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Multi-level evolutionary algorithms resource allocation utilizing model-based systems engineering

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MULTI-LEVEL EVOLUTIONARY ALGORITHMS RESOURCE ALLOCATION UTILIZING MODEL-BASED SYSTEMS ENGINEERING

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ABSTRACT

This research presents an innovative approach to solve the resource allocation problems using Multi-level Evolutionary Algorithms. Evolutionary Algorithms are used to solve resource allocation problems in different domains and their results are then incorporated into a higher level system solution using another Evolutionary Algorithm to solve base camp planning problems currently faced by the U.S. Department of Defense.

Two models are introduced to solve two domain specific models: a logistics model and a power model. The logistic model evaluates routes for logistics vehicles on a daily basis with a goal of reducing fuel usage by delivery trucks. The evaluation includes distance traveled and other constraints such as available resource levels and priority of refilling. The Power model incorporates an open source electrical distribution simulator to evaluate the placement of structures and generators on a map to reduce fuel usage.

These models are used as the fitness function for two separate Evolutionary Algorithms to find solutions that reduce fuel consumption within the individual domains. A multi-level Evolutionary Algorithm is then presented, where the two Evolutionary Algorithms share information with a higher level Evolutionary Algorithm that combines the results to account for problem complexity from the interfacing of these systems. The results of using these methods on 5 different base camp sizes show that the techniques provide a considerable reduction of fuel consumption. While the Evolutionary Algorithms show significant improvement over the current methods, the multi-level Evolutionary Algorithm shows better performance than using individual Evolutionary Algorithms, with the results showing a 19.25 % decrease in fuel consumption using the multi-level Evolutionary Algorithm.

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1. INTRODUCTION

Systems engineering is flexible and general approach for designing and managing complex systems. These complex systems often consist of component systems that operate asynchronously. Large-scale complex systems typically consist of many simultaneously operating and interacting elements working together to produce a set of services. Difficulties arise when these elements and interfaces are not consistent and have conflicting objectives. This makes the task of designing feasible solutions for these systems challenging and improving the final product even more daunting.

A crucial part of systems engineering has always been the improvement of engineered solutions. Once a solution is found, efforts are made to make it more efficient, less costly, or improve the design in some way. Because of the large number of interfaces and potential conflicts traditional optimization is normally not possible. To find solutions to these challenging problems, optimization techniques are needed that not only optimize the individual components, but can also manage the interfaces between the systems and find high performance assembly solutions that cannot be realized with simpler optimization techniques.

1.1. EVOLUTIONARY ALGORITHMS

Evolutionary Algorithms (EAs) are computational problem solving tools capable of finding high quality solutions to complex problems to find solutions with high utility. Evolutionary algorithms provide a way to approach optimization of complex systems inspired by biological evolution mechanisms, such as reproduction, mutation, recombination, and selection. Even with these benefits, some systems are too complex for an EA to find a solution in a useful amount of time.

Bi-level evolutionary algorithms are a new method recently introduced that can augment the ability of EAs to find solutions. These techniques can be used to choose candidate solutions that guarantee the meeting of deadlines and satisfy constraints regarding a complex problem in applied areas. Bi-level multiobjective optimization [Deb, and Sinha, 2011] problems differ from multi-level optimization in that it operates on two low level optimization problems that must be combined at the higher level. The upper level optimization is the main problem and lower level optimization is the secondary problem, which follows the main problem. There is no decision making involved at the lower level and all lower level solutions are passed to the upper level. Lower level problems are used to solve subsystems and the upper level is to solve integration problems. The decision maker like a planner acts at the lowest level possible and chooses a solution, which suits the best to the problem. This eventually becomes the only solution at the upper level. The lower level algorithm finds building blocks that are then assembled by the higher level integration algorithm. Approximate solution techniques are usually applied to handle bi-level problems with simplifying assumptions like smoothness, linearity or convexity. The primary limitation of these approaches is that the complexity of the explicit solution can grow rather quickly with problem size. For complex multi-level optimization problems, classical methods normally fail due to practical difficulties like non-differentiability, discreteness etc.

Pure evolutionary methods are not very practical because of their long computational time. Under this case, a hybrid solution could be a solution. Identifying the limitations of both the approaches, the research presented here proposes a multi-level EA technique, which is the combination of architecture representation and evolutionary algorithms to develop real-time solutions. In this research, an evolutionary algorithm is developed to generate a range of options. A method has been proposed in this research, for using an evolutionary algorithm to find the high efficient solution taking into account multiple input parameters from a particular model point of view. In addition, the algorithm takes into account of the other models, which optimizes the overall needs of that problem.

There are several applications areas that are multi-level by nature. This includes the areas of economics (decision making policy) [Sinha, Malo, and Deb, 2013], transportation (optimal network design) [Migdalas, 1995], and engineering design (optimal design solution) [Dempe, 2003]. There have been number of studies conducted on Bi-level Optimization [Dempe, Dutta and Lohse, 2006, Sinha, Malo, and Deb, 2013], including a Toll setting problem [Brotcorne, Labbe, Marcotte and Savard, 2001], Stackelberg games [Fudenberg, 1993; Stackelberg, 1952], Environmental economics [Sinha, Malo, Frantsev and Deb, 2013], Structural optimization [Bendsoe, 1995] and Defense applications [Brown, Carlyle, Harney, Skroch and Wood, 2009]. Complex real time practical problems are normally converted into an easier single level optimization problem, which are solved to arrive at satisfying and sufficient solution instead of an optimal solution.

Base camp planning is a complex problem that involves multiple sub-systems that must be integrated to solve the overall objectives of the facility, implementing good decisions out of the best options available. Two major considerations when evaluating base camp designs are the use of energy and the use of water. In this context, of logistics distribution and power distribution planning that these algorithms are being applied. Both algorithms carry and gather very useful information for delivery of logistics on camp and placement of structures on the map from power distribution point of view and perform other useful functions. The introduction of subsystems that support the decision making to suit changing conditions is an important step in providing systems with improved functionalities. Unfortunately, present planning techniques lack formal mechanisms to help decision-makers explore the solution space of the problem and thereby challenge the assumptions about the number and range of options available.

Little research has been conducted in logistic delivery combined with utility usage in any application similar to the evaluation of base camps or small communities. In addition, considering single and/or multiple trips for logistics and the placement of structures and power consumption/losses has received little attention. The multi-level evolutionary algorithm proposed here provides a method to approach this complex optimization problem. The multi-level EA is composed of two linked optimization problems that share information with a higher level integrating EA. Internally, the first EA is the Power EA, which is considered as a combinatorial problem, and the second is the Logistics EA, which is a non-linear programming problem. The exact solution of the overall multi-level EA can be obtained by a complete enumeration of all feasible combination of all the components present in Power EA, which could be a massive number. Then, the Logistics model is solved for each feasible combination. Basically, the high dimension of the possible solution space is the real difficulty in solving the problem.

In addition to the above problem, arriving at that solution in reasonable good amount of time is also a challenge.

Evolutionary algorithms have been applied to routing problems, a class of search problems where an optimal route from an origin to a destination must be found within a given time. In a practical system, when traffic congestion changes during driving, the route should be re-evaluated before the car reaches the next intersection. As with other algorithms like Dijkstra algorithm [Golden, 1976], it always determines the optimal route, but cannot guarantee that realistic deadlines will be met. In contrast, as evolutionary algorithms always have solutions in a population during a search, they can provide alternative routes using other solutions in the shortest time. Modern society increasingly is faced with complex computational problems for which EAs are appropriate solvers. The ability of evolutionary algorithms to search a solution space and selectively focusing on promising combinations makes them ideally suited to such complex decision making problems.

1.2. FORWARD OPERATING BASES OVERVIEW

Forward Operating Bases (FOBs), or base camps, are temporary military contingency bases established to support and facilitate tactical operations on foreign soil. The term loosely applies to all temporary U.S. Combatant Command (COCOM) facilities on foreign ground, including but not limited to tactical bases, logistical supply bases, fire bases, patrol bases, and combat outposts [Noblis, 2010]. FOBs are typically mission-specific, and can vary widely in terms of function and necessary structures depending on the size of the population supported, mission type, mission duration, types of military units supported, and the availability of local infrastructure. Population sizes of FOBs range from 50 to 20,000 depending on these operational parameters.

In addition to having varied missions and functions, base camps also evolve over time. Typically this is due to the scope of the mission changing based on the duration of the mission. For example, a temporary base camp established quickly on a foreign soil to establish a presence and basic support might have to offer more complex services if the duration of mission changes. This includes both the facilities to be installed and the logistics that are needed to support the FOB. Construction planning processes, logistics considerations, utility needs, and the necessary structures and facilities define the sustainability of a Forward Operating Base to perform the necessary missions over the base camp life cycle. Two areas critical to base camp success that are affected by complexities from this dynamic system environment are the logistic network design and power distribution. The proper consideration of logistics and power distribution alternatives and how they interact within a FOB has a large impact on the effectiveness and sustainability of a FOB during the planning process.

1.3. LOGISTICS IMPORTANCE

Logistics have been an important factor in the success of missions throughout history for both civilian and military endeavors. The development of economic globalization has increased the importance of enterprise services supported by global supply chain and world-wide logistics to the business world. Because of this, managing efficient logistics systems has become a key issue for many businesses to control their costs. For these reasons complex logistic network design is gaining more attention from business organizations around the world. Similar to these organizations, the desire to reduce logistics supply cost is of utmost importance within Forward Operating Bases.

Today, logistics involves half of all Department of Defense (DoD) personnel and consumes a third of DoD budget [Armory, 2010]. A proper understanding of tangibles like Potable Water, Fuel and Waste consumed and produced at FOBs is necessary to identify the appropriate planning processes. Previous attempts have been made to standardize planning techniques and policies to be used for the distribution of logistics within base camps. Manuals such as the 'Redbook' [Contingency Operations, 2001] and 'Sandbook' [U.S. Central Command, 2009] provide some general guidelines for FOB planning; however, the techniques involved to distribute logistics inside a particular FOB are theatre specific and do not take into account the use of strategies such as the co-location, usage, etc., of the facilities involved. The lack of a systems-based approach has resulted in poor designs and operations maintenance in terms of health and safety, loss of operational flexibility and excessive capital and operating costs (i.e. cost of utilities/unit and overall capital/soldier/year).

Extended operations of troops in multiple theaters has highlighted a need for more advanced FOBs that are more sustainable, have reduced utility costs, are more efficient logistics support and have fewer casualties. A framework that enables the sustainment of military power is needed for improving the planning capabilities to increase effectiveness and eventually the efficiency of the base camp operations. The framework should synchronize all components of the logistics system to deliver the right equipment at the right time to the right place. Efficient prediction of the amount of utilities consumed in theatre will enable supporting more forces by fewer logistics assets. Accurate estimates of the logistics needs will assist FOB planners to organize and execute the movement of forces and materiel for deployment.

1.4. POWER DISTRIBUTION IMPORTANCE

FOBs have commonly had problems with inefficient electrical systems designs [Defense Management, 2009]. Most FOB power distribution systems are designed in an ad-hoc way whereby facilities, such as power generation, are selected based on historical uses rather than from an analysis of the size and mission of the base under consideration. In addition, FOB power distribution systems are typically a collection of diverse units that are electrically connected without regard to their efficiency, safety, or reliability.

There is a need of a technique which will help to identify the interfaces in the models and facilitate the exchange of data between them to optimize the main problem. For example, if bringing more generators into the power distribution system is needed, then this information should be shared with the logistics system so that appropriate amount of water can be brought in to cool the generators, which becomes a required interface with the logistics model. Traditional electrical system techniques are time-consuming and difficult to implement for most base camp designers. By using an automated power distribution system, the base camp planner can quickly design different networks that are feasible in a reasonable amount of time. These automated techniques and tools will increase flexibility to the military as it plans the electrical system for deployed FOBs and make the use of evolutionary computation methods to create FOB designs possible.

1.5. PROBLEM DISCUSSION

The U.S. Army is currently seeking methods to increase the efficiency of base camp operations, including logistics vehicle scheduling and energy distribution. To achieve these goals, techniques and models must take into account different constraints such as the individual facility needs and priorities. This requires multiple tradeoffs and compromises at the interfaces of the subsystems that must be taken into account when designing FOBs to reach an optimum and sustainable solution. To solve this problem, the multi-level EA method proposed in this research is applied to multiple base camp configuration problems similar to those currently faced by the U.S. Department of Defense. This method is applied to multiple example base camp layouts, and the results/advantages of this method are presented in this research.

The utility model developed here for base camp modeling take a logistics based approach to handling these resources and waste streams. The model uses an EA to optimize the distance travelled by logistics vehicles during the day, depending upon constraints such as available resource levels, priority of refilling, etc. With the appropriate topographical data available in a digitized form, this proposed EA places water and waste facilities in locations to minimize fuel consumption by the logistics vehicles. Buildings are automatically spaced at specified distances, clustered and positioned relatively to one another as appropriate.

The power EA is designed to evolve highly effective electrical grids quickly for base planners and field engineers using an open source power simulation engine. Distances between structures and power requirements (loads) are input as parameters, as well as the types of generators and transformers currently on hand. The EA makes use of

OpenDSS^{TM} solvers to determine the most efficient electrical grid design. Similar to the logistics model, buildings may be designed in clusters with individual generators, or the entire base integrated into a single grid based on the user's specification. It is important to note that the EA will generate only a 'naked' grid design void of protection systems (for the sake of expediency in completing the project); therefore an engineer would be required to finalize the design prior to its implementation in the field.

The two individual EAs for Optimized Logistics model and Automated Power Model are then combined into one multi-level EA with a primary purpose of satisfying the overall needs of the base camp. The solutions found using this method consider both individual placement of components and optimization of resource needs. This technique addresses the shortcomings that are currently present in the planning and design, construction and deconstruction, and operations and maintenance of base camps.

The multi-level EA chooses the best solution that fits the needs of the overall base camp rather than choosing the best individual solutions that are possible. The two individual EAs communicate and pass different solutions to the higher level EA to arrive at a best solution for that particular base camp. This technique helps to identify the interfaces in the models where data can be exchanged so that it is possible to consider the interfaces between subsystems to provide high performance solutions to the main problem.

1.6. OVERVIEW OF MODELS PRESENTED IN THIS RESEARCH

The modeling methods introduced in this research increase the planning capabilities for base camps using a model-based systems engineering approach. The models address issues faced by the Department of Defense related to unexpected second, third, and higher order effects observed on base camps, determined to be caused by the interactions between the base camp utility systems. The models introduced in this research allow the base camp planner to effectively transfer information between multiple analysis tools and integrate subsystem solutions into a larger analysis tool.

Section 2 describes the background of evolutionary algorithms, the need for accurate estimation of resources, and previous work performed by other researchers. Section 2 also discusses the problems approached and goes into details of how a multi-level evolutionary algorithm could be used to solve other complex problems using similar methodology. In section 3, a mathematical model (resource calculator) that focuses on estimation methods is introduced for improving the efficiency of FOBs by accurately estimating the quantities of resources required by a given FOB based on its operational parameters. The resource calculator introduced in this research is a dynamic model which takes into account all the important aspects of the base camp. The mathematical model is based on a coupled mathematical system of equations that captures the relationships between various base camp subsystems and their respective inputs and outputs. Subsystems are objectified and their various inputs and outputs (fuel, power, water, waste, maintenance, etc.) are parameterized to solve the system of equations simultaneously each time there is a change in base camp design. An example result for a 600-soldier size FOB and a 100-soldier size FOB is provided. This model is able to predict the overall resource requirements of a given base camp based on its operational parameters and the predicted relationships between the subsystems of the FOB.

The logistic model introduced in section 4 allows planners to do an analysis of vehicle routing for a particular base camp size configuration. The models presented in section 4 take a logistics-based approach to handling these resources and waste streams. The logistics network model uses an evolutionary algorithm to optimize the route to be the travelled by the vehicles each day using either single or multiple trucks based on facility/facilities constraints such as resource usage, current capacity level, truck specifications, and priority of supply.

The results of the mathematical model are also used as initial conditions for the power model described in section 5. The power model performs an in-depth power analysis and reports a wide variety of results to the designer. An evolutionary algorithm is presented that provides recommendations on the placement of structures and electric distribution resources on a map to reduce losses. The flexible model will assist the designer in a better selection and placement of facilities.

The models developed in sections 4 and 5 provide an extensible framework that makes it possible to incorporate information from other models into the base camp design process. In section 6 the models in section 3, 4 and 5 are incorporated into a larger base camp planning evolutionary algorithm to evaluate a holistic base camp design. As a proof of concept, a base camp layout is considered, with the logistics and power distribution models exchanging information with a higher level model to determine placement of structures to improve overall performance. The effectiveness and efficiency of the proposed approaches are evaluated on overall fuel usage and compared to other techniques.

2. BACKGROUND AND PREVIOUS RESEARCH

2.1. TRADITIONAL MULTIOBJECTIVE OPTIMIZATION TECHNIQUES

Many problems in the real world involve multiple simultaneous optimizations of several objective functions. Normally, these functions are not consistent and/or have conflicting objectives. Multiobjective optimization with those conflicting objective functions tends to lead to a set of optimal solutions instead of one optimal solution. Optimality of many solutions is difficult due to the fact there is no guarantee that any one solution can be considered better than the others with respect to all objective functions. These multiple optimal solutions in different parameters are known as Pareto-optimal solutions. Generally, in multiobjective optimization problem, any two solutions can have one of the two possibilities: one solution dominates the other solution or none of the solutions dominates the other. Nondominated solutions present in the entire search space are denoted as Pareto-optimal set.

The crucial aspect of the weighted sum method [Dhillon, Parti and Kothari, 1993; Xu, Chang and Wang, 1996] is that a set of non-inferior solutions can be obtained by changing the weights. Unfortunately, this requires multiple runs. In addition, this method cannot be applied to problems having a non-convex Pareto-optimal front to find Pareto-optimal solutions. To overcome this problem, the e-constraint method for multiobjective optimization was presented in [Yokoyama, 1998] and [Abou and Abido, 1992]. In this e-constraint method, optimization of the most preferred objective is done taking into account of other objectives as constraints bounded by some allowable levels "e". The problems with this approach are that it is time-consuming and tends to find weakly non-dominated solutions. The recent research direction is to consider both objectives concurrently as competing objectives. A fuzzy multiobjective optimization technique for solving this type of problem was proposed in [Srinivasan, Chang and Liew, 2004]. However, the solutions obtained using these techniques are suboptimal and the algorithm does not provide a suitable framework for directing the search toward the Pareto-optimal front. A multiobjective stochastic search technique for a multiobjective problem was proposed in [Das and Patvardhan, 2008]. However, the technique is computationally sophisticated, time-consuming, and the genetic drift and the search bias are severe problems that results in premature convergence. Studies on evolutionary algorithms indicate that these methods can be efficiently used to overcome most of the above problems of classical methods [Fonseca and Fleming, 2005; Farina, Deb and Amato, 2004]. Since evolutionary algorithms use a population of solutions in their search, multiple pareto-optimal solutions can be found in a single run. Based on these results, further attempts should be done to conserve the diversity of the nondominated solutions to explore the creation of more solutions.

In general, the limitations associated with classical optimization methods can be summarized as follows:

- An algorithm has to be applied many times to find multiple pareto-optimal solutions.
- Many algorithms require some knowledge about the problem being solved.
- Some algorithms are sensitive to the shape of the pareto-optimal front.
- The spread of pareto-optimal solutions depends on efficiency of the single objective optimizer.

2.2. IMPORTANCE OF EVOLUTIONARY ALGORITHMS

Evolutionary Computation (EC) is the research field of nature and evolution inspired computational methods used to solve real-world problems, and their toy scientific models. We divide the history of the EC field into two parts: early approaches proposed before the first International Conference on Genetic Algorithms (ICGA) in 1985, and modern approaches proposed after this conference. According to an analysis by [Alander, 1994] of 2500 papers published on Genetic Algorithms, Evolution Strategies, Evolutionary Programming, etc., only 215 papers were published between 1957 and 1984, compared to 928 published between 1985 and 1990. Now the number of published papers per year is still growing, and while the exact number of papers is difficult to estimate, it might lie in order of tens of thousands, given that for one of the most cited researchers of the field of evolutionary multiobjective optimization.

“The Genetical Theory of Natural Selection” by Ronald Fisher [Fisher, 1930] is probably the second most influenced book on evolutionary biology after Darwin’s book “On the Origin of Species” [Darwin, 1859]. Fisher claimed that natural selection is not evolution, as it was identified in biological sciences, but an independent principle worthy of scientific study.

Another key sub-field of Evolutionary Computation is Evolutionary Programming, introduced by Lawrence J. Fogel also in the 1960s, leading to the book “Artificial Intelligence through Simulated Evolution” [Fogel , 1966]. Fogel proposed to evolve the population of Finite State Machines (FSMs) to solve problems of prediction and control in an environment, defined as a set of sequences from a finite alphabet. Evolution strategies (ESs) [Rechenburg, 1984; Schwefel, 1975] and evolutionary programming [Fogel, Owens, and Walsh, 1966] are similar techniques but use different methods for evolving solutions.

Evolution Strategies from the beginning have addressed continuous optimization problems. Several attempts have been made to extend ESs to mixed integer optimization [Bäck and Schütz, 1995, Li et al., 2006], but unfortunately have not attracted much attention in the field. The latest results show that mixed-integer optimization is challenging and the premature convergence is possible even for relatively simple problems [Hansen, 2011, Li et al., 2011].

The Economic Dispatch Problem (EDP) is the optimal allocation of the load demand among the running units while satisfying the power balance equations and the unit's operating limits. The Unit Commitment Problem (UCP) is the problem of selecting what type of generating units to be in service during a scheduling period and for how long. In 1994, Dasgupta [Dasgupta and McGregor, 1993] presented a paper, which discusses the application of an EA to solve the short term Unit Commitment Problem (UCP). In this work, the problem is considered as a multi-period process and a simple EA is used for commitment scheduling. In 1995, [Yang, Yang and Huang, 1995] proposed an innovative EA approach to solve the thermal UCP in power generation industry through a constraint satisfaction technique. Due to a large variety of constraints to be satisfied, the solution space of the UCP is highly nonconvex, and therefore the UCP cannot be solved efficiently by the standard EA. In 1999, [Juste, Kita, Tanaka and Hasegawa, 1999] proposed algorithm to employ the evolutionary programming (EP) technique, in which populations of contending solutions are evolved through random changes, competition, and selection. In 2003, [Mashhadi, Shanechi and Lucas, 2003] proposed an improved EA to solve the UCP. In order to improve the convergence of the EA, a new local optimizer for the UCP based on Lamarck theory [Ross, 1999] in the evolution, has been proposed. This local optimizer, which tries to improve the fitness of one chromosome in the population, effectively uses the information generated in calculating the fitness.

The vehicle routing problem is known to be NP-hard (non-deterministic polynomial-time hard). To solve the vehicle routing problem, a number of approaches are proposed in the literature. To solve moderate-size problems, heuristics [Clarke and Wright, 1964] are proposed and utilized in practice. In the past three decades, several metaheuristics (e.g. Tabu search, evolutionary algorithms, simulated annealing, neural networks) have been proposed to solve the vehicle routing problems. Gendreau [Gendreau, Alain and Laporte, 1994] proposed a Tabu search heuristic to solve the vehicle routing problem with route length and capacity restrictions. Baker and Ayechew [Baker and Ayechew, 2003] developed a genetic algorithm for the basic vehicle routing problem with weight limit and travel distance limit on the vehicles. Breedam [Breedam, 1995] proposed simulated-annealing based improvement heuristics for the vehicle routing problems.

Overall, the main advantages of using EAs in solving power distribution and base camp logistics problem are:

- Self-adaptively control the entire search process through random optimization technique.
- Multiple Pareto-optimal solutions can be found in minimal number of runs.
- Diversity control of the nondominated solutions.

2.3. BUILDING AN EVOLUTIONARY ALGORITHM

An EA is a population-based optimization algorithm that uses artificial evolution to produce solutions to problems for varying difficulty, examples of which are provided in Figure 2.1 and Figure 2.2 [Nwamba, 2009]. It has three inputs: a fitness function, a representation, and a set of strategy parameters. The representation specifies the form of a candidate solution for the problem to be optimized. Commonly used examples of representations are bit strings, real valued vectors and trees. The fitness function maps each representation to a metric that determines how well that representation solves the problem. The final input, the set of parameters, controls how the EA will perform by managing how the various EA operators behave. These parameters include the population size, the offspring size and the mutation rate, among others.

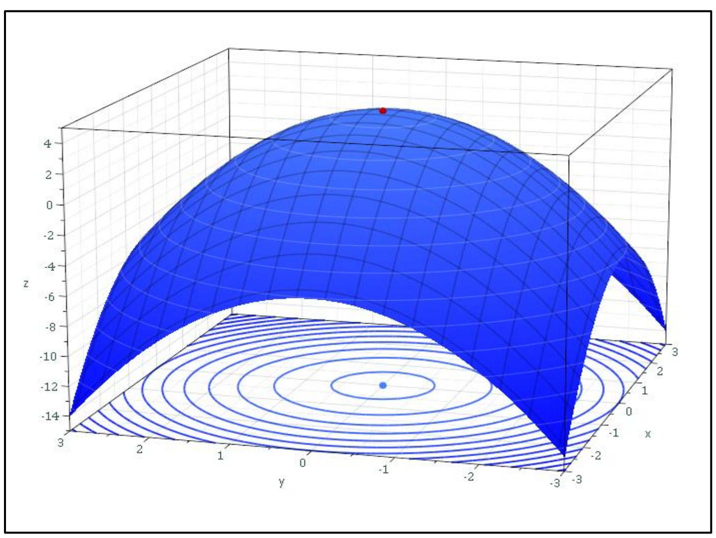

Figure 2.1. Example of Well-behaved Search Space [Nwamba, 2009].

The internal processes of a typical EA are shown in Figure 2.3. The first step is the creation of an initial population comprised of individuals encoding candidate solutions. Initialization can be performed in a variety of ways, including randomly, with a user defined heuristic, with results seeded from a previous run, or any combination of these or other methods. Each of these individuals is then evaluated and assigned a fitness value, indicating the quality of its particular solution. At this point, the evolutionary cycle begins. The first step in the evolutionary cycle is to select parents that will produce offspring. These parents can be selected in many ways, either randomly or by introducing some form of bias towards picking fitter individuals.

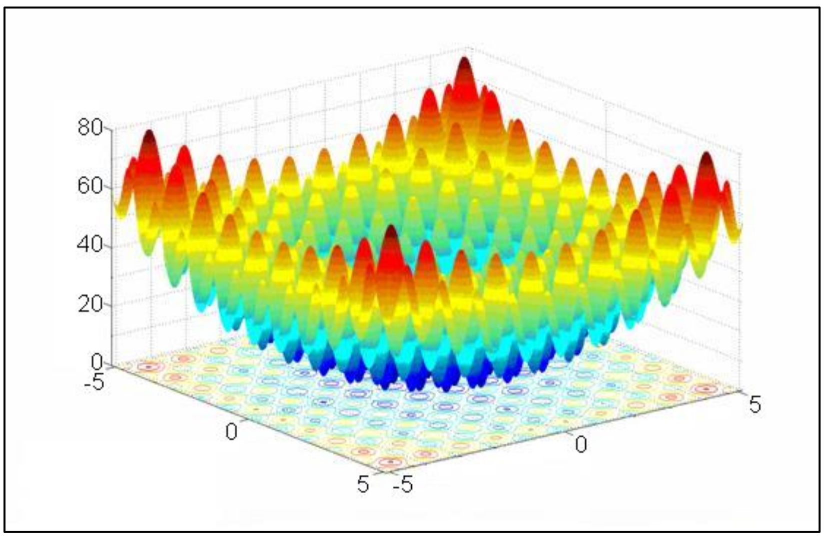

Figure 2.2. Example of an Ill-behaved Search Space [Nwamba, 2009].

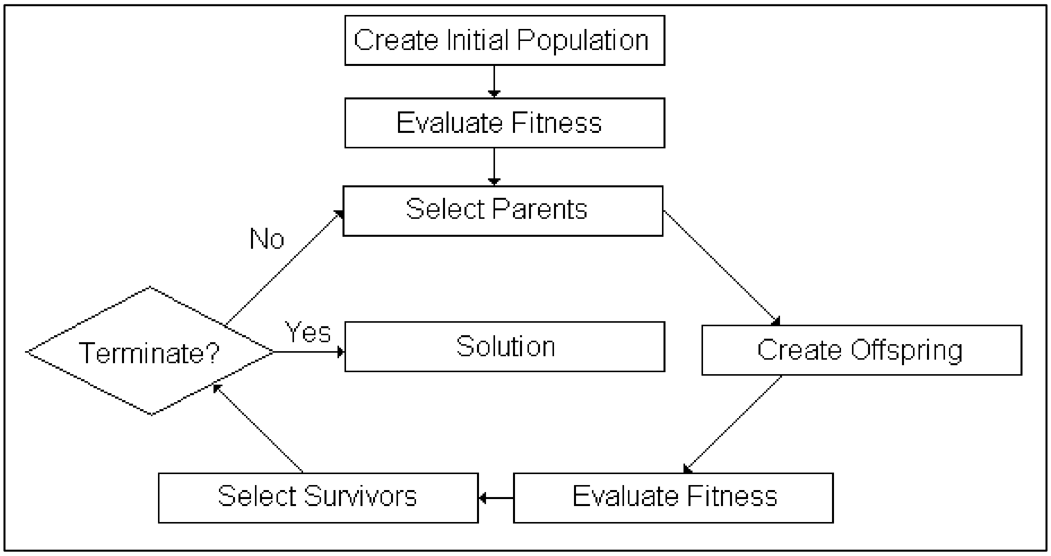

Figure 2.3. The Evolutionary Cycle [Nwamba, 2009].

After parents are selected, an offspring is created by using recombination. This results in an offspring that has some of the information contained in each parent participating in the offspring's creation. After being generated, the offspring undergoes mutation, modifying its genes slightly, altering the solution that it represents. This modification can vary significantly in severity, and might not even happen at all for a given offspring. Mutation exists to introduce new genetic material and maintain some level of diversity in the population, as without it, genes needed to produce a particularly good solution might disappear from the population entirely, assuming they were ever present to begin with. The offspring are evaluated and assigned a fitness value, just as the initial population was. The final step in the evolutionary cycle is to select survivors. These survivors will continue to exist in the algorithm and possibly generate more offspring for at least another generation.

There are many different ways to select survivors, most of which are biased towards selecting stronger individuals to survive. The survivors that are selected repeat the evolutionary cycle, creating offspring and selecting survivors until some termination criteria are met. These criteria can be based on a variety of things such as the number of fitness evaluations used, the amount of time that has passed, or the quality of the best available solution. Once the stopping criteria is met, the individual with the highest fitness value ever found produces the EAs output in the form of its encoded solution, representing the best solution that was discovered.

2.4. DIVERSITY IN AN EVOLUTIONARY ALGORITHM

Evolutionary Algorithms have been used for optimization, automatic programming, data analysis and prediction, genomics, evolutionary neural networks, and so forth [Mitchell, 1998]. Reducing computation time needed to reach optimal solutions would be beneficial. It is expected that if the initial population is more diverse, then the performance of the algorithm may be improved [Burke, Gustafson and Kendall, 2004; Zitzler, Deb and Thiele, 2000]. Usually the initial population is generated randomly and sized empirically [Eiben, Hinterding and Michalewicz, 1999]. The use of diversity can help to address the population size, at least for problems where diversity can be determined [Diaz-Gomez and Hougen, 2007].

It is recognized that diversity is important in evolutionary computation [Leung, Gao and Xu, 1997] both to avoid premature convergence [Back, 1996] and as a stopping criterion. The literature regarding population size is rich [Pelikan, Goldberg and Bayesian, 2000] and important because the initial population provides diversity to the EA

[Mitchell, 1998]. If the population's diversity is not high enough, then an optimum cannot be reached [Alander, 1992]. Further, if the population is quite large, then the algorithm could expend more computation time in finding solutions [Alander, 1992]. Additionally, the quality of the input is quite important. The initial population problem is to provide the building blocks necessary to solve the problem [Goldberg, Deb and Clark, 1992]; if there are not enough building blocks, then it is almost impossible for the algorithm to reach the goal [Goldberg, Deb and Clark, 1992].

In most of the evolutionary algorithms the search for the local optima depends on two critical processes: exploration of the search space and exploitation of the knowledge base collected during the search process. The evolutionary algorithms is said to have a good behavior when equilibrium is obtained between the two processes. If the exploitation process is dominant with respect to the exploration process, the population loses its diversity and the evolutionary algorithm remains into a situation called premature convergence. Similarly, if the exploration process is dominant with respect to the exploitation process, the evolutionary algorithm wastes too much time on exploring unwanted and uninteresting places of the search space, leading to slow convergence.

The question arises of how to control the relationship between exploration and exploitation processes, so that a good convergence can be obtained. Careful selection of evolutionary algorithm operators and their parameters can assure equilibrium between exploration and exploitation. Since exploration of the evolutionary algorithm depends directly on the population diversity, this can be considered as an importance subject which influence the exploration and exploitation processes. So, finding a suitable tradeoff between exploration and exploitation processes can be done by controlling the population diversity.

Different ways of affecting the population diversity in evolutionary algorithms are based on:

- Introducing new and ideally useful information into the population space (by replacing some bad solutions with new solutions) when its diversity level is very low [Smuc, 2002].
- Use alternatively mutation or recombination with selection, based on the current population diversity [Ursem, 2002]. The reason behind this logic is that mutation normally increases the population diversity while recombination and selection decrease it.
- Separating the population into sub-populations on which separate independent algorithms are executed, the information exchange between the sub-populations being guaranteed by a migration process. The migration can inject a "restoring" of a sub-population with low diversity [Cantu-Paz, 1999]. Since the parameters of the evolutionary algorithm greatly influence the evolution of the population diversity, the method proposed in this research combines the problem of controlling the population diversity and that of parameter adaptation are mixed with the final objective of injecting a good behavior of the algorithm.

Building blocks are answers to sub-parts of a problem which can assist in the development of good solutions to the whole problem. Building blocks are normally identified as important elements in the successful implementation of evolutionary algorithms. In this research different models are used as building blocks in understanding the structure of problem, fine tuning the EA, and eventually arriving at a good solution for the whole problem.

2.5. MULTI-TRAVELING SALESMAN PROBLEM

The idea of the Traveling Salesman Problem (TSP) is to find a tour of a given number of cities, visiting each city exactly once and returning to the starting city, where the length of this tour is minimized. The first instance of the traveling salesman problem was from Euler in 1759, whose problem was to move a knight to every position on a chess board exactly once. The standard or symmetric traveling salesman problem can be stated mathematically as follows: Given a weighted graph G = (V, E) where the weight c_{ij} on the edge between nodes i and j is a non-negative value, find the tour of all nodes that has the minimum total cost.

The traveling salesman problem has many different real world applications, making it a very popular problem to solve. For example, some instances of the vehicle routing problem can be modelled as a traveling salesman problem. Here the problem is to find which customers should be served by which vehicles and the minimum number of vehicles needed to serve each customer. There are different variations of this problem including finding the minimum time to serve all customers. We can solve some of these problems as the TSP.

In general, an algorithm that gives an optimal solution in a shorter amount of time is the best. Traveling salesman problem has been proven to be NP-hard [Bryant, 2000], so there is no known algorithm that will solve it in polynomial time. Sacrifices have to be made in terms of optimality in order to get a good answer in a shorter time. Many algorithms have been tried for the traveling salesman problem. The scheduling of jobs on a single machine given the time it takes for each job and the time it takes to prepare the machine for each job is also TSP. Here the main aim is to minimize the total time to process each job. A robot must perform many different operations to complete a process. In this research, as opposed to the scheduling of jobs on a machine, there are precedence constraints. This is an example of a problem that cannot be modelled by a TSP, but methods used to solve the TSP may be adapted to solve this problem.

To date, no efficient algorithm exists for the solution of a large scale multi-TSP, such as having multiple sources and facilities. Generally, facilities are clustered together and assigned to different trucks, thus converting the large scale multi-TSP problem into multiple small scale TSP problems. Unfortunately, a traditional greedy algorithm mechanism doesn’t help decision-makers explore the correct solution space. Also, exact solutions using greedy algorithms become infeasible as the problem size drastically increase due to large increase in computation time [Bektas, 2006]. So, in this research an evolutionary algorithm is developed to generate a range of solutions for a given search space. The ability of evolutionary algorithms to search a solution space and selectively focus on promising combinations of criteria makes them ideally suited to these type of complex decision problems.

2.6. FOBs BACKGROUND

FOBs provide critical support for soldiers during tactical operations on foreign soil. At the height of recent operations, the total number of U.S. and coalition FOBs were approximately 400 in Afghanistan and 300 in Iraq [Defense Management, 2009]. Department of Defense expenditures on FOBs show how important FOBs are to U.S. peacekeeping efforts. The annual amount of money spent on construction of FOBs increased to $6.2b from $4.5b spent by the U.S. Army Corps of Engineers (USACE) between 2002 and 2008 [Defense Management, 2009]. Table 2.1 illustrates the types of FOBs which are built depending on duration, base type and population size.

Table 2.1. FOB Types [Noblis, 2010].

By Duration					
US Army Corps of Engineers			**Contingency**		**Enduring**
	Organic <90 days	Initial <6 months	Temporary <24 months	Semi-permanent	Permanent
Army FM 3-34		Initial <6 months	Temporary 6-24 months	Semi-permanent 2-10 years	
USAREUR "Red Book"		Initial <6 months	Temporary 6-24 months	Semi-permanent 2-25 years	
USCENTCOM "Sand Book"			**Contingency**		**Permanent**
	Expeditionary	Initial	Temporary		
By Base Type	Forward Operating Base		Main Operations Base		Enduring Base
By Size	Platoon-Company		Battalion- Brigade		Division

A typical FOB (Table 2.2) may contain some or all of the following facilities based on the mission supported: life support areas, toilet/shower facilities, logistical support facilities, dining facilities, postal facilities, laundry collection and distribution point, aviation facilities, communication and network center facilities, medical facilities, motor pool facilities, fuel storage facilities, waste collection facilities, ammunition supply points, training facilities, morale-welfare-recreation (MWR) facilities, mortuary facilities, fire protection , force protection, barber facilities, tailoring facilities and detention centers [Department of the Army, 2008]. Other types of FOBs have variations of the above facilities in terms of equipment used and the number of people the facility can support. Based on Table 2.2, five different sizes of base camps are constructed, to test the efficiency of EAs developed in this research. The components involved with all the five base camp sizes are carefully chosen in such a way that the layouts represent a very small, small, medium, large and a very large size base camp.

Table 2.2. Facilities Modeled for Battalion Size (600-1000 soldiers).

Dining Facilities	Parking Lot	Direct Exchange	Wastewater Treatment	Training Area
Laundry	Motor Pool	Barber	Solidwaste Treatment	Tailoring
Kennel	Ammunition Holding Area	Religious Services	Security Checkpoint1	Mortuary
Latrines	Direct Support Maintenance	Electrical Generators	Security Checkpoint2	Military Police
Showers	Fire Protection	Electrical Distribution	Tactical Operations Center	Bunkers
Medical	Supply Warehouse	Water Purification	Administrative Services	Airfield
Communication /Network Center	Postal facility	Water Storage	Morale Welfare center	Staging Areas
Housing	Roads	Water Distribution	Educational Services	Detention Areas

The designs used in the planning of U.S. Army base camps, Life support areas, Advanced operations base, etc., have not changed considerably in the last 200 plus years [Department of Army, 2009]. The current capabilities of the U.S. Army do not address base camp problems from a holistic systems based approach. Lack of systems based approaches has resulted in poor designs and operations maintenance in-terms of health and safety, loss of operational flexibility and excessive capital and operating costs (i.e. cost of utilities/unit and overall capital/soldier/year). Inefficient design resulted in excessive consumable resource demands namely fuel, water, and food.

2.7. NEED FOR OPTIMIZED TECHNIQUES

The optimized techniques for logistics distribution inside the base camp considering priority based on-demand supply of resources at each facility will be able to increase the efficiency of the operation of the facilities and decrease the fuel consumed by the delivery trucks. The current scope of FOB discussed in this research includes base camps of different sizes ranging from 50 to 2,000 personnel. For base camps of these sizes Potable Water, Sanitary Waste (Grey and Black Water) and Solid Waste are handled by on camp logistics vehicles using trucks and tankers.

Planning techniques and the policies [Trainor, Brazil & Lindberg, 2008] for building FOBs vary widely between different camps. Manuals such as ‘Redbook’ [Contingency Operations, 2001] and ‘Sandbook’ [United States Central Command, 2009] serve to create some guidelines for FOB planning; however, these resources are theatre specific, and do not contain adequate data regarding resource utilization, which is much-needed information for logistical planning. Very little data seems to have been collected regarding resource utilization for FOBs, leading to increased difficulty in base camp planning. These in turn create inefficiency, waste, and longer lead times in deployment of essential facilities and force protection, which may increase risk exposure to Soldiers. Poor planning of FOBs can result in logistical difficulties, which may increase transportation time and expense, and increase risk exposure to convoys and support personnel.

When considered from the point of view of a city planner, power utilities and logistics require a long-term perspective and long-term infrastructure operation and maintenance commitments. From a financial perspective, investment decisions based on cost benefits will be realized only over a long period of time. In this case, all the utility infrastructure investments throughout all the utility sectors could best be forced through the planning that takes place in the development phase, before the infrastructure solutions are selected and designed [Planning for Sustainability, 2012]. The mission of the entire city planning from utilities perspective is to provide utilities which are in compliance with all applicable standards at an affordable price. Unlike cities, most base camp facilities share interdependencies with other facilities, requiring coordinated strategies to improve resource utilization. Because of this, base camp design requires a system-wide approach to planning, which can drive a strategic shift from a facility-by-facility focus to one of utilities as systems.

With proper techniques, the models can be used to optimize the logistic needs inside the camp and eventually minimize fuel consumption and logistic delivery cost. Optimization and redesign of the utility input and output streams will be critical in developing a more sustainable FOB; in terms of how much of these streams can be converted to Power, Fuel and Energy.

A need exists for standardization and modularization in base camp planning in order to increase the efficiency and operational effectiveness of FOBs. Preliminary research efforts are being undertaken to develop methods of modeling and designing of FOBs using a general approach so that they may be applied to various mission types.

2.8. INTERRELATIONSHIPS BETWEEN FACILITIES

Figure 2.4 and Figure 2.5 show some of the feedback loops between the models and the data that need to be taken into consideration while planning. Different colors in Figure 2.4 and Figure 2.5 represent different modules and utilities. The complex interrelationships between the models and the data represent the dynamic operating systems of a FOB. The data and system analysis are unique to each model and the interaction with other models makes the FOB a complex system. Some other interrelationships that should be taken into account include, for example: the greater the number of generators in the design, the greater the fuel usage and so more personnel are needed to support the fuel delivery and maintenance. Or higher bottled water usage generates more solid waste and so more trucks are needed to pick up the solid waste. Proper understanding of the complex interactions between base camp subsystems makes it possible to develop models and algorithms required to find and eliminate sources of inefficiency currently found in FOBs.

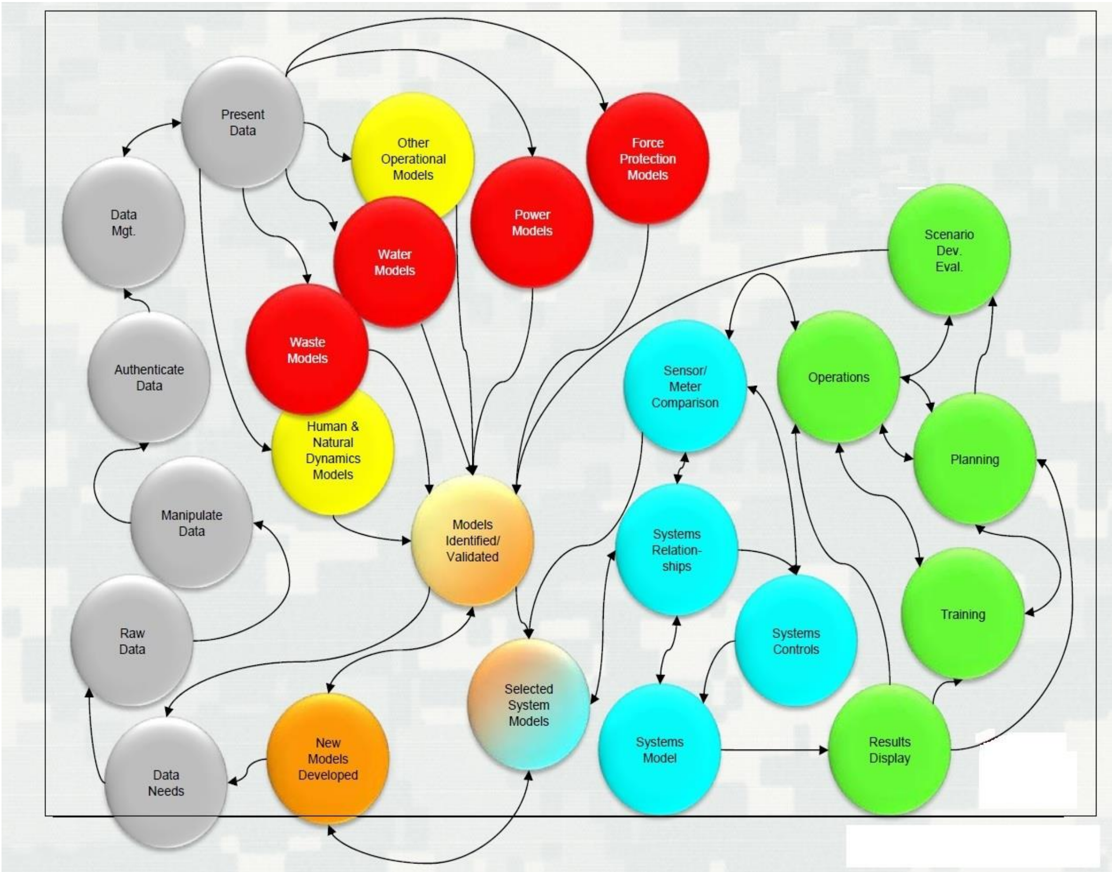

Figure 2.4. FOB Feedback Loops.

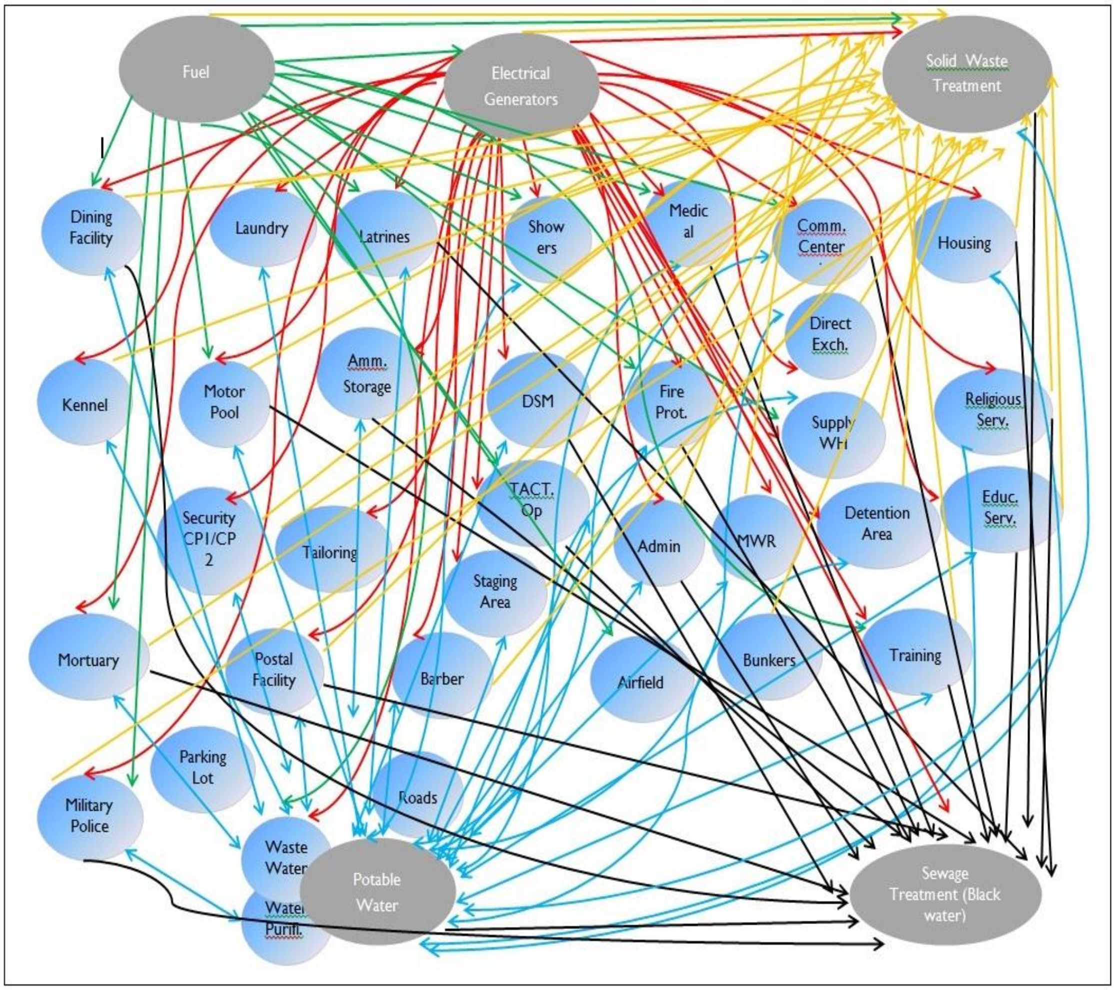

Figure 2.5. FOB Facilities Interactions.

2.9. NEED FOR ACCURATE ESTIMATION OF RESOURCES

Accurate estimation of the resource requirements namely power, fuel, water and waste taking into consideration different operational parameters is critical to improve the efficiency and effectiveness of operations and life cycle impacts. The overall approach should integrate all the complex adaptive systems involved for use in a real time predicative and analytical manner. Inaccurate estimation of the resource demands resulted in shortage of resources, which affected the day to day operation of the base camp. The fact that no life cycle approach has been taken into consideration while planning has resulted in U.S. Army competing with host nations for local resources, which had a detrimental impact on the overall mission. The better the estimation of the resources, the better is the overall efficiency of the FOB.

To apply a systems engineering approach with regard to improving FOB design, it is necessary to understand how existing FOB subsystems interact and operate. A systems engineering methodology should be applied across all three functional components of base camp development: planning/design, construction/deconstruction, and operations/management [Department of the Army, 2009]. Advanced planning of resource utilization should not only result in reduced government expense but in lower risk exposure to personnel during logistical operations.

2.10. PREVIOUS WORK

There are only a few tools currently available in modeling of base camps, such as Theater Construction Management System (TCMS) and Geographical Base Engineer Support Tool (GeoBEST) [United States Army, 2011]. The tools provide a list of base camp and facility designs to help the base camp planner. But the present techniques used in modeling base camps in both the tools involve static models, where coupled effects of interdependencies are not taken into account, making the existing models less efficient in terms of resource estimation [Marlart, 2003]. Some of the other interrelationships that have to be taken into account are, for example: more the number of generators in the design more is the fuel usage and so more personnel are needed to support the fuel delivery and maintenance. Another example could be, more bottled water usage generates more solid waste and so more trucks are needed to pick up the solid waste. Proper understanding of the complex interactions between base camp subsystems will make it possible to develop the models and algorithms required to find and eliminate sources of inefficiency currently found in FOBs. In this research, a resource calculator that focuses on methods is introduced for improving the efficiency of FOBs by accurately estimating the quantities of resources required by a given FOB based on its operational parameters. The resource calculator introduced is a dynamic model which takes into account all the important aspects of the base camp.

The Detail Component Analysis Model (DCAM) and tool were developed using the research performed by Putnam [2012]. The main intent of the research was to make a realistic model of a 150-man Force Provider Kit. Other goals of his research were to reduce the number of components used by changing the layout of the design by increasing the efficiency of components. The kit is a collection of prior known components that are normally sent to the base camp location. Research performed by Gealy [2012] looked into general logistics modeling and project management practices for contingency basing. Research performed by Nottage [2014] looked into using adaptive agents and hybridization of those agents to improve resource allocation in dynamic systems and environments. The agents developed are applied to base camps using Model-based Systems Engineering (MBSE) processes to accomplish the goals. Although, all the researches were really efficient internal to a particular model, none of the improvements particular to a model could be transferred to other models/tools for a better overall base camp design.

3. MATHEMATICAL MODEL FRAMEWORK

Operational and logistical inefficiencies, excessive resource demands, and increased costs are some of the issues caused by poor initial planning of contingency bases. Base camp planning requires broad support across a diverse set of personnel, which includes designers, planners, soldiers and maintenance personnel. After identification of a need for a FOB, designers and planners adopt different tools to model the facilities. The occupants, namely the supported units will add extra details to the design and the contractors and/or soldiers then start construction of the facilities. During the optimization of FOBs, concerns from all the parties must be taken into account. The whole planning process is the result of balancing various compromises between mission effectiveness and overall cost of construction, operation, and maintenance by continuously altering the design at each step.

The U.S. military is currently seeking methods to increase the effectiveness and efficiency of base camps, driven largely by the amounts of money being spent on fuel and water logistics for FOBs. Finding ways to reduce costs while maintaining operational effectiveness and flexibility are key Department of Defense (DoD) priorities. One key area of emphasis is finding ways to minimize the logistical footprint of FOBs by developing more effective resource allocation schemes. Finding ways to increase efficiency without reducing effectiveness of base camp operations will lead to reduced requirements for contractor support systems and personnel.

The mathematical model introduced in this section, helps the planner to accurately understand and modify the coupled effects of logistics, and also allows helps in identifying missing data for the design under consideration. The dynamic architecture model provides designers with a flexible tool for base camp design and operational evaluation of facilities, and is extensible to allow for other dynamic design tools, such as automated generation of power distribution system design for the base. The output of the mathematical model allows the designer to make a better selection regarding the quantity and type of facilities required to increase the base camp's operational effectiveness and logistical support system capabilities. Once a combination of facilities are selected by the designer, the logistic model in section 4 and power model in section 5 can be used for in-depth analysis.

3.1. METHODOLOGY

Applying systems engineering approach to the design of base camps requires a thorough understanding of the sub-system interactions within a FOB. Mathematical modeling of FOBs [Poreddy & Daniels, 2012] begins with identifying the various functional blocks or structures acquired from structural diagramming of FOB subsystems. Forty facility types were identified and necessary mathematical relationships were developed. This model was developed using an abstract modeling technique to represent the resource requirements for bases of various sizes. For the purpose of developing the mathematical model we will use a hypothetical base camp involving 600 operational soldiers performing the mission, and the necessary support personnel to operate the base camp.

Each facility within the base camp is treated as an 'object,' with its own input and output parameters. These parameters are the resource requirements of the object and resources created by the object. The primary resources are:

1. Electricity (Watts): The total electricity that will be consumed/generated
2. Fuel (Gallons): The total fuel required
3. Potable Water (Gallons): Total potable water consumed across all facilities
4. Bottled Water (Gallons): Total bottled water consumed across all facilities
5. Storage area (Sq. ft.): Storage space used across all facilities
6. Personnel (Number): Number of support personnel required
7. Gray Waste Water (Gallons): Waste water (Gray) generated from all the facilities
8. Black Waste Water (Gallons): Waste water (Black) generated from all the facilities
9. Solid Waste (lbs.): Total solid waste generated from all the facilities
10. Food Service (lbs. of food/day): Food consumed per day
11. Footprint (Sq. ft.): Total footprint area
12. Maintenance (Hrs. per day): Total Maintenance hours for all the facilities

Many of the base camp facilities will be mission specific and user defined. For example, the planner may decide that the base camp requires a kennel. A kennel is a mission-specific facility; however, it will generate demand for water, power, support staff, waste management, and other resources. This will have a discrete impact on the base camp, for example, more support personnel requires more habitation, which in return will result in more power and water demand, which in return will require more power and water personnel. The model should capture all the important interrelationships between the forty facilities and the important resources. The calculation of the overall resource requirements should take into account all the changes in the interrelationships every time. Based on the relationship, a change in the resource requirement not only changes the requirement of that structure but may affect other structure resource requirement.

3.2. ESTABLISHING THE MODEL

Some of the individual consumption/generation numbers for the FOB facilities are taken from the field manuals, although a significant amount of data was generated during the project with the cooperation of Department of Defense personnel. This was necessary to compensate for a general lack of available data. This data was generated using a combination of observations from United States Army Corps of Engineers personnel and the results of engineering estimations to provide realistic representations of base camp components. The average distributions of the combination of observations are used as coefficients of linear equations. The set of linear equations are solved at the end of the simulation to calculate the resource needs of the base camp considered.

Figure 3.1 represents the overall resource calculator block diagram. Number of soldiers, Mission type and Geographic location form the overall inputs of the resource calculator. All the consumption/generation numbers of the FOB facilities are used as coefficients of set of linear equations. A set of initial coefficients based on the past data are used to solve a list of equations, and the outputs represent the 12 requirement needs for that base camp size. The coefficients are further refined by taking into account a combination of subject matter experts' advice plus linear distributions of the past data. Once the refined coefficients are available, the list of equations is solved again with the updated coefficients to get the final 12 resource requirement needs for the base camp under consideration.

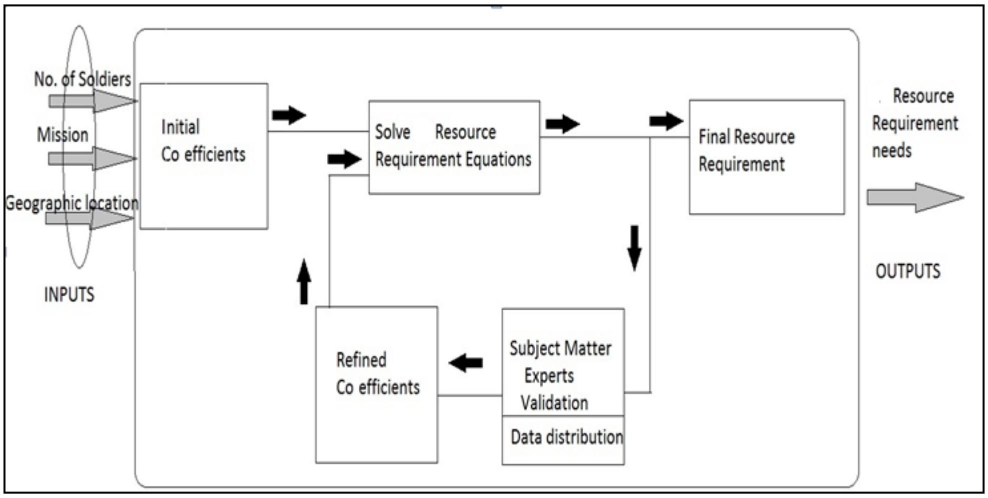

Figure 3.1. Resource Calculator Block Diagram.

The initial coefficients and the linear distributions used in the simulation vary a lot based on the number of soldiers selected, mission type and geographic location. From the data gathered and generated for the model, a system of approximately 500 linear equations was compiled to represent the resource inputs and outputs of all the facilities. With any incremental change in resource requirements, the system of linear equations is re-solved to compensate for the change. An advanced integrated linear algebra equation solver module was written in python programming language to solve the equations on the go and calculate the total estimated resource values for all facilities based on the interdependencies between facilities in the base camp. Table 2.2 and Table 3.1 show some of the list of facilities that were taken into account while modeling a 600 soldier sized camp and 200 soldier sized camp.

Table 3.1. Facilities Modeled for Force Provider Size (100-200 soldiers).

Dining Facilities	Electrical Distribution	Force Protection	Housing	Latrines
Laundry	Showers	Tactical Operations center	Water Distribution	

Equation (1) and Equation (2) are sums of the total electricity and diesel fuel consumed across all facilities inside the battalion sized FOB. Similar equations exist for potable water, bottled water, required storage area, support personnel, gray water and black water waste, solid waste, food service, total camp area, and maintenance hours required. The code snippet shown in Figure 3.2 shows how the array values are set up in solver for a Dining Facility. Figure 3.3 shows the constants used in the solver for calculating the total resource requirements for a 600 soldier sized camp. A similar procedure is used to set up the array values for each of the remaining 39 facilities listed in Table 2.2. No entry for a coefficient in the model is substituted by taking a linear average distribution of past data.

ElectricityConsumedkW = $\sum_{1}^{40} Electricity\ Coefficient(i) * \ Facility(i)$ ------ (1)

DieselFuel = $\sum_{1}^{40} DieselFuel\ Coefficient(i) * \ Facility(i)$ -------- (2)

Resource calculator introduced in this section has significant advantages over the existing methods used for base camp planning such as:

1. Present techniques used involve static models, whereas resource calculator introduced in this section is a dynamic model which takes into account different aspects of the base camp like mission, location and size of the camp.
2. The dependencies between facilities for each base camp can be easily accessed and modified.
3. The resource calculator takes minimalistic run-time in executing the code for a proposed base camp design.
4. The resource calculator could be used to drive other detailed engineering analysis tools such as serving as input to power distribution analysis tool.
5. The resource calculator could be easily tied to external problem solvers such as Evolutionary algorithms to add intelligence to the overall design and to study the overall mission dynamics.

Sample 12 Dining Facility Coefficients		
Electricity	0.225	
Fuel	0.04	
Potable Water	0.15	
Bottled Water	0.6	
Storage Area	0.267	
Personnel	0.1	
Gray Water	0.06	
Black Water	0.08	
SolidWaste	0.3	
Food	0.9	
Footprint	0.07	
Maintainence	0.235	

Figure 3.2. Dining Facilities Array Numbers in Equation Solver for a Battalion Size.

Figure 3.3. Constants Used in Equation Solver for a Battalion Size.

3.3. OUTPUTS OF MATHEMATICAL MODEL

Figure 3.4 shows the output of the solver code which is the cumulative total consumption/generation across all 40 facilities modeled for a 600 soldier sized base camp. Figure 3.5 shows the output of the solver code which is the cumulative total consumption/generation across all 9 facilities modeled for a 200 soldier sized base camp.

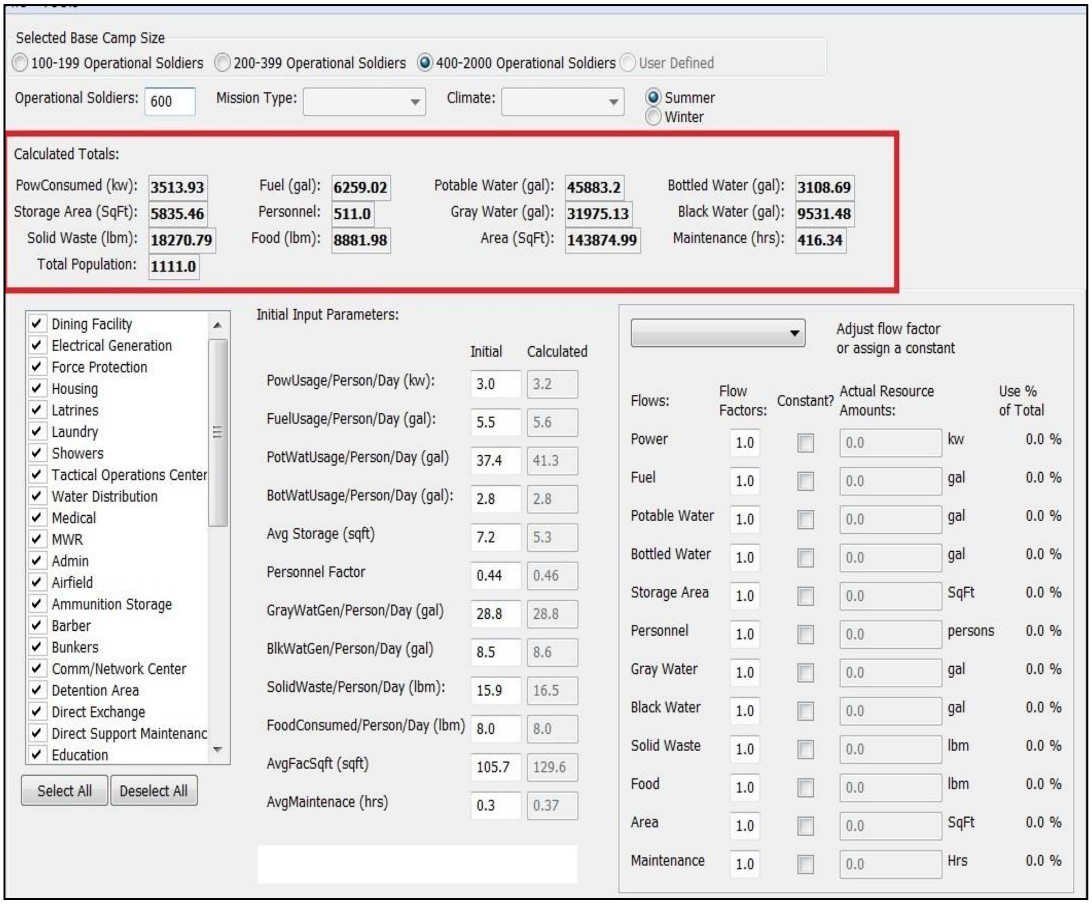

Figure 3.4. Total Consumption/Generation Numbers across all 40 facilities- Battalion Size (600 soldiers).

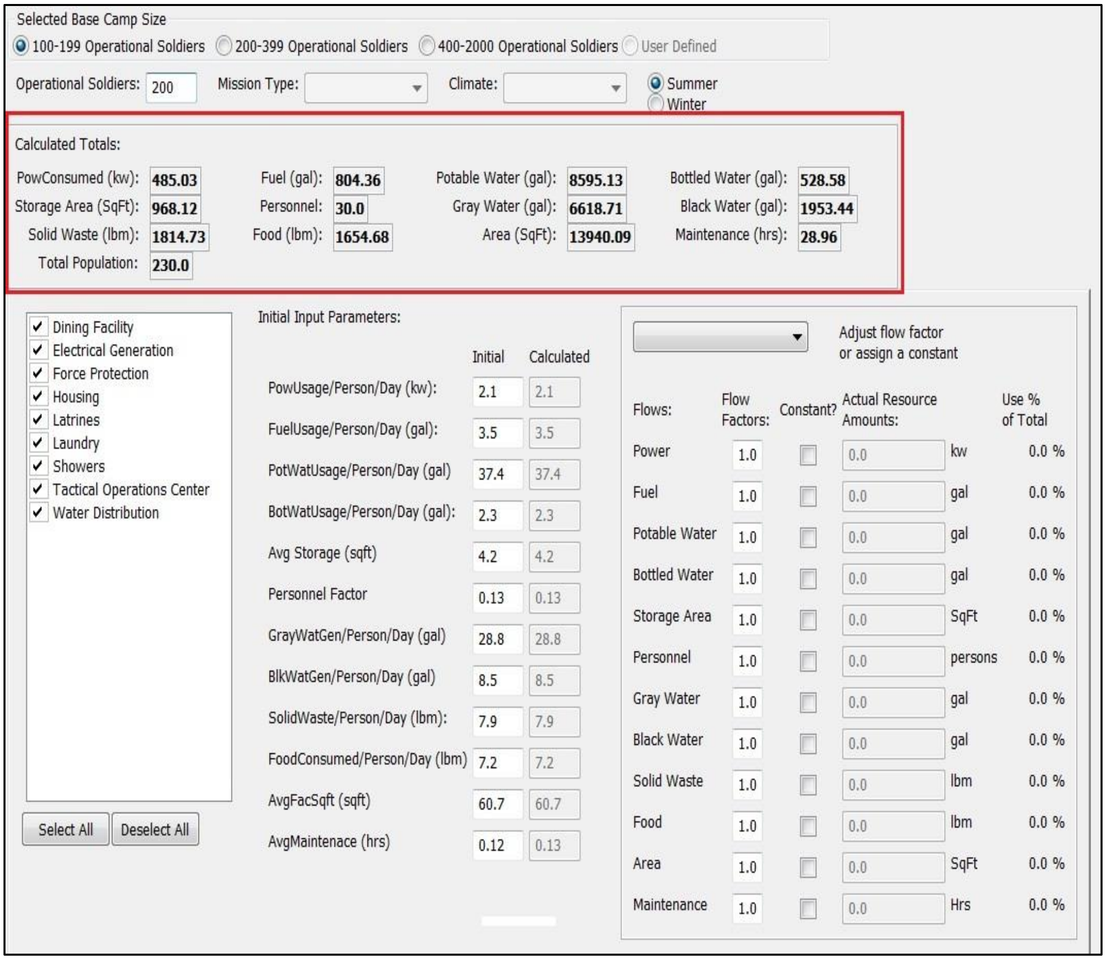

Figure 3.5. Total Consumption/Generation Numbers across all 9 Facilities- Force Provider Size (200 soldiers).

3.4. EXISTING METHODOLOGIES COMPARISON

Table 3.2 is the current utility requirement estimation methodology used by planners which only takes into account of the number of soldiers on base [Noblis, 2010]. The utility requirements per person per day are constant for base camp size ranging from 500 to 10,000 (Table 3.3). Using this general estimation methodology for all the base camp sizes ranging from 500 to 10,000 resulted in over-estimation of resources for small base camps and under-estimation of resources for large base camps. The over and under estimation of resources for different base camp sizes is a result of the general estimation methodology not giving high importance to the number and types of facilities for different base camp sizes.

Table 3.2. General Utility Requirements Using Existing Methodologies [Noblis, 2010].

Base camp size	Potable Water (Gallons Per Day)	Sewage (Gallons Per Day)	Electricity (KW)
100 (Very Small)	2,500	1,750	36.4
300 (Small)	7,500	5,250	109.2
500 (Medium)	12,500	8,750	182
1,500 (Large)	37,500	26,250	486
3,000 (Very Large)	75,000	52,500	988
10,000 (Super FOB)	250,000	175,000	3,293

Table 3.3. General Utility Requirements (Per Person Per Day) [Noblis, 2010].

Base camp size	Potable Water (Gallons Per Day/Person)	Sewage (Gallons Per Day/Person)	Electricity(KW/day/ Person)
100 (Very Small)	25	17.5	0.364
300 (Small)	25	17.5	0.364
500 (Medium)	25	17.5	0.364
1,500 (Large)	25	17.5	0.364
3,000 (Very Large)	25	17.5	0.3293
10,000 (Super FOB)	25	17.5	0.3293

Table 3.4 reports the results of the dynamic mathematical model introduced in this section for different base camp sizes. The model considered number of factors such as the number of soldiers on base camp, mission provided, number of facilities, type of facilities and location information before estimating the utility requirements for different base camp sizes. Table 3.5 tabulates the results from the mathematical model for different base camp sizes. When compared with existing methodologies the results from the model introduced indicate a more accurate representation with less usage of utility requirements (per person per day) for smaller base camps and high usage of utility requirements (per person per day) for larger base camps.

Table 3.4. General Utility Requirements Using Dynamic Mathematical Model.

Base camp size	Potable Water (Gallons Per Day)	Sewage (Gallons Per Day)	Electricity (KW)
100 (Very Small)	4,300	4,300	243
300 (Small)	15,550	15,529	939
500 (Medium)	38,236	34,589	2,928
1,500 (Large)	114,708	103,769	8,784
3,000 (Very Large)	124,200	123,900	10,500
10,000 (Super FOB)	413,000	410,000	35,000

Table 3.5. General Utility Requirements (Per Person Per Day).

Base camp size	Potable Water (Gallons Per Day/Person)	Sewage (Gallons Per Day/Person)	Electricity (KW/day/Person)
100 (Very Small)	37.4	37.3	2.1
300 (Small)	37.4	37.3	2.3
500 (Medium)	37.4	37.3	3.0
1,500 (Large)	37.4	37.3	3.0
3,000 (Very Large)	41.4	41.3	3.5
10,000 (Super FOB)	41.4	41.3	3.5

3.5. GOODNESS OF FIT TEST FOR LINEARITY

Although, the model only solves linear equations, the model takes into account lot of non-linearities. The non-linearities are handled by the model through facility interrelationships. If the shower facility has an increase in potable water usage, then this would extend to the overall water distribution system as it requires more transportation of water. More transportation increases the fuel requirements. Since the model is an iterative process, the non-linearities are continuously taken into account through the change in coefficients in the next iteration and solved again. Effectively the coefficients in the model in one iteration become cross-correlation coefficients in the next iteration. It should be noted that the coefficients for these facilities are not linearly scalable.

Larger size camps coefficients and values will not always work for smaller camps. Each coefficient has an associated soldier population range it is accurate for. Some coefficients, especially for smaller base camp’s facilities have constants instead of percentages. For example, a medical facility requires 2 personnel, regardless if there are 50 soldiers or 100 soldiers.

With a significance level (alpha = 0.05) and degrees of freedom (=3), the test statistic ($X^2 = \sum ((Oi - Ei)^2 / Ei)$) becomes 0.3 (Table 3.6). Since the calculated value does not lie in the critical region for this observation. There is no evidence, at the 5% significance level, to suggest that the model is not fair in terms of linearity.

Table 3.6. Chi-square Test for Goodness of Fit (For 300 Soldier Size Base camp Power Model Samples).

Score	Oi	Ei	$(Oi - Ei)^2 / Ei$
1	2.8	3.0	0.013
2	3.2	3.0	0.013
3	3.8	3.0	0.213
4	3.0	3.0	0

3.6. VALIDATION OF MATHEMATICAL MODEL

Validation of mathematical model was done in multiple stages where a subject matter expert (Department of Defense (DOD) personnel) was in the loop of this model to validate the coefficients used to solve a particular base camp size, and the overall results. Some of the data was generated using a combination of observations from United States Army Corps of Engineers personnel and the engineering estimation results to provide realistic representations of base camp components. The average distributions of the combination of observations are used as coefficients of linear equations. With any type of change in resource requirements, the systems of linear equations are re-solved to compensate for the change. No entry for a coefficient in the model is substituted by taking a linear average distribution of past data. If past data is missing, data is collected from multiple subject matter experts who worked on similar locations, and using the above procedure, it is refined further to suit that particular type of base camp size. In addition to the soldiers on the base camp, the model considers the contractors associated with the base camp and their dependencies and coupled effects of facilities on other facilities.

After running the model for numerous combinations involving number of soldiers, mission type and geographic locations with selected facilities, the results and other facility data were distributed to numerous DoD personnel who designed and worked on similar environments to test the validity of the data. Positive feedback was given by the most of the personnel who verified the validity of the data, although the given military nature, the true values of an exact base camp type and facility combinations cannot be given in this work. Part of the feedback was suggestions on how the model can be further improved by adding/modifying existing facility components to make it even more accurate. When compared with existing policies [Noblis, 2010] where there is no holistic systems approach, the mathematical model started with treating each facility/component as an object having variety of properties which can be passed on to other objects. All the interactions in the mathematical model considered were different, based on the type of camp and also tailored to fit wide variety of conditions. In comparison, the existing policies are very generic in nature, where similar principles are used in estimating the resources needed for all the types of base camps.

3.7. COMPARISON WITH METERED DATA

In order to do a direct comparison between the mathematical model and existing model (Noblis, 2010); to the best of the knowledge the camp site and other parameters information are simulated in the mathematical model. The data from the mathematical model is then directly compared with the existing data (Noblis, 2010) related to a particular site. The U.S. Army Logistics Innovation Agency (LIA) is currently metering energy consumption on three contingency bases as part of its Contingency Base Demand Data Collection project. Given the military nature, the values of all the utilities and camp site information cannot be given in this work. Only few metered utility consumption values recorded will be used from the report [Contingency Base Demand Data, 2015] to compare data from the mathematical model to the [Noblis, 2010]. Three different types of base camp metered energy values for six types of facilities provided in the report [Contingency Base Demand Data, 2015] were used for comparison purposes. An example comparison is discussed below.

- Metered shower facility peak power [kW] from [11] = 33 kW
- Estimated shower facility value (from mathematical model) = 30.47 kW (-8% deviation from metered value)
- Estimated shower facility value (from [Noblis, 2010] report) = 22 kW(-33% deviation from metered value)

When compared with existing methodologies (maximum of 42% deviation from the metered value for six types of facilities), the results from the mathematical model introduced in this research indicate a more accurate representation (maximum of 16% deviation from the metered value for six types of facilities) of the base camps with less usage of utility requirements (per person per day) for smaller base camps and high usage of utility requirements (per person per day) for larger base camps. The results of this model using this mathematical representation provided a better representation of the actual needs on a base camp when compared to previous methods [Noblis, 2010].

3.8. BENEFITS OF MATHEMATICAL MODEL

The model introduced in this section is used to estimate the resources required for each subsystem and for the overall base camp. The results of this model using this mathematical representation provided a higher level of accuracy when compared to previous methods [Noblis, 2010], although the given the military nature of the true values a comparison cannot be given in this work. The model framework is being applied to a forward operating base to synchronize all of the components of utility and logistic systems to deliver the right materiel at the right time to the right place. The information from the model can be used immediately by planners to improve FOB designs as well as logistical support systems [Bastian, 2011].

The dynamic mathematical model in combination with external algorithms add intelligence to the overall base camp design and allows the manager/decision maker to study overall mission dynamics. In addition to the soldiers on the base camp, the model considers the contractors associated with the base camp and their dependencies and coupled effects on other components.

Since model takes into account the first, second and third order effects of all components involved, the elements of the model can be modified and used for other complex system problems where there is a need to predict the resource utilization and associated interactions of each component present in the design. The framework easily allows the planner to do sensitivity analysis of required utilities for different base camp designs. The analysis could be used to check where the design might potentially break and subsequently giving the design planner a chance to improve the overall design.

The framework could be further extended to provide the link between the energy system modeling software to the base camp system level model and the other lower level system needs. The models could be used to educate/train new personnel involved with the base camp. The mathematical model could also be used to drive in-depth analysis models which would assist the designer by calculating the exact needs of each component. For example the energy system model may be composed of individual electrical component models, which populate the electrical distribution system models, which are tightly coupled to the logistics, fuel, and manpower models, invoking behaviors which are translated to the appropriate component models.

The information available with this model can also be used within an advanced design tool discussed in section 8, which has been proposed for automating and optimizing the design process of FOBs. Such a tool would be very useful for base camp planners in visualizing an FOB before it is created, or to visualize proposed changes to an existing FOB. These tools would lead to an increase in efficiency of resource utilization for FOBs, with the goal of reducing government expenditures and decreasing risk exposure to convoys and logistical support personnel.

4. LOGISTICS MODEL

4.1. CURRENT BASE CAMP LOGISTIC DISTRIBUTION TECHNIQUES

For most base camps, tactical assets are used for logistics delivery, when the delivery is done by the Army. When the contractors do come into delivery process for logistics delivery, they follow their own policies for delivery. If in case, a logistic delivery such as potable water is delivered using a tanker, remaining water after initial delivery is dumped just as a safety precaution. When it comes to bulk fuel delivery, estimated fuel (which is normally little less than the maximum storage capacity) is delivered by trucks and the remaining fuel if any is completely emptied into the storage system. Wastage pickup follows a similar logic like potable water: wastage from each facility is dumped at a collection point individually by the tactical assets. Multiple round trips by the tactical assets consume extra fuel creating a big inefficiency in the delivery scheme. So, there is a big need for accurate estimation of the logistics needs and efficient logistic delivery schemes to be followed inside a base camp to reduce the wastage of logistics.

Base camp logistic delivery planning can be considered as a type of multi-TSP, but not a straight forward TSP. Base camp logistic delivery planning involves delivery of logistics using multiple delivery trucks to multiple facilities present on camp every day. Thus, each facility in the camp must be visited exactly once by any of the trucks. The key characteristics of the multi-TSP problem under consideration are to determine the source (single source, or multiple sources) and destination (fixed destination, or non-fixed destination for the overall multi-level EA). In the logistic planning case, all trucks depart from a single source. Additionally, every truck must return to the starting source thus has a fixed destination. In addition to the above conditions, there are other conditions that have to be considered are listed in section 4.2., which makes it a multi-objective optimization, where finding a good solution in terms of optimal distance and processing speed have to be taken into account by all the algorithms, which could solve this problem.

4.2. GENERAL LOGISTIC MODEL

Figure 4.1 depicts a simple model [Gealy, 2012] of how logistics is handled inside the base camp. Each of the facilities (up to 200 facilities) inside the base camp is assumed to be connected to a local bladder of known capacity that is periodically filled by the logistic vehicle, which is either a truck or a tanker. Vehicles of known capacity are assumed to deliver logistic supplies inside the base camp based on the usage rate of each facility. Some of the facilities are assigned higher priority than other facilities, and those local bladders will be filled more regularly. The goal of this model is to optimize the route to be travelled by the logistics vehicles with set of constraints, using single/multiple trucks based on the resource needs of different facilities.

The main goal in this model is to optimize the route travelled by one truck/multiple trucks at the start of the day, based on distance and priority of the facilities with following constraints taking into account.

1. The route should start from the source bladder, and if you run out of a logistic in the truck for example: water, the truck can only return to the source for refilling of water.
2. Each truck has its own capacity (e.g. 5,000 gallons) and vehicle specifications (e.g. fuel consumption, connect/disconnect times).

3. Each facility has its own consumption (e.g. 10,000 gallons/day) and Capacity (e.g. 20,000 gallons local bladder).
4. Each facility has its own minimum and maximum capacity level of the local bladder that it prefers to be maintained at.
5. At the start of the simulation, the initial water level for each local bladder is known.

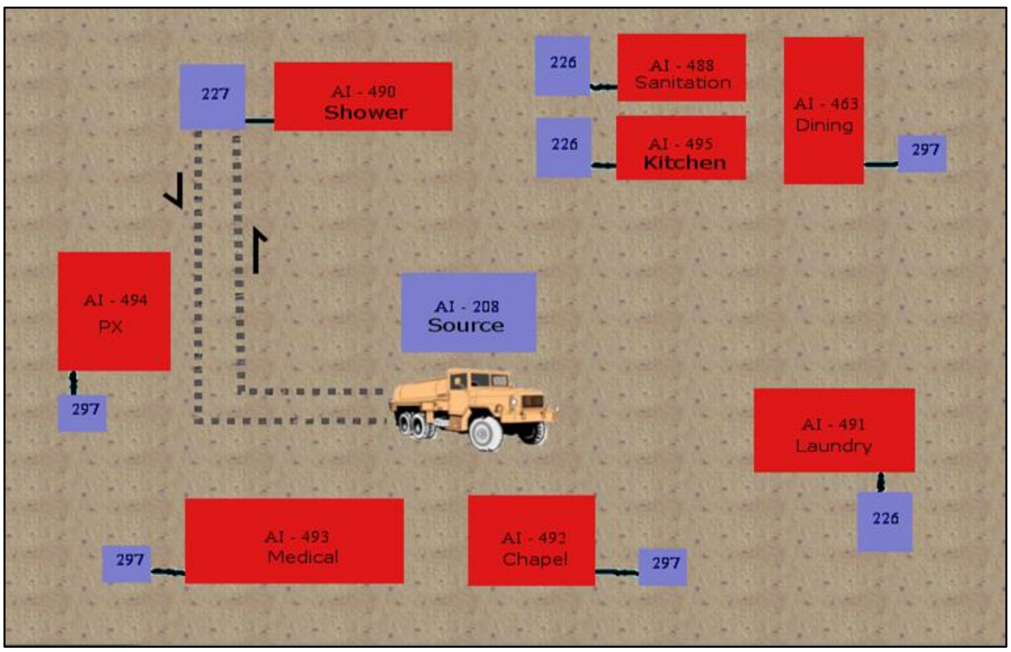

Figure 4.1. Simple Logistics Model.

4.3. EA INITIAL SETTINGS

Before running the simulation it is assumed that the minimum and maximum water levels maintained at all the facilities are known. All the initial values, truck specifications, initial water levels, and the usage rates are stored in a data base. The algorithm iterates through a preset number of days, to determine the routes that will be followed to maintain the water levels within these bounds. At the start of each day, the algorithm will check each facility to determine, whether the water level has gone below the minimum required level. If the water level of any facility goes down below the minimum required water level, that facility is added to a list that must be serviced that day. The algorithm optimizes the distance to be travelled by the truck with the priorities of the facility/facilities taken into account. The optimized schedule for the truck recommended by the algorithm is based on the above considerations ensuring that a sufficient amount of water is delivered by the truck on that day, and that the delivery eventually increases the water level of the facility/facilities served to the maximum water level. At the start of the day, if the water level of any of the facility/facilities is above the minimum water level, the algorithm simply ignores that facility for the truck to visit that particular day. The main logic behind ignoring the facility/facilities that are above the minimum level on that particular day is that the facilities are going to be taken care off the next day when the water level falls below the minimum level. At the end of the day, it is assumed that the water level decreases by the usage rate of that facility. Multiple refilling strategies are studied in this section to analyze the effect of particular refilling strategy for a given period of time.

4.4. EA REPRESENTATION

An evolutionary algorithm is used to determine the best refilling strategy. Figure 4.2 shows how a simple problem is represented and solved based on the truck capacity. Facility ‘0’ represents the water source where the truck starts the day and ends the day. Facilities ‘1-5’ represent the components that are connected to source ‘0’. The main job of the truck is to deliver sufficient water to the components that are connected to the source. Based on the shortest distance between facilities, the left side of the Figure 4.2 represents the route to be followed by the truck assuming infinite truck capacity. The problem is represented and solved in an EA using a chromosome of length 6 bits (6 components for this example) and the end solution is represented using a chromosome of 7 bits long (solution size), which represents the route to be followed by the truck. The complexity increases as we add extra constraints, such as fixed truck capacity and usages of the facilities. The end solution, which is the route to be followed drastically changes, when the number of bits is increased from 7 bits to 25 bits for this simple case as shown on the right side of the Figure 4.2. Two-point crossover at a rate of 0.9 and random single bit mutation at a rate of 0.01 is used for running all the simulations in this section. Source and component facility connections with the location(x, y, z) co-ordinates are read from VFOBLITE™ layout tool which internally uses ArcGIS [ArcGIS, 2013] for the exact geo-rectified values. Values of the truck specifications, local bladder capacities and usage values of each facility are read from army asset list database [TCMS, 2004].

InfiniteTruck Capacity		
Source	**Facility**	**Usage**
0	1	2500
	2	10000
	3	20000
	4	10000
	5	5000
Route Followed		
0 -- 4 -- 5 -- 2 -- 1 -- 3 --0		

Truck Capacity: 5000g		
Source	**Facility**	**Usage**
0	1	2500
	2	10000
	3	20000
	4	10000
	5	5000
Route Followed		
0 -- 4 -- 0 -- 4 -- 5 -- 0 --5 -- 2 -- 0 --2 --0 --2 --1 --0 -- 1 --3 --0 --3 --0 --3 --0--3 --0 --3 -- 0		

Figure 4.2. Simple Routing Problem Representation.

4.5. ALGORITHM VARIATIONS

A different minimum and maximum level is added to the model for each facility to study the effects of different ways of filling the local bladders on the overall sustainability of the base camp. In this research, three different variations of the facility refill techniques are studied and the algorithm developed is applied to each case. The three refill techniques are referred to as 'fill regardless of level', 'fill only if below minimum level and completely fill' and 'fill only if below minimum level and fill only to a maximum level' are studied over a term of 1 day, 7 days, 1 month, 1 year and 5 years. The variations will help the base camp planner to have more information to decide which algorithm variation is best applicable for the base camp under design.

4.6. ALGORITHM OUTPUTS

The algorithm outputs are the route for the truck/trucks to be followed each day, travel times, distances covered, water delivered at each facility, total fuel consumed by the truck and breaks in the route (based on the truck maximum run-time), so that it can be covered by other trucks. Other logistics supply models follow the same procedure as potable water while the logistics pickup such as waste follows an exact opposite logic of potable water. Rather than delivering water, the truck picks up waste from the local waste collection centers and dumps at the source, but the algorithm is the same.

4.7. SOLUTION EXAMPLES

For the purpose of experimental analysis, an example case is considered and the three scenarios described in the Algorithm Variations section are applied to study the long term effects of the algorithm variations. The case considered consists of 1 source connected to 11 different facilities with each having different daily water usages, initial water levels and location information (x, y, z coordinates). The minimum and maximum level of the facilities to fill, for two of the algorithm variations are kept constant at 25% and 75% of the local bladder capacity respectively. Two trucks with different truck specifications and capacities of 5000 gallons and 1000 gallons are used to solve the problem using the three different algorithms discussed earlier.

For a total of 50 runs, Figure 4.3, Figure 4.5 and Figure 4.7 summarizes the Average Water Delivered, Average Travel times and Average Source Refill Plots for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years using 5000 gallons capacity truck respectively using both evolutionary algorithm and simulated annealing techniques for the three algorithm variations namely ‘fill regardless of level’, ‘fill only if below minimum level and completely fill’ and ‘fill only if below minimum level and fill only to a maximum level’. Figure 4.4, Figure 4.6 and Figure 4.8 summarizes the Average Water Delivered, Average Travel times and Average Source Refill summary for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years using 1000 gallons capacity truck respectively using both evolutionary algorithm and simulated annealing techniques for the three algorithm variations. Of the three variations, ‘fill only if below minimum level and fill only to a maximum level’ performs better than the other two variations in terms of fewer gallons of water delivered, less travel time by the truck and fewer number of source refill rates.

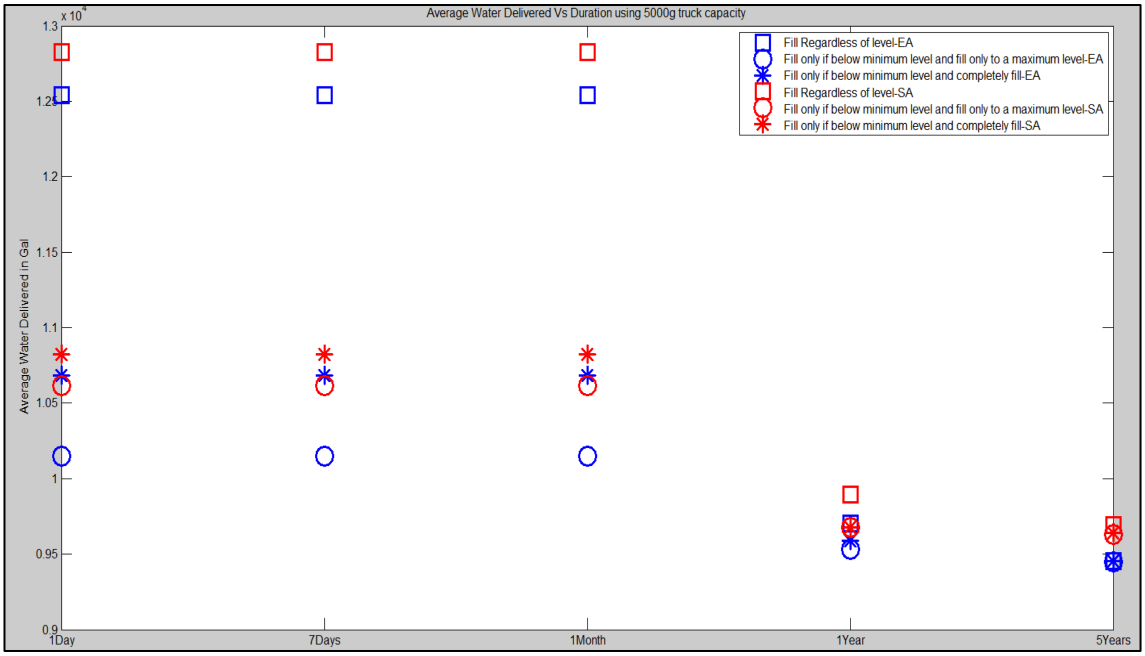

Figure 4.3. Average Water Delivered for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 5000Gallon Capacity Truck.

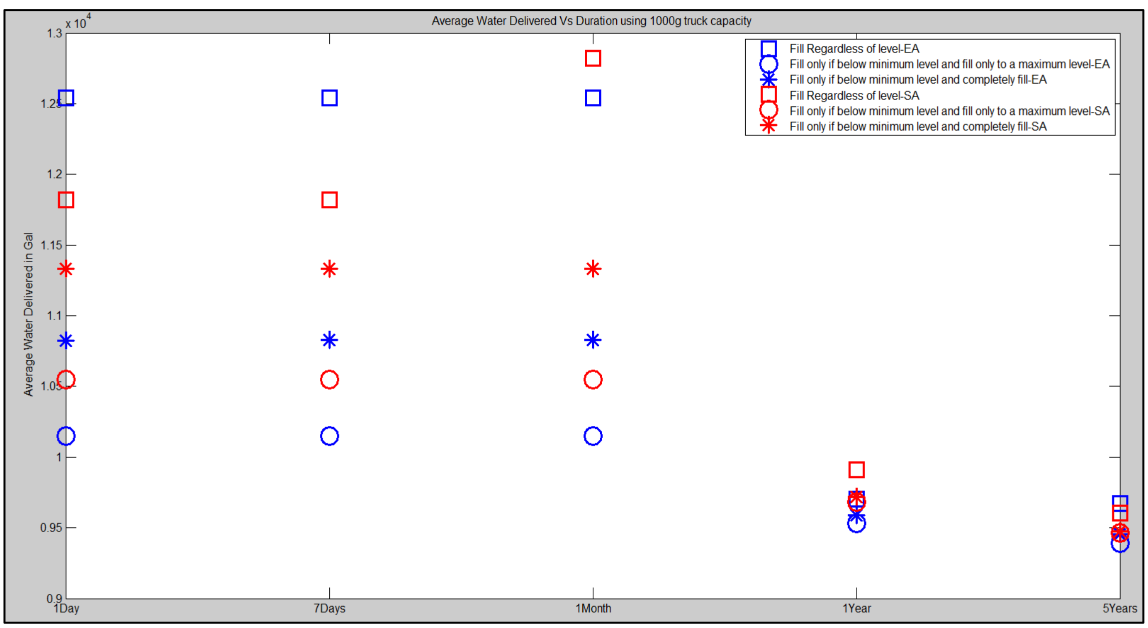

Figure 4.4. Average Water Delivered for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 1000Gallon Capacity Truck.

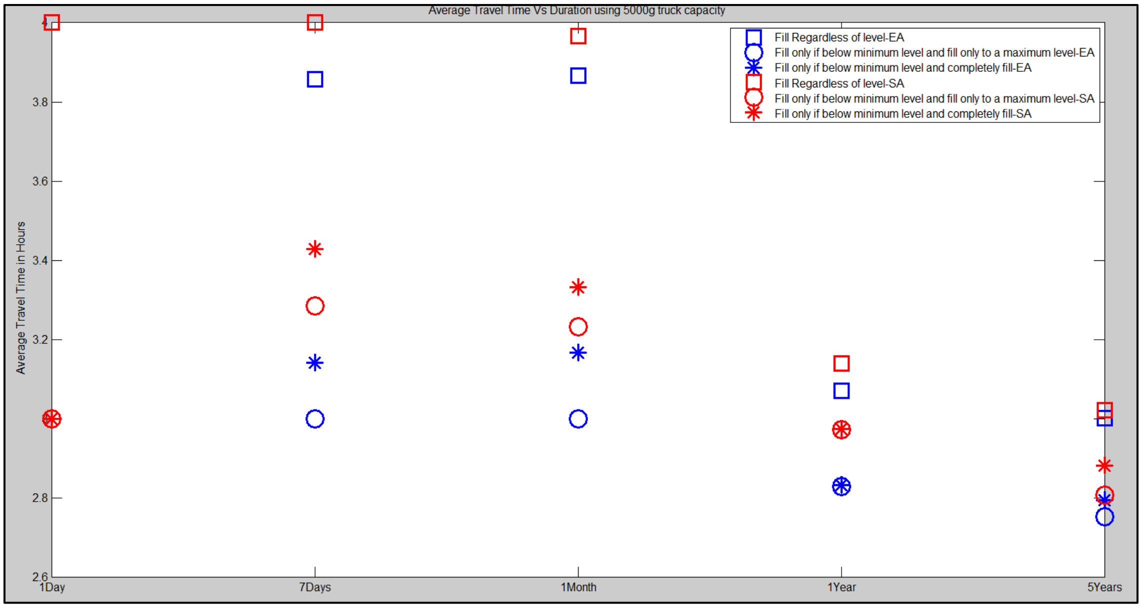

Figure 4.5. Average Travel Time for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 5000Gallon Capacity Truck.

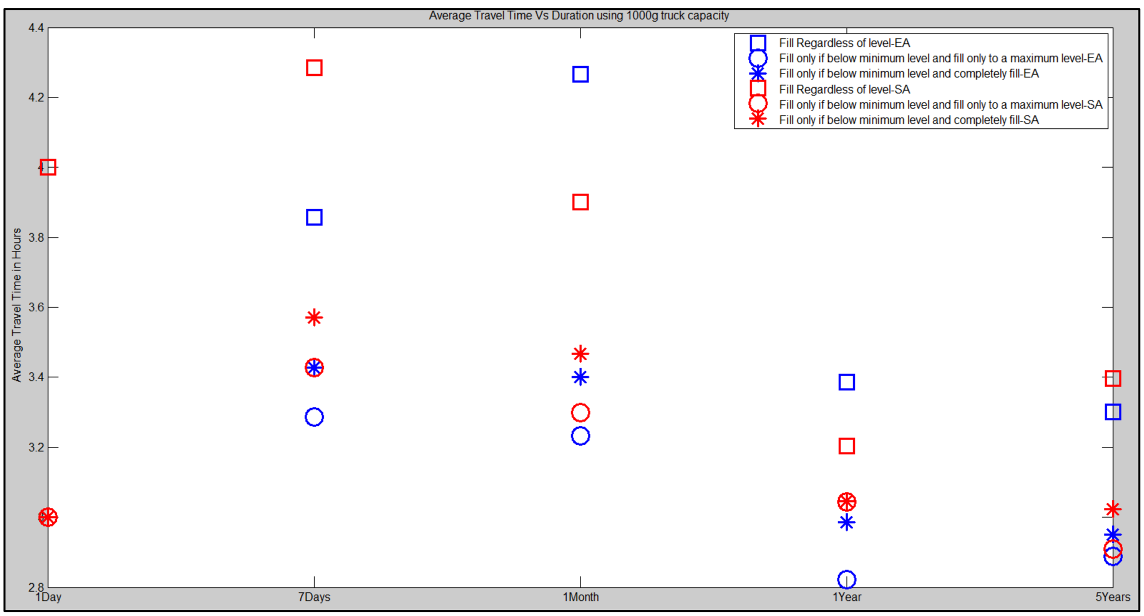

Figure 4.6. Average Travel Time for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 1000Gallon Capacity Truck.

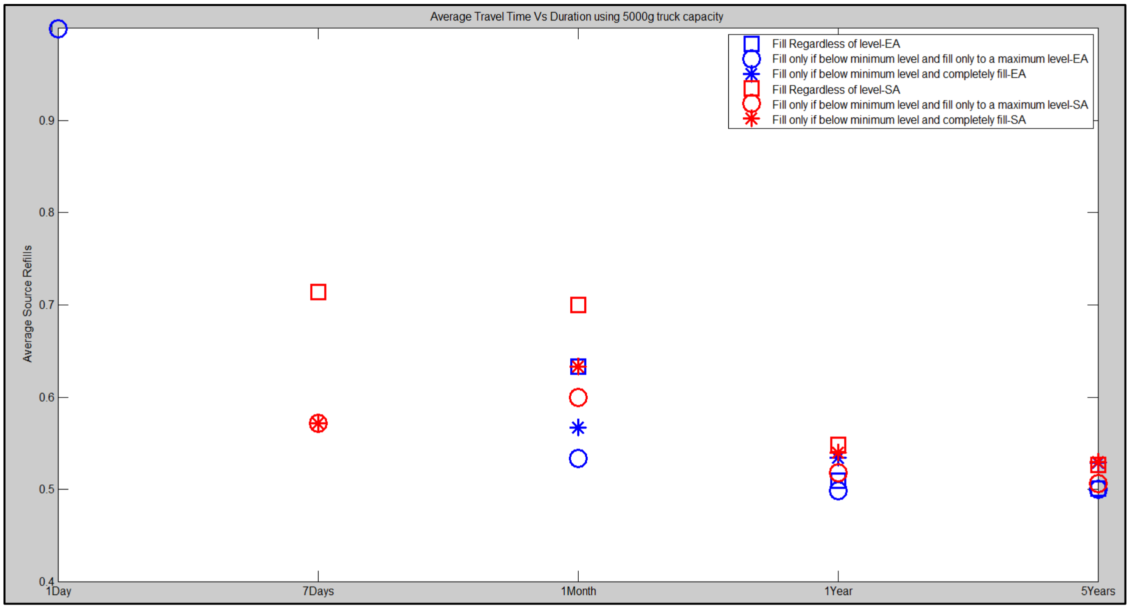

Figure 4.7. Average Source Refills for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 5000Gallon Capacity Truck.

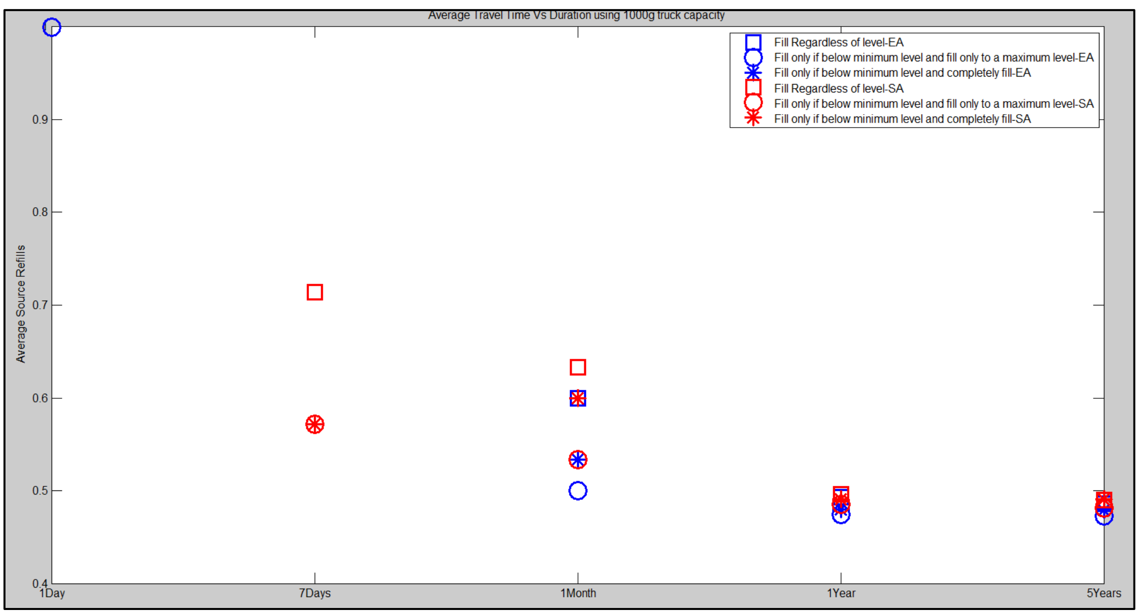

Figure 4.8. Average Source Refills for 1 Day, 7 Days, 1 Month, 1 Year and 5 Years Using 1000Gallon Capacity Truck.

4.8. COMPARISON OF TECHNIQUES

In this section, logistic base camp planning problem is solved using simulated annealing technique and compared with evolutionary algorithm performance. The comparison between both techniques are performed to understand to what level the evolutionary algorithm can contribute in terms of fuel consumption savings by the delivery truck. Simulated annealing is a technique of locating a good approximation to the global optimum of a given function in a large search space. This technique is similar to annealing in metallurgy, which involves heating and controlled cooling of a material to increase the size of its crystal and reduce their defects. This notion of slow cooling is implemented in simulated annealing algorithm as a slow decrease in the probability of accepting worse solutions as it explores the solution space. Accepting worse solutions is a fundamental property of metaheuristics because it allows for a more extensive search for the optimal solution.

In comparing the evolutionary algorithm and existing base camp techniques solutions (Table 4.1), the evolutionary algorithm often provided the best solution to the base camp logistic planning problem with shorter tour distances and less fuel usage. In comparing the EA and simulated annealing methods, the evolutionary algorithm often provided a better solution to the base camp logistic planning problem with shorter tour distances. Table 4.1 summarizes the distances for both the methods and the increase in processing time incurred through using the evolutionary algorithm. Simulated annealing makes greedy choices by choosing to iteratively visit the closest unvisited facility. The algorithm sorts the facilities based on ascending distance and choses to visit the closest unvisited facility. Although this algorithm produces good solution matches, it does not guarantee that the total distance will be minimized. For some specific cases, this technique has been shown to produce the worst possible solution.

However, processing time also increased with an average increase of 49.7 seconds. Although, the processing time may change depending on the complexity and size of the problem, the results summarized in Table 4.1 indicates that evolutionary algorithms provide a competitive alternative to simulated annealing technique and existing base camp techniques in solving the logistic problem.

Table 4.1. Comparison Between Existing Base Camp, Simulated Annealing and EA Techniques.

No of Facilities	Distance (Existing Techniques)-miles	Distance (Simulated Annealing)-miles	Distance (EA) – miles	% Fuel Consumption Increase between Existing and EA technique (Gal)	Processing time increase between Simulated annealing and EA technique (seconds)
11	2.4	1.39	1.31	45.1	3.1
23	3.62	2.27	1.97	46.4	7.8
37	4.1	2.9	2.41	29.2	19.2
51	6.8	4.8	4.26	37.3	38.9
127	15.9	11.1	9.3	41.5	179.5

When using evolutionary algorithms to solve this type of problem, the following considerations should be made:

- The selected evolutionary algorithm options (initial size of the population, rate of mutation and crossover, selection type, and termination criterion) may affect the ability to converge to an optimal solution. These values should be selected with care using a trial-and-error approach to ensure that the evolutionary algorithm does not converge to a sub-optimal solution.
- Evolutionary algorithms are not guaranteed to find the global optimum. Various factors including the selected options and deceptive individual strength can cause premature convergence. If a certain individual emerges early in the search as being a strong competitor, it may bias the search to converge on a local optimum that represents the competitor rather than a global optimum.

Based on the above comparisons and discussions, it can be concluded that evolutionary algorithm is better than other techniques for the base camp logistic planning optimization problem since true pareto-optimal solutions with satisfactory diversity characteristics have been produced in this simulation. In comparing evolutionary algorithm and other solutions, the evolutionary algorithm often provided the best solution to the base camp logistic planning problem with shorter tour distances and more fuel savings. In the next section, an EA for power model is developed to understand, whether further fuel consumption savings can be achieved by using an EA.

5. POWER MODEL

A stand-alone power model is discussed in this section, does in-depth power analysis in conjunction with an open source distribution simulator, and reports a wide variety of results to the designer. Also in this section, an evolutionary algorithm is developed to assist the base camp designer to help determine the placement of structures on a map. The flexible model will assist the designer in a better selection and placement of facilities.

5.1. OpenDSS

The Distribution System Simulator (DSS) is an open-source tool with its own language 'OpenDSS' which may be used to design and model electrical distribution systems. OpenDSS does not automatically create an electrical distribution system, but facilitates the design process by providing a framework for modeling the distribution system and a solver for calculating losses and other relevant information.

In this research, OpenDSS is extended in a way to take information about electrical loads of base camp facilities (from the mathematical model) and distances between facilities (from GeoBEST) to create an electrical distribution system design for the base camp. OpenDSS is used here in this research to manually create and test an electrical grid design, and also incorporated into an automated electrical distribution system design package as proposed here. The mathematical model drives the OpenDSS engine and assists the designer of the base camp by calculating the exact needs of each facility.

The proof of concept for this part of this research is provided here by providing the link between the energy system modeling software (OpenDSS) to the base camp system level model and the other lower level system needs. The main idea behind this analysis is, if the framework processes necessary for the system design are captured and analyzed at the architecture design phase, an optimum framework of the proposed system can be obtained and visualized before committing to the detailed system and thus cost and time can be saved.

Figure 5.1 represent the interactions between the front end user layout interface (VFOBLite^{TM}) and OpenDSS. The base camp planner using VFOBLite as the front end interface selects and connects facilities and creates a layout of a base camp using a wide variety of components like cables, junction boxes and loads present in the VFOB database. The VFOB database contains the specifications of all the components selected in the design. The specifications are used by the wrapper code (Figure 5.1) written in python to create a script representing the design at the end to do a detailed analysis of the layout. The XML File described in Figure 5.1 represents the connection information of all the components in one file. It has all the information such as inputs/outputs, load values and component name of all the components present in the design.

The wrapper code extracts all the connection and configuration information from the XML file, and creates a '.dss' file representing the front end layout. The wrapper code before creating the file also extracts appropriate data (specifications of components) needed from the database and creates object libraries. Once the individual libraries are created, the final '.dss' file having the configuration information is presented to OpenDSS simulator to do a detailed analysis of the design. For each run, the wrapper

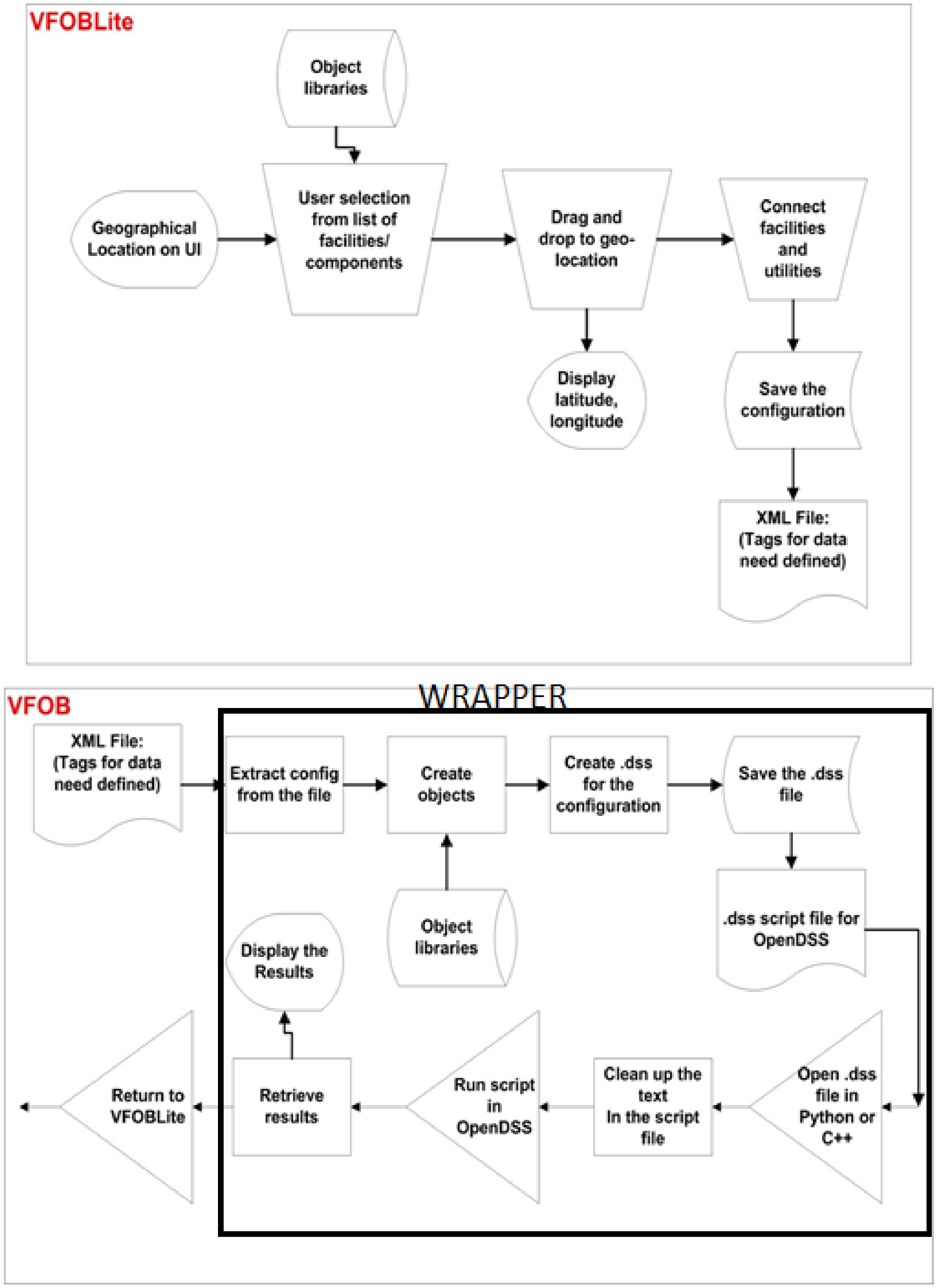

Figure 5.1. UI and OpenDSS Interactions.

code extracts all the results from the OpenDSS simulator and displays the overall results with all the problems encountered if any. At the front end interface, a wide variety of in-depth results are presented to the base camp planner so that appropriate action can be taken to rectify problems encountered in the design if there are any.

5.2. EXAMPLE LAYOUT DISCUSSION

This section discusses an Example layout from the power model point of view. A sample xml file represents the example layout. Overall this file has connection information of 3 generators connected to 11 loads and 61 cable lines. For each component the specification is read from the database. A sample database specification of a component is shown in Figure 5.2.

ID	Isc1	Isc3	MVAsc1	MVAsc3	pu	kv	Vpu	Vminpu	Vmaxpu	kw
54	7216.9	7216.9	1	3	1	0.24	1	0.9	1.1	60
55	7216.9	7216.9	1	3	1	0.24	1	0.9	1.1	100
56	21650.6	21650.6	3	9	1	0.24	1	0.9	1.1	750
233	3608.4	3608.4	0.5	1.5	1	0.24	1	0.9	1.1	30
334	21650.6	21650.6	3	9	1	0.24	1	0.9	1.1	750
487	7216.9	7216.9	1	3	1	0.24	1	0.9	1.1	60
506	1804.2	1804.2	0.25	0.75	1	0.24	1	0.9	1.1	10
531	28867.5	28867.5	4	12	1	0.24	1	0.9	1.1	1500
649	21650.6	21650.6	3	9	1	0.24	1	0.9	1.1	500
650	14433.8	14433.8	2	6	1	0.24	1	0.9	1.1	200
660	2081.8	2081.8	0.25	0.75	1	0.208	1	0.9	1.1	15
661	28867.5	28867.5	4	12	0.95	0.24	1	0.9	1.1	1500

Figure 5.2. Sample Database Specifications.

Figure 5.3, Figure 5.4 and Figure 5.5 represent a snippet of generator, line and load information extracted by the wrapper code. Line information displays the current flowing through each cable with appropriate normal values. Load information displays the load required by each load and whether the load is served approximately or not by the design.

Generators

GENERATOR ENERGY METER VALUES

Name	kWh	kvarh	Max kW	Max kVA	Hours	$
ai-487-h8vf4l0rwmhvu	0.0	0.0	0.0	0.0	0.0	0.0
ai-487-ty4925fqu5qdv	0.0	0.0	0.0	0.0	0.0	0.0
ai-487-qy9caymnrgpf7	0.0	0.0	0.0	0.0	0.0	0.0

Name	kV	kvar	kW	PF	Phases
ai-487-h8vf4l0rwmhvu	0.24	45.0	60.0	0.8	3
ai-487-ty4925fqu5qdv	0.24	45.0	60.0	0.8	3
ai-487-qy9caymnrgpf7	0.24	45.0	60.0	0.8	3

Figure 5.3. Generators Information.

Lines

Line Currents and Monitors

Name	Amp(max)	%Norm	%Emerg
ai-595-x0rydfs4avaep	134.38	143.97	95.98
ai-595-rm6e7pu6pa1uy	134.39	183.25	122.17
ai-595-9tmq8jw29r0ho	134.39	183.25	122.17
ai-469-f36f7w3t0hc7o	134.39	143.98	95.99
ai-469-f36f7w3t0hc7o-1	131.94	141.36	94.24
ai-469-f36f7w3t0hc7o-2	3.20	3.43	2.28
ai-611-yg5ftgjlcsvbe	131.94	141.36	94.24
ai-610-9c81mupxyju9r	3.20	22.85	15.99
ai-611-87jx4ffff0k8q	131.94	141.36	94.24
ai-471-tjtatkusli4gp	131.94	141.36	94.24
ai-471-tjtatkusli4gp-1	129.53	138.79	92.52
ai-471-tjtatkusli4gp-2	3.19	3.41	2.28
ai-614-mhknfgd7wmlp0	129.53	925.24	647.67
ai-614-ojje0ensib9t6	3.19	22.77	15.94
ai-463-yxwg855emwbxn	129.53	925.24	647.67
ai-479-0olhjux9wl3jn	3.19	22.77	15.94
ai-471-foiohttqbte9f	3.20	3.43	2.28
ai-471-foiohttqbte9f-1	3.20	3.43	2.28

Figure 5.4. Lines Information.

Loads

--LOADS-- kW

Name	Required	Actual	Served?
ai-463-yxwg855emwbxn	30.50	40.16	1
ai-479-0olhjux9wl3jn	1.00	1.32	1
ai-479-rj9r6xt6ylaq7	1.00	1.33	1
ai-479-h6sm870hgt2r7	1.00	1.35	1
ai-488-jise8bqsv5pbv	10.00	13.51	1
ai-479-sl4hxp8owxhbf	1.00	1.35	1
ai-489-9y019g3njqfw1	10.00	13.51	1
ai-495-2ookdjhcvw6to	20.00	26.91	1
ai-633-4oe7dgu23u9p8	3.00	4.04	1
ai-633-lj4qfl3e8r1jq	3.00	4.04	1
ai-633-lj4qfl3e8r1jq	3.00	4.04	1

Figure 5.5. Load Information.

Figure 5.6 shows overall losses information and overall load power involved with the design under consideration. Figure 5.7 shows the overall summary of the design. This tab has all the information of each and every component present in the design. If there are any problems in the design, the reason code indicate the problem associated with each component. Using this information, the base camp planner will able to visualize if all the loads are served or not. This automated way gives the planner a flexible way to edit the design and overcome the problems.

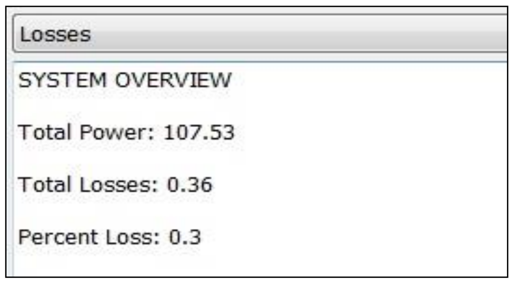

Figure 5.6. Overall Losses Information.

The automated power model has the following advantages:

1. Models generators, loads (including seasonal demand changes), line cables, transformers, loads, protection, and switches.
2. Shows design flaws and failure points.
3. Failure points can be addressed on the fly.
4. Detailed reporting of the power characteristics.
5. Design variations can quickly be built and analyzed using the libraries.

```
Summary

GENERATORS:
Gen 1:
--UID: ai-487-h8vf4l0rwmhvu
--kW: 60 kW
--Capacity: 60.5
--Power Consumed: 43.1 kW
--Power Available: 17.4 kW
--Status: 1
--Reason: 0

Gen 2:
--UID: ai-487-ty4925fqu5qdv
--kW: 60 kW
--Capacity: 61.1
--Power Consumed: 29.8 kW
--Power Available: 31.3 kW
--Status: 1
--Reason: 0

Gen 3:
--UID: ai-487-qy9caymnrgpf7
--kW: 60 kW
--Capacity: 61.1
--Power Consumed: 35.1 kW
--Power Available: 26.0 kW
--Status: 1
--Reason: 0


=============================================

LOADS:
Load 1:
--UID: ai-463-yxwg855emwbxn
--Required: 30.5
--Delivered: 40.2
--Status: 1
--Reason: 0

Load 2:
--UID: ai-479-0olhjux9wl3jn
--Required: 1.0
--Delivered: 1.3
--Status: 1
--Reason: 0

Load 3:
--UID: ai-479-rj9r6xt6ylaq7
--Required: 1.0
--Delivered: 1.3
--Status: 1
--Reason: 0
```

Figure 5.7. Summary of the Design.

5.3. POWER EVOLUTIONARY ALGORITHM

An independent evolutionary algorithm for power model is developed to decrease the amount of cable losses, if possible for the design under consideration. In the automated process, once the layout is read by the wrapper code, the information is used by power model evolutionary algorithm to optimize the placement of the structures present in the layout from the power model point of view. Power Model EA has a constraint of distance between the facilities to be more than 100ft. This flexible way will allow the base camp planner to add more constraints to the design making it more practical, rather than randomly dropping facilities at arbitrary locations. The results of the power EA, for the example discussed in section 5.2 are tabulated in section 6.3. The results indicate the power EA was able to decrease the total amount of losses from 0.36kw to 0.34kw.

The research presented in the next section proposes a multi-level EA technique, which is the combination of logistic model EA and power model EA to develop real-time solutions. In this multi-level EA, an evolutionary algorithm is developed to generate a range of options. A method has been proposed in section 6, for using an evolutionary algorithm to find the high efficient solution taking into account of both the models and optimize the fuel savings of the delivery truck.

6. MULTI-LEVEL EVOLUTIONARY ALGORITHM

6.1. GENERAL OVERVIEW

A general multi-level evolutionary algorithm architecture overview is given below. Use of the planning algorithm will occur in several primary stages:

1. Power Model EA solves and selects structures which satisfy resource requirements and generates the power distribution system
2. Logistic Model EA solves and generates a routing scheme
3. Power Model EA and Logistic Model EA exchange relevant data to the higher level EA
4. Multi-level EA generates a viable solution considering the goal of the overall base camp using Power model EA solution space and Logistic Model EA solution space

This technique will help to identify the interfaces in the models and facilitate the exchange of data between them to optimize the main problem. For example, if bringing more generators into the power model is a need, then it is useful if this information is shared with the logistics model so that appropriate amount of water can be brought in to cool the generators which can be eventually used in the logistics model. At a later stage minor additions include adding a penalty function to individual components of the model to increase the efficiency of the overall design.

6.2. FITNESS FUNCTION AND SOLUTION REPRESENTATION

Figure 6.1 is the pseudo code for the evolutionary algorithm used for the base camp. The function Population (M) generates M random solutions. For the base camp planning purpose, if there exists a design which represent a solution, then that solution would be the starting point. The solution is represented as a chromosome which represents the design under consideration. If no design exists, random solutions could be used as the starting point. All the simulations are run for 100 generations having 100 solutions.

```
Steady-state()
Population(M) while the stopping criterion is not satisfied do
        P1, P2 ← ParentsSelection (Population)
        O1 ← Crossover (P1,P1)
        O2 ← Mutation (O1)
        R ← SolutionOutSelection (Population)
        Replace (O2,R)
end while
```

Figure 6.1. Psuedo EA Code for Base Camp.

Based on either a provided design or a random layout, the initial chromosome size having variable number of bits represents all the components present in the design. For a design under consideration from the power model point of view, this chromosome contains information about the generators, cables, junction boxes and load information. The specifications for each of the components are read from the database to calculate the overall power losses. The bits are arranged sequentially from the generator to the load with 3 bits used to represent each component. The components are rearranged to find a better solution with good characteristics. Fitness function of power model is minimizing the overall losses present in the system. After each generation, the solutions are examined and the best 5 solutions having least power losses are retained.

From the logistics model point of view, this chromosome contains information about the type of facility like the location information, and other setting information like the present water level. The specifications for each of the components present in water model are read from a database. Numerical number is assigned to each facility present in the system. The components are rearranged to find a better parent with good characteristics. Fitness function of logistic model is minimizing the travel distance by the trucks. So, after each generation, the solutions are examined and the best 5 solutions having least distances are retained.

New population selection is done by selecting the best 5 ranked solutions out of 100 (size) and doing double crossover (randomly selected left and right position for crossover) with a crossover rate of 0.80, and doing a single bit mutation (randomly selected bit) with a mutation rate of 0.01 for over 100 generations. Minimum power losses is the ranking criteria from the power model point of view. Least power loss combination of components has the highest rank. Minimum distance is the ranking criteria from the logistic model point of view. Least distance combination of components has the highest rank. Double crossover (randomly selected left and right position for crossover) is the crossover used and single bit mutation (randomly selected bits to mutate).

6.3. MULTI-LEVEL EA AND INDIVIDUAL EA'S

Steps 1 to 4 discussed in section 6.1 are explained in-depth in this section using 5 examples. In all five examples, an xml file is used to read the configuration of the layout. Once the layout is read by the wrapper code, the information is used by power model evolutionary algorithm to optimize the placement of the structures present in the layout from the power model point of view. The logistics model evolutionary algorithm optimizes the routes (Fuel consumption) to be travelled by the trucks. Table 6.1 represents the base line fuel consumption data that the individual and multi-level EA will be compared to.

Table 6.1. Baseline Fuel Consumption for 5 Years [Noblis, 2010].

Fuel Consumption	Overall Consumption (Gal)	Power Model Fuel Consumption (50%) (Gal)	Logistic Truck Fuel Consumption (Gal)	Power and Logistics Model Combined Fuel Consumption (Gal)
Fuel Consumed /day	804	402	80.4	482.4
Fuel Consumed /7days	5,628	2,814	562.8	3,376.8
Fuel Consumed /30days	24,120	12,060	2,412	14,472
Fuel Consumed /1year	289,440	144,720	28,944	173,664
Fuel Consumed /5years	1,467,300	733,650	146,730	880,380

In the multi-level EA, the Power Model EA solution is combined with the Logistic Model EA to determine the placement of structures and a new solution is obtained by the multi-level EA. The individual EAs and the multi-level EA are compared to the baseline fuel consumption values. The comparison is done to check if the individual EAs perform as well as or better than the baseline techniques, and to check if the multi-level EA performs as well as or better than the individual EAs fuel consumption.

6.4. BASE CAMP EXAMPLES DISCUSSION

Five different sizes of base camps are used to test the efficiency of the individual EAs and the multi-level EA. Each load in all the base camps represents a physical facility. Example1 can be considered as a very small size base camp, has 3 generators connected to 11 loads using 61 cable lines and 1 water source. Example 2 can be considered as a small size base camp, has 6 generators connected to 23 loads using 135 cable lines and 1 water source. Example 3 can be considered as a medium size base camp, has 11 generators connected to 37 loads using 151 cable lines and 1 water source. Example 4 can be considered as a large size base camp, has 16 generators connected to 51 loads using 169 cable lines and 2 water sources. Example 5 can be considered as a very large size base camp, has 24 generators connected to 127 loads using 223 cable lines and 6 water sources.

The components involved with all the examples are carefully chosen in such a way that the examples represents a very small (100 soldiers), small (300 soldiers), medium (500 soldiers), larger (1,500 soldiers) and a very large size base camps (3,000 soldiers). These examples are used here to check if the developed multi-level EA can be actually scalable and whether it can be used for all types of base camp sizes.

In all five sizes, Power Model EA has a constraint of distance between the facilities to be more than 100ft. This will allow the base camp planner to add more constraints to the design rather than randomly dropping facilities at arbitrary locations. Two-point crossover at a rate of 0.88 and random single bit mutation at a rate of 0.01 is used for running all the simulations of Power Model EA. Two-point crossover at a rate of 0.9 and random single bit mutation at a rate of 0.015 is used for running all the simulations of Logistic Model EA. Two-point crossover at a rate of 0.9 and random single bit mutation at a rate of 0.01 is used for running all the simulations of multi-level EA. All five sizes are run for a duration of 1day, 7days, 1month, 1year and 5years to check if the multi-level EA performs better over time in terms of fuel consumption. Calculations in all the tables in section 6 are done based on a 4 mpg logistic truck considering all the idle times and with an average speed of 20 miles/hr (5 gallons per hour).

For very small size base camp, the power losses of the overall layout without and with using an individual power model EA are shown in Table 6.2. Fuel consumption without and with using an individual logistic model EA are shown in Table 6.3, for over a period of 5 years. Individual power model EA fuel consumption and overall fuel consumption using individual EAs for very small size base camp are also tabulated in Table 6.3. Also tabulated is the fuel percentage decrease from the baseline data, which was obtained using individual EAs for over a period of 5 years.

Table 6.2. Very Small Size Base Camp - Power Model Savings Using Individual EA.

Power Model	Without Power model EA (kw)	With Power model EA (kw)
Total Power	107.53	106.28
Total Losses	0.36	0.34
Percentage of Losses	0.334	0.319

Table 6.3. Very Small Size Base Camp - Fuel Consumption Savings.

Fuel Consumption Very Small Size Base camp	Logistic Model Fuel Consumption - without EA (Gal)	Logistic Model Fuel Consumption –with EA (Gal)	Power Model Fuel Consumption –with EA (Gal)	Power and Logistics Model Fuel Consumption – with EA (Gal)	% Fuel decrease
Fuel Consumed /day	55	32	397.32	429.32	11.003
Fuel Consumed /7days	94	66.5	2,781.2	2,847.7	15.66
Fuel Consumed /1month	388	275	11,899.2	12,174.2	15.87
Fuel Consumed /1year	3,255	3,200.5	142,710.2	145,910.7	16
Fuel Consumed /5years	11,910.5	10,402	725,121.56	735,523.56	16.45

For small size base camp, the power losses of the overall layout without and with using an individual power model EA are shown in Table 6.4. Fuel consumption without and with using an individual logistic model EA are shown in Table 6.5, for over a period of 5 years. Individual power model EA fuel consumption and overall fuel consumption using individual EAs for small size base camp are also tabulated in Table 6.5. Also tabulated is the fuel percentage decrease from the baseline data, which was obtained using individual EAs for over a period of 5 years.

Table 6.4. Small Size Base Camp- Power Model Savings Using Individual EA.

Power Model	Without Power model EA (kw)	With Power model EA (kw)
Total Power	273.93	267.69
Total Losses	1.61	1.57
Percentage of Losses	0.587	0.586

Table 6.5. Small Size Base Camp- Fuel Consumption Savings.

Fuel Consumption – Small Size Base camp	Logistic Model Fuel Consumption - without EA (Gal)	Logistic Model Fuel Consumption –with EA (Gal)	Power Model Fuel Consumption –with EA (Gal)	Power and Logistics Model Fuel Consumption – with EA (Gal)	% Fuel decrease
Fuel Consumed /day	59	34.5	392.84	427.34	11.41
Fuel Consumed /7days	96	73	2,749.9	2,822.9	16.4
Fuel Consumed /1month	396	300.5	11,759	12,059.7	16.68
Fuel Consumed /1year	4,752.5	3,200.5	140,405.2	143,605.7	17.28
Fuel Consumed /5years	12,308.5	10,604.5	716,937.7	727,542.2	17.36

For medium size base camp, the power losses of the overall layout without and with using an individual power model EA are shown in Table 6.6. Fuel consumption without and with using an individual logistic model EA are shown in Table 6.7, for over a period of 5 years. Individual power model EA fuel consumption and overall fuel consumption using individual EAs for medium size base camp are also tabulated in Table

Table 6.6. Medium Size Base Camp- Power Model Savings Using Individual EA.

Power Model	Without Power model EA (kw)	With Power model EA (kw)
Total Power	310.63	297.23
Total Losses	1.92	1.68
Percentage of Losses	0.61	0.56

Table 6.7. Medium Size Base Camp- Fuel Consumption Savings.

Fuel Consumption – Medium Size Base camp	Logistic Model Fuel Consumption - without EA (Gal)	Logistic Model Fuel Consumption –with EA (Gal)	Power Model Fuel Consumption –with EA (Gal)	Power and Logistics Model Fuel Consumption – with EA (Gal)	% Fuel decrease
Fuel Consumed /day	62	36.9	384.65	421.5	12.6
Fuel Consumed /7days	99	78	2,692.6	2,770	17.9
Fuel Consumed /1month	431.2	320.8	11,539.8	11,860.5	18.04
Fuel Consumed /1year	5,102.5	3,340	138,477	141,817	18.3
Fuel Consumed /5years	12,891.2	10,691.8	702,001.7	712,693.5	19.04

6.7. Also tabulated is the percentage decrease from the baseline data, which was obtained using individual EAs for over a period of 5 years.

For large size base camp, the power losses of the overall layout without and with using an individual power model EA are shown in Table 6.8. Fuel consumption without and with using an individual logistic model EA are shown in Table 6.9, for over a period of 5 years. Individual power model EA fuel consumption and overall fuel consumption using individual EAs for large size base camp are also tabulated in Table 6.9. Also tabulated is the fuel percentage decrease from the baseline data, which was obtained using individual EAs for over a period of 5 years.

Table 6.8. Large Size Base Camp- Power Model Savings Using Individual EA.

Power Model	Without Power model EA (kw)	With Power model EA (kw)
Total Power	368.58	351.36
Total Losses	2.68	2.38
Percentage of Losses	0.72	0.67

Table 6.9. Large Size Base Camp- Fuel Consumption Savings.

Fuel Consumption – Large Size Base camp	Logistic Model Fuel Consumption - without EA (Gal)	Logistic Model Fuel Consumption –with EA (Gal)	Power Model Fuel Consumption –with EA (Gal)	Power and Logistics Model Fuel Consumption – with EA (Gal)	% Fuel decrease
Fuel Consumed /day	63.9	41.9	383.2	425.1	11.8
Fuel Consumed /7days	102.8	86.2	2,682.5	2,768.7	18
Fuel Consumed /1month	440.2	349	11,496.5	11,845.5	18.14
Fuel Consumed /1year	5,328	4,101.9	137,958.7	142,060	18.19
Fuel Consumed /5years	13,509	11,957.8	699,374	712,331.8	19

For very large size base camp, the power losses of the overall layout without and with using an individual power model EA are shown in Table 6.10. Fuel consumption without and with using an individual logistic model EA are shown in Table 6.11, for over a period of 5 years. Individual power model EA fuel consumption and overall fuel consumption using individual EAs for very large size base camp are also tabulated in Table 6.11. Also tabulated is the fuel percentage decrease from the baseline data, which was obtained using individual EAs for over a period of 5 years.

Table 6.10. Very Large Size Base Camp- Power Model Savings Using Individual EA.

Power Model	Without Power model EA (kw)	With Power model EA (kw)
Total Power	450.88	431.3
Total Losses	3.34	3.04
Percentage of Losses	0.740	0.704

Table 6.11. Very Large Size Base Camp- Fuel Consumption Savings.

Fuel Consumption – Very Large Size Base camp	Logistic Model Fuel Consumption - without EA (Gal)	Logistic Model Fuel Consumption with EA (Gal)	Power Model Fuel Consumption with EA (Gal)	Power and Logistics Model Fuel Consumption with EA (Gal)	% Fuel decrease
Fuel Consumed /day	65.5	45.5	384.54	430.04	10.85
Fuel Consumed /7days	111.5	91.5	2,691.7	2,783.2	17.4
Fuel Consumed /1month	446	367	11,500.7	11,867.7	17.99
Fuel Consumed /1year	5,595.5	4,600.75	137,704.2	142,304.95	18.05
Fuel Consumed /5years	14,707	12,646.5	701,790.3	714,436.8	18.84

6.5. MULTI-LEVEL EA RESULTS

For all base camp sizes discussed in section 6.4, fuel consumption using a multi-level EA are shown in Table 6.12, for over a period of 5 years. Tabulated in Table 6.13 is the fuel percentage decrease from the baseline data, which was obtained using multi-level EA for over a period of 5 years.

Table 6.12. Multi-level EA Total Fuel Consumption.

Multi-level EA	Very Small Size Base camp (Gal)	Small Size Base camp (Gal)	Medium Size Base camp (Gal)	Large Size Base camp (Gal)	Very Large Size Base camp (Gal)
Fuel Consumed /day	429.32	427.34	421.5	423.6	426.04
Fuel Consumed /7days	2,847.7	2,811.7	2,759.2	2,761.7	2,747.8
Fuel Consumed /1month	12,152.5	12,019.1	11,797	11,803.5	11,745.2
Fuel Consumed /1year	145,695	143,529.2	141,008.2	141,460.2	140,887.2
Fuel Consumed /5years	734,938.2	727,101.2	711,200.2	710,839.8	712,606.5

Table 6.13. Multi-level EA Percentage Fuel Decrease.

Multi-level EA	Very Small Size Base camp (%)	Small Size Base camp (%)	Medium Size Base camp (%)	Large Size Base camp (%)	Very Large Size Base camp (%)
Fuel Consumed /day	11.003	11.41	12.6	12.2	11.6
Fuel Consumed /7days	15.66	16.73	18.2	18.2	18.6
Fuel Consumed /1month	16.02	16.94	18.4	18.4	18.84
Fuel Consumed /1year	16.1	17.35	18.8	18.54	18.9
Fuel Consumed /5years	16.52	17.41	19.21	19.25	19.05

Figure 6.2, Figure 6.3, Figure 6.4, Figure 6.5, and Figure 6.6 represent overall fuel consumption versus duration plots for Very Small, Small, Medium, Large and Very Large base camp sizes for over a period of 1 day, 7 days, 1 month, 1 year and 5 years for baseline data, individual EA and multi-level EA respectively. Figure 6.7, Figure 6.8, Figure 6.9, Figure 6.10, and Figure 6.11 represent overall fuel consumption versus all five base camp sizes plots for 1 day, 7 days, 1 month, 1 year and 5 years for baseline data, individual EA and multi-level EA respectively.

Figure 6.12, Figure 6.13, Figure 6.14, Figure 6.15, and Figure 6.16 represent percentage fuel consumption decrease from baseline data plots for individual EA and multi-level EA for Very Small, Small, Medium, Large and Very Large base camp sizes for over a period of 1 day, 7 days, 1 month, 1 year and 5 years respectively.

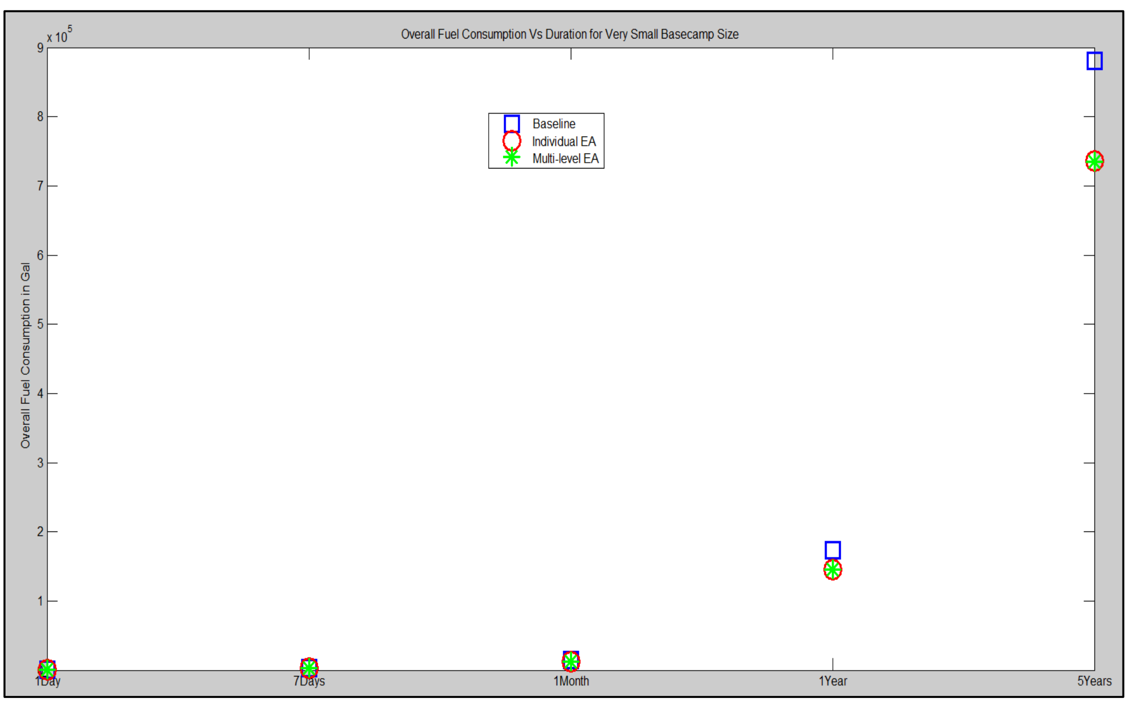

Figure 6.2. Overall Fuel Consumption vs Duration for Very Small Base Camp Size.

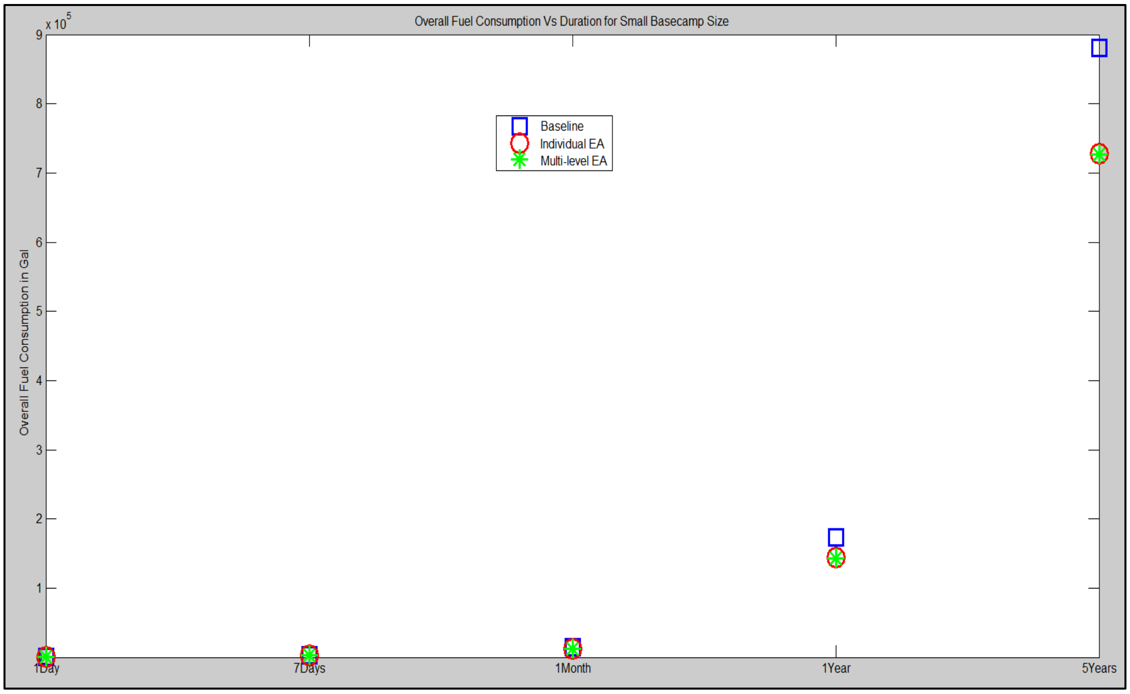

Figure 6.3. Overall Fuel Consumption vs Duration for Small Base Camp Size.

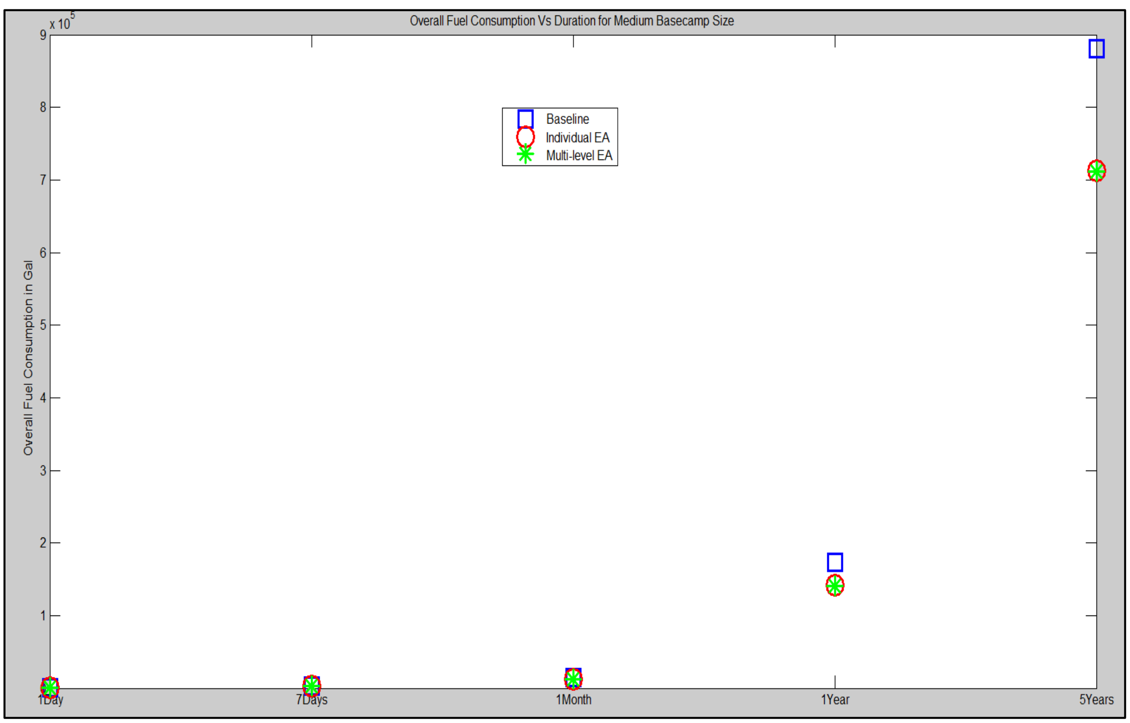

Figure 6.4. Overall Fuel Consumption vs Duration for Medium Base Camp Size.

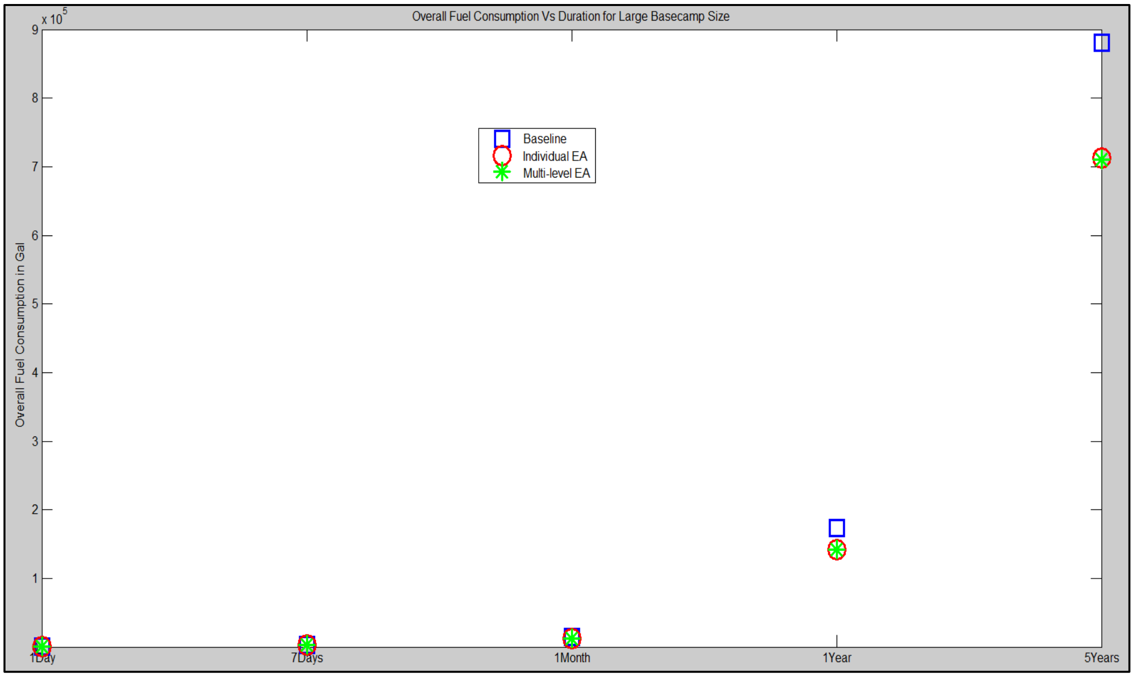

Figure 6.5. Overall Fuel Consumption vs Duration for Large Base Camp Size.

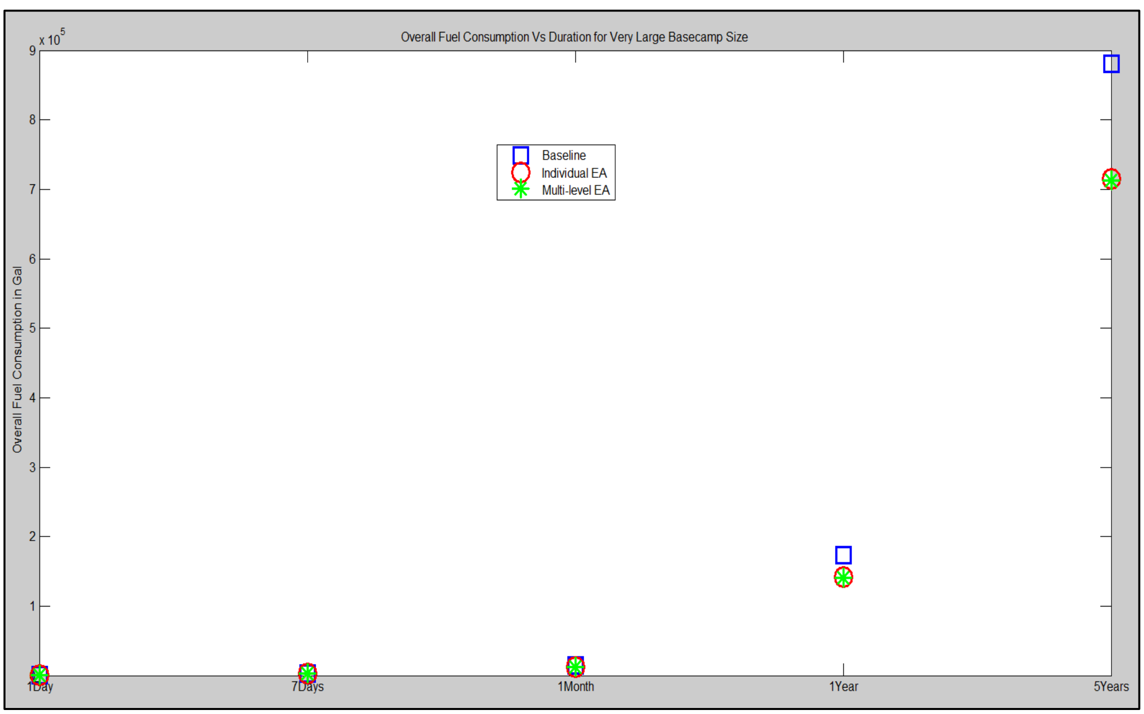

Figure 6.6. Overall Fuel Consumption vs Duration for Very Large Base Camp Size.

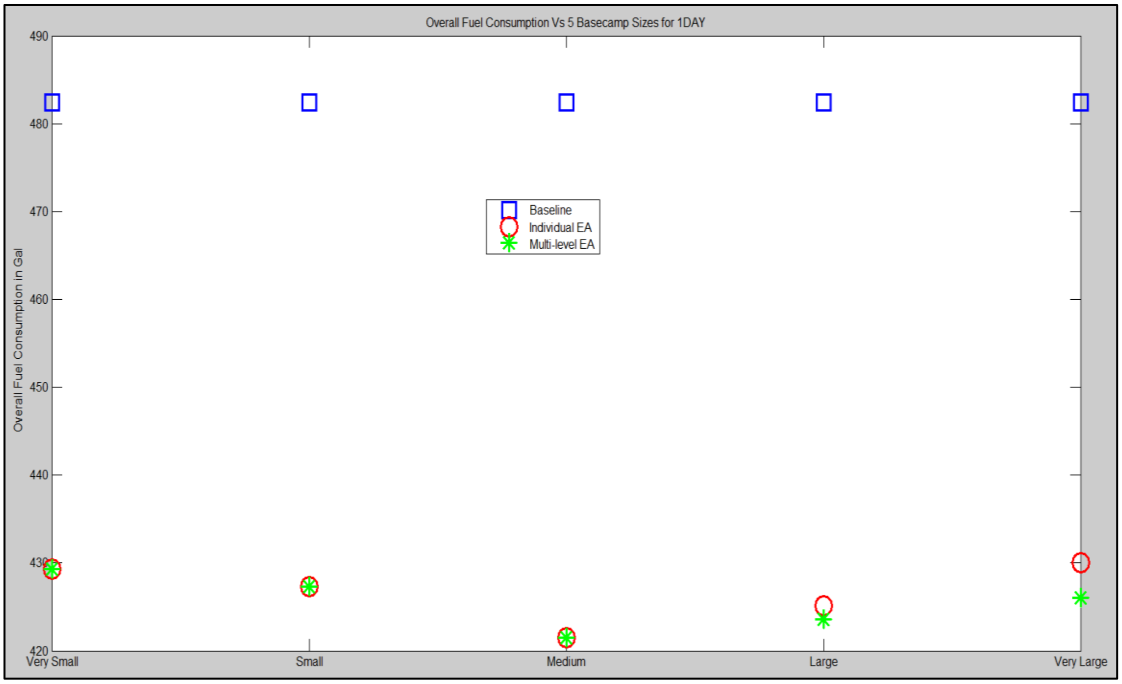

Figure 6.7. Overall Fuel Consumption vs 5 Base Camp Sizes for 1 Day.

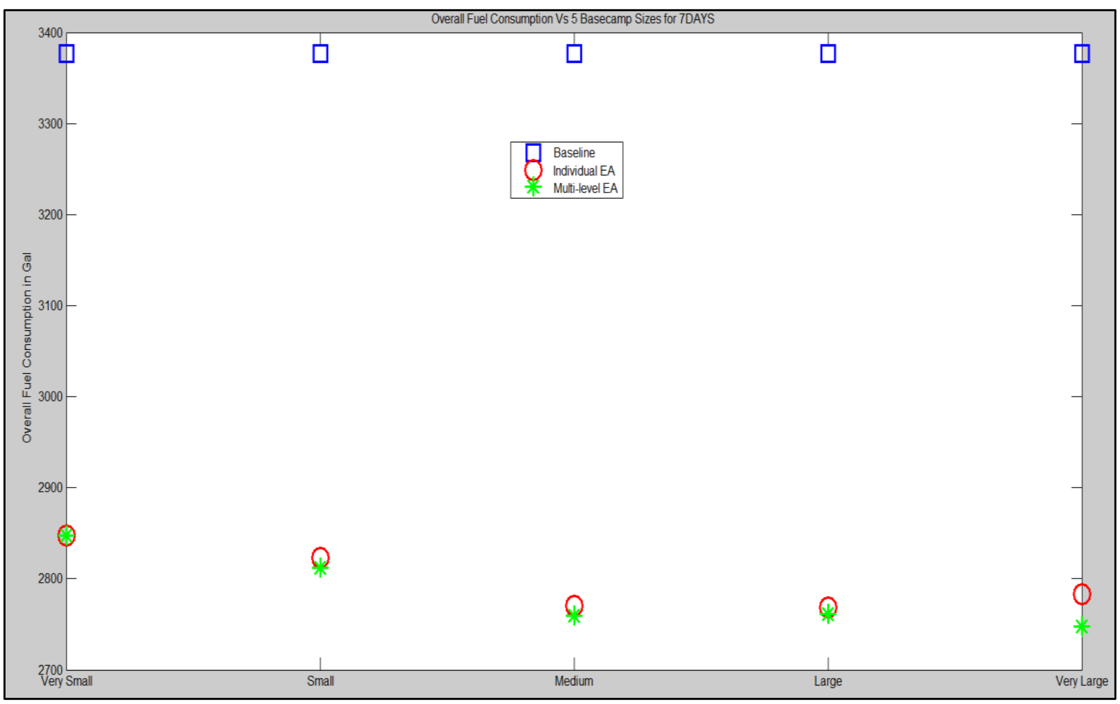

Figure 6.8. Overall Fuel Consumption vs 5 Base Camp Sizes for 7 Days.

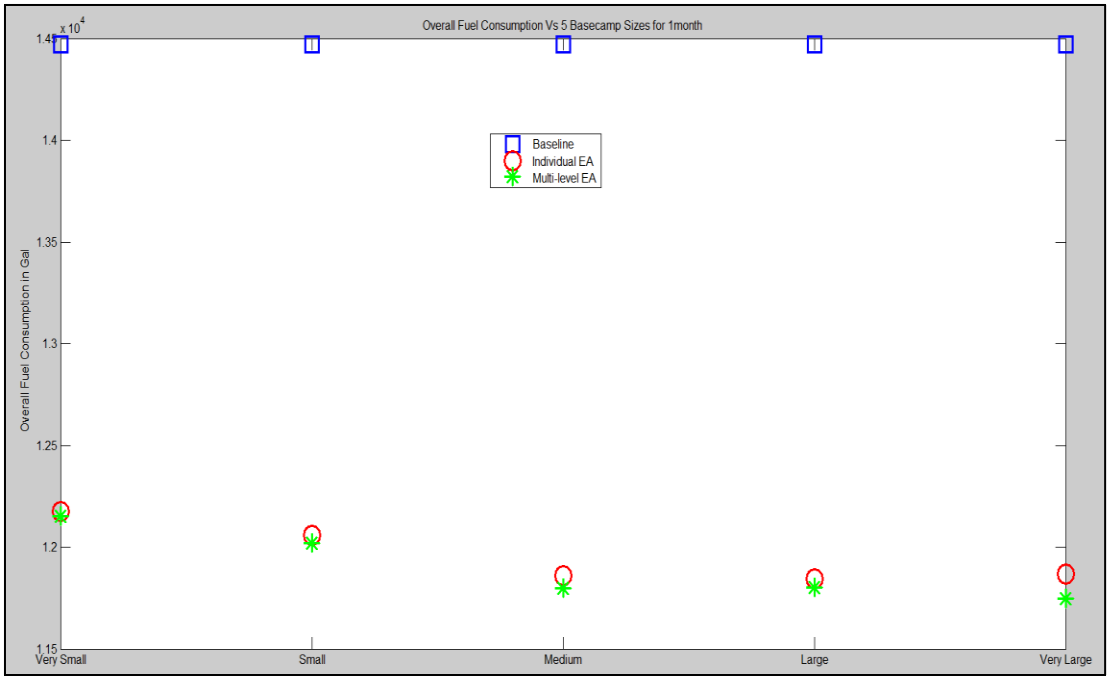

Figure 6.9. Overall Fuel Consumption vs 5 Base Camp Sizes for 1 Month.

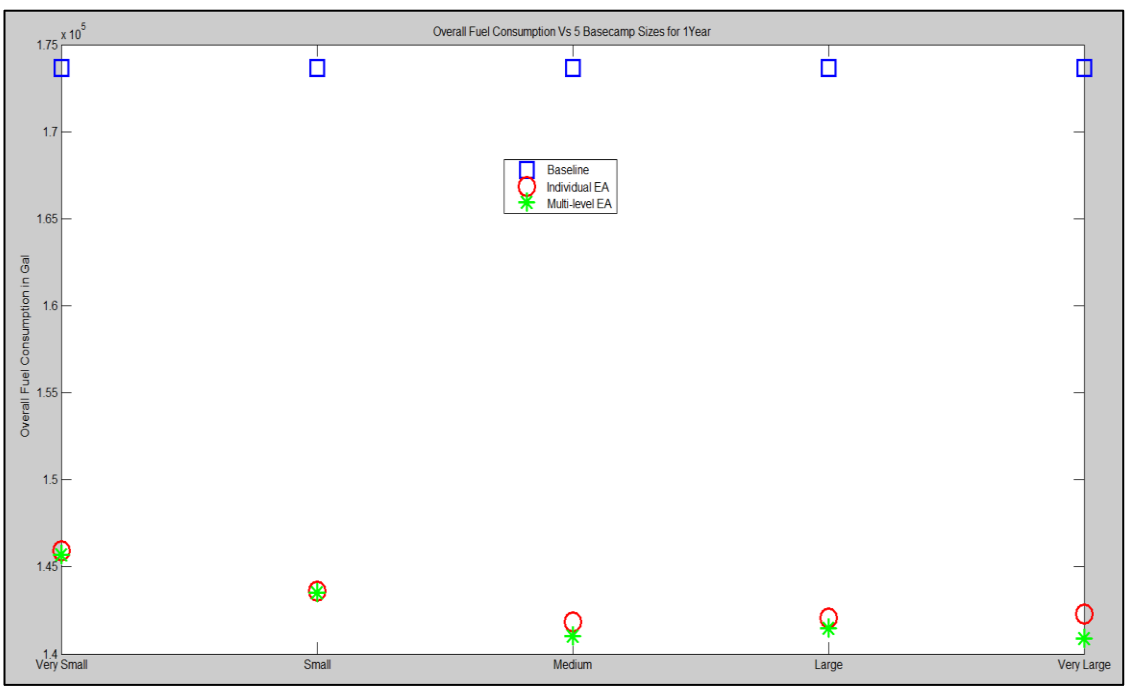

Figure 6.10. Overall Fuel Consumption vs 5 Base Camp Sizes for 1 Year.

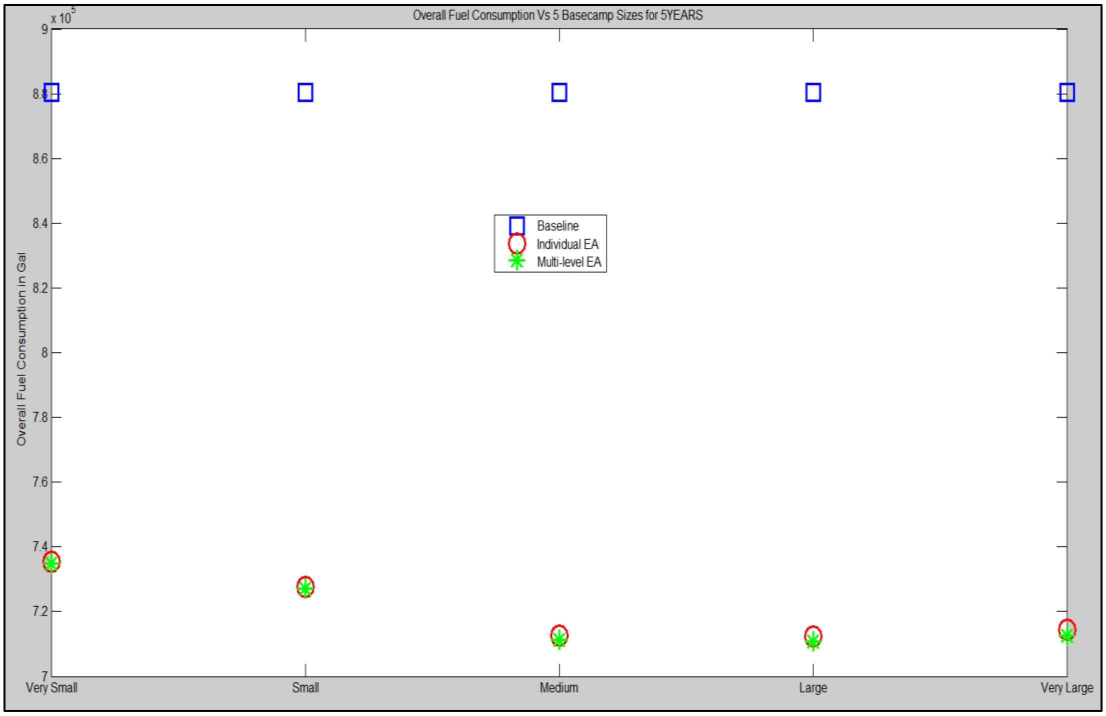

Figure 6.11. Overall Fuel Consumption vs 5 Base Camp Sizes for 5 Years.

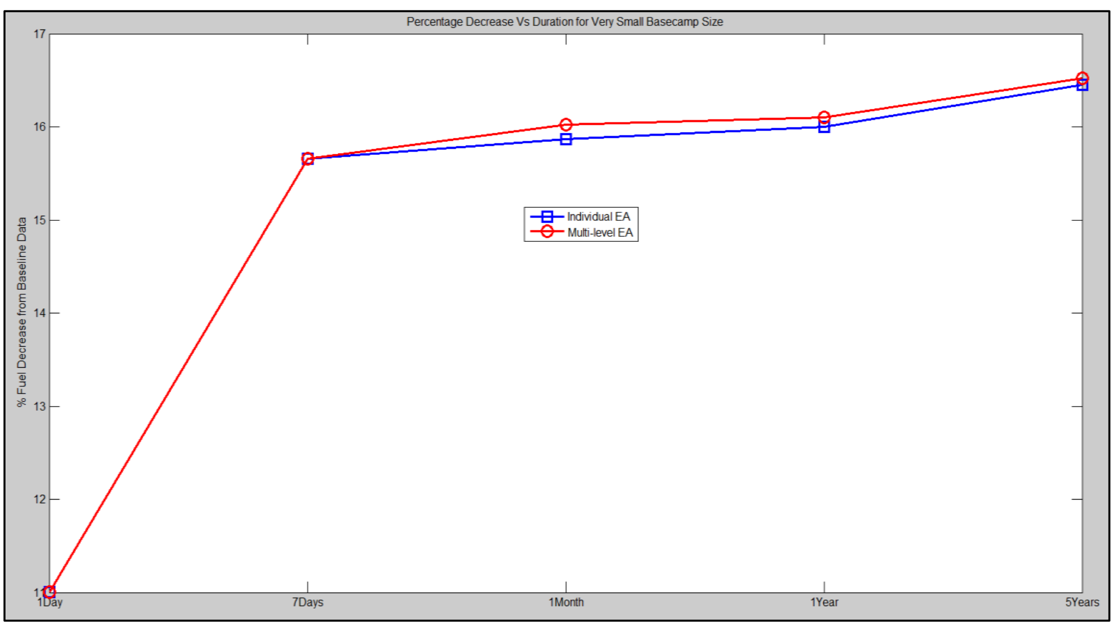

Figure 6.12. Percentage Fuel Savings from Baseline Data for Individual and Multi-level EA for Very Small Size Base Camp.

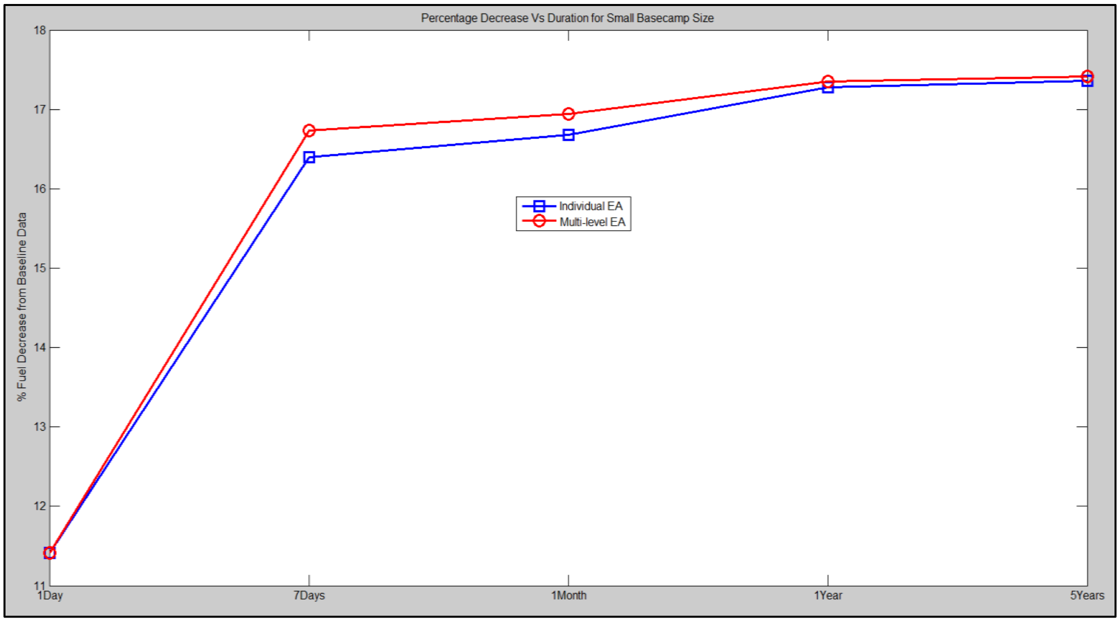

Figure 6.13. Percentage Fuel Savings from Baseline Data for Individual and Multi-level EA for Small Size Base Camp.

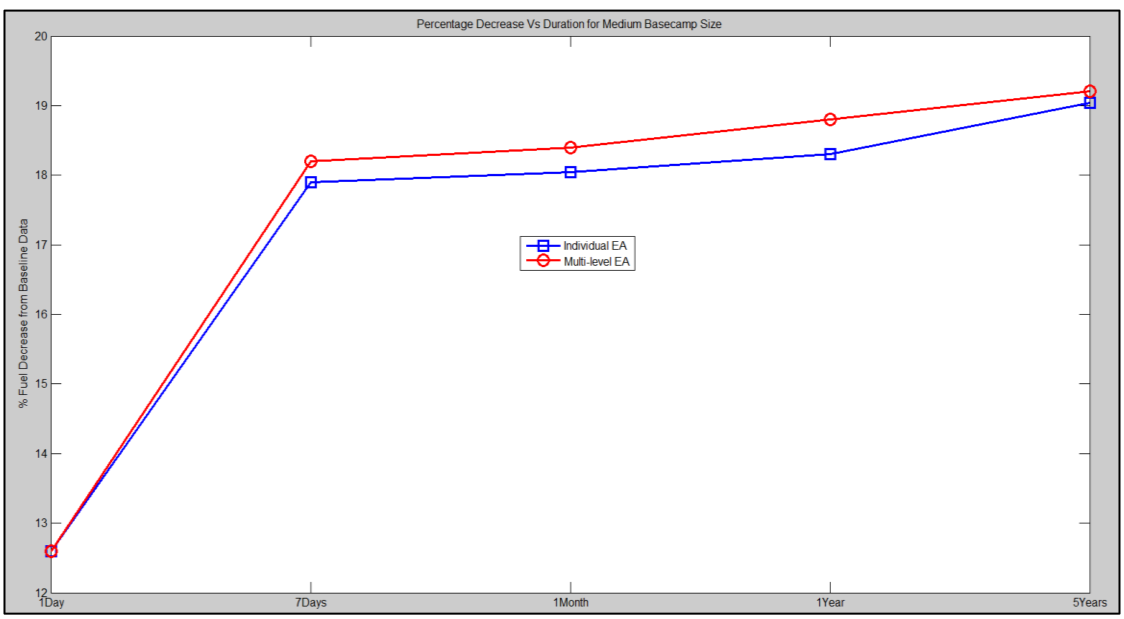

Figure 6.14. Percentage Fuel Savings from Baseline Data for Individual and Multi-level EA for Medium Size Base Camp.

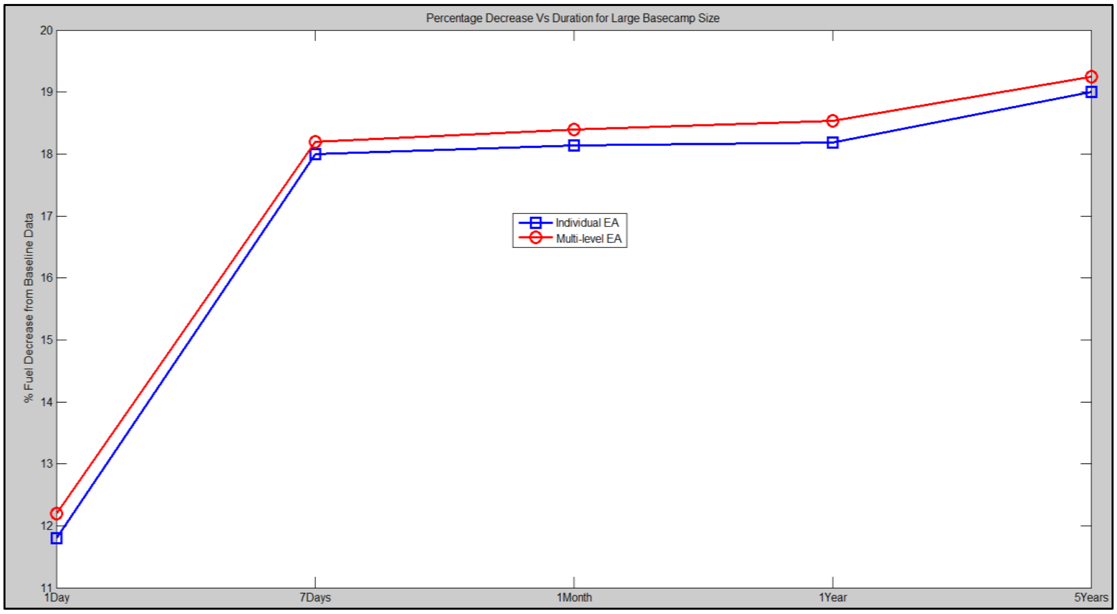

Figure 6.15. Percentage Fuel Savings from Baseline Data for Individual and Multi-level EA for Large Size Base Camp.

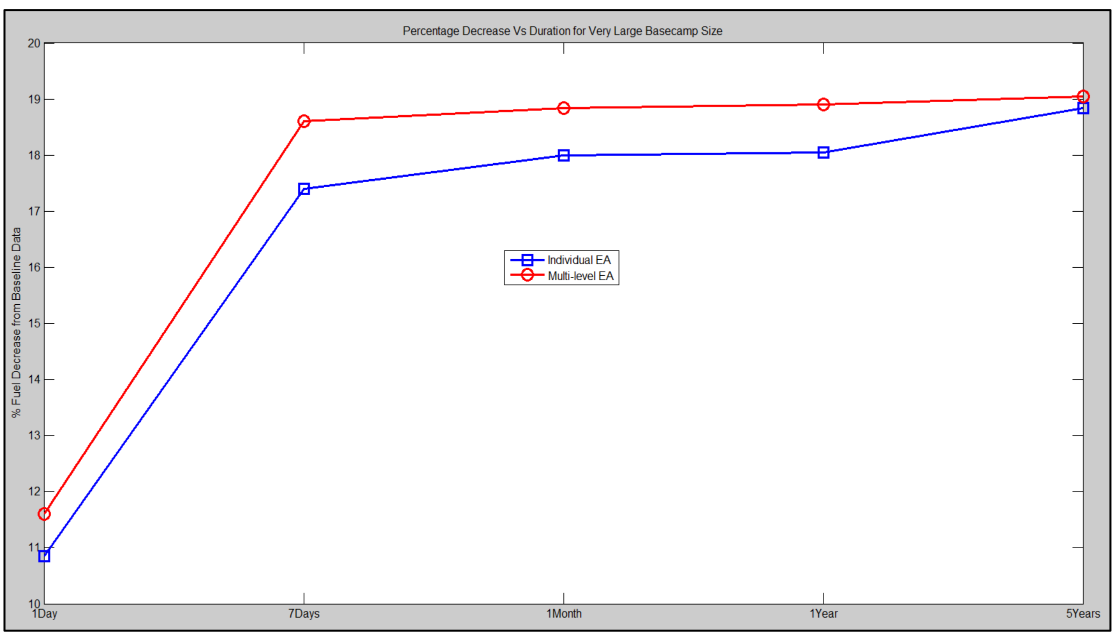

Figure 6.16. Percentage Fuel Savings from Baseline Data for Individual and Multi-level EA for Very Large Size Base Camp.

Table 6.14, Table 6.15, Table 6.16, Table 6.17 and Table 6.18 lists the 95% confidence interval and 'p' values of overall fuel consumption for 50 runs for very small, small, medium, large and very large base camp size respectively using individual EAs and multilevel EA. Since the 'p' values for all the observations are greater than the threshold (0.05), it provides evidence to support the null hypothesis (value obtained is well within the expected value). Table 6.19 lists the correlation coefficients between individual EAs and multi-level EAs for all base camp sizes.

Table 6.14. Very Small Base Camp Size 95% Confidence Interval.

	Individual EA			Multi-level EA			
	Mean	Standard Deviation	Confidence interval (± %)	Mean	Standard Deviation	Confidence interval (± %)	P
1 Day	429.32	0.56	0.5	429.32	0.56	0.5	1.0
7 Days	2,847.7	7.07	0.7	2,847.7	7.07	0.7	1.0
1Month	12,174.2	7.07	0.1	12,152.5	2.82	0.06	0.9
1 Year	145,910.7	7.07	0.02	145,695	5.65	0.01	0.79
5 Years	735,523.56	4.24	0.002	734,938.2	4.24	0.001	0.9

Table 6.15. Small Base Camp Size 95% Confidence Interval.

	Individual EA			Multi-level EA			
	Mean	Standard Deviation	Confidence interval (± %)	Mean	Standard Deviation	Confidence interval (± %)	P
1 Day	427.34	0.14	0.01	427.34	0.14	0.01	1.0
7 Days	2,822.9	1.41	0.1	2,811.7	4.24	0.04	0.89
1Month	12,059.7	2.82	0.01	12,019.1	1.41	0.003	0.92
1 Year	143,605.7	1.41	0.007	144,029.2	1.41	0.004	0.73
5 Years	727,542.2	5.65	0.003	727,101.2	2.82	0.001	0.8

Table 6.16. Medium Base Camp Size 95% Confidence Interval.

	Individual EA			Multi-level EA			
	Mean	Standard Deviation	Confidence interval (± %)	Mean	Standard Deviation	Confidence interval (± %)	P
1 Day	421.5	0.56	0.04	421.5	0.56	0.04	1.0
7 Days	2,770	0.14	0.03	2,759.2	2.82	0.02	0.81
1Month	11,860.5	2.82	0.006	11,797	2.82	0.006	0.9
1 Year	141,817	2.82	0.005	141,008.2	5.65	0.002	0.71
5 Years	712,693.5	4.24	0.003	711,200.2	4.24	0.002	0.8

Table 6.17. Large Base Camp Size 95% Confidence Interval.

	Individual EA			Multi-level EA			
	Mean	Standard Deviation	Confidence interval (± %)	Mean	Standard Deviation	Confidence interval (± %)	P
1 Day	425.1	0.14	0.2	423.6	0.14	0.2	1.0
7 Days	2,768.7	2.82	0.2	2,761.7	2.82	0.2	0.93
1Month	11,845.5	2.82	0.06	11,803.5	1.41	0.04	0.91
1 Year	142,060	4.24	0.008	141,460.2	4.24	0.007	0.87
5 Years	712,331.8	5.65	0.003	710,839.8	2.82	0.001	0.88

Table 6.18. Very Large Base Camp Size 95% Confidence Interval.

	Individual EA			Multi-level EA			
	Mean	Standard Deviation	Confidence interval (± %)	Mean	Standard Deviation	Confidence interval (± %)	P
1 Day	430.04	0.56	0.03	426.04	0.40	0.02	0.95
7 Days	2,783.2	4.24	0.04	2,747.8	2.82	0.03	0.91
1Month	11,867.7	4.24	0.01	11,745.2	2.82	0.006	0.89
1 Year	142,304.95	7.07	0.002	140,887.2	5.65	0.001	0.78
5 Years	714,436.8	7.07	0.0004	712,606.5	7.07	0.0003	0.88

Table 6.19. Correlation Coefficient (Individual EA and Multi-level EA).

	Very Small Size Base camp	Small Size Base camp	Medium Size Base camp	Large Size Base camp	Very Large Size Base camp
Corelation Coefficient	0.99	0.99	0.99	0.99	0.99

6.6. SOLUTION PERFORMANCE

One of the objectives of this research was to determine the potential impact of using randomly generated or a knowledge based solution as a starting point on solution time. Each of the 5 examples discussed in section 6.5. are designed based on existing knowledge. A total of 50 test runs were completed and time to obtain the solution were saved. When a random starting solution was used for the 5 examples, and 50 test runs were completed and time to obtain the solution were saved. The time to solution for both cases are compared to study the effect of initial solution on solution time.

The major impact can be summarized by saying that choice of initial solution substantially affects solution time, but does not affect the solution quality. Table 6.20 summarizes the solution time for all the cases. A good initial solution based on prior knowledge, considerably decreases the solution time.

Table 6.20. Impact of Initial Solution on Solution Time.

	Randomly Generated		Knowledge based Initial Solution	
Base camp Size	Minimum (sec)	Maximum (sec)	Minimum (sec)	Maximum (sec)
Very Small Size	242.6	259.8	209.5	215.8
Small Size	320.5	389.6	221.6	229.1
Medium	489.9	654.2	301.2	328.2
Large	6,028.9	9,842.1	3,219.1	6,124.2
Very Large	38,205.8	56,207.4	14,850.2	22,557.1

7. CONCLUSION

The goal of this research is to develop a multi-level system of evolutionary computational techniques to design solutions to complex problems while improving their effectiveness and efficiency. The ability of evolutionary algorithms to search a solution space and selectively focusing on promising combinations makes them ideally suited to such complex decision making problems. The algorithm presented here can take into account the needs of individual models to optimize the overall needs of a complex problem. The general scope of this research centers upon combining different individual evolutionary algorithms representing subsystems into a multi-level EA, to choose candidate solutions that guarantee the meeting of deadlines and satisfy constraints regarding a complex problem. The experimental results of the base camp design scenarios examined in this research showed that the multi-level evolutionary algorithm has excellent performance in solving a system design problem composed of several sub-systems. The technique developed with the combination of architecture representation and evolutionary algorithms can be useful in developing real-time solutions for multiple base camp configuration problems currently faced by the U.S. Department of Defense.

Base camp planning decisions are often evaluated on the basis of quality of processes. Multiple individual models and algorithms carry useful information to perform wide variety of functions. It is necessary for the individual models to be user friendly and aid in decision making for base camp planners. The mathematical model introduced in this research can be used to estimate the resources required for each subsystem and for the overall base camp. When compared with the existing methodologies, the mathematical model takes into consideration a variety of factors that directly affect a particular base camp size. Results of the mathematical model indicate that the model provided a greater level of accuracy with respect to metered data, when compared to previous methods [Noblis, 2010]. The mathematical model provides a more realistic estimation of base camp resources, with lower utility requirements for smaller base camps and higher requirements for larger base camps. The mathematical model framework is currently being applied to a forward operating base to synchronize all of the components of utility and logistic systems to deliver the right materiel at the right time to the right place. In addition to the soldiers on the base camp, the model considers the contractors associated with the base camp and their dependencies and coupled effects on other components. Since model takes into account the first, second and third order effects of all components involved, the elements of the model can be modified and used for other complex system problems where there is a need to predict the resource utilization and associated interactions of each component present in the design.

The evolutionary algorithm framework developed in this research is extended to provide the link between the energy system modeling to the base camp system level model and the other lower level system needs. The models introduced could also be used to drive in-depth analysis models, which would assist the designer by calculating the exact needs of each component. For example, the OpenDSS model composed of individual electrical component models, populates the electrical distribution system models, coupled to the logistics, fuel, and manpower models, and invokes behaviors, which are translated to the appropriate component models.

The multi-level EA based technique provides a realistic approach to solve problems encountered by base camp planners. The fuel percentage decrease in Tables

6.3, 6.5, 6.7, 6.9 and 6.11 indicate that the individual EAs perform better over time. Communication of information between the EAs in the multi-level EA decrease the fuel consumed by the delivery truck. The higher fuel percentage decrease in Table 6.13 compared to the individual EAs indicates that the multi-level EA perform better than the individual EAs. For all five base camp sizes, the multi-level EA performs very well in terms of less fuel consumption when compared to the individual EAs and baseline data. In addition, it can be inferred from the plots that the amount of fuel savings increases as the time duration increases. When the multi-level EA technique was applied to different base camp sizes, experimental results showed an improvement of up to 19.25% over current methods of calculating resource usages. The multi-level EA builds upon the information exchange between different utility models and improves the overall efficiency of the base camp. A simple information exchange between the power model and logistic model resulted in significant fuel consumption savings compared to existing methodology for a particular base camp.

The proposed multi-level EA framework provides a method to represent the system of systems interactions adding to the complexity that must be managed in a system. The elements of the multi-level EA framework can be modified and used for other complex system problems where there is a need to solve resource allocation and associated interactions of each component present in the design.

8. FUTURE WORK

A great amount of new applied problems in the area of energy networks has recently arisen that can be efficiently solved only as mixed-integer bi-level programs [Kalashnikov, Dempe, Pérez-Valdés, Kalashnykova, and Camacho-Vallejo, 2015]. Among them are the natural gas cash-out problem, the deregulated electricity market equilibrium problem, biofuel problem, a problem of designing coupled energy carrier networks, and so forth, if we mention only part of such applications [Kalashnikov, Dempe, Pérez-Valdés, Kalashnykova, and Camacho-Vallejo, 2015]. Multi level models to describe migration processes are also in the list of the most popular new themes of bi-level programming. There are many areas that can be improved and where capabilities can be added to the existing models presented in this research to suit a particular problem. This research will be resourceful, and capable of automating majority of the design process using developed optimization techniques.

The multi-level EA framework easily allows the planner to do sensitivity analysis of required utilities for different base camp designs. The analysis could be used to check where the design might potentially break and subsequently give the design planner a chance to improve the overall design. The information from the model can be used immediately by planners to improve FOB designs as well as logistical support systems. The dynamic models introduced in this research in combination with external algorithms add intelligence to the overall base camp design and allows the planner to study overall mission dynamics. The information available with the models introduced in this research can also be used within an advanced design tool, which has been proposed for automating and optimizing the design process of FOBs. Such a tool would be very useful for base camp planners in visualizing an FOB before it is created, or to visualize proposed changes to an existing FOB. These tools would lead to an increase in efficiency of resource utilization for FOBs, with the goal of reducing government expenditures and decreasing risk exposure to convoys and logistical support personnel.

This research will make contributions to the systems engineering field through the use of an integrated system architecture development environment and open source system tools development. In future work, a system of computational methods and solvers can be merged into a single cutting-edge tool for solving wide variety of problems. The adaptable behavior of the components can be easily incorporated and solved by the EA resulting in a flexible technique which can be applied to similar planning problems.

8.1. MULTI-LEVEL DIVERSITY CONTROL

In this research, the diversity is controlled in the solution population. The idea is to control the diversity through the two common genetic operators (crossover and mutation). Few sets of experiment were conducted to demonstrate the independent effect of crossover and mutation on diversity. Each set of parameters were tested 4 times to study the convergence effects on diversity. When crossover rate was increased in steps of 0.1 and mutation rate in steps of 0.05 the following observations were made.

- Both operators promote diversity by all measures.
- By increasing crossover rate, the decrease of gradient convergence descent does not change much.
- Increasing mutation rate puts greater force of diversification right from the start.

Diversity control methods for future include:

- Apply order-based crossover operators such as matched crossover, order crossover and cycle crossover.
- Use of adaptive function on the rates of crossover and mutation to maintain diversity at a target level.
- Develop diversity measure such as standard deviation of fitness value in a population.

8.2. AUTOMATED & INTEGRATED LAYOUT PLANNING TOOL

A general architecture overview of the envisioned automated and integrated layout planning tool is given below in Figure 8.1. Use of the planning algorithm will occur in several primary stages. Once the user made sufficient number of changes, the end result would be the efficient solution considering all the different point of view.

1. User inputs mission-specific facilities, number of soldiers and likely base service duration (primary goal of the EA)
2. Mathematical model generates a list of required resources
3. Power Model EA solves and selects structures which satisfy resource requirements and generates the power distribution system
4. Logistic Model EA solves and generates a routing scheme
5. Power Model EA and Logistic Model EA exchange relevant data
6. Multi-level EA generates a viable solution considering the goal of the overall base camp using Power model EA solution space and Logistic Model EA solution space
7. User is prompted to make changes if necessary

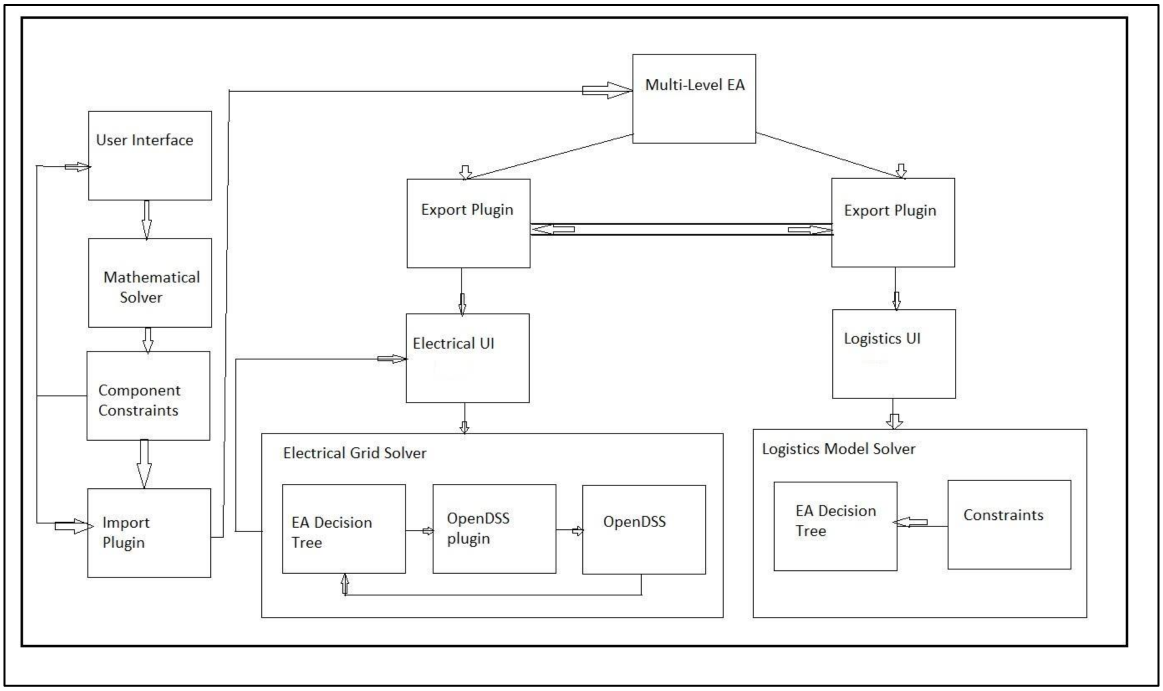

Figure 8.1. Integrated Planning Tool.

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