modes, a low-power mode and a high-power mode. The high-power load (PL) is used to perform in the mission. The energy storage device (ES) can provide backup power during missions or system disturbance as well as compensate for load dynamics. The zonal loads (ZL), including some vital loads and non-vital loads, are connected through converters (CM). The layout of zonal loads can increase the survivability of the IEP, because if one zone is damaged, the operation of other zones will not be affected.

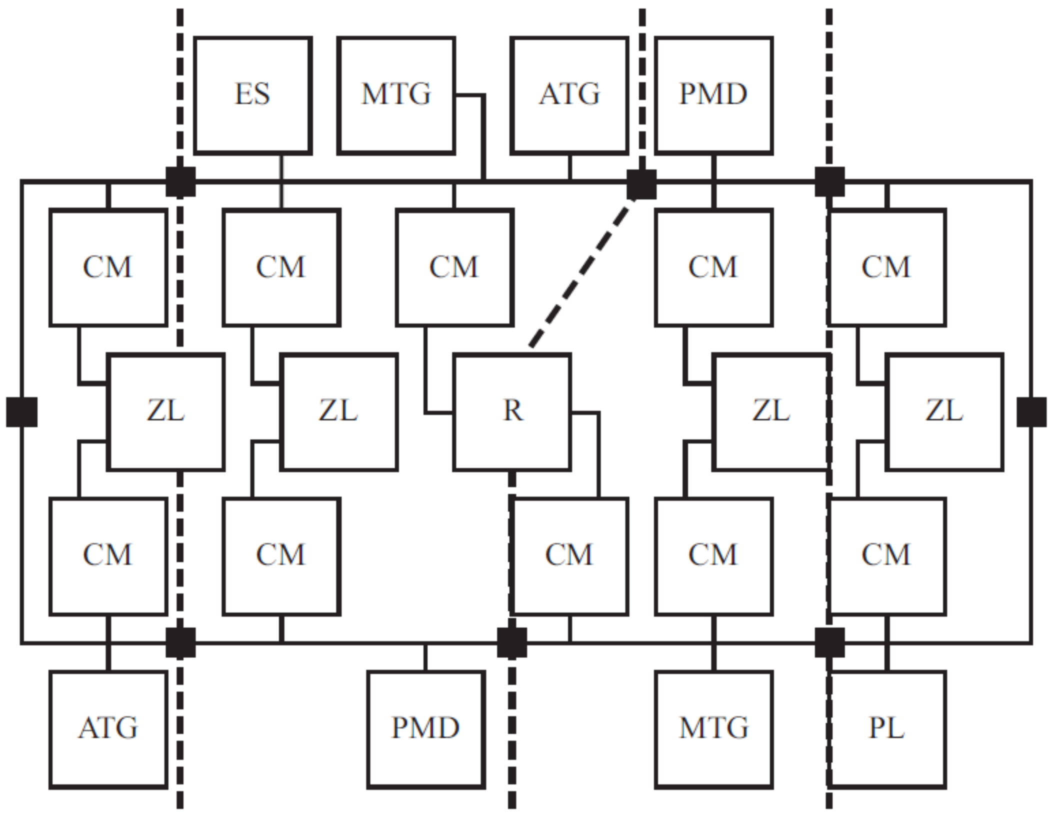

Fig. 3.2. Notional medium-voltage dc system (MVDC) [41]

The thermal management system is used for cooling the shipboard electrical components and is critical to the survival and endurance of a warship [42]. The warship is also divided into cooling zones to increase the survivability. In [42], the major components of the cooling system are included in the ac plant, which is defined as a typical marine refrigeration cycle including compressor, condenser, expansion valve and evaporator cycle. The ac plant removes heat from the chilled water system and dumps heat to a seawater system. There are strong dynamic interdependencies between the electrical and thermal management systems [43], but the thermal management system is not considered further in this thesis.

3.3 Simplified Integrated Engineering Plant

Loads on a simplified IEP model can be categorized in three groups: vital load, non-vital load, and mission load. Vital load is most prioritized at all times. During mission modes, mission load also needs to be supported. If both the generator and energy storage cannot provide enough power for the whole system, part of (all) non-vital load will be shut down until sufficient power is available. The power flow of this simplified IEP model is illustrated in Fig. 3.3.

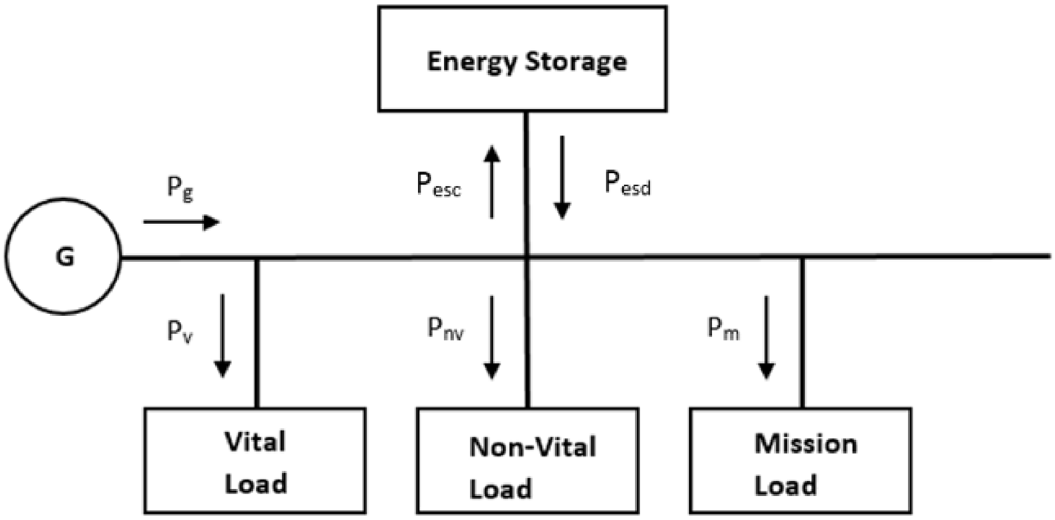

Fig. 3.3. A simplified IEP

The power flow of the IEP model can be expressed as

$$P_g + P_{esd} - P_{esc} - P_v - P_{nv} - P_m = 0, \tag{3.1}$$

where P_g is the power of the generator, P_{esd} is the discharging power of the energy storage, P_{esc} is the charging power of the energy storage, P_v is the power of the vital load, P_{nv} is the power of the non-vital load, and P_m is the power of the mission load. It should be noted that each of these variables represent aggregations of many such components.

It is convenient to denote system status with S_{ij}, $i, j = 0, 1, 2$, where i represents the state of mission, and j represents the state of damage. When $i = 0$, it means the mission has not start yet; when $i = 1$, it means there is a mission running; when $i = 2$, it means the mission is over. When $j = 0$, it means there is no fault in the system; when $j = 1$, it means the power system is damaged; when $j = 2$, it means the damage has been (partly or completely) recovered. The status transition relationships are illustrated in Fig. 3.4.

S_{00} No mission, no fault	→	S_{01} No mission, damaged	→	S_{02} No mission, damage recovered
↓		↓		↓
S_{10} Mission starts, no fault	→	S_{11} Mission starts, damaged	→	S_{12} Mission starts, damage recovered
↓		↓		↓
S_{20} Mission ends, no fault	→	S_{21} Mission ends, damaged	→	S_{22} Mission ends, damage recovered

Fig. 3.4. System status

As described above, there are three mission states (pre-mission, mission, post-mission) and three damage states (normal, damage, recovery). Hence, the total states are nine, as shown in Fig. 3.4.

In the pre-mission state, the vital and non-vital loads are commanded to full power. During the mission state, the mission load is commanded to a given power level associated with the mission. In the post-mission state, the mission load is again deactivated.

When the damage state is normal, the generator and mission load are capable of full operation. When the system is damaged, the generator and mission load capabilities are reduced by a given fraction associated with the damage scenario. When the system recovers, a given fraction of the lost capability of the generator and mission load is restored associated with temporary or recoverable damage.

3.4 Mathematical Model

Each type of load, as well as the generator and energy storage device, is assigned with a particular weight, w (\$/W), defined as the unit cost of power, which indicates the significance of that load/device.

In order to get the optimum expected performance over a time frame, the approximate behavior at each time step needs to be calculated. Then calculate the integral of these discrete behaviors, the result is the optimum performance over time.

In previous work [35], [36], approaches involving linear programming to model the action of the power system are proposed. A linear programming problem is a method to maximize or minimize a linear function, subject to linear equality and linear inequality constraints. In this thesis, a similar but simpler model is formulated as [35] and [36].

The linear programming approach to model the electrical power system can be expressed in the following form:

$$\max \boldsymbol{c}^T \boldsymbol{x} \tag{3.2}$$

subject to

$$\boldsymbol{Ax} \leq \boldsymbol{b} \tag{3.3}$$

$$\boldsymbol{A}_{eq}\boldsymbol{x} = \boldsymbol{b}_{eq} \tag{3.4}$$

$$\boldsymbol{x} \geq \boldsymbol{0}. \tag{3.5}$$

The elements of $\boldsymbol{x}$ represents the vectors of variables, which describe the power flow of the power system. The vector $\boldsymbol{c}$ denotes the weights assigned to the power flows for the objective function, while $\boldsymbol{Ax} \leq \boldsymbol{b}$, $\boldsymbol{A}_{eq}\boldsymbol{x} = \boldsymbol{b}_{eq}$, and $\boldsymbol{x} \geq \boldsymbol{0}$ are the linear equality and inequality constraints that the solution must satisfy.

The objective function is to maximize the performance of the electrical power system. Since the power flow of the energy storage is bidirectional, there will be two elements of $\boldsymbol{x}$—one element for charging and the other one for discharging. The power flows of the generator and the different loads are unidirectional; hence, they correspond to single elements of $\boldsymbol{x}$.

Each component, different types of load, generator, and energy storage device, are assigned with their particular weights, which indicate the significance of that component. Generally, these weights are event-specific and probably time-varying [5]. For example, in this thesis, the vital load and mission load are rather important, hence, the weights assigned to them are relatively higher; the non-vital load is less critical so the weight is much lower. The charging and discharging weights associated with the energy storage are to be determined in order to get the optimum performance.

The detailed linear program problem is as follows:

$$\max w_v P_v + w_{nv} P_{nv} + w_m P_m + w_{esc} P_{esc} - w_{esd} P_{esd} - w_g P_g \tag{3.6}$$

subject to the following linear constraints:

$$P_g + P_{esd} - P_{esc} - P_v - P_{nv} - P_m = 0 \tag{3.7}$$

$$0 \leq P_g \leq P_{gmax} \tag{3.8}$$

$$0 \leq P_v \leq P_{vmax} \tag{3.9}$$

$$0 \leq P_{nv} \leq P_{nvmax} \tag{3.10}$$

$$0 \leq P_m \leq P_{mmax} \tag{3.11}$$

$$0 \leq P_{esc} \leq P_{escmax}\ (P_{escmax} \to 0 \text{ as } E_{es} \to E_{esmax}) \tag{3.12}$$

$$0 \leq P_{esd} \leq P_{esdmax}\ (P_{esdmax} \to 0 \text{ as } E_{es} \to 0) \tag{3.13}$$

$$\frac{dE_{es}}{dt} = P_{esc} - P_{esd}, \tag{3.14}$$

where w is the weight of each load or other device, P is the power of the load or other device, E_{es} is the energy stored in the energy storage unit. The relationship between E_{es} and P_{esxmax} (P_{escmax} and P_{esdmax}) is described by the equations below and shown in Fig. 2.1:

$$P_{escmax} = \begin{cases} P_{esmax}, & E_{es} \leq E_{esmax} - \tau P_{esmax} \\ f(E_{esmax} - E_{es}), & E_{esmax} - \tau P_{esmax} < E_{es} < E_{esmax} \\ 0, & E_{es} \geq E_{esmax} \end{cases} \tag{3.15}$$

$$P_{esdmax} = \begin{cases} 0, & E_{es} \leq 0 \\ f(E_{es}), & 0 < E_{es} < \tau P_{esmax} \\ P_{esmax}, & E_{es} \geq \tau P_{esmax}, \end{cases} \tag{3.16}$$

where $f(\Delta E)$ is formulated as

$$P_{esxmax} = f(\Delta E) = a\Delta E^3 + b\Delta E^2 + c\Delta E + d \tag{3.17}$$

subject to

$$f(\tau P_{esmax}) = P_{esmax} \tag{3.18}$$

$$f(0) = 0 \tag{3.19}$$

$$f'(\tau P_{esmax}) = 0 \tag{3.20}$$

$$f'(0) = 0. \tag{3.21}$$

Application of these constraints yields the following coefficients:

$$a = -\frac{2}{\tau^3 P_{esmax}^2} \tag{3.22}$$

$$b = \frac{3}{\tau^2 P_{esmax}} \tag{3.23}$$

$$c = 0 \tag{3.24}$$

$$d = 0. \tag{3.25}$$

When the energy storage is full, it stops charging, so the maximum charging power approaches to zero; when the energy storage is empty, it stops discharging, so the maximum discharging power approaches to zero.

Fig. 3.5. Stored energy vs. maximum power

For the study, the loads or devices are weighted according to the weights provided in Table 3.1. As the energy storage both charges and discharges, the weight of charging and weight of discharging are assigned to the energy storage device, respectively.

Table 3.1. Linear program weight matrix

Load/Device	Weight ($/W)
Generator	0.5
Vital load	25
Non-vital load	3
Mission load	20
Energy storage charging	To be calculated
Energy storage discharging	To be calculated

Other parameters of the power system in the study are listed in Table 3.2.

Table 3.2. Parameters of power system

Total generation	85 MW
Total vital load	20 MW
Total non-vital load	60 MW
Mission load	20 MW
Energy storage	20 MW, 5 GJ

The MATLAB package linprog [44] is used to formulate and solve the linear programs; the ode23tb solver [44] are used to integrate the differential equations.

3.5 Stochastic Engagement Model

In this thesis, hostile disruptions and missions are assumed to occur randomly, which means the system is modeled in a stochastic environment.

The occurrence of the disturbances/failures of the IEP can be modeled by many probability distributions, one common model is the exponential failure distribution, which is applied in the study. The missions are assumed to occur with a given mean time between occurrences and are modeled using a similar exponential distribution. The exponential distribution is the probability distribution which describes the time interval between event occurrences continuously and independently at a constant average rate. This rate, is a constant with respect to time, which means the distribution is memoryless. The probability density function of an exponential distribution with parameter λ is

$$f(x;\lambda) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{3.26}$$

Inverse transform sampling is used in the study to generate exponential variates:

$$T = \frac{-\ln(U)}{\lambda}, \tag{3.27}$$

where T is the time interval between events, random variate U is uniform on (0, 1), and λ is the frequency which the disturbance or mission occurs.

The time frame of the study is 900 s, and the probability of mission or disturbance occurs is set to 0.5. Under this assumption for the study, the probability of the four categories of scenarios are all equal to 25%. The four categories of scenarios are no fault nor mission, fault occurs but no mission, mission occurs but no fault, and both fault and mission occur during the study. The occurrence rate used in the study is calculated as

$$\lambda = \frac{-\ln(0.5)}{900} = 7.7016e^{-4} \tag{3.28}$$

The duration of a mission is uniformly distributed between 120 s to 600 s; the length of the recovery period (time between entering the damage and recovery states) is uniformly distributed between 60 s to 300 s.

In this study, the hostile disturbances are only restricted to occur at generator and mission load; whereas in reality, damages may apply to any part of the power system — other loads and the energy storage units.

The commanded power of the mission load is uniformly distributed between 50% to 100%, and for the remaining four stochastic variables, generator damage degree, generator recover degree, mission load damage degree, and mission load recover degree, they are all uniformly distributed between 0 and 100%.

In [5], [35], [37], the notion of event is introduced. An event $\theta \in \Theta$ is a vector whose elements represents all the information necessary to predict the response of the system. The information may include the external environment in which the system is operating (e.g., the mission of the warship), the internal conditions of the system prior to the disruption and the disruption itself [37]. In this study, an event contains the following information of the system: mission start point, mission end point, damage start point, damage end point, mission load initial state, generator damage degree, generator recover degree, mission load damage degree, and mission load recover degree.

Some example random events are shown below to demonstrate the simulation model. For calculation convenience, all the power parameters are converted into per unit values; accordingly, the energy storage is also divided by base power, and the unit becomes second (Joule/Watts). The value of charging and discharging weights are both 1.75, according to the test results below.

Event with mission but no damage

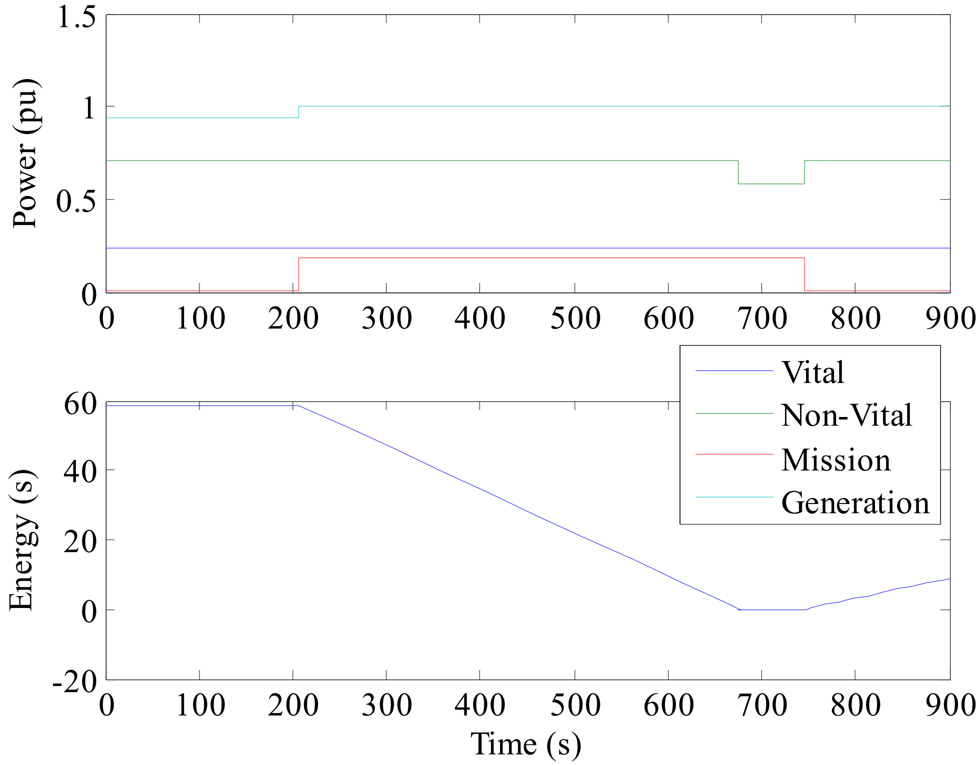

Fig. 3.6. Event with mission but no damage

Fig. 3.6 illustrates the response of the system to an event with a mission but no damage. The vital load fully operates through the duration of the scenario. The mission load starts operating at 206 s, and the mission ends at 746 s. After the mission starts, the generator cannot provide enough power for the entire system. Thus, the energy storage begins to discharge. Before the energy storage depletes, the mission load as well as the non-vital load can fully operate. When the energy storage is completely discharged (after 680 s), the non-vital load is partly shut down to prioritize the function of the vital and mission loads. The energy storage resumes charging after the mission ends.

Event with mission after recovery

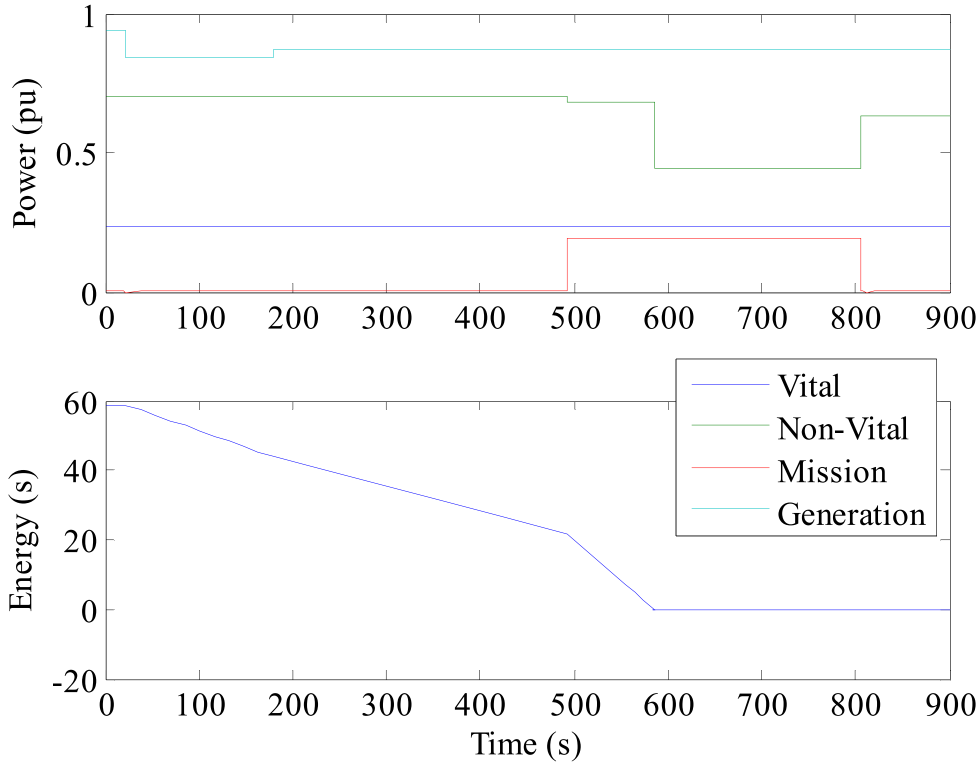

Fig. 3.7. Event with mission after recovery

Fig. 3.7 indicates the response of the system to an event with mission after recovery. During this event, the vital load is fully functioning during the whole time. There is a generator failure at 22 s, and the generator capacity is reduced by 15%. The failure is partially recovered at 179 s, and the generator recovers to 87% capacity. During the generator fault, energy storage keeps discharging to power the vital and non-vital load. At 493 s the mission starts and lasts until 806 s. The mission load only operates at 79% of its rated power after it recovers from the initial damage. Before the mission starts, all loads can work normally. When the mission starts while the energy storage has not completely discharged (around 580 s), the non-vital load is partly shut down to prioritize the function of vital and mission load. When the energy storage depletes, the non-vital load is shut down further. Even though the mission ends, the non-vital load still cannot fully operate due to the generation loss.

Event with damage during mission

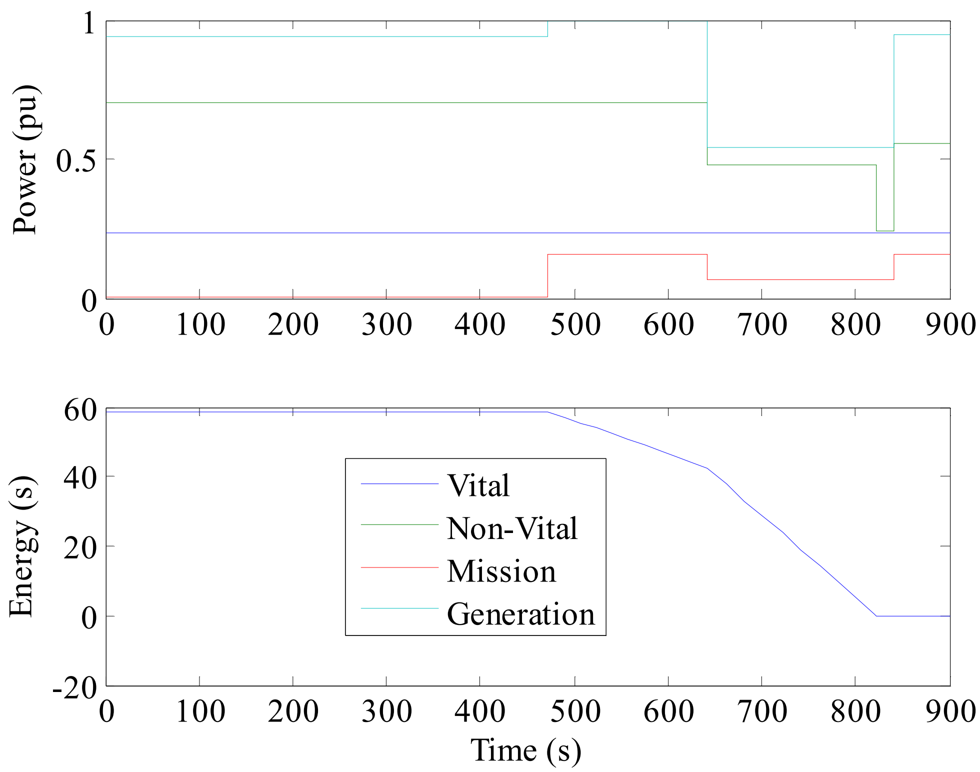

Fig. 3.8. Event with damage during mission

Fig. 3.8 shows a complicated case, an event with damage during mission. The disruptions occur in the middle of the mission. The energy storage starts discharging at 473 s, when the mission starts. The mission load operates at 66% of the rated power at first. At 643 s, the generator is damaged, reducing its capacity to 54%, and the mission load is also damaged, reducing its capacity to 47%. During the system failure, the non-vital load is greatly reduced so that the vital and mission load can work well. When the energy storage is completely depleted, the non-vital load is shut down further. At 841 s, the generator capacity recovers to 95%, while the mission load capacity recovers to 80%, the non-vital load resumes operation given the extra additional power. Because the mission load power is 66%, the mission load is able to resume at the full power required for the mission after recovery.

3.6 Simulation Method

In this study, repeated random sampling is needed to obtain the final results. Hence, Monte Carlo simulation is used herein. Monte Carlo methods are mainly applied in optimization, numerical integration, and generating draws from a probability distribution. Monte Carlo simulation is a problem solving method running multiple trial simulations, using random variables, to produce the approximated distributions of possible outcome values. It then calculates results recurrently, each time using a different set of random values from the input probability functions (iteration), and the resulting outcome from that sample is recorded. Depending on the uncertainties and the ranges of the problem, a Monte Carlo simulation could involve thousands or tens of thousands of recalculations before complete [45].

A Monte Carlo simulation is used by a GA for fitness evaluation. As introduced in Chapter 2, GA is a search metaheuristic that mimics natural evolutions. GAs generate possible solutions to optimize problems by improving the fitness of the solutions [25]. The value of fitness is the value to be optimized, and the basic steps of a typical GA are: initialization, evaluation, selection, crossover, mutation, and insertion. When the stopping criteria is met, the algorithm is terminated.

Two weights are to be optimized by the GA. As the GA seeks the optimized charging and discharging weights, the average performance of the IEP is maximized.

In order to improve MATLAB code performance by speeding up executions, MATLAB parallel computing is used in this study. The supercomputers at the University of Kentucky, which ranked as high as #66 on the world-wide Top 500 list supercomputers list, provide the High Performance Computing (HPC) environment so that the MATLAB code can run in parallel in several processors.

The University of Kentucky Information Technology department and Center for Computational Sciences is appreciated for computing time on the Lipscomb High Performance Computing Cluster and for access to other supercomputing resources. The Lipscomb High Performance Computing Cluster (dlx.uky.edu) is used to run the GA in parallel for the study. The cluster is named after Dr. William N. Lipscomb, Jr, an outstanding UK alumnus and Nobel Prize-winning chemist. It is built from a large number of commodity servers, a high speed interconnect, a unified file system, and a large mass storage system [46].

Chapter 4. Simulation Validation Study

4.1 GA Simulation Results Analysis

In order to find satisfactory results from the GA, the algorithm is executed for 100 generations with 100 individuals and tested several times.

The expected performance is estimated by averaging the performance over 100 samples. The performance of a single sample is formulated as

$$Performance = \frac{\int_0^{t_{end}}(w_v P_v + w_{nv} P_{nv} + w_m P_m)\,dt}{(w_v P_{vmax} + w_{nv} P_{nvmax}) t_{end} + w_m \int_0^{t_{end}} P_m^*\,dt}, \tag{4.1}$$

where t_{end} is the terminal time of the study, which is 900 s, w_v, w_{nv}, and w_m are the weights of vital, non-vital , and mission loads, respectively, P_v, P_{nv}, and P_m are the actual power of vital, non-vital, and mission loads, respectively, P_{vmax} and P_{nvmax} are the maximum power of vital and non-vital loads, respectively, and P_m^* is the commanded power of the mission load at each time.

The optimum weights of charging and discharging by which the GA find are based on equal allocation sampling of the fitness; in this study, each individual is sampled 100 times and the expected value of the 100 samples is considered as estimated performance. When the values are sought, more samples need to be performed to better estimate the true average performance associated with these parameters. Hence, a random set of 1,000 or 10,000 scenarios are selected to use as a proxy for the true average. In this way it can be determined if the GA was actually finding a good answer of being tricked by limited sampling. The reference performance is the average of the performance over 1,000 samples using a reference set Θ_{ref}.

The simulation results are shown in the following. Four major variables are evaluated for the validation of the simulation: optimum weight of charging and weight of discharging (final values at the termination of the GA), as well as the estimated performance at the termination of the GA. These three values are the final results of the GA, while the last result, reference performance, cannot be acquired from the GA.

Test 1

The results of Test 1 are listed in Table 4.1. Both the weight of charging and weight of discharging are between the weight of generator and the weight of non-vital load. The GA estimated performance is 98.52%, and the reference performance is 97.76%.

Table 4.1. Test 1 result

Optimum charging weight	0.7432
Optimum discharging weight	2.1684
GA estimated performance	98.52%
Reference performance	97.76%

The detailed reference performances of 1,000 samples are sorted in Fig. 4.1.

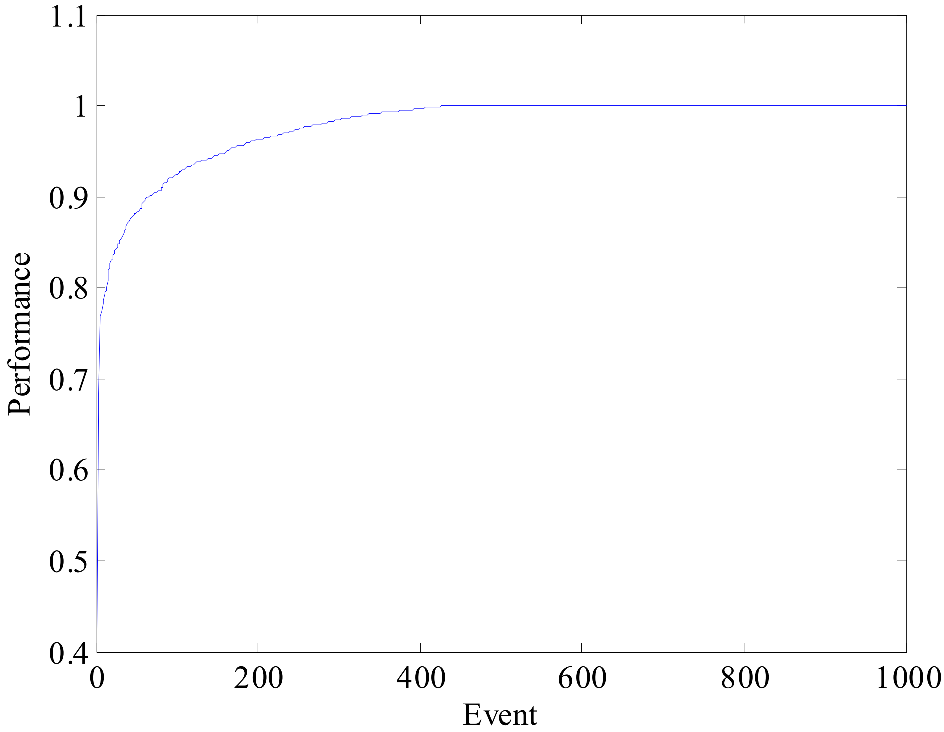

Fig. 4.1. Reference performance of Test 1

From Fig. 4.1, it can be concluded that most of the time (close to 60%) the performance is 1, which means there are neither missions nor disturbances occur during the test time. The probability is greater than 25%, which is because the study time interval is 900s, many missions and disturbances occur after 900s and those cases are not discussed in this study.

To validate that the use of 1,000 samples for reference performance is a good proxy for the true expected performance, using the same charging and discharging weight as Test 1, a larger set of events Θ_{ref2} with 10,000 samples is used. The detailed reference performance of 10,000 samples are sorted in Fig. 4.2.

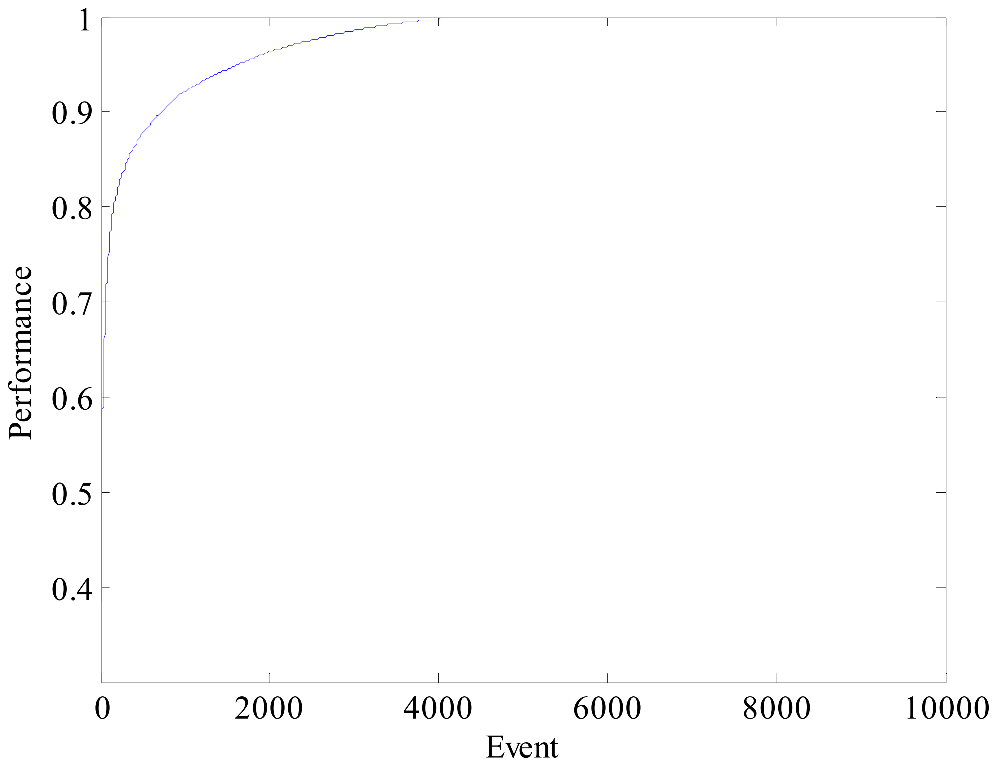

Fig. 4.2. Reference performance of 10,000 samples

Compared to Fig. 4.1, the curve patterns are very similar. The reference performance of 10,000 samples is 97.64%, a little less than the reference performance of 1,000 samples. This means as the number of samples increase, the number of bad cases may also increase. But the reference performance of 10,000 samples is close enough to the reference performance of 1,000 samples, which indicates that the reference performance of 1,000 samples could be a useful proxy to the true average performance.

Test 2

The results of Test 2 are listed in Table 4.2. The weight of charging and discharging are also in between of the weight of generator and the weight of non-vital load. The GA estimated performance is 98.54%, close to the GA estimated performance in Test 1; and the reference performance is 97.76%, same as the average performance in Test 1since the same reference events are applied.

Table 4.2. Test 2 result

Optimum charging weight	1.4679
Optimum discharging weight	2.3656
GA estimated performance	98.54%
Reference performance	97.76%

The detailed reference performances of 1,000 samples are sorted in Fig. 4.3, which show similar pattern as Test 1.

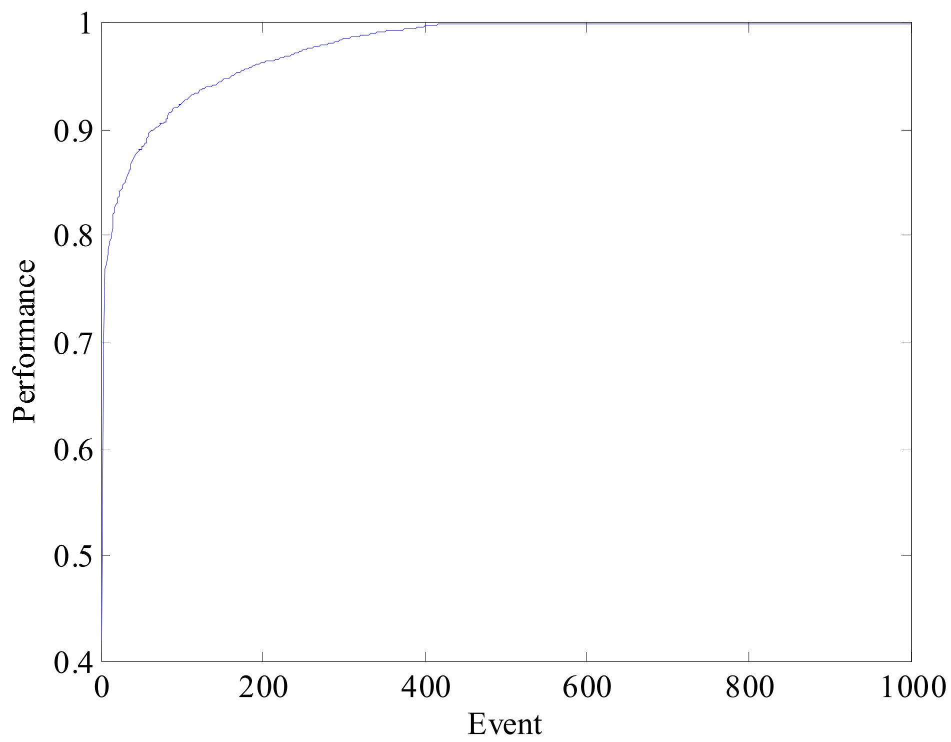

Fig. 4.3. Reference performance of Test 2

Test 3

The results of Test 3 are listed in Table 4.3. The charging weight is 2.1228, and the discharging weight is 1.3367, both are in the interval of 0.5 (weight of generator) to 3 (weight of non-vital load), which supports the results from the previous two tests. There is a small difference of GA estimated performance with the previous two test, which is caused by the random cases selected by GA. The reference performance is the same with the previous results.

Table 4.3. Test 3 result

Optimum charging weight	2.1228
Optimum discharging weight	1.3367
GA estimated performance	98.53%
Reference performance	97.76%

The detailed reference performances of 1,000 samples are sorted in Fig. 4.4, which show similar pattern as the previous tests.

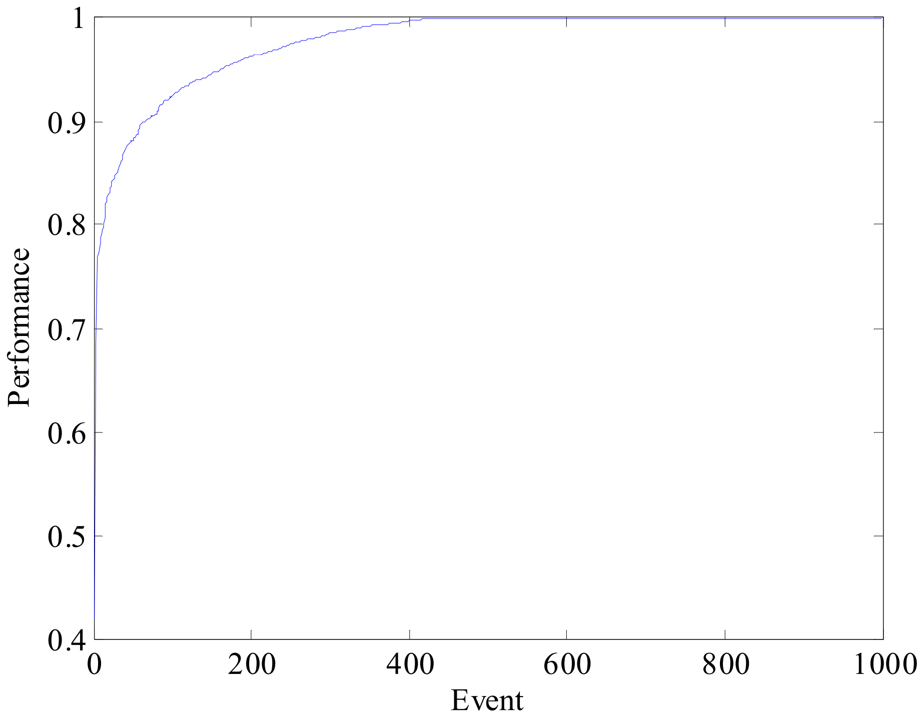

Fig. 4.4. Reference performance of Test 3

Test 4

The results of Test 4 are listed in Table 4.4. The weight of charging and weight of discharging are both in between the weight of generator and the weight of non-vital load, in the same interval as the previous results. The GA estimated performance is 98.52%, close to the previous results, and the reference performance is the same as the previous results.

Table 4.4. Test 4 result

Optimum charging weight	1.7930
Optimum discharging weight	1.1197
GA estimated performance	98.52%
Reference performance	97.76%

The detailed reference performances of 1,000 samples are sorted in Fig. 4.5, also show similar pattern as the previous tests.

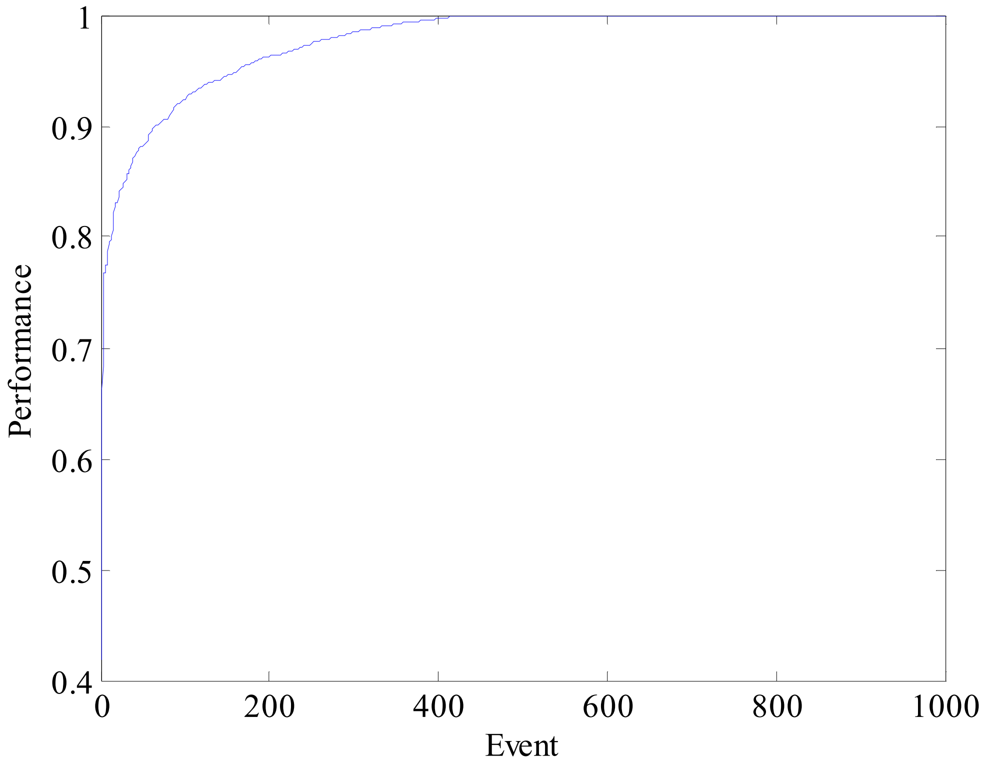

Fig. 4.5. Reference performance of Test 4

Test 5

The results of Test 5 are listed in Table 4.5. The optimum charging weight and discharging weight are within the interval between generator weight and non-vital load weight. The GA estimated performance is 98.87%, and the reference performance is the same with previous tests results.

Table 4.5. Test 5 result

Optimum charging weight	2.0969

Optimum discharging weight	1.8488
GA estimated performance	98.87%
Reference performance	97.76%

The detailed reference performances of 1,000 samples are sorted in Fig. 4.6, which show similar pattern as previous results.

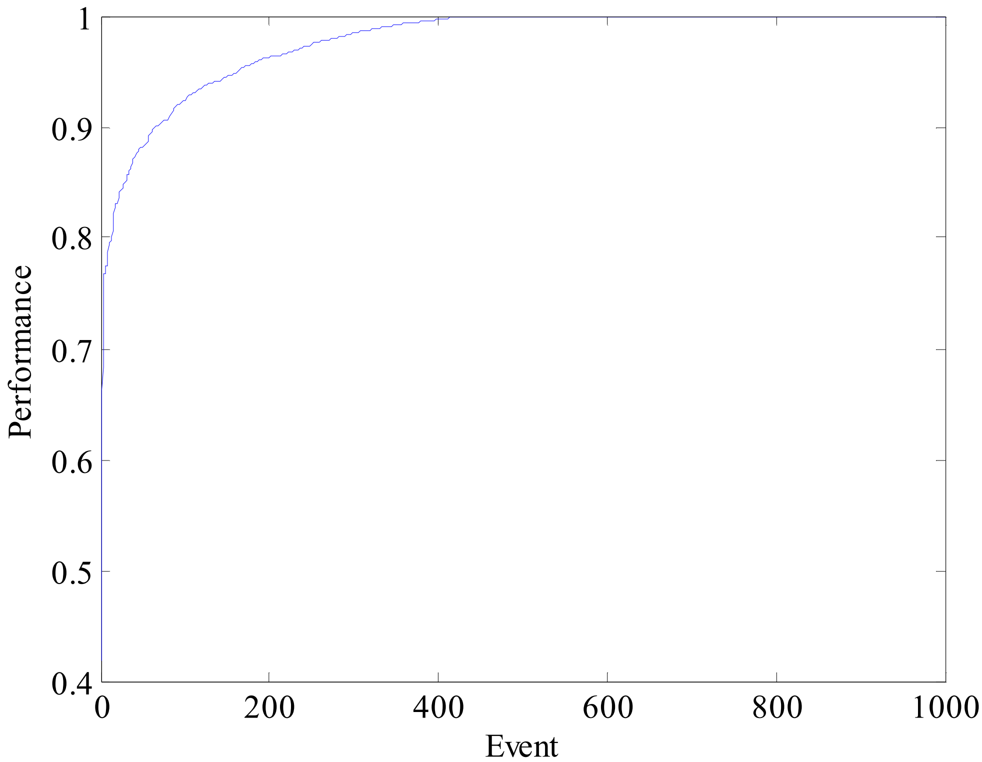

Fig. 4.6. Reference performance of Test 5

From the test results, it can be concluded that the GA works well, the weight of charging and weight of discharging converged in the same interval, between the weight of generator (0.5) and the weight of non-vital load (3). This is reasonable because if the weight of charging is smaller than the weight of generator, the energy storage will not charge. Once the optimum weights are found by the GA, further tests need to be performed to validate the results. The GA estimated performance is around 98.53%, except for Test 5, in which the estimated performance is better than the rest four tests. The reference performance is 97.76%, since in all five tests, the weight of charging and weight of discharging fall in the same interval and the reference events set is the same.

4.2 Baseline Cases Test

To validate the simulation results, some baseline cases are established. By using the same set of events, the difference among the results can only be caused by the charging and discharging weights. For these baseline cases, events set Θ_{ref} is applied.

Recall that the system weight matrix is given:

Table 4.6. System weight matrix

Load/Device	Weight
Generator	0.5
Vital load	25
Non-vital load	3
Mission load	20

According to the previous test results and (3.6), the weight of charging and weight of discharging are only sensitive to intervals. Herein, for the baseline tests, the weights of charging and discharging might fall in five intervals: less than the weight of generator, between the weight of generator and the weight of non-vital load, between the weight of non-vital load and the weight of mission load, between the weight of mission load and the weight of vital load, and greater than the weight of vital load. For each interval, one weight is picked as a baseline case. Hence, 25 cases are to be tested as baseline. The baseline cases are:

$$w_{esc} \in \{0.25, 1.75, 11.5, 22.5, 30\}$$

$$w_{esd} \in \{0.25, 1.75, 11.5, 22.5, 30\}.$$

Table 4.7 shows the reference performance of all baseline tests.

Table 4.7. Reference performance of baseline tests

Wesd\Wesc	0.25	1.75	11.5	22.5	30
0.25	95.77%	95.78%	95.78%	95.78%	95.77%
1.75	95.77%	**97.76%**	96.73%	96.62%	95.78%
11.5	95.77%	96.72%	96.66%	96.56%	95.78%
22.5	95.77%	96.61%	96.56%	96.54%	95.78%
30	95.77%	95.77%	95.77%	95.77%	95.77%

The reference performance of case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is the highest, which equals to the reference performance of what GA calculated. This validates the results of the GA studies, which is that the optimum charging and discharging weight shall fall between the weight of generator and the weight of non-vital load.

4.3 Risk Analysis

While the optimal expected performance has been found, it is known that rational decision makers seek a balance between performance and risk [47]. In [33], [37], several of risk metrics are discussed. Two traditional risk metrics are the variance and standard deviation, however, these two metrics cannot distinguish positive deviations from negative deviations, which are not good enough to measure the riskiness. Value at risk (VaR) is widely used in financial risk management, it is a given percentile of the distribution of the return of a specific portfolio over a specific time frame. VaR is not always incoherent. Two examples of coherent risk metrics are the worst case return and the expected shortfall, which is the conditional expectation of the return of a given bottom percentile. The expected shortfall is an alternative to VaR that is more sensitive to the shape of the loss distribution in the tail of the distribution.

In this study, 10% is applied to both VaR and expected shortfall.

Table 4.8 lists the standard deviation of baseline tests. The standard deviation of case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is the lowest, which proves that the deviation is the lowest, and the case is the optimum result.

Table 4.8. Standard deviation of baseline tests

Wesd\Wesc	0.25	1.75	11.5	22.5	30
0.25	6.96%	6.95%	6.95%	6.95%	6.96%
1.75	6.96%	**4.63%**	4.73%	4.96%	6.95%
11.5	6.96%	4.73%	4.84%	5.06%	6.95%
22.5	6.96%	4.96%	5.06%	5.11%	6.95%
30	6.96%	6.96%	6.96%	6.96%	6.96%

Table 4.9 lists the worst case of baseline tests. The result shows that the worst case scenario of case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is not the highest, this is reasonable because the study is not aim to optimize the worst case, but to optimize the expected performance.

Table 4.9. Worst case of baseline tests

Wesd\Wesc	0.25	1.75	11.5	22.5	30
0.25	25.94%	26.01%	26.00%	26.00%	25.93%
1.75	25.94%	**41.93%**	43.82%	43.87%	26.01%
11.5	25.94%	43.83%	43.83%	43.88%	26.04%
22.5	25.94%	43.88%	43.88%	43.88%	26.04%
30	25.94%	25.94%	25.94%	25.94%	25.94%

Table 4.10 lists the 10% VaR of baseline tests. The case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ has the highest VaR, which proves that it is the optimized case.

Table 4.10. 10% VaR of baseline tests

Wesd\Wesc	0.25	1.75	11.5	22.5	30
0.25	87.43%	87.44%	87.42%	87.42%	87.42%
1.75	87.43%	**92.43%**	90.92%	90.49%	87.44%
11.5	87.43%	90.92%	90.56%	90.09%	87.43%
22.5	87.43%	90.48%	90.06%	90.06%	87.43%
30	87.43%	87.43%	87.43%	87.43%	87.43%

Table 4.11 lists the 10% expected shortfall of baseline tests. The result also shows that the case of $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is the optimized case.

Table 4.11. 10% Expected shortfall of baseline tests

Wesd\Wesc	0.25	1.75	11.5	22.5	30
0.25	78.75%	78.80%	78.80%	78.80%	78.75%
1.75	78.75%	**86.55%**	85.59%	84.78%	78.80%
11.5	78.75%	85.58%	85.20%	84.45%	78.80%
22.5	78.75%	84.78%	84.45%	84.26%	78.80%
30	78.75%	78.75%	78.75%	78.75%	78.75%

Some risk metrics match the result of reference performance, but the worst case metric does not match the result of reference performance. From Table 4.9, it can be seen that the worst case of case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is not the highest, which is possible because in the study, the value to be optimized is the expected performance, not the worst-case performance. Other than worst case study, other risk metrics, including standard deviation, VaR, and expected shortfall analyses show that the case $\{w_{esc} = 1.75, w_{esd} = 1.75\}$ is the optimum baseline case, indicating that there is a connection between expected performance and risk.

4.4 Tests with More Complicated Optimization Problem

In the previous study, the weight of charging and discharging are set as constants. It is possible that superior performance may be obtained if the two weights are related to the instantaneous state of energy storage. For example, if the energy storage is full, it will stop charging. Hence, to explore the relationship between the charging/discharging weights and the state of energy storage, linear models are formulated as follows:

$$w_{esc} = (w_{esc1} - w_{esc0})\frac{E}{E_{max}} + w_{esc0} \tag{4.2}$$

$$w_{esd} = (w_{esd1} - w_{esd0})\frac{E}{E_{max}} + w_{esd0} \tag{4.3}$$

where, w_{esc0} is the charging weight when energy storage is empty, w_{esc1} is the charging weight when energy storage is full, w_{esd0} is the discharging weight when energy storage is empty, w_{esd1} is the discharging weight when energy storage is full, E is the instantaneous state of energy storage, and E_{max} is the maximum capacity of energy storage.

It is a larger searching space for the GA, in order to give the algorithm a fair chance to find a good answer, it would be reasonable to increase the combination of generation number, individual number, and sample number. In this study, the number of generations and the number of individuals are both increased from 100 to 200. The four-parameter test is run twice, and the results are listed in Table 4.12 and Table 4.13.

Test 6

Table 4.12. Test 6 result

Optimum charging weight (empty)	2.0238
Optimum charging weight (full)	1.7517
Optimum discharging weight (empty)	2.5153
Optimum discharging weight (full)	0.6701
GA estimated performance	98.63%
Reference performance	97.75%

Test 7

Table 4.13. Test 7 result

Optimum charging weight (empty)	1.9576
Optimum charging weight (full)	1.0196
Optimum discharging weight (empty)	2.3010
Optimum discharging weight (full)	1.7146
GA estimated performance	98.63%
Reference performance	97.75%

The reference performance of the four-parameter tests should be no worse than that of the two-parameter tests, because constant weights can be selected by the GA in the four-parameter tests. In the study, the reference performance of two-parameter tests is 97.76%, while the reference performance of four-parameter tests is 97.75%. The error is less than 0.01%, which is within the tolerance range. Also, the reference performance of case $\{w_{esc0} = 1.75, w_{esc1} = 1.75, w_{esd0} = 1.75, w_{esd1} = 1.75\}$ is also 97.75%. This proves that the model is correct and the optimum weights are validated.

Chapter 5. Conclusion

This thesis shows how to use GAs to optimally control the energy storage for stochastic problems, including hostile disruptions and special missions. Although the study involves a notional naval system, the approach is generic and it can be applied to other systems and platforms.

The MVDC is used as the system model in the study. A simplified IEP model is presented in the thesis, the power system of the presented IEP model is consisted with generator, vital load, non-vital load and energy storage module. A linear programed model is used to simulate the power system, and two sets of states, mission states and damage states are formulates to simulate the stochastic scenarios that the IEP may be confronted with.

A GA is used to find the optimal control variables for energy storage, and a Monte Carlo simulation is used by a GA for fitness evaluation. The estimated performance that GA calculated is the average of 100 samples, hence, more samples are performed to better estimate the true average performance. In the study, the average performance of 1,000 samples using the same set of events is used as the reference performance to proximate the true average performance. Some baseline cases and risk metrics analyses are also performed to validate the correctness of the GA simulation results.

In the end of the thesis, a more complicated optimization problem is considered. It is possible that superior performance may be obtained if the two weights are related to the instantaneous state of the energy storage. Hence, both the charging and discharging weights are formulated as linear functions of the energy storage state. The reference performance for the four-parameter tests is no worse than that for the two-parameter tests. This result is expected because the solutions located by the two-parameter tests are contained within the search space of the four-parameter tests. However, no further improvement in performance has been located using linear energy storage weights. More study might be needed to determine if another energy storage control method would yield a better result.

For future study, the stochastic problems can be more complicated, for example, the energy storage can be faulted and several faults may not happen at the same time. Operational vignettes are proposed in [41], those vignettes may be applied to the stochastic model of this study Also, alternative sampling methods could be explored to reduce computation efforts and to obtain a more accurate consistency analysis.

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