Capital investment strategies for target revenue generation under performance based contracting for aviation assets: Use of evolutionary algorithms.

G Srikantha Sharma, Dr. Kamal Vagrecha

Abstract: Aviation capital assets are characterised by huge Capital, long pay-off period, deep technology and maintenance intensive over their life cycle. Decision making on Capital investment on these assets hence involve not just the one time acquisition cost but also the maintenance infrastructure that needs to be established to maintain the levels of availability. Performance based contracting (PBL) is fast becoming the preferred mode of contracting for maintenance of these assets. The revenue structure in PBL is a stepped incentivisation and penalty system. The availability of the asset is a stepped function on the investment in maintenance infrastructure. Investment appraisal on design and maintenance infrastructure for targeted revenue generation involves a multi objective optimisation which cannot be analysed using traditional approaches. Calculus based approach fail when the functions are discontinuous and non linear. Models developed on the Evolutionary algorithm approach serve to address multi-objective optimisation with discontinuous variables by following heuristic processes. This approach, thus far used in chemical formulation developing and similar laboratory applications forms a potent tool for capital investment appraisal with discontinuous functions. This paper analyses the Evolutionary algorithm approach and illustrates the same with a case study on Helicopter maintenance decision making in Performance contracting regime.

Key words: Aviation asset maintenance, Base infrastructure, Design investments, Discontinuous functions, Evolutionary Algorithm, Multi-objective optimisation, Performance Based Contracting.

1. BACKGROUND

Equipment intensive organisations including Defence, Aerospace, Infrastructure and Manufacturing sector are constantly challenged by the need to operate at a high level of operational availability of their Capital assets. Decision making on investment in capital assets forms a major managerial activity of Project Managers, Investment planners and Entrepreneurs. Capital equipment investment decisions have long standing impact on business performance and need to be carefully analyzed.

Aviation Capital Assets like aircrafts and helicopters involve huge investments with long pay back periods. These assets need high levels of maintenance during the life span of the equipment to maintain the required operational availabilities.

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2. INTRODUCTION

2.1. Aviation asset maintenance

An Aircraft is a high value capital investment with advanced technologies and system complexities. It calls for high levels of safety, reliability and quality assurance requirements. This is achieved through a series of planned maintenance interventions. Airborne assets are highly maintenance intensive. Other than the scheduled maintenance, a lot of unscheduled maintenance, checks and repair activities are required to be carried out to maintain the high levels of safety and reliability. Thus far, most of the maintenance activity is carried out by the operator and the Aircraft is routed to the OEM only for deep maintenance. Accordingly, the operator plans for both the spares as well as the maintenance infrastructure at the bases. The operator is responsible for stocking of the items and replacing them on the aircraft as and when they become defective. This system is called **spares contracting**, wherein the operator plans, funds and maintains the spares and the OEM is contracted to provide the spares on the terms and conditions contracted.

A lot of research has been carried out on optimal spares provisioning by the operator to minimise his operating costs yet maintain the performance desired, while research is sparse on impact of reliability, reparability and maintainability on the life cycle cost. With the increasing complexity of the technology used on the platforms and the increased investment and planning associated with maintenance, operators have realised the need to shift some of the risks associated with maintenance funding to the OEM so as **to obtain guaranteed operations.**

2.2 Performance Based Contracting (PBL)

With the increasing technological complexity of the assets, the customer is unable to carry out much of the repairs by himself. Also, he would prefer to be rid of the burden of maintenance planning, spares provisioning, maintenance crew and associated costs and would rather concentrate on his primary operations of asset utilization and leave the activity of maintenance to a third party or the OEM. It is in this context that Performance Contracting is emerging as the preferred mode of reparable asset maintenance.

Performance Based Contracting began as a logistic support program in the US Department of Defence (DoD) under the heading of Performance Based Logistics (PBL) and gradually enlarged its scope to cover not just logistics but also maintenance and service. The Performance Based Contract is a contract for maintenance of the reparable asset by the OEM at pre-targeted performance levels. There is a step wise incentive-penalty regime associated with the levels of availability achieved by the PBL provider. The PBL provider, who invariably is the OEM, has now to plan the initial investment in reliability not just to meet the basic performance requirements but also the enhanced returns from increased availability. Further, the PBL provider also has to invest in repair infrastructure, including spares to meet the targeted revenue generation from the PBL contract. Performance Based Logistics (PBL) and Performance Based Contracting (PBC) are used interchangeably in Literature and in practise.

2.3. Multi objective PBL function

The objective of entering into a PBL contract for both customer and service provider is enhanced revenue generation by greater uptime. The PBL contract specifies graduated revenue for the service provider based on the uptime achieved. To provide this service, the service provider (who also is the OEM) has to invest in product reliability and maintenance infrastructure. While design investments have a proportional relationship with availability within the operating spectrum, infrastructure investment has a stepped relation with availability depending on the number of repair bases established. Both the decisions involve capital investment and the service provider has a cap on the maximum investment that can be done while quoting for a PBL embedded procurement of a product. At the same time, he has to meet the targeted revenues from the PBL contract. This multi-objective problem with stepped function needs to be optimised to arrive at a suitable investment strategy.

2.4. Evolutionary Algorithms

Multi-objective stepped or discontinuous functions which cannot be solved using traditional Simplex or calculus based approaches can be optimised using heuristic methods. Heuristic methods follow an iterative approach with progressive refinement of the solution space and arrive at a range of optimal solutions. Heuristic algorithms fall into two categories: the Evolutionary Algorithms (EA) and the Related search algorithms. The Evolutionary algorithm (EA) is also called the Genetic Algorithm (GA) and follows the Darwinian concept of evolution principles for selection of the optimization values.

Evolutionary algorithms operate on a population of potential solutions applying the principles of survival of the fittest to produce better and better approximations to a solution. At the beginning of the computation, a set of values of the variables are randomly initialized to form the first generation population. The objective function is then evaluated for these individuals. The first generation is produced. If the optimization criteria are not met, the creation of a new generation starts. The process continues till no refinement within the iteration limits is obtained. EA formulations are usually optimised using computer programs with sufficient processing capabilities.

3. LITERATURE SURVEY

The objective of decision making in investment in reparable assets is to optimise the initial investments while generating maximum performance from the asset. Maintenance of costly reparable assets like military aviation assets have been traditionally under the spares contracting mode wherein the customer contracts for supply of maintenance spares and evolves his own maintenance infrastructure, echelons and spares management systems. Accordingly, literature in the field has focussed on optimal spares management and choice of number of echelons for maintenance. The first attempt at developing a mathematical model for evolving a criterion for reparable assets control was carried out by Craig C. Sherbooke who developed the Multi Echelon Techniques for Recoverable Items Control acronymed METRIC. The mathematical model describes stocking of replaceable

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spares at multiple bases and develops a computer algorithm to minimise the number of back orders.

The METRIC concept is taken further by Stephen C Graves to characterise the system performance for a given level of inventory stocking. Another variation of the METRIC model is presented by Manuel Rosetti in which he studies the spares parts inventory across the supply chain like suppliers, manufacturers, distributors, retailers etc,. This paper extends the METRIC model by taking into account not just the means but also the variances of the demand level. Hence the model is labelled as VARI-METRIC model.

The above models look at procurement of spares and routing of reparable assets under spares contracting. Organisations are moving from spares contracting to Performance Based Contracting (PBL) especially for costly and maintenance intensive systems like aviation assets. PBL is a new concept and owes its genesis to experiments done in the US Department of defence, initially in the field of services contracts and later moving into aircraft systems and sub-systems.

One of the first successful PBL contracts is the one between Michelin, Lockheed Martin and the US Navy for supply of tyres for the Aircrafts operated by US Navy with Lockheed Martin providing the supply chain services. Devi Mahadevia et all who have researched the contract in detail have identified a robust incentivising of initial reliability improvement efforts by the OEM as the key to success of the PBL contract.

Another such spares support PBL between Honeywell and US DoD for supply of Auxiliary Power Unit researched by Clifford J Landreth et al has revealed a reduction in logistics foot print as a result of PBL but no significant increase in performance. The researchers believe an absence of incentivisation for investment in upfront design but only a one sided minimum performance requirement could be a factor for this experience.

Success of a PBL program requires upfront investment and commitment from the OEM both in reliability design and in maintenance infrastructure coupled with an attractive incentivisation scheme .The challenge is to optimise the level of investment in design and maintenance based on the long term returns from the PBL program. The modelling can be carried out by identifying the constraint variables and decision variables and evolving the relationships. Many of these relationships are stepped functions in terms of investment–returns trade-offs. Performance improvements by increasing the number of bases and revenues of PBL in the three zones of operations, penalty and rewards are examples of such stepped functions.

Solution of such multivariate objective functions can be carried out by many traditional and non-traditional methods. Evolutionary algorithms are a new model of solving multivariate optimisation functions especially for large number of variables and discontinuous functions. Evolutionary algorithms originated from Darwin's theory of origin of species. The principles of cross over, mutation and natural selection have been modelled by researchers for adaptability in intersectional areas.

Evolutionary algorithms were first developed by Computer scientist John Holland in the 1970s wherein he experimented if computer programs could evolve and self-learn using the Darwinian concept of evolution. This was further developed as Evolution strategies by Rechenberg in Germany and Evolutionary programming by Fogel et al. Each of three programming algorithms proved capable of yielding approximately optimal solutions for complex multimodal, on-differential, discontinuous and possibly noisy search spaces. An improvement in the EA processes has been the incorporation of mutation and elitism to ensure that the program does not converge on to a local optimum but searches for global optimum. However EA does not guarantee a global optimal solution unless iterated over a number of times.

One of the first applications of Evolutionary algorithms has been in General Electric's Computer aided design for evolving design specifications within the constraint envelopes. This was used in the design optimisation of jet engines for the Boeing 777 program. EA also has been used in deriving the optimal combination of chemicals in pharmaceutical formulations. Limited applications have been carried out in the financial discipline. Some applications have been used in portfolio selection, time series prediction and predictive trading rules. This paper is among the first attempts to use Evolutionary Algorithm principles for investment appraisal for multi-modal discontinuous functions in the Aviation field.

4. PROBLEM DEFINITION

This paper addresses the problem of selecting an optimal mix of decision functions to meet the multiple objectives of the Capital investment for reparable aviation assets under Performance Based contracting. The OEM of the airborne asset would like to invest more upfront in design of the product as well as the maintenance support systems so as to accrue reduced costs during maintenance as well as reduction in down time. However, he has a cap on the maximum funds that he can invest in the PBL linked asset supply program. PBL is a relatively new field and not much empirical data or adequate literature is available in this field.

The OEM carrying out an investment appraisal for a capital procurement under Performance Contracting has to consider the target performance levels to be achieved. This targeted level of performance determines the target PBL revenues which the OEM can accrue. The targeted performance levels can be achieved by a combination of investment in design and investment in base infrastructure, since it affects the reliability and maintainability of the equipment respectively.

The investment appraisal comprises of identifying the quantum of investment to be carried out in design of the product and the quantum to be invested in base infrastructure necessary to obtain the targeted PBL revenues. A model for such an investment analysis is sought to be developed in the paper. A mathematical model will be developed relating the various variables involved.

In a PBL approach, the revenue generation is a stepped function of the PBL reward-penalty regime. Further, investment in number of bases for maintaining the aviation asset impacts the availability of the asset and hence the revenue generated is a discontinuous variable. Traditional methods of multivariate problem solving cannot be used for discontinuous non linear variables. The paper will explore alternate methodologies to solve the multi-variate resource optimisation problem and illustrate it with a case study on a helicopter platform.

5. MODEL FORMULATION FOR AVIATION ASSET MAINTENANCE UNDER PBL

A mathematical model for investment strategy involves identification of the objective functions and the decision variables that impact the objective function. The intermediate variables that relate the two also need to be identified, defined and relationship established.

As discussed earlier, in the PBL contracting of Aviation assets, the objective functions are two:Maximising PBL revenues(y) and Minimising initial investment (i). The decision maker, while seeking to attain the above objectives has two decisions he has to make:Amount to be invested in Design to achieve the levels of reliability (d) and amount to be invested in maintenance infrastructure to attain the levels of maintainability (b). The first objective function can be written as

$$i = d + b \tag{1}$$

The second objective function is to maximise PBL revenues.

PBL revenues (y)

= Revenue from support – Cost of maintenance

Revenues from the PBL contract is a function of hours flown per year (h) and the reward- penalty regime of the PBL contract.

$$Revenues = (h * K_1 * p) * K_2$$

Where K_1 represents the assured revenues per hour of flying and K_2 represents the reward or penalty factor for exceeding target or missing target. Hence revenue generation is a stepped function. The hours flown per year is given by

$$h = \frac{\text{Uptime}}{(Uptime + Downtime)}$$

$$= \frac{MTBF}{(MTBF + MTTRS)}$$

Where MTBF = Mean time between failure
MTTRS = Mean Time to restore system

MTBF = $K_3/\boldsymbol{\lambda}$

Where

K_3= Number of flying days in a year
$\boldsymbol{\lambda}$ = Failure rate in a year

Further,

MTTRS= MTTR + MLDT

Where

MTTR (μ) = Mean Time To Repair
MLDT (L) = Mean Logistics Down Time

Hence,

$$h = \frac{K_3/\lambda}{[(K_3/\lambda)+ (\mu+L)]} \tag{2}$$

The Mean Time To Repair $\boldsymbol{\mu}$ depends on the DFMA(Design For Maintenance and Assembly) investment in design and can be represented as

$$\mu= K_{11} + K_7/ d \tag{3}$$

The Mean Logistics Down Time (L) depends on the number of repair bases established and the level of spares stocked at each repair base.It is a step relationship given by the equation

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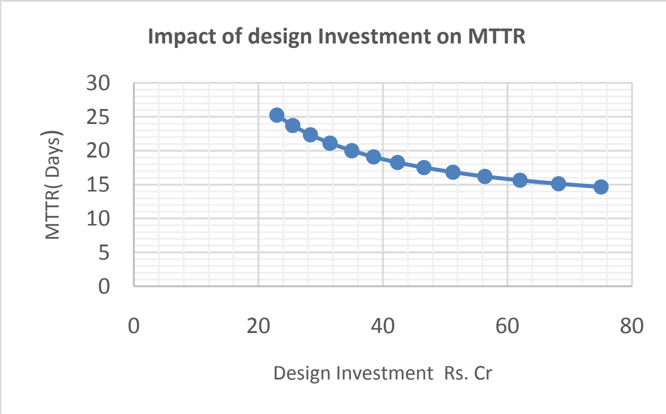
$L = K_8/s + K_9/b$ (4)

The impact of design investment (d) on MTTR and the relationship on base investment (b) on MLDT can be represented graphically as below:



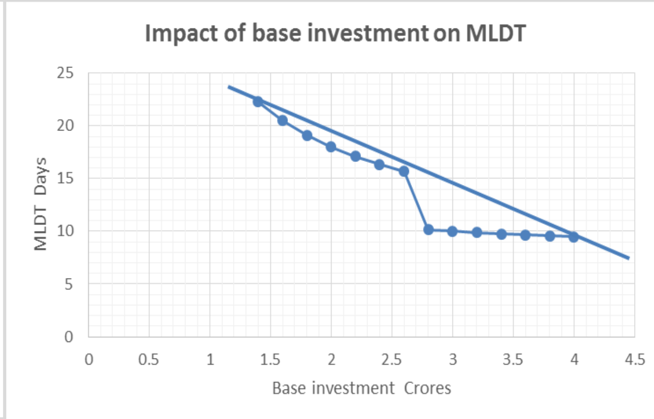


FIG 1
RELATION BETWEEN INVESTMENT AND MTTR / MLDT

Replacing the values of , µ and L from Equation (3) and (4) in Eqn (2) ,

We get
$h = K_3/\lambda/[(K_3/\lambda)+ (K_{11} + K_7/ d) + (K_8/s + K_9/b)]$ (5)

Maintenance of an Aircraft has three components: Snag rectification maintenance to rectify defect before turning around the aircraft for next flight, periodic maintenance mandated by design to maintain continued airworthiness and major overhaul of the aircraft after specified flying hours.

Accordingly, maintenance cost (m)

$m = (\lambda * c_i * p + p/p_{pm} *C_{pm} + p/p_o * C_o) *1/(1-r^p)$

The failure rate λ is given by

$\lambda = f (d)$

$\lambda = K_3 / (K_6 * d + K_{10})$ (6)

The constants K_6 and K_{10} represent the impact of design investment on failure rate, with K_{10} representing the base reliability and K_6 representing the reduction in annual failure rate with increase in design investment.

Substituting these values, we get the second objective function as

Maximise PBL revenues given by

$y = (h*K_1 – ((K_3/(K_6* d + K_{10}) \lambda *C_i * p + p/p_{pm} * C_{pm} + p/p_o * C_o)* K_2 * p * 1/(1-r^p)$ (7)

Where,

h	= hours flown in a year	
d	= investment in design	
λ	= failure rate in a year	
p	= period of operations	
p_{pm}	= Periodicity of preventive maintenance	
p_o	= Periodicity of overhaul	
C_i	= Cost of repairs	
C_{pm}	= Cost of periodic maintenance	
C_o	= Cost of major overhaul	
r	= Rate of interest (Discount factor)	

Introducing slack and surplus variables to convert the functions into a Goal programming model, we get the objective function as

Minimise $Wi * D_i^+ + 0 * D_i^- + 0 * D_y^+ + W_y * D_y^{--}$

Subject to constraints

a) $i = d + b – W_i * D_i^+ + 0 * D_i^-$ (8)

b) $y = (h*K_1 – ((K_3/(K_6* d + K_{10}) \lambda * c_i * p + p/p_{pm} * C_{pm} + p/p_o * C_o)* K_2 * p * 1/(1-r^p) - 0 * Dy^+ +W_y * Dy^-$ (9)

c) $d, b, p, s, D_i^-, D_i^+, D_h^-, D_h^+ >_= 0$
(10)
(Non negativity constraints)

The weights for negative deviation on investment and the positive deviation in PBL revenues is given as zero since the objective is to minimise investment and maximise PBL revenues. In this Goal Programming model two parameters are non-continuous and non-linear: One is the reward-penalty system of the PBL contract. If the hours flown is within a specified range, the revenues generated is a function of the hours flown. If the hours flown increases beyond a set value, it is multiplied by a reward factor and if it goes below a specified value it gets diminished by the penalty factor. This factor is represented by the constant K_2 which takes on values

= 1 for the PBL range of hours
>1 if hours flown exceeds upper limit
< 1 if hours flown falls short of lower limit

The second discontinuous variable is the impact of base investment. If a decision is taken to invest in more than one base, then there is a step reduction in the Mean Logistics Down Time and hence a corresponding step increase in hours flown in a year and consequent revenues from operations. Different methodologies are adopted to optimise the multi-variate non-linear inequalities of the Goal programming model.

6. Multi variate resource optimisation

6.1 Simplex approach

Linear optimisation using Simplex algorithm is the standard method to solve multi-variate inequalities. The Simplex algorithm was invented by George Dantzig in 1947 and is used to solve multiple objective optimization problems using the Gauss-Jordanian computation methodology. By this process, the algorithm tests adjacent vertices of a feasible set in sequence so that in each new vertex, the objective function improves till no further improvement is possible. The iterations proceed along the line of one objective function upto its vertex where-after it shifts to another line representing another constraint equation. The Simplex process requires a straight line approach from one vertex to another. If the function is non-linear, Simplex Algorithm fails to arrive at the optimum values. The model derived for investment appraisal in previous paragraph is a nonlinear equation and hence Simplex fails to provide an optimum solution.

6.2 Calculus based approach

Calculus based algorithms are used for non-linear inequalities. The most frequent calculus based algorithm is the Generalised Reduced Gradient (GRG) algorithm. Calculus based algorithms work on the principle of identifying that point on the objective function map which has the minimum slope in any direction. Such a point is an inflection point. There are likely to be many inflection points for a given surface representing the objective function. The goal is to identify the global minima from the local minima. Calculus based algorithms which depend on identifying the least gradient are called gradient descent algorithms or reduced gradient algorithms. These are first order optimization problems in the sense that they consider first derivative of the objective function. Based on the sign of the derivative, the point is moved by an incremental step opposite to the direction of the gradient so that the function slips down to a smaller value than the initialized value. By iterative incremental slipping down the gradient, the function descends to the minima around the initial value. Calculus based algorithms many times converge onto local minima ignoring the global minima. But the most important disadvantage of Calculus based algorithms is that it needs a continuous function with derivatives at all points on the function. If the function is discontinuous or stepped like in the model that we have developed for investment appraisal, Calculus based approaches fail.

6.3 Heuristic based approach

Multi objective stepped or discontinuous functions which cannot be solved using traditional Simplex or Calculus based approaches can be optimised using heuristic methods. The Evolutionary algorithm is a heuristic approach mimicking Darwin's concept of evolution, mutation and selection of the best fit values from a randomised population.

7. Use of Evolutionary Algorithm for capital investment appraisal

Heuristic methods can be applied on complex problems with large amounts of variables even when the variables are discontinuous, non-differentiable and possibly noisy target functions. Heuristic methods follow an iterative approach with progressive refinement of the solution space and arrive at a range of optimal solutions. Heuristic algorithms fall into two categories: the Evolutionary Algorithms (EA) and the Related search algorithms. The Evolutionary algorithm (EA) is also called the Genetic Algorithm (GA) and follows the Darwinian concept of evolution principles for selection of the optimization values.

Evolutionary algorithms operate on a population of potential solutions applying the principles of survival of the fittest to produce better and better approximation to a solution. At the beginning of the computation, a number of individuals are randomly initialized to form the first generation population. The objective function is then evaluated for these individuals. The first generation is produced. If the optimization criteria are not met, the creation of a new generation starts.

7.1The EA Methodology in Multi objective optimization process

To solve Multi-objective investment appraisal problem using the Evolutionary Algorithm (EA) process, the individuals of the population have to represent a possible solution set of independent variables which will provide a particular value for the objective function. The quality of this particular value is called the fitness φ of the solution. The step by step process of EA is as below:

Step 1: Create initial population: The initial population is created by randomly selecting μ number of solution sets from the set of possible investment combinations. This is called generation 0. Use of a population rather than a single initial solution for further analysis enables EA to work parallely on a range of values and arrive at a set of optimal solutions rather than fine tuning on a single value.

Step 2: Evaluate fitness function: The fitness function for each member of the population is evaluated. Fitness function is the value of the objective functions for the value of the independent variable set represented by that individual and is denoted by the symbol "φ". If any of the fitness function meets the optimization criteria, the process is stopped. If not, action is taken to create the next generation.

Step 3: Selection: In order to choose the individuals for forming the new population, the individuals are ranked by the optimality of their objective function. Individuals with a better fitness function φ have a higher probability p_μ of getting selected for the next step. This is known as application of cyclic evolutionary pressure and is one of the means to sift out poor candidates from further analysis.

Step 4: Cross-over: Cross over resembles the genetic cross-over in sexual reproduction. In this case, some values of the investment decision variable from one parent and remaining values of the other decision variables from the other parent is combined to form a new set of values for decision variables.

Step 5: Mutation: After the new population has been created, randomly selected members of the population will undergo mutation. Mutations are small perturbations in the value of the decision variables constituting the individual (akin to the chromosome) intentionally induced to get a set of individuals from outside of the initial population who may have a better fitness function. Mutation avoids the solution to gravitate to a local optimum and opens the possibility of the algorithm seeking a global optimum solution.

Step 6: Reinsertion & Elitism: After carrying out crossover and mutation, the fitness function is computed for the new generation off-springs and those off-springs which have a better fitness function from their parents replace their parents in the new population.

Step 7: New population: A new population having the same number of members is formed in the new generation. The fitness function of the members is evaluated. If any member satisfies the objective criteria, the iteration is stopped, else the iteration is continued.
The flow chart of the EA algorithm applied to capital investment appraisal is illustrated below.

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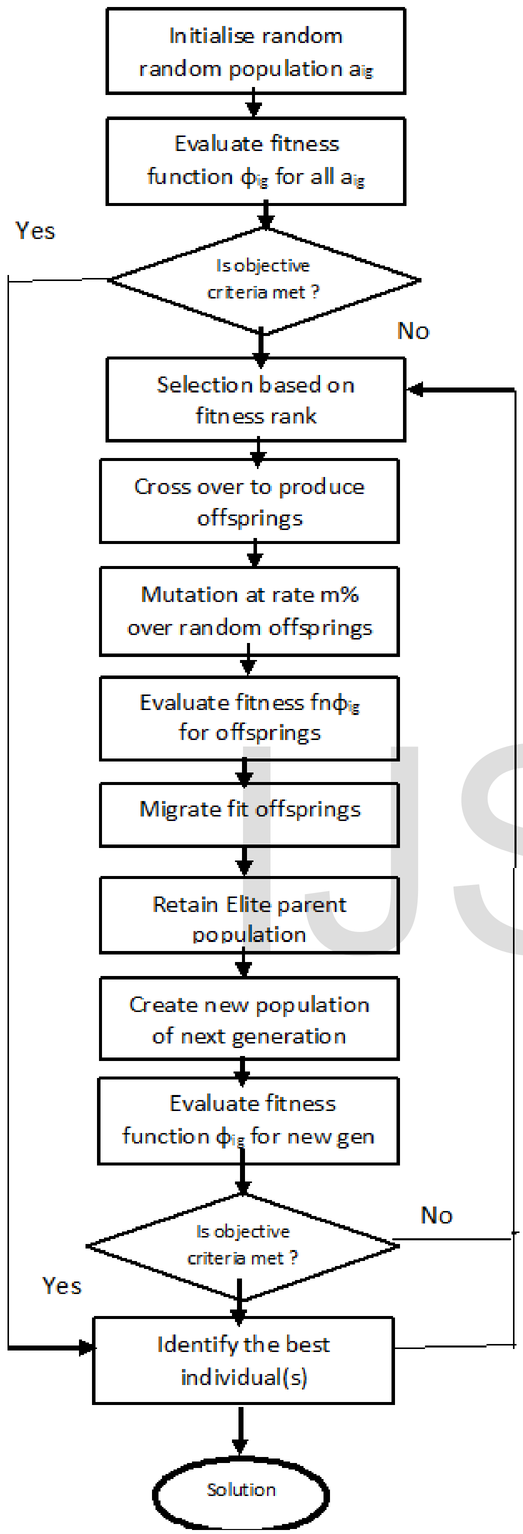

FIG II
EVOLUTIONARY ALGORITHM FLOW DIAGRAM

8. Application of EA technique for investment analysis of helicopters

Formulation of the model for capital investment analysis and solving the same using EA approach is illustrated by the case study on helicopter procurement. The paramilitary forces released a request for procurement of a squadron of reconnaissance and surveillance helicopters for coastal patrolling involving supply and maintenance of the helicopter squadron under a Performance Based contracting model. As per the contract, supplier has to provide a Performance Based Contract for maintenance of the helicopter under the following terms:

i) Initial term of PBL is 5 years extendable by one year every year thereupon.

ii) Supplier has to provide the targeted 270-275 hours of flying each year per helicopter. Reward- penalty factor of 20% for flight above 275hrs and flight below 270 hrs is adopted.

8.1 Determination of the Goals of the GP function

The supplier organisation instituted an investment appraisal for design, manufacture, supply and support for the Capital equipment under Performance contracting. The appraisal was carried out using the EA approach. The supplier who has to quote for the tender has two constraints. First is the decision on how much to invest in taking up the project. The investment comprises of investment in design, base infrastructure and insurance spares. Further, having invested, the supplier expects adequate return on Investment. The returns obtained by the PBL provider are in terms of revenues by the maintenance contract.

8.1.1 Goal 1**:** The Company has limitations on investable cash based on the position of its reserves and surplus as well as running and upcoming projects which need investment. The Finance department has earmarked an investment of Rs. 40 Crores in the program. This is based on interaction with designers, production and maintenance Managers who have given an estimated break up as under:

a)	Design , Development & Testing (Design estimates)	: 1500 Lakhs
b)	Product realization & certification (Prodn estimates for 2 T H/c)	: 2000 Lakhs
c)	Base infrastructure	: 300 Lakhs
d)	Insurance spares (@ 7.5% of product cost)	: 150 Lakhs
e)	Contingencies	: 50 Lakhs

Accordingly, the first goal is

Minimize I $\leq$ 40,00,00,000 Rs. (11)

8.1.2. Goal 2: The supplier provides the PBL maintenance support to the equipment. Considering the investment involved and the risks in the maintenance activity, a base return of 10% on investment is the minimum. Hence

PBL revenue for a year = 10% * 40,00,00,000

PBL revenues for a 10 year
expected period of usage = 40 crores.

Accordingly, the second goal is

Maximize y >= 40,00,00,000Rs. (12)

Converting the goals into the Goal programming format and introducing the deviation variables and penalty weights, we get the objective function as

$$i = f(d, b,) - W_i * D_i^+ + 0 * D_i^- = 40,00,00,000$$

$$y = f(h, c,) - 0 * D_y^+ + W_y * D_y^- = 40,00,00,000$$

By substituting the functions, the Goal programming equation set becomes

Minimise $Wi * D_i^+ + 0 * D_i^- + 0 * D_y^+ + W_y * D_y^-$

Subject to

a) $i = d + b - W_i * D_i^+ + 0 * D_i^- = 40,00,00,000$

b) $y = (h*K_1 - ((K_3/(K_6 * d + K_{10})\ \lambda * c_i * p + p/p_{pm} * C_{pm} + p/p_o * C_o)* \ K_2 * p * 1/(1\text{-}r^p) - 0 * Dy^+ + W_y * Dy^- = 40,00,00,000$

c) $d, b, p, s, D_i^-, D_i^+, D_y^-, D_y^+ >= 0$

8.2. Solution of the Capital appraisal model

The investment appraisal model was configured in the computer. The Excel Solver program developed by Microsoft was utilized for the model development. The step function conditions for PBL reward-penalty and MLDT have been incorporated. The initial formulation of the problem with the values of the constants is placed below:

TABLE I
FORMULATION OF THE COMPUTER MODEL

FORMULATION OF COMPUTER MODEL

Decision variables		Deviation variables				Constraint variables			
d	b	D^+_i	D^-_i	D^+_y	D^-_y		Description	Soln	Limits
Design cost	Base infra	1	-1	1	-1	i	Initial investment	$_i + D^+_i + D^-_i$	= Target value
di	bi	D^+_i	D^-_i	D^+_y	D^-_y	Yi	PBL revenues	$_{Yi} + D^+_y + D^-_y$	= Target value
Lower bounds							Objective function		
0	0	0	0	0	0		Minimise $Z = (1 * D^+_i * W_i) - (1 * D^-_y * W_y)$		
	Penalty weights	W_i	0	0	W_y				

OBJECTIVE FUNCTIONS

1	Minimise intial investment	
	i = d + b	i
2	Maximise PBL revenues	
	y=(K1*h - c*λ)K2*p	yi

INTERMEDIATE FUNCTIONS

1	Bandwidth hours flown in a year	
	h= (K3/λ)/[(K3/λ)+μ+l]*K3	h_i
2	Failure rate	
	λ=K3/(K6*d + K10)	λ_i
3	Mean Time to repair	
	μ=K7/d + K11	μ_i
4	Mean Logistics down time	
	l= K8/s + K9/b	l_i

CONSTANTS

K1=assured revenues per hour	350000
K2=Reward or penalty factor	K2i
K3=No. of working days in a year	360
K6= Design reliability relationship	0.0000002
K7=design reparability relationship	3500000000
K8= MLDT spares relationship	160000000
K9= Base investment MLDT relationship	K9i
K10=Design reliability constant	50
K11=design reparability constant	10
c=Unit cost of repair	20000000
p= period of usage	10
s= spares investment	20000000

Reward/Penalty condn for K2i	Addnal base step condn for K9i	INITIAL VALUES	
IF(hi <270, (K2= 0.8),ELSE	IF(bi >30000000,(GO TO NEXT),(ELSE K9=200000000)	d	di
IF(hi >275,(K2= 1.2),(ELSE K2=1))	IF(bi >40000000,(K9=50000000),(ELSE K9= 100000000)	b	bi

The solver software was run using Simplex method. Simplex could not solve the problem because some of the functions are non-linear. Simplex can solve only linear functions. Next the problem was taken up in Generalised Reduced Gradient methodology. While the GRG algorithm could solve a uniform function, since the PBL revenues and the base infrastructure both were step functions, GRG could not solve once the step constraint was introduced.

A similar exercise was carried out using evolutionary algorithm. Convergence was set at 0.8 with a mutation rate of 0.05. A population size of 100 was selected and the time for stabilization was set at 300 seconds. The first iteration took 31.329 seconds. The second iteration was carried out using the revised values. The second iteration took 71.172 seconds. The solution was nearer to objective function. In the next iteration, discontinuity in the constraint equation was introduced. Unlike the GRG algorithm, Evolutionary Algorithm could compute the results.

The optimum values of investment based on Evolutionary algorithm is Rs. 31.73 Crores for design investment and Rs. 6.58 Crores for base infrastructure. A single base is to be established. The PBL contract provides for 285 hours of flying per year which results in a reward factor of 20% on the PBL revenues. An MTTR of 21 days and an MLDT of 8.84 days is obtained. The PBL revenues of Rs. 43.55 crores and the initial investment of Rs. 38.32 crores is within the targets set by the Goal programming model.

A summary of the result is placed below:

TABLE II
OPTIMISED RESULTS USING EVOLUITONARY ALGORITHM

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Microsoft Excel 15.0 Answer Report
Worksheet: [PBL Investment model -EA.xlsx]Sheet2
Report Created: 13-05-2016 13:21:44
Result: Solver has converged to the current solution. All Constraints are satisfied.
Solver Engine
Engine: Evolutionary
Solution Time: 98.766 Seconds.
Iterations: 0 Subproblems: 72723
Solver Options
Max Time Unlimited, Iterations Unlimited, Precision 0.1
Convergence 0.8, Population Size 100, Random Seed 4, Mutation Rate 0.05, Time w/o Improve 300 sec
Max Subproblems Unlimited, Max Integer Sols Unlimited, Integer Tolerance 0%, Assume NonNegative

Objective Cell (Min)

Cell	Name	Original Value	Final Value
$I$10	value : Objective function	0	0

Variable Cells

Cell	Name	Original Value	Final Value	Integer
$B$7	Design cost	250000000	317375137	Contin
$C$7	Base infra	20000000	65842786	Contin
$D$7	D1+	0	0	Contin
$E$7	D1-	0	0	Contin
$F$7		0	0	Contin
$G$7		0	0	Contin

Constraints

Cell	Name	Cell Value	Formula	Status	Slack
$B$9	Lower bound Design cost	0	$B$9>=0	Binding	0
$C$9	Lower bound Base infra	0	$C$9>=0	Binding	0
$D$9	Lower bound D1+	0	$D$9>=0	Binding	0
$E$9	Lower bound D1-	0	$E$9>=0	Binding	0
$F$9	Lower bound	0	$F$9>=0	Binding	0
$G$9	Lower bound	0	$G$9>=0	Binding	0
$J$5	PBL revenues Soln	435546366	$J$5>=$K$5	Not Binding	35546366
$J$6	investment Soln	383217923	$J$6<=$K$6	Not Binding	16782076.76

9. Discussions

The Evolutionary Algorithm can be optimally used to find an optimal investment strategy with multiple objective functions. While Simplex algorithm evaluates only interesting vertices, Evolutionary Algorithm takes random points within the sample space. The number of initial sample points and the convergence determines the computational efforts and the time taken to achieve optimality. The solution obtained is not necessarily optimal but the best among the random sample selected. To fine tune the exercise, the solution obtained from the first iteration is taken as the initial value and the process repeated till no substantial change in result values are obtained.

The Evolutionary algorithm involves lot of computing and can be done only by a computer program. Excel solver by Microsoft has developed an add-on feature of computing using evolutionary algorithm with flexibility to choose the convergence and mutation rates. The present case involved only two decision variables and two constraint variables. It is possible to expand the scope of the problem by adding additional constraint and decision variables to represent secondary influences also.

9.1 EA Algorithm for Investment appraisal: Comparison over Traditional processes

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Evolutionary algorithms provide some distinct advantages with respect to classical calculation based approach when applied to capital investment analysis.

a) Population versus single best solution: The EA process begins with a population of random size unlike classical optimization algorithms which updates an initial solution and refines it in subsequent stages. This approach provides three distinct benefits :
   i) Parallel processing power achieving a computational quick overall search.
   ii) Multiple optimum solutions for comparing alternate set of investment options from strategic perspective.
   iii) Option to normalize the decision variables within an evolving population.

b) Randomness versus deterministic operation: EA relies on random sampling both while initializing the population as well as while identifying the child sample for mutation. This stochastic process used in EA results in different options available in a set of equally optimal solutions from which tradeoffs can be evaluated.

c) Creating new solutions through mutation: The EA process intentionally brings in variables from a space outside the redefined space. This enables EA to have a greater probability of finding the global optima and not getting restricted to local optima.

d) Survival of the fittest through Elitism: The process by which most fit decision variables are retained and in fact provided more opportunities in the iterations navigates the algorithm towards optimum solutions faster.

e) Handling discontinuity: One of the major advantages of the EA algorithm over the classical calculus based algorithms is that it does not depend upon the existence of derivatives and hence can be applied for discontinuous and noisy functions also. Capital investment appraisals are beset with step functions in infrastructural investment which can be solved only using evolutionary algorithms.

However the EA methodology also has a few limitations. The EA has no concept of optimum solution or any way to test whether the solution is optimal. It can only determine a better solution from a random population. For this reason, the EA never knows when to stop the cycle. External conditions like maximum length of time or maximum number of iterations or a convergence value needs to be provided.

10. Scope for further work

The key to utilising generic algorithms to optimise decision making is in modelling the mathematical function to represent the effects of the various constraint parameters on the decision variables. Many of such constraints do not lend themselves amenable to mathematical formulation because the functions are complex and sometimes discontinuous. The success of application of search algorithms depends on the ability to develop the system of curves, or rather surfaces which represent the search space for the system. As the number of variables increases, the function generation becomes more complex. Use of past data and incomplete information to generate the first order equations and inequalities and refine the same as more information gets available requires the formulation of self-learning algorithms which needs further research. Incorporation of machine learning protocols within the EA algorithm for dynamic decision making is an interesting area for further research.

13. Additional Resources

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