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Multi-objective optimization of product life-cycle costs and environmental impacts

Relatore: Chiar.mo Prof. Marco TAISCH

Correlatore: Ing. Jacopo CASSINA

Dott. Sergio TERZI

Daniele CERRI matr.752072

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ABSTRACT

Introduction

Today, in an increasingly competitive world, Western companies need new tools to attempt to stay on the market.

These companies are forced to seek new ways to be competitive in the global market, because of globalization and of the competition with companies around the world, particularly from Far East, where labor costs less and there aren't strict environmental regulations.

Since it's very difficult to compete with the mere final cost of the product of Far East companies, Western companies have begun to aim at reducing the life cycle cost as a new competitive tool. So the interest in LCC is driven by finding new competitive leverages, different by the classical ones (e.g. lower cost of acquisition). For example, with life cycle cost analysis, western companies can offer energetically efficient services and/or machine, or reducing the use of labor. Other examples can be the reduction in the cost of spare parts or of the maintenance time and so of the maintenance costs. In addition, more and more costumers require in the proposal a life cycle cost analysis (some of them an accurate one, others a less rigorous one).

Another new competitive tool that some companies have begun to use is the reduction of environmental impact. This choice has been dictated by increasingly strict regulations as Kyoto protocol and ISO 14000.

In the literature there are methodologies that help to calculate the costs and environmental impacts along the whole life-cycle: they are the LCC (Life Cycle Cost) and the LCA (Life Cycle Assessment).

Life Cycle Costs (LCC) are "cradle-to-grave" costs summarized as an economic model of evaluating alternatives for equipment and projects. [Bar 03]

Life Cycle Assessment (LCA) is a technique to assess environmental impacts associated with all stages of a product's life from-cradle-to-grave. [Sai 06]

These methodologies explain step by step how to conduct an analysis of costs or of environmental impacts along the life-cycle, but they don't optimize this values. Also in the literature there are just few papers that attempt to optimize costs or environmental impacts along the life-cycle, while most of them explain how to conduct a LCC or LCA analysis.

So in our work we apply a multi-objective optimization, based on genetic algorithm, to LCC (Life Cycle Cost) and LCA (Life Cycle Assessment) methodologies.

When we speak about LCC and LCA optimization we refer to optimization of the results and not of the methodologies.

Genetic algorithm has been selected because it has no problems with dealing with multi-objective optimization, instead linear programming cannot handle problems of this type. In addition genetic algorithm is more efficient than linear programming when the number of variables increases.

Reasons

Companies

Companies (particularly western companies) need new competitive leverages to survive in the global market. Two of these new tools are life cycle cost and environmental impacts, they are so interesting because of the impossibility to compete with the final cost of product of Far East companies.

We have access to the results of a questionnaire given to 3 western companies: Aker, Comau and Volkswagen. This questionnaire was submitted to the companies as part of an European project.

From a question it is possible to analyze which are the main factors considered by the companies during their design/development processes. Typical factors have been defined from a literature analysis. We consider only the economics and environmental factors.

As shown hereafter, in ***Table 1***, the economic and environmental factors are important or very important for all the companies.

So this work is based on existing needs of enterprises and our model ,that optimizes both LCC and LCA, can really help many companies.

How would you rate the company's consideration (i.e. factors used for evaluating alternative solutions) of the following factors/criteria during the design / development process?			
Factors	**Aker**	**Comau**	**VW**
Final Cost of the Product			
Costs along the Product Lifecycle			
ROI - Return of Investment			
Environmental aspects			

Legend	
Very Low	
Low	
High	
Very High	

Table 1 Importance of economics and environmental factors

<u>Literature</u>

The literature of LCC and LCA is very wide. In the last years the number of papers is significantly increased, particularly the literature regards LCA.

However many of these works are not relevant, they treat briefly these methodologies; in fact many of these papers simply apply LCC or LCA, without adding anything new, in some of them there are not even calculations . Just few papers are innovative or, at least, complete.

This shows how this methodologies need to be further studied in-depth, because they are not accessible to the majority, although they are not a new concept (they were born in the 1960s).

So it is necessary to do an exhaustive search in the literature, in order to find the relevant papers.

We have analyzed 39 papers of LCC application and 40 papers of LCA application. These are the papers that we considered relevant.

Figure 1 and ***Figure 2*** show where LCC and LCA are applied.

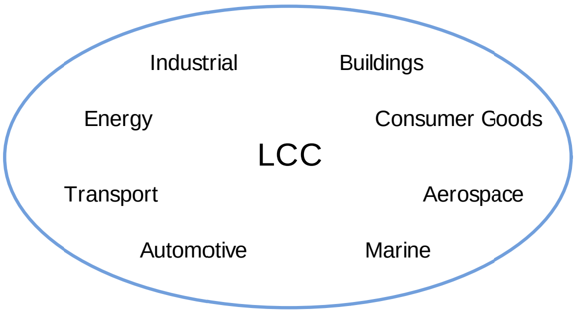


Figure 1 Field of application of LCC

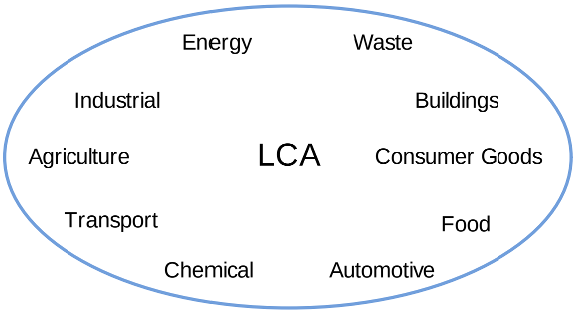


Figure 2 Field of application of LCA

Figure 3 and ***Figure 4*** show the percentage of LCC or LCA optimization in the literature.

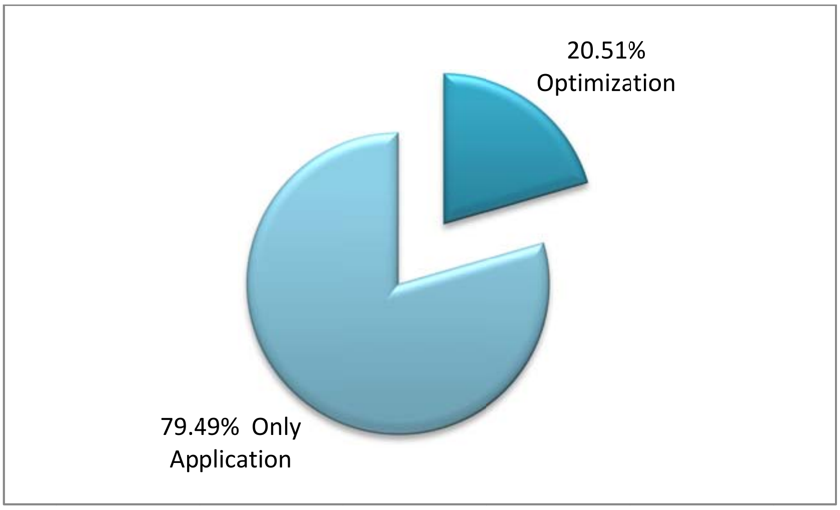


Figure 3 LCC Optimization percentage

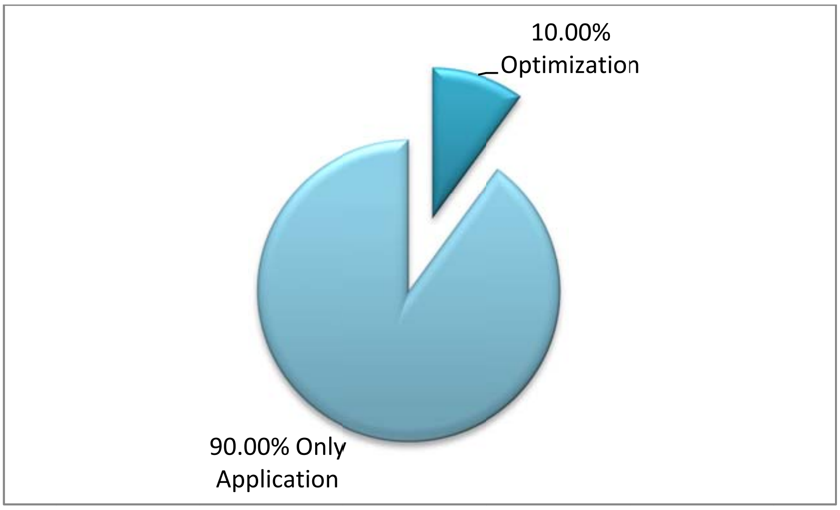


Figure 4 LCA Optimization percentage

As we can see, only about the 20% of papers presents a LCC optimization, while, for LCA optimization, only the 10% of papers shows an optimization.

Table 2 reports a summary of the literature analysis.

	% of paper analyzed	**% of evolutionary algorithms**	**Other optimization?**
LCC optimization	20.51%	75%	No
LCA optimization	10.00%	50.00%	Yes (cost or production)

Table 2 Summary of paper analysis

The major problem of these papers is the lack of information regards models (objective functions and constraints) and used data. This makes any comparison or evaluation difficult.

From the paper analysis we can say that the route of LCC and LCA optimization is still open. Our work aims to continue and deepen this way.

Life Cycle Cost

Life cycle costs (LCC) are "cradle-to-grave" costs summarized as an economic model of evaluating alternatives for equipment and projects. [Bar 03]

Figure 5 Phases of LCC

As shown in the attached diagram (***Figure 5***), Life Cycle Costing is a six-staged process. The first four stages comprise the Life Cost Planning phase with the last two stages incorporating the Life Cost Analysis phase. The six stages are:

- Stage 1: Plan LCC Analysis
- Stage 2: Select/Develop LCC Model
- Stage 3: Apply LCC Model
- Stage 4: Document and Review LCC Results
- Stage 5: Prepare Life Cost Analysis
- Stage 6: Implement and Monitor Life Cost Analysis [Nsw 04]

Life Cycle Assessment

Life cycle assessment is a technique to assess environmental impacts associated with all the stages of a product's life from-cradle-to-grave.

The LCA process is a systematic, phased approach and consists of four components: goal definition and scoping, inventory analysis, impact assessment and interpretation. (***Figure 6***)

This process is explain in ISO 14040 Environmental Management - Life Cycle Assessment - Principles and Framework.

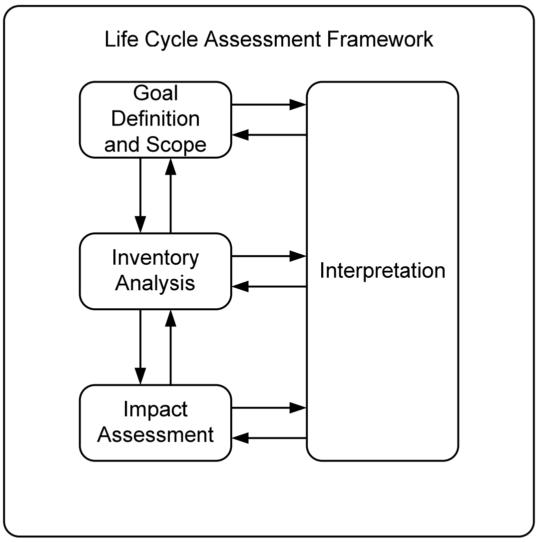


Figure 6 Phases of an LCA [Iso 97]

1. Goal Definition and Scoping - Define and describe the product, process or activity. Establish the context in which the assessment is to

be made and identify the boundaries and environmental effects to be reviewed for the assessment.

2. Inventory Analysis - Identify and quantify energy, water and materials usage and environmental releases (e.g., air emissions, solid waste disposal, waste water discharges).
3. Impact Assessment - Assess the potential human and ecological effects of energy, water, and material usage and the environmental releases identified in the inventory analysis.
4. Interpretation - Evaluate the results of the inventory analysis and impact assessment to select the preferred product, process or service with a clear understanding of the uncertainty and the assumptions used to generate the results. [Sai 06] [Iso 97]

Optimization Method (Genetic Algorithm)

Genetic algorithms (GAs) are a subclass of evolutionary algorithms where the elements of the search space G are binary strings ($G = B^*$) or arrays of other elementary types.

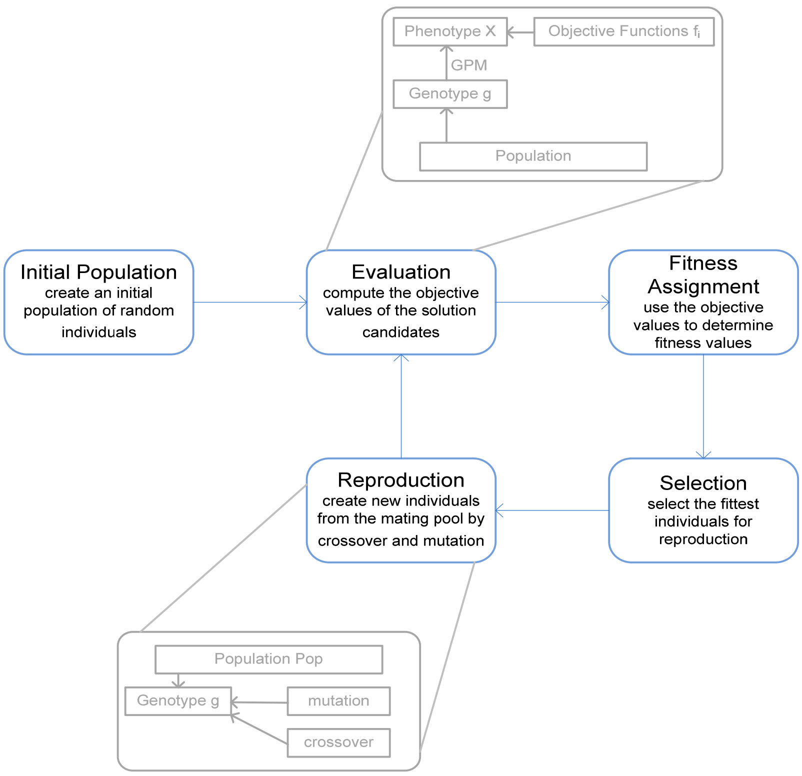


Figure 7 The basic cycle of genetic algorithms[Wei 09]

All genetic algorithms proceed in principle according to the scheme illustrated in ***Figure 7***:

1. Initially, a population Pop of individuals p with a random genome p.g is created.
2. The values of the objective functions f ∈ F are computed for each solution candidate p.x in Pop. This evaluation may incorporate complicated simulations and calculations.
3. With the objective functions, the utility of the different features of the solution candidates have been determined and a fitness value v(p.x) can now be assigned to each of them. This fitness assignment process can, for instance, incorporate a prevalence comparator function cmp_F which uses the objective values to create an order amongst the individuals.
4. A subsequent selection process filters out the solution candidates with bad fitness and allows those with good fitness to enter the mating pool with a higher probability. Since fitness is subject to minimization in this context, the lower the v(p.x)-values are, the higher is the (relative) utility of the individual to whom they belong.
5. In the reproduction phase, offspring is created by varying or combining the genotypes p.g of the selected individuals p ∈ Mate by applying the search operations searchOp ∈ Op (which are called reproduction operations in the context of EAs). These offspring are then subsequently integrated into the population.
6. If the termination Criterion is met, the evolution stops here. Otherwise, the algorithm continues at step 2. [Wei 09]

We use NSGA-2 (Non Dominated Sorting Genetic Algorithm).

NSGA-2 is one of the most popular multi objective optimization algorithms with three special characteristics: fast non-dominated sorting approach, fast crowded distance estimation procedure and simple crowded comparison operator. [Deb 02]

Model

We introduce a model to optimize product life-cycle costs and environmental impacts together. The model is developed with genetic algorithm and compared to linear programming. The three developed models (one with genetic algorithm, two with linear programming) are compared by using test cases with invented data.

To develop genetic algorithm model we use NSGA-2, while as linear programming models we use Weighted Sum Model and a model in which we turn the bi-objective problem into a single objective one, where an objective appears in the objective function, the other is displayed as a constraint.

Weighted Sum Model

The Weighted sum model (WSM) is the best known and simplest multi-criteria decision analysis (MCDA) / multi-criteria decision making method for evaluating a number of alternatives in terms of a number of decision criteria. It is very important to state here that it is applicable only when all the data are expressed in exactly the same unit. If this is not the case, then the final result is equivalent to "adding apples and oranges." [Fis 67] [Tri 00] [Wik 02]

From bi-objective to single objective problem

We must optimize the problem in two objective (Life Cycle Cost and Life Cycle Assessment). Here we call the two objective *A* and *B*.

We have created this technique to solve this problem and to obtain a curve similar to Pareto curve.

Firstly we have solved a model with single objective *B*, finding the maximum (*Max*) and the minimum (*Min*) of the objective function.

Then we have divided this range (*Max* – *Min*) for a number of intervals *X* achieving a value equal to *Y*.

$$Y = \frac{(Max - Min)}{X}$$

So we have created values from *Max*, *Max – Y*, *Max – 2*Y*, ... to *Min*.

Finally we have solved the other objective (A) in a single objective problem, respecting the constraint derived from the previous resolution of B. The constraint is written as (equation of the constraint is expressed as $EQ.$):

- If B is to maximize, the constraint is: $EQ.>Min$ for the first iteration; then $EQ.>Min + Y$,... until $EQ.>Max$ for the last iteration.
- If B is to minimize, the constraint is: $EQ.<Max$ for the first iteration; then $EQ.<Max - Y$,... until $EQ.<Min$ for the last iteration.

In this way we have obtained a curve similar to Pareto curve.

A weakness of this strategy is that it can produce solutions that are not Pareto efficient.

NSGA-2

The procedure of NSGA-2 is:

1- Create a random parent population P_0 of size N. Set $t = 0$.

2- Apply crossover and mutation to P_0 to create offspring population Q_0 of size N.

3- If the stopping criterion is satisfied, stop and return to P_t.

4- Set $R_t = P_t \cup Q_t$.

5- Using the fast non-dominated sorting algorithm, identify the non-dominated fronts $F_1, F_2, ..., F_k$ in R_t.

6- For $i = 1, ..., k$ do following steps:

   1- Calculate crowding distance of the solutions in F_i.

   2- Create P_{t+1} as follows:

      Case 1: If $| P_{t+1} | + | F_i | \leq N$, then set $P_{t+1} = P_{t+1} \cup F_i$;

      Case 2: If $| P_{t+1} | + | F_i | > N$, then add the least crowded $N - | P_{t+1} |$ solutions from F_i to P_{t+1}.

7- Use binary tournament selection based on the crowding distance to select parents from P_{t+1}. Apply crossover and mutation to P_{t+1} to create offspring population Q_{t+1} of size N.

8- Set $t = t+1$, and go to Step 3. [Deb 02] [Kon 06]

To realize the genetic algorithm NSGA-2 we use the software GANetXL (Savic et al.), an add-in for Microsoft Excel.

Tests' Scenarios

We have created three different scenarios to compare the three optimization methods, that we have used. Scenario A has a unique optimal solution. Scenario B has more optimal solutions arranged on a Pareto Front. Scenario C is equal to the second with the addition of a constraint.

Table 3 reports a summary of the characteristics of the Scenarios.

	Data Input	Optimal Solutions	Constraint
Scenario A	A	Unique	No
Scenario B	B	Pareto Front	No
Scenario C	B	Pareto Front	Yes (1)

Table 3 Summary of the characteristics of the Scenarios

Below there are the comparison between the three optimization methods.

We suppose to have a generic product composed of 10 subgroups. Each subgroup has two alternatives to be realized. Each alternative has this data input:

- *Cin*: initial cost;
- *Cmnt*: maintenance cost;
- *Cen*: energy cost;
- *Cmdpmn*: cost of manpower for maintenance;
- *BOL*: environmental impact in beginning of life;
- *MOL*: environmental impact in middle of life;
- *EOL*: environmental impact in end of life.

These data consider all the life cycle of the product so, for example, *Cmnt* is the maintenance cost during all the life cycle.

The units of measurement are a generic unit of cost for LCC and a generic unit of environmental impact for LCA.

LCC is calculated as:

$$LCC = \sum_{i=1}^{n} (Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$$

while LCA is calculated as:

$$LCA = \sum_{i=1}^{n} (BOL_i + MOL_i + EOL_i) * x_i$$

where x_i is a binary variable which assumes value 1 if the subgroup *i-th* is used to realize the product, otherwise it assumes value 0.

The two objectives are:

- Minimize the Life Cycle Cost (LCC);
- Minimize the Life Cycle Assessment (LCA).

In weighted sum model (WSM) the model is written as:

Minimize $w * \frac{LCC}{LCC^*} + k * \frac{LCA}{LCA^*}$

Subject to $LCC = \sum_{i=1}^{20}(Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

$LCA = \sum_{i=1}^{20}(BOL_i + MOL_i + EOL_i) * x_i$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5, \dots ,19$

$w + k = 1$

$w, k \geq 0$

$x_1, x_2, \dots , x_{20} \in (0,1)$

The two objectives are dimensionally different: LCC has a cost dimension while LCA has an environmental impact dimension. If we want to add LCA and LCC we must make LCA and LCC dimensionless. So firstly we solve a single objective problem, maximizing one time LCA and one time LCC. We obtain LCA^* and LCC^*. We put this values in objective function as shown above. So we make LCA and LCC dimensionless and we can sum them. Iteratively we change the values of *w* and *k*, respecting the constraint, to obtain the different solutions of the problem. We start from *w*=1 and *k*=0 to arrive at *w*=0 and *k*=1, passing through intermediate values as *w*=0.55 and *k*=0.45.

In the other linear programming method the model is written as:

Minimize $LCC = \sum_{i=1}^{20}(Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

Subject to $\sum_{i=1}^{20}(BOL_i + MOL_i + EOL_i) * x_i \leq TV$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5, \dots ,19$

$x_1, x_2, \dots , x_{20} \in (0,1)$

where *TV* is the Target Value.

In Multi-Objective Genetic Algorithm (we have used NSGA-2) there's a chromosome (which represent the generic product) composed of ten genes (which represent the subgroups). Each gene can assume only two values (for example gene 1 can be 1 or 2, gene 2 can be 3 or 4, ..., gene 10 can be 19 or 20). Genetic algorithm optimizes the two objective simultaneously creating a curve similar to Pareto front. Here we have used a population size of 50, an one point crossover with a rate of 0.95 and a single mutation by gene with rate 0.05.

All the above-described is valid for all scenarios.

Scenario A

In this scenario the data input are reported in ***Table 4***:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	5	10	-2
2	15	6	0	2	8	15	0
3	20	7	0	3	10	20	-6
4	25	8	0	4	15	25	-3
5	30	9	0	5	12	24	-5
6	35	10	0	6	15	28	-2
7	5	2	0	1	2	8	-1
8	10	3	0	2	4	13	3
9	20	4	10	7	10	20	5
10	25	5	11	8	15	25	10
11	50	12	5	11	20	29	-1
12	55	13	7	12	25	33	2
13	70	21	20	20	50	100	-15
14	75	22	25	21	60	130	-5
15	85	35	0	31	50	35	-15
16	90	36	0	32	60	45	-5
17	50	12	0	10	20	10	5
18	55	13	0	11	30	15	10
19	10	5	0	3	20	10	0
20	15	6	0	4	35	25	10

Table 4 Data Input for Scenario A

In this scenario the data are arranged, so that we obtain a unique solution reported in ***Table 5***.

Product Subgroups	1	3	5	7	9	11	13	15	17	19
Min LCC	589									
Min LCA	430									

Table 5 Solution of Scenario A

Every optimization method reaches this solution.

Scenario B

In this scenario the models are equal to those of the previous scenario, while the data input changes. In ***Table 6*** we report the new Data Input:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	10	18	2
2	15	6	0	2	8	15	0
3	20	7	0	3	18	28	9
4	25	8	0	4	15	25	-3
5	30	9	0	5	17	29	0
6	35	10	0	6	15	28	-2
7	5	2	0	1	6	14	4
8	10	3	0	2	4	13	3
9	20	4	10	7	19	27	12
10	25	5	11	8	15	25	10
11	50	12	5	11	28	35	4
12	55	13	7	12	25	33	2
13	70	21	20	20	65	145	0
14	75	22	25	21	60	130	-5
15	85	35	0	31	67	52	0
16	90	36	0	32	60	45	-5
17	50	12	0	10	34	18	12
18	55	13	0	11	30	15	10
19	10	5	0	3	40	27	12
20	15	6	0	4	35	25	10

Table 6 Data Input for Scenario B

In Scenario B there isn't a unique solution, but the solutions are distributed on a Pareto Curve.

A graphical comparison is reported in ***Figure 8***.

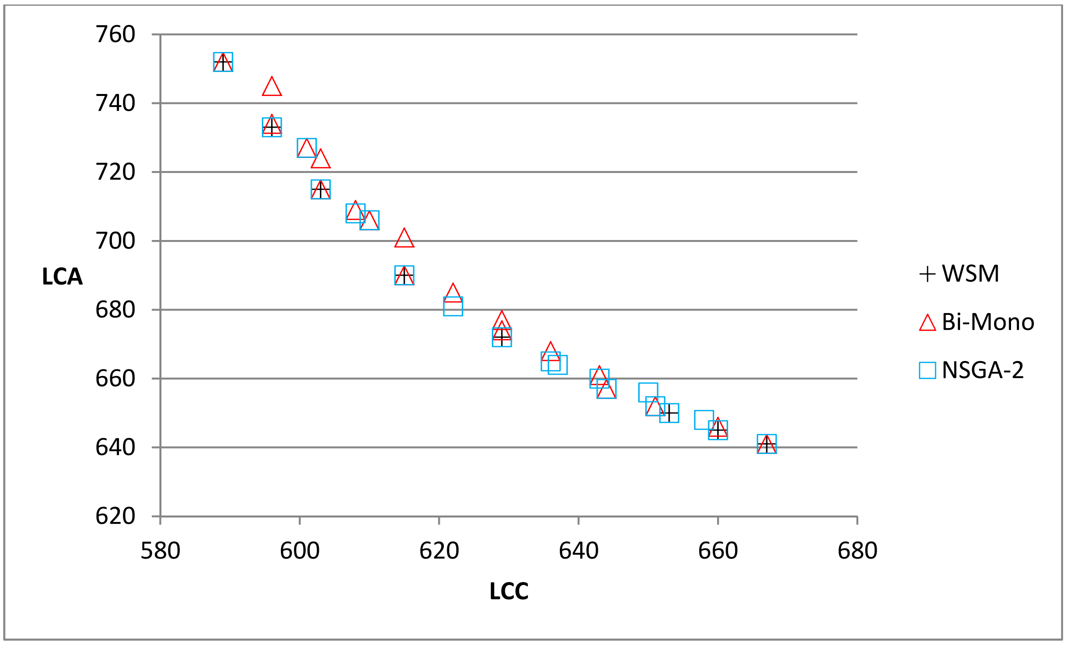


Figure 8 Graphical Comparison of the solutions

Scenario C

In this scenario the data input and models are equal to the second scenario, with the addition of a column of values which must comply the following constraint, added in the models:

$$\sum_{i=1}^{20} g_i * x_i \le G$$

where g_i is a generic value of the *i-th* subgroup and G is the threshold value.

The Data Input is reported in ***Table 7***.

	LCC				LCA			
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**	**g**
1	10	5	0	1	10	18	2	20
2	15	6	0	2	8	15	0	15
3	20	7	0	3	18	28	9	35
4	25	8	0	4	15	25	-3	40
5	30	9	0	5	17	29	0	0
6	35	10	0	6	15	28	-2	0
7	5	2	0	1	6	14	4	0
8	10	3	0	2	4	13	3	0
9	20	4	10	7	19	27	12	30
10	25	5	11	8	15	25	10	20
11	50	12	5	11	28	35	4	25
12	55	13	7	12	25	33	2	15
13	70	21	20	20	65	145	0	40
14	75	22	25	21	60	130	-5	35
15	85	35	0	31	67	52	0	0
16	90	36	0	32	60	45	-5	0
17	50	12	0	10	34	18	12	0
18	55	13	0	11	30	15	10	0
19	10	5	0	3	40	27	12	25
20	15	6	0	4	35	25	10	20

Table 7 Data Input for Scenario C

A graphical comparison is reported in ***Figure 9***.

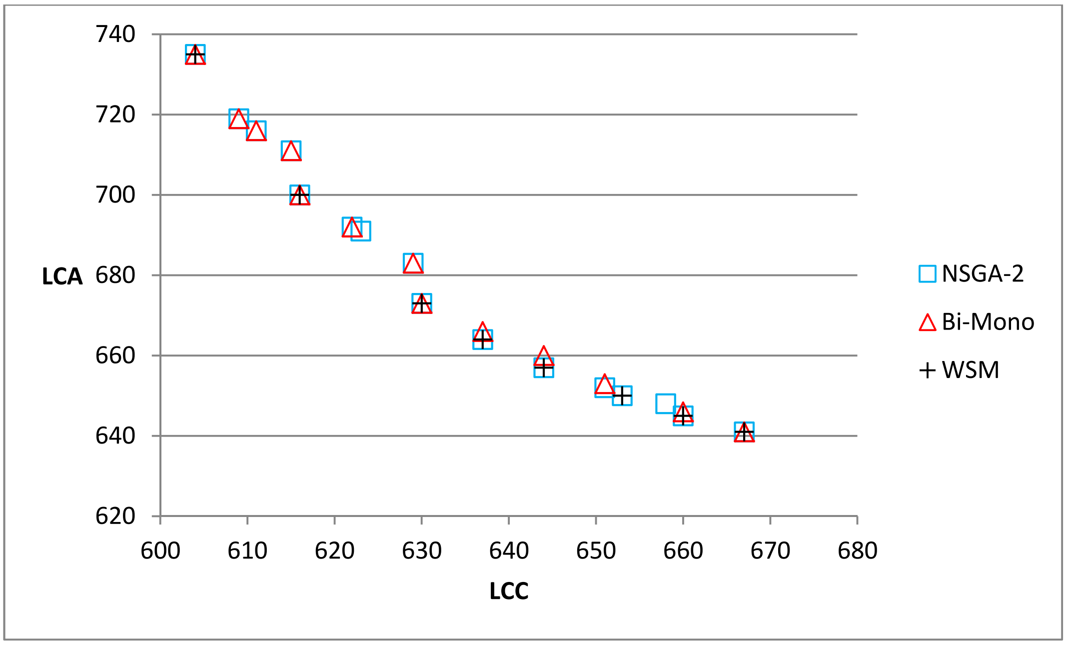


Figure 9 Graphical comparison of the solutions

Comparison

We compare three optimization methods: WSM, Bi-Mono and NSGA-2.

The results of this analysis are:

- NSGA-2 provides a major number of non dominated solutions than the other two optimization methods;
- NSGA-2 is a robust and reliable optimization method (it provides optimal solutions: we can say this by comparing NSGA-2 solutions with WSM solutions);
- WSM finds optimal solutions, but less than NSGA-2;
- Bi-Mono finds a good number of solution, but some of these are dominated.

Table 8 reports a summary of results of the tests.

	Number of solutions	Optimal solutions	Dominated Solutions
Bi-Mono	Medium	Low	Yes
NSGA-2	High	All (Should)	No
WSM	Low	All	No

Table 8 Summary of results of the tests

Application Case: Comau

The Comau industrial case focuses on a real assembly line, the Short block SDE (Small Diesel Engine) Assembly line, of which we consider a fraction.

The focus is on 5 locations: OP180, OP190, OP200, OP210 and OP220.

OP180 is a location for silicon coating, OP190 assemblies the base, in OP200 10 screws are filled in, OP210 fills in 10 another screws and pallets rotate in 180°, at the end there is OP220, in which the screwing in under base is done.

All of these locations can have automatic, semi-automatic or manual stations.

For these locations we have 6 alternatives: 3 automatic, 2 semi-automatic and 1 manual stations.

Data

In this paragraph we explain all the data, that we have used to conduct the analysis.

Table 9 summarizes the time horizon and the units of measure used for costs and environmental impacts.

Time Horizon	Bank Rate (Discount Rate)	Unit of measure (costs)	Unit of measure (environmental impacts)
10 years	1.5%	Generic Unit Cost (invented)	Milli-points (Eco-Indicator 99)

Table 9 Summary

The unit of measure of costs has been camouflaged from euro to a generic unit cost, maintaining the proportion between the various costs. The unit of measure of environmental impacts is the milli-point, that is used in Eco-Indicator 99.

Bank Rate is assumed as a constant for all 10 years.

Here we list costs and environmental impacts we use for LCC and LCA analysis:

- Cin = initial cost, that is the acquisition cost of the station;
- Ce = electric energy cost. The equation to calculate it is:
  - $Ce = ehc(kwh) * nhy\left(\frac{h}{year}\right) * euc(\frac{cost}{kw})$ where e*hc* is the average hourly consumption, *nhy* is the number of hours per year of plant operation and e*uc* is the unit cost of electric energy;

- Cric = spare parts cost (1% of initial cost per year, for Comau);
- Cop = labor cost (on 1 manual or semi-automatic station we have 1 worker, on 1 automatic station we have 0.2 worker);
- Ccon = consumables cost (sum of cost of consumables as oil and grease, for example);
- Cair = air cost. The equation to calculate it is similar to that to calculate Ce, replacing e*hc* with the average hourly consumption of air and *euc* with the unit cost of air;
- Cmo = preventive maintenance cost. The equation is:
    - $Cmo = nhpm\left(\frac{h}{years}\right) * 1.5 * hmc\ (\frac{cost}{h})$ where $nhpm$ is number of hours per year for preventive maintenance and *hmc* is the hour maintainer cost. 1.5 is the average maintainers involved;
- Cmorip = corrective maintenance cost. The equation is:
    - $Cmorip = \frac{nhy(\frac{h}{years})}{MTBF(h)} * MTTR(h) * 1.5 * hmc(\frac{cost}{h})$ where *nhy* is the number of hours per year of plant operation, *MTBF* is the mean time between failure, *MTTR* is the mean time to repair and *hmc* is the hour maintainer cost. 1.5 is the average maintainers involved;
- EIst = environmental impact of the station. We know that Comau station are principally made of Steel Low Alloy, so the equation to calculate it is:
    - $EIst = mst(kg) * Isla(\frac{millipoints}{kg})$ where mst is the mass of the station and $Isla$ is the tabular value of steel low alloy's environmental impact (Eco-Indicator 99);
- EIel = environmental impact of electric energy. The equation is similar to the previous:
    - $EIel =\ ehc(kwh) * nhy\left(\frac{h}{year}\right) * Iel(\frac{millipoints}{kwh})$ where e*hc* is the average hourly consumption, *nhy* is the number of hours per year of plant operation and *Iel* is the tabular value of electric energy's environmental impact (we considered Electricity LV Europe in Eco-Indicator 99);
- A = availability of the station. The equation is:

- $A = MTBF(h)/(MTBF + MTTR)(h)$ where *MTBF* is the mean time between failure and *MTTR* is the mean time to repair.

Since the time horizon is 10 years and since LCC uses discounted costs, incurred costs over the years will be discounted by a certain Bank Rate (or Discount Rate), that we have set to the value of 1.5%.

So the equation to calculate incurred costs over the years is:

$$C = {}^{C_t}\!/_{(1+br)^t}$$

where *C* is a generic discounted cost, C_t is a generic cost incurred in year *t* and *br* is the Bank Rate.

Table 10 shows when the costs and environmental impacts have been incurred during the years.

		Year										
		0	1	2	3	4	5	6	7	8	9	10
Costs	Cin	x										
	Ce	x	x	x	x	x	x	x	x	x	x	x
	Cric	x	x	x	x	x	x	x	x	x	x	x
	Cop	x	x	x	x	x	x	x	x	x	x	x
	Ccon	x	x	x	x	x	x	x	x	x	x	x
	Cair	x	x	x	x	x	x	x	x	x	x	X
	Cmo	x	x	x	x	x	x	x	x	x	x	X
	Cmorip	x	x	x	x	x	x	x	x	x	x	X
Environmental Impacts	EIst	x										
	EIel	x	x	x	x	x	x	x	x	x	x	X

Table 10 Costs and environmental impacts incurred over the years.

Model

The model for the Comau case is very simple and it was made under instructions from Comau.

The model has two objective function, one that minimizes the product life cycle costs and one that minimizes the environmental impacts during the whole life cycle.

The model has two types of constraints: the availability of the fraction of the assembly line must be greater than 0.95; all the locations must have a station, it's automatic, semi-automatic or manual.

Below we report the model written in analytical form:

$$\min \sum_{i=1}^{30} (Cin * x_i + Ce * x_i + Cric * x_i + Cop * x_i + Ccon * x_i + Cair * x_i + Cmo * x_i + Cmorip * x_i)$$

$$\min \sum_{i=1}^{30} (EIst * x_i + EIel * x_i)$$

Subject to

$$\sum_{i=1}^{6} A_i x_i * \sum_{i=7}^{12} A_i x_i * \sum_{i=13}^{18} A_i x_i * \sum_{i=19}^{24} A_i x_i * \sum_{i=25}^{30} A_i x_i \geq 0.95$$

$$\sum_{i=1}^{6} x_i = 1$$

$$\sum_{i=7}^{12} x_i = 1$$

$$\sum_{i=13}^{18} x_i = 1$$

$$\sum_{i=19}^{24} x_i = 1$$

$$\sum_{i=25}^{30} x_i = 1$$

$x_i \in \{0,1\} \; i = 1,2, \ldots ,30$

where the various costs, environmental impacts and availabilities are previously described, x_i is a binary variable.

We have conducted two analysis: one in which the line is installed in Eastern Europe (where labor is cheaper) and one in which the line is installed in Western Europe (where labor is more expensive).

Eastern Europe Scenario

In ***Table 11*** we report sustained costs and environmental impacts along the life-cycle.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	EI st	EI el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	1737.771	235.1102	191.1549	22.99992	723.5773	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	1737.771	153.3328	151.2883	18.39993	482.9982	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	8688.857	143.1106	17.37771	1.609994	45.99983	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	1737.771	245.3324	197.697	24.37991	793.1521	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	1737.771	275.999	199.7415	26.4499	848.8119	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	8688.857	214.6659	23.25547	2.75999	75.43972	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	8688.857	143.1106	15.75239	1.149996	45.99983	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984

Table 11 Costs and environmental impacts for all alternatives

Type indicates if the station is automatic (aut), semi-automatic (saut) or manual (m).

The model described is applied with the genetic algorithm (NSGA-2) and with the WSM (Weighted Sum Model) to verify the results obtained with genetic algorithm.

In ***Table 12*** we report the parameters of NSGA-2.

Population	100
Crossover	Simple Multi-point (rate = 0.9)
Selector	Crowded Tournament
Mutator	Simple by gene (rate = 0.15)
Generations	200

Table 12 Parameters of genetic algorithm

The results are reported in ***Figure 10.***

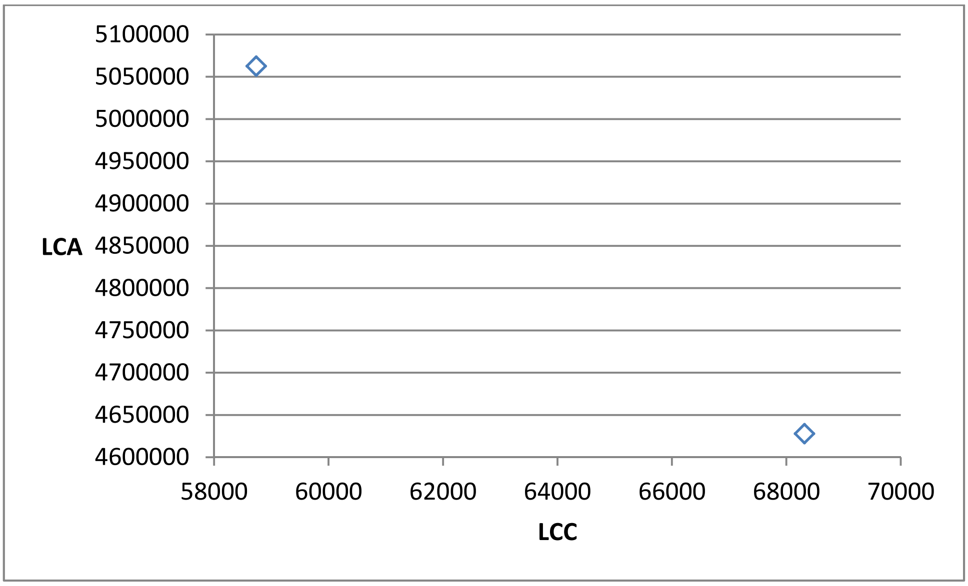


Figure 10 Results

The results show that the best solution for LCC is the line with all manual stations.

To validate the results we asked to Comau if it is possible a solution with all manual stations. They have responded affirmatively, because cheap labor favors the installation of manual stations.

Western Europe Scenario

In ***Table 13*** we report sustained costs and environmental impacts along the life cycle.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	EI st	EI el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	6082.195	235.1102	191.1549	68.99975	2170.732	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	6082.195	153.3328	151.2883	55.1998	1448.995	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	30410.98	143.1106	17.37771	4.829982	137.9995	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	6082.195	245.3324	197.697	73.13973	2379.456	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	6082.195	275.999	199.7415	79.34971	2546.436	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	30410.98	214.6659	23.25547	8.279969	226.3192	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	30410.98	143.1106	15.75239	3.449987	137.9995	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984

Table 13 Costs and environmental impacts for all alternatives

The parameters we used are the same to those of the previous scenario (see ***Table 12***)

The results are reported in ***Figure 11.***

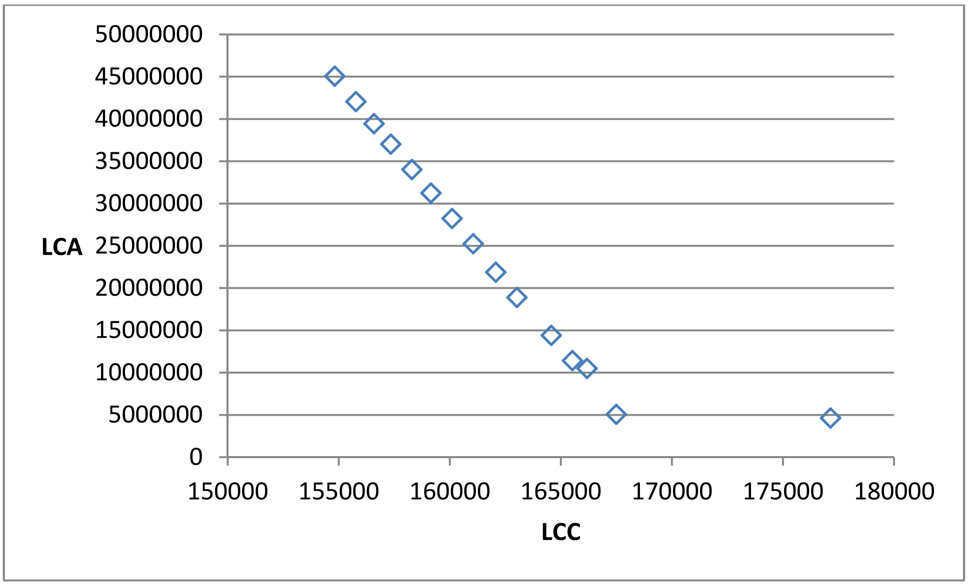


Figure 11 Results

The best for LCC is the line with all automatic stations.

These results have been subjected to Comau, they have validated them.

Conclusion

Benefits and problems in the Comau application

The best way to understand if the model is useful or not is to subject it to the company of the real case.

So we asked to Comau about the usefulness of the developed model.

Firstly it's better to remember how Comau estimates LCC.

So we report the phases of manufacturing Machinery and equipment Life Cycle (***Figure 12***)

Figure 12 Phases of manufacturing Machinery and equipment Life Cycle

Phase 1 (Concept) is research and limited development or design and it usually ends with a proposal.

Comau tells us that the phase of proposal is a very long process. They think that this model can help them to offer a faster and more efficient proposal to the costumer: in fact now all LCC calculation are hand-made with the help of a

software such as Excel. So our model makes the preparation process of the proposal faster and more efficient than the existing one.
We also have to remember that the case is a fraction of assembly line (only 5 locations), while the entire assembly line is composed of about 100 locations, so the potential of the developed model is very high.
It also suggests the choice of the genetic algorithm.
The solutions obtained in the model must be tested in a simulator, in order to verify the respect of constraints imposed by the costumer.
To be more complete, our model should evaluate the performances (in this case, for example, the throughput) , instead now with the existing process or with our model Comau spends considerable time in simulation.
In fact if we were able to include the performances by analytical formulas in the model, we could reduce the time dedicated to simulation.
This would be another great benefit.
Furthermore we should organize the database, so that the retrieval of data for the model would be immediate.
Figure 13 shows the time savings achievable.

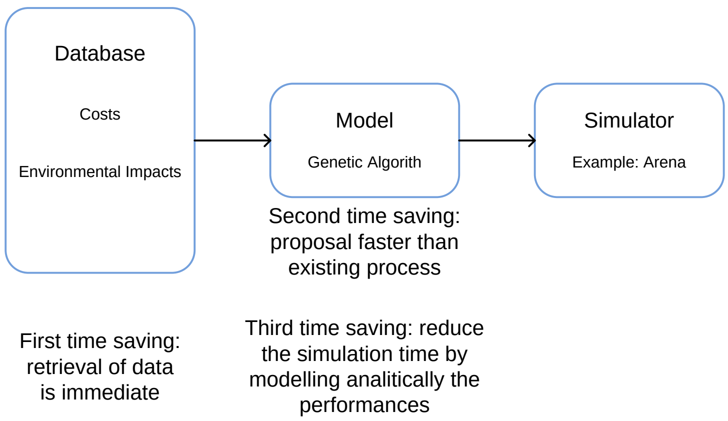


Figure 13 Time savings

A request asked us to Comau is to turn the environmental impacts into costs, transforming the optimization problem from bi-objective (to minimize the product life-cycle environmental impacts and costs) to single objective (to minimize the product life-cycle costs).

This would be possible using these equations:

$$min \sum_{i}^{n} LCC_i + \sum_{j}^{k} pc_j * eEI_j$$

$$EI_j - eEI_j \leq tvEI_j \qquad \forall j$$

where LCC_i is the life cycle cost of component *i-th*, pc_j is the penalty cost of *j-th* environmental impact, eEI_j is the excess of *j-th* environmental impact, EI_j is the *j-th* environmental impact and $tvEI_j$ is the threshold value of *j-th* environmental impact.

This surely minimizes the product life-cycle costs and it respects the environmental regulations, but this is a reactive approach. Instead the aim of our work is to use a proactive approach to the environmental issues.

Table 14 summarizes benefits, criticisms and possible future developments encountered in the Comau case.

Benefits	*Criticisms*	*Possible Future Developments*
Reduce the time for the proposal	Performances are not evaluated	1- Evaluate performances in the model 2-Organize the database 3-Transform environmental impacts into cost

Table 14 Benefits, Criticisms and Possible Future Developments.

Our considerations

The aim of our work is to develop a multi-objective optimization of product life-cycle costs and environmental impacts.

With the test cases and real case we have succeeded.

Comau also found our work interesting, despite it has shown some weaknesses, which are now listed:

- LCA cannot to be well investigated due to lack of data;
- We cannot assess robustness of LCA due to lack of tabular values of the other perspectives;
- We haven't compared NSGA-2 with other multi-objective genetic algorithms or with other parameters value;
- Our model doesn't evaluate the performances.

The strengths of our work are:

- It was considered relevant by Comau;
- The comparison between linear programming and genetic algorithm;
- It is more complete than those in the literature (which lack of information);
- The analysis of reasons and of literature.

The main future developments are:

- System effectiveness equations of LCC and LCA (Effectiveness/LCC and Effectiveness/LCA) (see Chapter 2 section 2.2.6.5) and system performances equations (Performances/LCC and Performances/LCA);
- To deepen the use of LCA, using other databases in addition to Eco-Indicator 99.

ABSTRACT

Introduzione

Oggi, in un mondo sempre più competitivo, le imprese dei paesi occidentali devono cercare nuovi strumenti per sopravvivere sul mercato.

Queste imprese sono costrette a trovare nuovi modi per essere competitivi nel mercato globale, a causa della globalizzazione e della competizione con le imprese mondiali, in particolare quelle del sud-est Asiatico, dove la manodopera costa meno e non ci sono normative ambientali stringenti.

Poichè è molto difficile competere con il costo finale di prodotto delle compagnie orientali, le imprese occidentali hanno iniziato ad utilizzare come nuova leva competitiva la riduzione del costo del ciclo di vita del prodotto (LCC). Quindi l'interesse nell'LCC è guidato dal trovare nuove leve competitive, differenti dalle classiche (i.e. minor costo di acquisizione). Per esempio, con l'LCC le aziende occidentali possono offrire servizi e/o macchine energeticamente efficienti, o ridurre l'uso della manodopera. Altri esempi possono essere la riduzione del costo dei ricambi o del tempo di manutenzione, quindi dei relativi costi. Inoltre sempre più clienti richiedono nel preventivo un'analisi del costo del ciclo di vita del prodotto (alcuni di essi in modo più accurato, altri meno).

Un altro strumento competitivo che alcune imprese hanno iniziato ad utilizzare è la riduzione dell'impatto ambientale. Questa scelta è stata dettata da normative sempre più stringenti, come il protocollo di Kyoto e l'ISO 14000.

Nella letteratura ci sono metodi che aiutano a calcolare i costi e gli impatti ambientali lungo l'intero ciclo di vita: sono l'LCC (Life Cycle Cost) e l'LCA (Life Cycle Assessment).

Il Life Cycle Costs (LCC) sono costi "dalla culla alla tomba", sintetizzati come un modello economico di valutazione delle alternative dei progetti e delle attrezzature. [Bar 03]

Il Life Cycle Assessment (LCA) è una tecnica per valutare l'impatto ambientale associato ad ogni fase della vita di un prodotto dall'inizio alla fine. [Sai 06]

Questi metodi spiegano passo dopo passo come condurre un'analisi dei costi o dell'impatto ambientale lungo il ciclo di vita, ma non ottimizzano i risultati. Anche in letteratura solo alcuni articoli sono finalizzati ad ottimizzare i costi o l'impatto ambientale lungo il ciclo di vita, mentre la maggior parte spiega come condurre un'analisi LCC o LCA.

Quindi nel nostro lavoro applichiamo un'ottimizzazione multi-obiettivo, basata su un algoritmo genetico, alle metodologie LCC (Life Cycle Cost) e LCA (Life Cycle Assessment).

Quando parliamo dell'ottimizzazione di LCC e LCA ci riferiamo all'ottimizzazione dei risultati e non delle metodologie.

L'algoritmo genetico è stato scelto perchè non ha problemi a lavorare con un'ottimizzazione multi-obiettivo, invece la programmazione lineare non può maneggiare problemi di questo tipo. Inoltre l'algoritmo genetico è più efficiente della programmazione lineare quando il numero delle variabili aumenta.

Motivazioni

Imprese

Le aziende (in particolare quelle occidentali) hanno bisogno di nuove leve competitive per sopravvivere nel mercato globale.

Due di questi nuovi strumenti sono l'LCC e l'LCA, che suscitano un certo interesse a causa dell'impossibilità di competere con il costo finale dei prodotti delle imprese orientali.

Abbiamo avuto accesso ai risultati di un questionario sottoposto a 3 compagnie occidentali: Aker, Comau e Volkswagen. Questo questionario è stato loro presentato in quanto parte di un progetto europeo.

Da una domanda, in particolare, è possibile analizzare quali siano i fattori considerati più significativi dalle compagnie durante il loro processo di sviluppo/design prodotto. Da un'analisi della letteratura è stato possibile definire i fattori tipici, tuttavia noi consideriamo solo i fattori economici e ambientali.

Come mostrato di seguito, nella ***Tabella 1***, i fattori economici ed ambientali sono più o meno importanti per tutte le imprese.

Quindi questo lavoro è basato su reali necessità delle imprese e il nostro modello, che ottimizza l'LCC e l'LCA, può realmente aiutare molte aziende.

Come valutate la considerazione dell'impresa (i.e. fattori usati per valutare soluzioni alternative) riguardo i seguenti fattori/criteri durante il processo di sviluppo/design?			
Fattori	**Aker**	**Comau**	**VW**
Costo finale del prodotto			
Costi lungo il ciclo di vita del prodotto			
ROI – Ritorno dell'investimento			
Aspetti ambientali			

Legenda	
Molto Basso	
Basso	
Alto	
Molto Alto	

Tabella 1 Importanza dei fattori economico ed ambientale

Letteratura

La letteratura dell'LCC e dell'LCA è molto ampia. Negli ultimi anni il numero di articoli è aumentato significativamente, in particolare quelli riguardanti l'LCA.

Tuttavia molti di questi lavori non sono rilevanti, trattano solo brevemente questa metodologia; infatti molti di questi lavori semplicemente applicano l'LCC o l'LCA, senza aggiungere nulla di nuovo, alcuni addirittura non riportano i calcoli.

Solo alcuni articoli sono innovativi o, perlomeno, completi. Ciò mostra come queste metodologie debbano essere studiate più in profondità, perché non sono accessibili alla maggior parte degli addetti ai lavori, sebbene essi non siano un nuovo concetto (sono nati negli anni '60).

Quindi è necessario fare una ricerca approfondita, al fine di trovare i documenti rilevanti.

Abbiamo quindi analizzato 39 documenti di applicazione dell'LCC e 40 per l'LCA. Questi sono quelli che riteniamo maggiormente interessanti.

Le ***Figure 1*** e ***2*** mostrano dove l'LCC e l'LCA sono applicati.

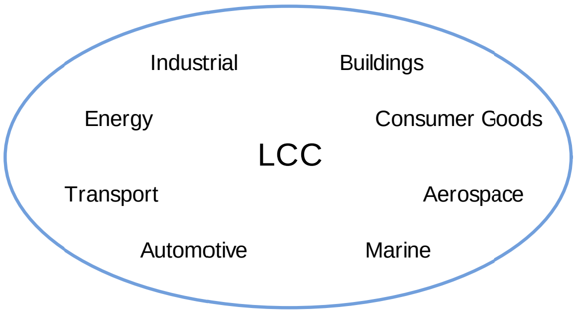


Figura 1 Campi di applicazione dell'LCC

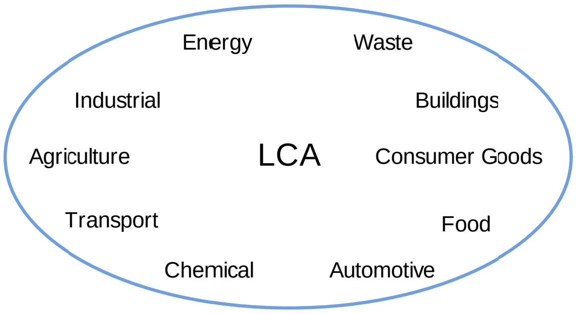


Figura 2 Campi di applicazione dell'LCA

Le ***Figure 3*** e ***4*** mostrano la percentuale di ottimizzazione dell'LCC e dell'LCA nella letteratura.

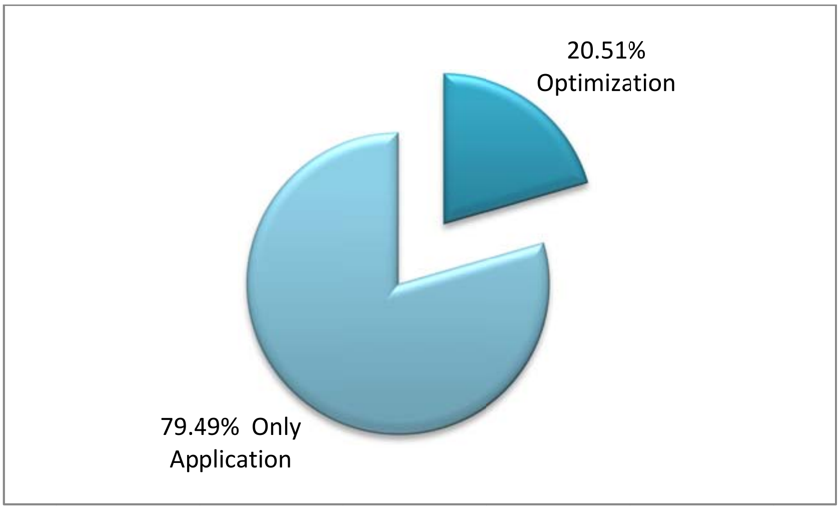


Figura 3 Percentuale di ottimizzazione dell'LCC

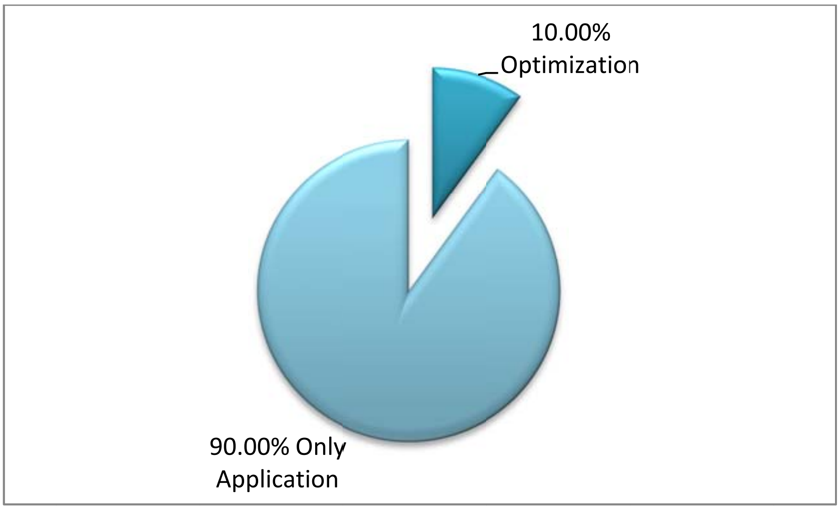


Figura 4 Percentuale di ottimizzazione dell'LCA

Come possiamo vedere solo il 20% circa degli articoli ottimizza l'LCC mentre, per l'ottimizzazione dell'LCA solo il 10% degli articoli mostra un ottimizzazione

La ***Tabella 2*** riporta un riassunto dell'analisi della letteratura.

	% di articoli analizzati	**% di algoritmi evoluzionari**	**Altre ottimizzazioni?**
Ottimizzazione dell'LCC	20.51%	75%	No
Ottimizzazione dell'LCA	10.00%	50.00%	Sì (costi o produzione)

Tabella 2 Riassunto dell'analisi della letteratura

Il principale problema di questi articoli è la mancanza di informazioni riguardo i modelli (funzione obiettivo e vincoli) ed i dati utilizzati. Questo rende ogni paragone o valutazione difficile.

Dall'analisi della letteratura possiamo dire che la via dell'ottimizzazione dell'LCC e dell'LCA è ancora aperta. Il nostro lavoro ha l'obiettivo di continuare questa via.

Life Cycle Cost

Il Life Cycle Costs (LCC) sono costi "dalla culla alla tomba", sintetizzati come un modello economico di valutazione delle alternative dei progetti e delle attrezzature. [Bar 03]

Figura 5 Fasi dell'LCC

Come mostrato nel diagramma (***Figura 5***), il Life Cycle Costing è un processo a 6 fasi. I primi 4 stadi includono la fase di Life Cost Planning mentre gli ultimi 2 incorporano la fase di Life Cost Analysis. I sei stadi sono:

- Stage 1: Pianificare l'analisi dell'LCC
- Stage 2: Selezionare/Sviluppare il modello dell'LCC
- Stage 3: Applicare il modello dell'LCC
- Stage 4: Documentare e revisionare i risultati dell'LCC
- Stage 5: Preparare la Life Cost Analysis
- Stage 6: Implementare e monitorare la Life Cost Analysis [Nsw 04]

Life Cycle Assessment

Il Life Cycle Assessment (LCA) è una tecnica per valutare l'impatto ambientale associato ad ogni fase della vita di un prodotto dall'inizio alla fine.

Il processo dell'LCA è un approccio sistematico che consiste in 4 fasi: definizione dell'obiettivo, analisi dell'inventario, valutazione dell'impatto e interpretazione. (***Figura 6***)

Questo processo è spiegato nell'ISO 14040 Environmental Management - Life Cycle Assessment - Principles and Framework.

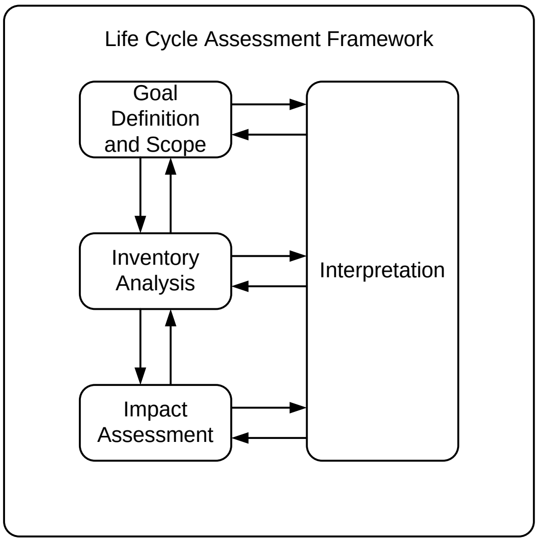


Figura 6 Fasi dell'LCA [Iso 97]

1. Definizione dell'obiettivo – Definizione e descrizione di prodotto, processo o attività. Scelta del contesto nel quale deve essere svolta la valutazione ed identificazione dei vincoli e degli effetti ambientali da esaminare per la valutazione.
2. Analisi dell'inventario – Identificazione e quantificazione dell'uso di energia, acqua e materiali e dei rilasci nell'ambiente (e.g., emissioni nell'aria, rifiuti solidi, scarichi di acque reflue).
3. Valutazione dell'impatto - Valutazione degli effetti potenziali umani ed ecologici dell'uso di energia, acqua e materiali e dei rilasci ambientali identificati nell'analisi dell'inventario.
4. Interpretazione – Valutazione dei risultati dell'analisi dell'inventario e valutazione dell'impatto per selezionare il prodotto, processo o servizio preferito, con una chiara comprensione delle incertezze e delle ipotesi usate per generare i risultati. [Sai 06] [Iso 97]

Metodo di ottimizzazione (Algoritmo Genetico)

Gli algoritmi genetici (GAs) sono una sotto-classe degli algoritmi evoluzionari dove gli elementi dello spazio di ricerca G sono stringhe binarie ($G = B^*$) o vettori di altri valori elementari.

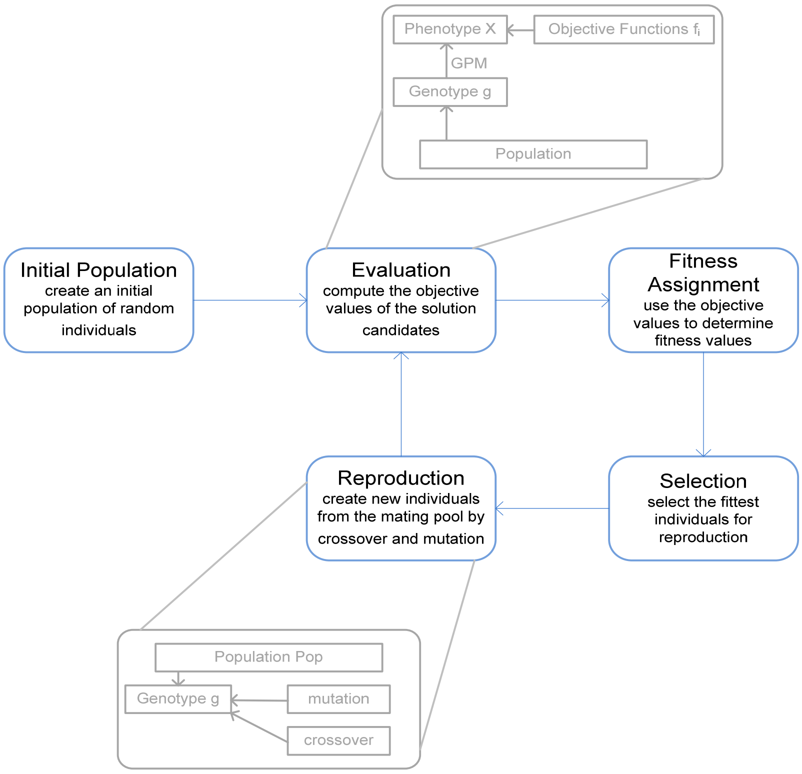


Figura 7 Il ciclo base dell'algoritmo genetico [Wei 09]

Tutti gli algoritmi genetici seguono lo schema illustrato nella ***Figura 7***:

1. Inizialmente è creata una popolazione Pop di individui p con un genoma casuale p.g.
2. I valori delle funzioni obiettivo $f \in F$ sono calcolati per ogni soluzione candidata p.x in Pop. Questa valutazione può includere simulazioni e calcoli complicati.
3. Con le funzioni obiettivo, l'utilità delle diverse caratteristiche delle soluzioni candidate sono determinate e un valore fitness v(p.x) può essere assegnato ad ognuna di loro. Questo processo di assegnazione del valore fitness può, ad esempio, incorporare una funzione di comparazione della prevalenza cmp_F che utilizza i valori obiettivo per creare un ordine tra gli individui.

4. Un successivo processo di selezione esclude le soluzioni candidate con una pessima fitness e permette a quelle buone di entrare con maggiore probabilità nel pool di accoppiamento.
5. Nella fase di riproduzione, viene generata la prole mutando o combinando i genotipi p.g degli individui p ∈ Mate selezionati applicando le operazioni di ricerca searchOp ∈ Op (che sono chiamate operazioni di riproduzione nel contesto degli algoritmi evoluzionari). Questa prole è successivamente integrata nella popolazione..
6. Se il criterio di termine è raggiunto, l'evoluzione si ferma. Altrimenti, l'algoritmo reitera dal passo 2. [Wei 09]

Noi usiamo l'NSGA-2 (Non Dominated Sorting Genetic Algorithm).

L'NSGA-2 è uno dei più popolari algoritmi genetici multi-obiettivo con tre caratteristiche particolari: un veloce approccio all'ordinamento non dominato della popolazione, una veloce procedura di stima della distanza della popolazione ed un semplice operatore di comparazione della popolazione. [Deb 02]

Modello

Introduciamo un modello che ottimizza insieme i costi e l'impatto ambientale del prodotto lungo il ciclo di vita. Il modello è sviluppato con un algoritmo genetico e comparato con i modelli della programmazione lineare. I tre modelli sviluppati (uno con l'algoritmo genetico, due con la programmazione lineare) sono paragonati usando casi test con dati inventati.

Per sviluppare il modello con l'algoritmo genetico abbiamo usato l'NSGA-2, mentre come modelli di programmazione lineare abbiamo usato il Weighted Sum Model ed un modello in cui noi abbiamo trasformato il problema da bi-obiettivo a singolo obiettivo, dove un obiettivo compare nella funzione obiettivo, l'altro come vincolo.

Weighted Sum Model

Il Weighted sum model (WSM) è la più semplice e conosciuta analisi decisionale multi-criterio (MCDA) / metodo decisionale multi-criterio per valutare un numero di alternative secondo una serie di criteri di decisione. E' molto importante precisare che è applicabile solo quando tutti i dati sono espressi esattamente nella stessa unità di misura. [Fis 67] [Tri 00] [Wik 02]

Dal problema bi-obiettivo al singolo obiettivo

Dobbiamo ottimizzare il problema in due obiettivi (Life Cycle Cost and Life Cycle Assessment). Qui chiamiamo i 2 obiettivi *A* e *B*.

Abbiamo creato questa tecnica per risolverlo e ottenere una curva simile a quella di Pareto.

Inizialmente abbiamo risolto un modello con il singolo obiettivo *B*, trovando il massimo (*Max*) e il minimo (*Min*) della funzione obiettivo.

Poi abbiamo diviso questo range (*Max – Min*) per un numero di intervalli *X* ottenendo un valore pari a *Y*.

$$Y = \frac{(Max - Min)}{X}$$

Così abbiamo creato valori da *Max*, *Max – Y*, *Max – 2*Y*, ... a *Min*.

Infine abbiamo risolto l'altro obiettivo (*A*) in un problema a singolo obiettivo, rispettando il vincolo derivato dalla precedente risoluzione di *B*. Il vincolo è scritto come (l'equazione del vincolo è espressa come *EQ.*):

- Se *B* è da massimizzare, il vincolo è: *EQ.>Min* per la prima iterazione; poi *EQ.>Min + Y*,... fino a *EQ.>Max* per l'ultima iterazione.
- Se *B* è da minimizzare, il vincolo è: *EQ.<Max* per la prima iterazione; poi *EQ.<Max – Y*,... fino a *EQ.<Min* per l'ultima iterazione.

In questo modo abbiamo ottenuto una curva simile a quella di Pareto.

Una debolezza di questa strategia è quella che può produrre soluzioni che non sono efficienti in Pareto.

NSGA-2

La procedura dell'NSGA-2 è:

1. Creare una popolazione di genitori casuale P_0 di dimensione *N*. Settare $t = 0$.
2. Applicare il crossover e la mutazione a P_0 per creare una popolazione di figli Q_0 di dimensione *N*.
3. Se il criterio di stop è soddisfatto, fermarsi e ritornare a P_t.
4. Settare $R_t = P_t \cup Q_t$.

5. Usare l'algoritmo con approccio non dominato, identificando i fronti non-dominati F_1, F_2, ..., F_k in R_t.
6. Per $i = 1, ..., k$ svolgere i seguenti passi:
   a. Calcolare la distanza della popolazione dalla soluzione in F_i.
   b. Creare P_{t+1} come segue:
      i. Caso 1: Se $| P_{t+1} | + | F_i | \leq N$, poi settare $P_{t+1} = P_{t+1} \cup F_i$;
      ii. Caso 2: Se $| P_{t+1} | + | F_i | > N$, poi aggiungere almeno le soluzioni della popolazione $N - | P_{t+1} |$ da F_i a P_{t+1}.
7. Usare una selezione a torneo binaria basata sulla distanza della popolazione per selezionare i genitori da P_{t+1}. Applicare il crossover e la mutazione a P_{t+1} per creare la popolazione dei figli Q_{t+1} di dimensione N.
8. Settare $t = t+1$, e andare allo Step 3. [Deb 02] [Kon 06]

Per realizzare l'algoritmo genetico NSGA-2 abbiamo usato il software GANetXL (Savic et al.), un add-in per Microsoft Excel.

Scenari del test

Abbiamo creato tre differenti scenari per comparare i tre metodi di ottimizzazione usati. Lo Scenario A ha un'unica soluzione ottima. Lo Scenario B ha più soluzioni ottime distribuite sulla curva di Pareto. Lo Scenario C è uguale al secondo con l'aggiunta di un vincolo.

La ***Tabella 3*** riporta un sommario delle caratteristiche degli scenari.

	Input dei dati	Soluzioni ottime	Vincoli
Scenario A	A	Unica	No
Scenario B	B	Fronte di Pareto	No
Scenario C	B	Fronte di Pareto	Sì (1)

Tabella 3 Sommario delle caratteristiche degli scenari

Di seguito vi è il confronto fra i 3 metodi di ottimizzazione

Supponiamo di avere un prodotto generico composto da 10 sottogruppi. Ogni sottogruppo ha 2 alternative per essere realizzato. Ogni alternativa ha questo input di dati:

- *Cin*: costo iniziale;
- *Cmnt*: costo della manutenzione;
- *Cen*: costo dell'energia;

- *Cmdpmn*: costo del manutentore;
- *BOL*: impatto ambientale all'inizio del ciclo di vita;
- *MOL*: impatto ambientale a metà del ciclo di vita;
- *EOL*: impatto ambientale alla fine del ciclo di vita.

Questi dati considerano tutto il ciclo di vita del prodotto quindi, per esempio, *Cmnt* è il costo di manutenzione durante tutto il ciclo di vita.

Le unità di misura sono una generica unità di costo per l'LCC e una generica unità di impatto ambientale per l'LCA .

L'LCC è calcolato come:

$$LCC = \sum_{i=1}^{n} (Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$$

Mentre l'LCA è calcolato come:

$$LCA = \sum_{i=1}^{n} (BOL_i + MOL_i + EOL_i) * x_i$$

dove x_i è una variabile binaria che assume valore 1 se l'*i-esimo* sottogruppo è usato per realizzare il prodotto, altrimenti assume valore 0.

I 2 obiettivi sono:

- Minimizzare il Life Cycle Cost (LCC);
- Minimizzare il Life Cycle Assessment (LCA).

Nel weighted sum model (WSM) il modello è scritto come:

Minimizzare $w * \frac{LCC}{LCC^*} + k * \frac{LCA}{LCA^*}$

Soggetto a $LCC = \sum_{i=1}^{20} (Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

$LCA = \sum_{i=1}^{20} (BOL_i + MOL_i + EOL_i) * x_i$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5, \dots ,19$

$w + k = 1$

$w, k \geq 0$

$x_1, x_2, \dots , x_{20} \in (0,1)$

I due obiettivi sono dimensionalmente diversi: l'LCC ha una dimensione di costo mentre l'LCA ha una dimensione di impatto ambientale. Se vogliamo sommare l'LCA e l'LCC dobbiamo renderli adimensionali. Così inizialmente risolviamo un

problema a singolo obiettivo, massimizzando una volta l'LCA e una volta l'LCC. Otteniamo LCA* e LCC*. Mettiamo questi valori in una funzione obiettivo come quella mostrata sopra. Così rendiamo l'LCA e l'LCC adimensionali e possiamo sommarli. Iterativamente modifichiamo i valori di w e k, rispettando il vincolo, ottenendo le differenti soluzioni del problema. Iniziamo da w=1 e k=0 per arrivare a w=0 e k=1, passando attraverso valori intermedi come w=0.55 e k=0.45.
L'altro modello di programmazione lineare è scritto come:

Minimizzare $LCC = \sum_{i=1}^{20}(Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

Soggetto a $\sum_{i=1}^{20}(BOL_i + MOL_i + EOL_i) * x_i \leq TV$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5,\ldots,19$

$x_1, x_2, \ldots, x_{20} \epsilon (0,1)$

dove *TV* è il valore target.

Nell'algoritmo genetico multi-obiettivo (abbiamo usato l'NSGA-2) c'è un cromosoma (che rappresenta il prodotto generico) composto da 10 geni (che rappresentano i sottogruppi). Ogni gene può assumere solo 2 valori (per esempio il gene 1 può essere 1 o 2, il gene 2 può assumere valore 3 o 4, ..., il gene 10 può essere 19 o 20). L'algoritmo genetico ottimizza i due obiettivi simultaneamente creando una curve simile al fronte di Pareto. Qui abbiamo usato una popolazione di dimensione pari a 50, un punto a singolo crossover con un tasso di 0.95 e una mutazione singola del gene con tasso 0.05.

Tutto ciò che è descritto sopra è valido per tutti gli scenari.

Scenario A

In questo scenario l'input dei dati è riportato nella ***Tabella 4***:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	5	10	-2
2	15	6	0	2	8	15	0
3	20	7	0	3	10	20	-6
4	25	8	0	4	15	25	-3
5	30	9	0	5	12	24	-5
6	35	10	0	6	15	28	-2
7	5	2	0	1	2	8	-1
8	10	3	0	2	4	13	3
9	20	4	10	7	10	20	5
10	25	5	11	8	15	25	10
11	50	12	5	11	20	29	-1
12	55	13	7	12	25	33	2
13	70	21	20	20	50	100	-15
14	75	22	25	21	60	130	-5
15	85	35	0	31	50	35	-15
16	90	36	0	32	60	45	-5
17	50	12	0	10	20	10	5
18	55	13	0	11	30	15	10
19	10	5	0	3	20	10	0
20	15	6	0	4	35	25	10

Tabella 4 Input dei dati per lo Scenario A

In questo scenario i dati sono arrangiati in modo da ottenere un'unica soluzione riportata nella ***Tabella 5***.

Product Subgroups	1	3	5	7	9	11	13	15	17	19
Min LCC	589									
Min LCA	430									

Tabella 5 Soluzione dello Scenario A

Ogni metodo di ottimizzazione raggiunge questa soluzione.

Scenario B

In questo scenario i modelli sono uguali a quelli dello scenario precedente, mentre cambia l'input dei dati. Nella ***Tabella 6*** riportiamo il nuovo input dei dati:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	10	18	2
2	15	6	0	2	8	15	0
3	20	7	0	3	18	28	9
4	25	8	0	4	15	25	-3
5	30	9	0	5	17	29	0
6	35	10	0	6	15	28	-2
7	5	2	0	1	6	14	4
8	10	3	0	2	4	13	3
9	20	4	10	7	19	27	12
10	25	5	11	8	15	25	10
11	50	12	5	11	28	35	4
12	55	13	7	12	25	33	2
13	70	21	20	20	65	145	0
14	75	22	25	21	60	130	-5
15	85	35	0	31	67	52	0
16	90	36	0	32	60	45	-5
17	50	12	0	10	34	18	12
18	55	13	0	11	30	15	10
19	10	5	0	3	40	27	12
20	15	6	0	4	35	25	10

Tabella 6 Input dei dati per lo Scenario B

Nello Scenario B non c'è un'unica soluzione, ma le soluzioni sono distribuite su una curva di Pareto.

Una comparazione grafica è riportata nella ***Figura 8***.

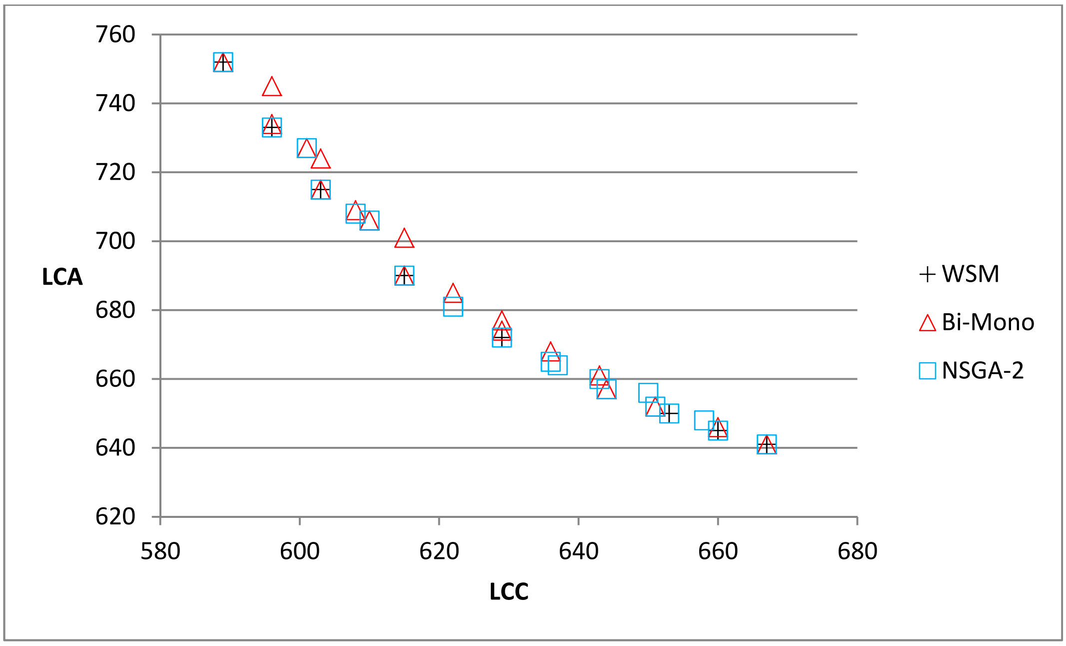


Figura 8 Comparazione grafica delle soluzioni

Scenario C

In questo scenario l'input dei dati è uguale a quello del secondo scenario, con l'aggiunta di una colonna di valori che deve soddisfare il seguente vincolo, da aggiungere nel modello:

$$\sum_{i=1}^{20} g_i * x_i \leq G$$

dove g_i è un valore generico di un *i-esimo* sottogruppo e G è il valore soglia.

L'input dei dati è riportato nella ***Tabella 7***.

	LCC				LCA			
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**	**g**
1	10	5	0	1	10	18	2	20
2	15	6	0	2	8	15	0	15
3	20	7	0	3	18	28	9	35
4	25	8	0	4	15	25	-3	40
5	30	9	0	5	17	29	0	0
6	35	10	0	6	15	28	-2	0
7	5	2	0	1	6	14	4	0
8	10	3	0	2	4	13	3	0
9	20	4	10	7	19	27	12	30
10	25	5	11	8	15	25	10	20
11	50	12	5	11	28	35	4	25
12	55	13	7	12	25	33	2	15
13	70	21	20	20	65	145	0	40
14	75	22	25	21	60	130	-5	35
15	85	35	0	31	67	52	0	0
16	90	36	0	32	60	45	-5	0
17	50	12	0	10	34	18	12	0
18	55	13	0	11	30	15	10	0
19	10	5	0	3	40	27	12	25
20	15	6	0	4	35	25	10	20

Tabella 7 Input dei dati per lo Scenario C

Una comparazione grafica è riportata nella ***Figura 9***.

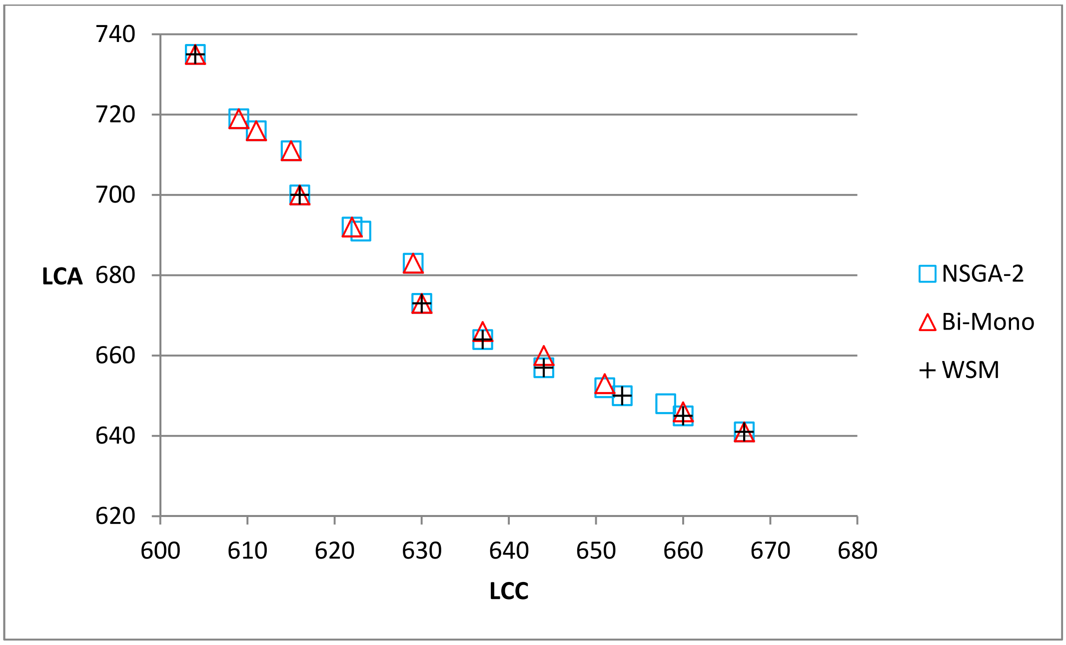


Figura 9 Comparazione grafica delle soluzioni

Paragone

Abbiamo comparato tre metodi di ottimizzazione : WSM, Bi-Mono e NSGA-2.

I risultati di questa analisi sono:

- L'NSGA-2 fornisce un maggior numero di soluzioni non dominate rispetto agli altri 2 metodi di ottimizzazione;
- NSGA-2 è un metodo di ottimizzazione robusto ed affidabile (fornisce soluzioni ottime: possiamo dirlo comparando le soluzioni dell'NSGA-2 con quelle del WSM);
- WSM trova soluzioni ottime, ma in numero minore rispetto all'NSGA-2;
- Bi-Mono trova un buon numero di soluzioni, ma alcune di queste sono dominate.

La ***Tabella 8*** riporta un riassunto dei risultati dei casi test.

	Numero di soluzioni	Soluzioni ottimali	Soluzioni dominate
Bi-Mono	Medio	Basso	Sì
NSGA-2	Alto	Tutte?	No
WSM	Basso	Tutte	No

Table 8 Riassunto dei risultati dei casi test

Caso applicativo: Comau

Il caso industriale Comau si focalizza su una linea di assemblaggio, la Short block SDE (Small Diesel Engine) Assembly line, di cui noi consideriamo una frazione.
Il focus è su 5 stazioni: OP180, OP190, OP200, OP210 e OP220.
L'OP180 è una stazione di spalmatura silicone, l'OP190 assembla la base, nella OP200 10 viti sono inserite, l'OP210 inserisce altre 10 viti e il pallet viene ruotato di 180°, alla fine la OP220, in cui avviene l'avvitamento del sottobasamento.
Tutte queste stazioni possono essere automatiche, semi-automatiche o manuali.
Per queste stazioni abbiamo 6 alternative: 3 automatiche, 2 semi-automatiche e 1 manuale.

Dati

In questo paragrafo spieghiamo tutti i dati utilizzati per condurre l'analisi.
La ***Tabella 9*** riporta l'orizzonte temporale e le unità di misura dei costi e degli impatti ambientali.

Orizzonte temporale	Tasso di sconto	Unità di misura (costi)	Unità di misura (impatti ambientali)
10 years	1.5%	Generica Unità di Costo (inventata)	Milli-points (Eco-Indicator 99)

Tabella 9 Riassunto

L'unità di misura dei costi è stata camuffata da euro a una generica unità di costo, mantenendo la proporzione tra i vari costi. L'unità di misura dell'impatto ambientale è il milli-point, che è usato nell'Eco-Indicator 99.
Il tasso di sconto è assunto costante per tutti i 10 anni.
Qui abbiamo una lista dei costi e degli impatti ambientali usati per l'analisi LCC e LCA:

- Cin = cost iniziale, ossia il costo di acquisizione della stazione;
- Ce = costo dell'energia elettrica. L'equazione di calcolo è:
  - $Ce = ehc(kwh) * nhy\left(\frac{h}{year}\right) * euc(\frac{cost}{kw})$ dove e*hc* è il consumo orario medio, *nhy* è il numero di ore annue di funzionamento impianto e e*uc* è l'unità di costo dell'energia elettrica;

- Cric = costo dei ricambi (1% del costo iniziale per anno);
- Cop = costo della manodopera (su una stazione manuale o semi-automatica lavora un addetto, su una stazione automatica 0.2 addetti);
- Ccon = costo dei materiali di consumo (somma dei costi dei materiali di consumo come olio e grasso, per esempio);
- Cair = costo dell'aria. L'equazione è simile a quella per calcolare Ce, sostituendo e*hc* con il consumo medio orario di aria e *euc* con l'unità di costo dell'aria;
- Cmo = costo della manutenzione preventiva. L'equazione è:
  - $Cmo = nhpm\left(\frac{h}{years}\right) * 1.5 * hmc\ (\frac{cost}{h})$ dove *nhpm* è il numero di ore annue per la manutenzione preventiva e *hmc* è il costo orario del manutentore. 1.5 è la media di manutentori coinvolti;
- Cmorip = costo della manutenzione correttiva. L'equazione è:
  - $Cmorip = \frac{nhy(\frac{h}{years})}{MTBF(h)} * MTTR(h) * 1.5 * hmc(\frac{cost}{h})$ dove *nhy* è il numero di ore annue di funzionamento impianto, *MTBF* è il tempo medio tra 2 guasti, *MTTR* è il tempo medio di riparazione *hmc* è il costo orario del manutentore. 1.5 è la media dei manutentori coinvolti;
- EIst = impatto ambientale della stazione. Sappiamo che le stazioni Comau sono principalmente fatte di acciaio di bassa lega, così l'equazione è:
  - $EIst = mst(kg) * Isla(\frac{millipoints}{kg})$ dove *mst* è la massa della stazione e *Isla* è il valore tabulare dell'impatto ambientale dell'acciaio di bassa lega (Eco-Indicator 99);
- EIel = impatto ambientale dell'energia elettrica. L'equazione è simile alla precedente:
  - $EIel = ehc(kwh) * nhy\left(\frac{h}{year}\right) * Iel(\frac{millipoints}{kwh})$ dove e*hc* è il consumo orario medio *nhy* è il numero di ore annue di funzionamento impianto e *Iel* è il valore tabulare dell'impatto ambientale dell'energia elettrica (consideriamo Electricity LV Europe in Eco-Indicator 99);

- A = disponibilità della stazione. L'equazione è:
    - $A = MTBF(h)/(MTBF + MTTR)(h)$ dove *MTBF* è il tempo medio fra 2 guasti e *MTTR* è il tempo medio di riparazione.

Siccome l'orizzonte temporale è di 10 anni e l'LCC usa costi "scontati" , i costi sostenuti durante gli anni sono scontati di un certo tasso di sconto ,che abbiamo settato al valore di 1.5%.

Così l'equazione per calcolare i costi sostenuti è:

$$C = {C_t}/{(1 + br)^t}$$

dove C è un generico costo scontato, C_t è un generico costo sostenuto all'anno t e br è il tasso di sconto.

La ***Tabella 10*** mostra quando i costi e gli impatti ambientali sono sostenuti durante gli anni.

		Anno										
		0	1	2	3	4	5	6	7	8	9	10
Costi	Cin	x										
	Ce	x	x	x	x	x	x	x	x	x	x	x
	Cric	x	x	x	x	x	x	x	x	x	x	x
	Cop	x	x	x	x	x	x	x	x	x	x	x
	Ccon	x	x	x	x	x	x	x	x	x	x	x
	Cair	x	x	x	x	x	x	x	x	x	x	X
	Cmo	x	x	x	x	x	x	x	x	x	x	X
	Cmorip	x	x	x	x	x	x	x	x	x	x	X
Impatti ambientali	EIst	x										
	EIel	x	x	x	x	x	x	x	x	x	x	X

Tabella 10 Costi e impatti ambientali sostenuti durante gli anni.

Modello

Il modello per il caso Comau è molto semplice ed è stato creato seguendo le istruzioni fornite da Comau.

Il modello ha 2 funzioni obiettivo, una che minimizza il costo del ciclo di vita del prodotto ed una che minimizza l'impatto ambientale durante tutto il ciclo di vita.

Il modello ha 2 tipi di vincoli: la disponibilità della frazione della linea di assemblaggio deve essere maggiore di 0.95; tutte le postazioni devono avere una stazione, che può essere automatica, semi-automatica o manuale.

Di seguito riportiamo il modello scritto in forma analitica:

$$\min \sum_{i=1}^{30} (Cin * x_i + Ce * x_i + Cric * x_i + Cop * x_i + Ccon * x_i + Cair * x_i + Cmo * x_i + Cmorip * x_i)$$

$$\min \sum_{i=1}^{30} (EIst * x_i + EIel * x_i)$$

Soggetto a

$$\sum_{i=1}^{6} A_i x_i * \sum_{i=7}^{12} A_i x_i * \sum_{i=13}^{18} A_i x_i * \sum_{i=19}^{24} A_i x_i * \sum_{i=25}^{30} A_i x_i \geq 0.95$$

$$\sum_{i=1}^{6} x_i = 1$$

$$\sum_{i=7}^{12} x_i = 1$$

$$\sum_{i=13}^{18} x_i = 1$$

$$\sum_{i=19}^{24} x_i = 1$$

$$\sum_{i=25}^{30} x_i = 1$$

$x_i \in \{0,1\} \;\; i = 1,2, \dots ,30$

dove i vari costi, impatti ambientali e disponibilità sono state descritti precedentemente, x_i è una variabile binaria.

Abbiamo condotto 2 analisi: una in cui la linea è stata installata nell'Europa dell'Est (dove la manodopera è più economica) e una nella quale la linea è stata installata nell'Europa occidentale (dove la manodopera è più costosa).

Scenario Europa dell’Est

Nella ***Tabella 11*** riportiamo i costi sostenuti e gli impatti ambientali lungo il ciclo di vita.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	EI st	EI el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	1737.771	235.1102	191.1549	22.99992	723.5773	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	1737.771	153.3328	151.2883	18.39993	482.9982	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	8688.857	143.1106	17.37771	1.609994	45.99983	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	1737.771	245.3324	197.697	24.37991	793.1521	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	1737.771	275.999	199.7415	26.4499	848.8119	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	8688.857	214.6659	23.25547	2.75999	75.43972	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	8688.857	143.1106	15.75239	1.149996	45.99983	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984

Tabella 11 Costi e impatti ambientali per le alternative

Type indica se la stazione è automatica (aut), semiautomatica (saut) o manuale (m).

Il modello descritto è applicato con l’algoritmo genetico (NSGA-2) e con il WSM (Weighted Sum Model) per verificare i risultati ottenuti con l’algoritmo genetico.

Nella ***Tabella 12*** riportiamo i parametri dell’NSGA-2.

Popolazione	100
Crossover	Multi-point semplice (tasso = 0.9)
Selettore	Crowded Tournament
Mutatore	Semplice dal gene (tasso = 0.15)
Generazioni	200

Tabella 12 Parametri dell’algoritmo genetico

I risultati sono riportati nella ***Figura 10.***

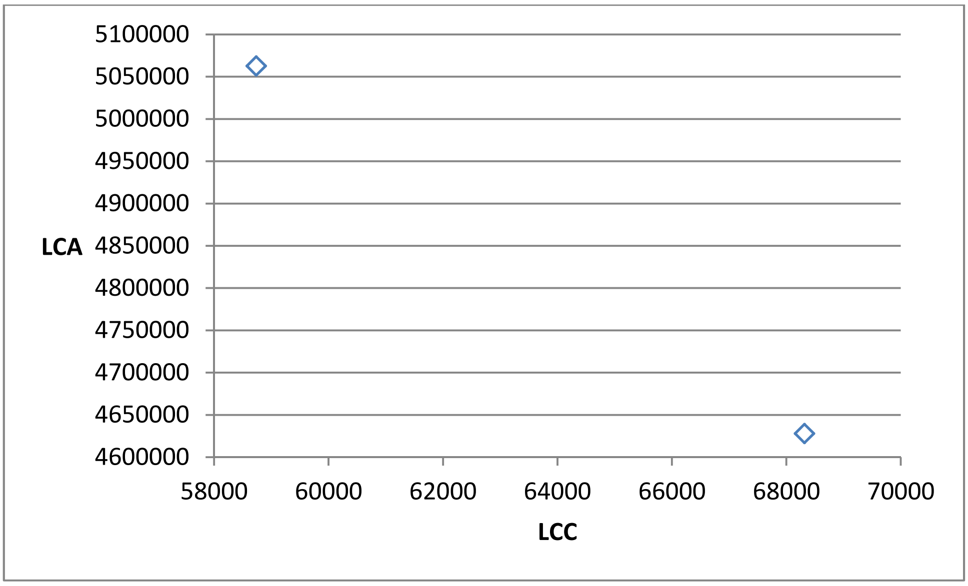


Figura 10 Risultati

I risultati mostrano che la soluzione migliore per l'LCC è la linea con tutte stazioni manuali. Per validare i risultati abbiamo chiesto alla Comau se fosse possibile una soluzione di questo tipo. Hanno risposto affermativamente, poiché la manodopera a basso costo favorisce l'installazione di stazioni manuali.

Scenario Europa occidentale

Nella ***Tabella 13*** riportiamo i costi sostenuti e gli impatti ambientali lungo il ciclo di vita.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	El st	El el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	6082.195	235.1102	191.1549	68.99975	2170.732	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	6082.195	153.3328	151.2883	55.1998	1448.995	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	30410.98	143.1106	17.37771	4.829982	137.9995	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	6082.195	245.3324	197.697	73.13973	2379.456	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	6082.195	275.999	199.7415	79.34971	2546.436	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	30410.98	214.6659	23.25547	8.279969	226.3192	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	30410.98	143.1106	15.75239	3.449987	137.9995	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984

Tabella 13 Costi e impatti ambientali per le alternative

I parametri utilizzati sono gli stessi dello scenario precedente (vedi ***Tabella 12***)

I risultati sono riportati nella ***Figura 11.***

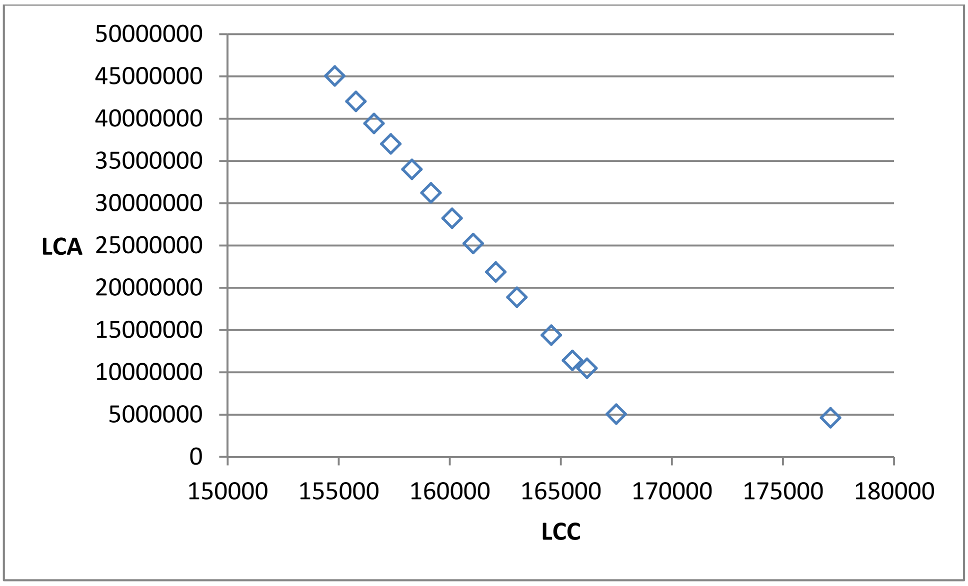


Figura 11 Risultati

L'ottimo per l'LCC è la linea con tutte stazioni automatiche.

Questi risultati sono stati sottoposti a Comau, che li ha convalidati.

Conclusioni

Benefici and criticità nel caso applicativo Comau

Il miglior modo per capire se il modello è funzionale o no è quello di sottoporlo all'azienda del caso reale.

Perciò abbiamo chiesto a Comau l'utilità del modello sviluppato.

E' bene però ricordare prima di tutto come Comau stima l'LCC.

Quindi riportiamo le fasi del ciclo di vita di produzione e attrezzatura macchine. (***Figura 12***)

Figura 12 Fasi del ciclo di vita di produzione e attrezzatura macchine

La fase 1 (Concept) è la ricerca e sviluppo e solitamente si conclude con un preventivo.

Comau ci ha detto che la fase di proposal è un processo molto lungo. Loro credono che questo modello possa aiutarli a offrire un preventivo più velocemente ed efficientemente ai clienti: infatti attualmente tutti i calcoli per l'LCC sono fatti a mano con l'aiuto di un software come Excel.

Perciò il nostro modello rende il processo di preparazione del preventivo più veloce ed efficiente di quello esistente.

Dobbiamo anche ricordare che il caso è una frazione della linea di assemblaggio (solo 5 postazioni), mentre l'intera linea di assemblaggio è composta da circa 100 postazioni, quindi il potenziale del modello sviluppato è molto alto.

Ciò suggerisce la scelta dell'algoritmo genetico.

La soluzione ottenuta nel modello deve essere testata in un simulatore, per verificare che rispetti i vincoli imposti dal cliente.

Per essere più completo, il nostro modello dovrebbe valutare le performance (in questo caso, per esempio, il throughput), invece ora con il processo esistente o con il nostro modello Comau spende un tempo considerevole nella simulazione.

Infatti, se fossimo capaci di includere le performance tramite formule analitiche nel modello, potremmo ridurre il tempo dedicato alla simulazione.

Questo sarebbe un altro grande beneficio.

Inoltre dovremmo organizzare il database in modo tale che il recupero dati per il modello sia immediato.

La ***Figura 13*** mostra la riduzione di tempo ottenibile.

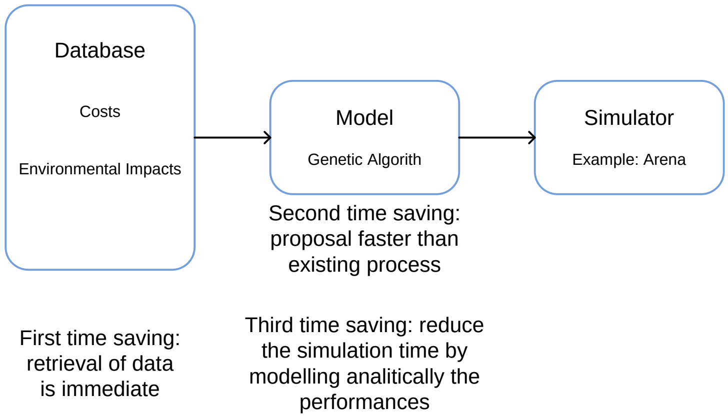


Figura 13 Riduzione di tempo

Una richiesta che ci è stata fatta da Comau è quella di costificare l'impatto ambientale, trasformando il problema di ottimizzazione da bi-obiettivo (minimizzare l'impatto ambientale e i costi del ciclo di vita del prodotto) a obiettivo singolo (minimizzare i costi del ciclo di vita del prodotto).

Questo sarebbe possibile usando queste equazioni:

$$min \sum_{i}^{n} LCC_i + \sum_{j}^{k} pc_j * eEI_j$$

$$EI_j - eEI_j \leq tvEI_j \qquad \forall j$$

dove LCC_i è il costo del ciclo di vita del componente *i-esimo*, pc_j è il costo penalità del *j-esimo impatto ambientale*, eEI_j è l'eccesso del *j-esimo* impatto ambientale, EI_j è il *j-esimo* impatto ambientale e $tvEI_j$ è il valore soglia del *j-esimo* impatto ambientale.

Questo sicuramente minimizza i costi del ciclo di vita del prodotto e rispetta le norme ambientali, ma è un approccio reattivo.

Invece l'obiettivo del nostro lavoro è usare un approccio proattivo verso le tematiche ambientali.

La ***Tabella 14*** riassume benefici, punti critici e possibili sviluppi futuri incontrati nel caso Comau.

Benefici	*Criticità*	*Possibili sviluppi futuri*
Ridurre il tempo per il proposal	Le performance non sono valutate	1- Valutare le performance nel modello 2-Organizzare il database 3-Trasformare l'impatto ambientale in costo

Tabella 14 Benefici, punti critici e possibili sviluppi futuri.

Nostre considerazioni

L'obiettivo del nostro lavoro è sviluppare un'ottimizzazione multi-obiettivo di costi e impatti ambientali nel ciclo di vita del prodotto. Con i casi test e il caso reale abbiamo avuto successo. Comau ha anche ritenuto il nostro lavoro interessante. Tuttavia il nostro lavoro ha mostrato alcune debolezze, che sono elencate di seguito:

- L'LCA non può essere bene analizzata a causa della mancanza di dati;
- Non possiamo valutare la robustezza dell'LCA a causa della mancanza di valori tabulari di altre prospettive;
- Non abbiamo paragonato l'NSGA-2 con gli altri algoritmi genetici multi-obiettivo e con altri valori dei parametri;
- Il nostro modello non valuta le performance.

I pregi del nostro lavoro sono:

- Esso è stato considerato rilevante da Comau;
- Il paragone tra l'algoritmo genetico e la programmazione lineare;
- Esso è più completo di quelli presenti in letteratura (che mancano di informazioni);
- L'analisi delle ragioni e della letteratura.

I principali sviluppi futuri sono:

- Le equazioni di efficacia del sistema di LCC e LCA (Effectiveness/LCC e Effectiveness/LCA) (vedi il Capitolo 2 sezione 2.2.6.5) e le equazioni di performance del sistema (Performances/LCC e Performances/LCA);

- Approfondire l’uso dell’LCA, usando altri database oltre l’Eco-Indicator 99.

Index

CHAPTER 1

Introduction

1.1 Introduction

Today, in an increasingly competitive world, Western companies need new tools to attempt to stay on the market.

These companies are forced to seek new ways to be competitive in the global market, because of globalization and of the competition with companies around the world, particularly from Far East, where labor costs less and there aren't strict environmental regulations.

Since it's very difficult to compete with the mere final cost of the product of Far East companies, Western companies have begun to aim at reducing the life cycle cost as a new competitive tool.

So the interest in LCC is driven by finding new competitive leverages , different by the classical ones (e.g. lower cost of acquisition). For example, with life cycle cost analysis, western companies can offer energetically efficient services and/or machine, or reducing the use of labor. Other examples can be the reduction in the cost of spare parts or of the maintenance time and so of the maintenance costs. In addition, more and more costumers require in the proposal a life cycle cost analysis (some of them an accurate one, others a less rigorous one).

Another new competitive tool that some companies have begun to use is the reduction of environmental impact. This choice has been dictated by increasingly strict regulations as, Kyoto protocol and ISO 14000.

In the literature there are methodologies that help to calculate the costs and environmental impacts along the whole life-cycle: they are the LCC (Life Cycle Cost) and the LCA (Life Cycle Assessment).

Life Cycle Cost (LCC) is “cradle-to-grave” cost summarized as an economic model of evaluating alternatives for equipment and projects. [Bar 03]

LCC starts to develop in the mid-1960s.

LCC helps to change provincial perspectives for business issues with emphasis on enhancing economic competitiveness by working for the lowest long term cost of ownership which is not an easy answer to obtain. [Bar 96]

Life Cycle Assessment (LCA) is a technique to assess environmental impacts associated with all stages of a product’s life from-cradle-to-grave. [Sai 06]

LCA starts to be studied in 1960s.

LCA can help decision-makers to select the product or process that results in the least impact to the environment. This information can be used with other factors, such as cost and performance data to select a product or process. LCA data identifies the transfer of environmental impacts from one media to another and/or from one life cycle stage to another. If an LCA were not performed, the transfer might not be recognized and properly included in the analysis because it is outside of the typical scope or focus of product selection processes.

This ability to track and document shifts in environmental impacts can help decision makers and managers fully characterize the environmental trade-offs associated with product or process alternatives. [Sai 06]

These methodologies explain step by step how to conduct an analysis of costs or of environmental impacts along the life-cycle, but they don’t optimize this values. Also in the literature there are just few papers that attempt to optimize costs or environmental impacts along the life-cycle ,while most of them explain how to conduct a LCC or LCA analysis.

So in our work we apply a multi-objective optimization, based on genetic algorithm, to LCC (Life Cycle Cost) and LCA (Life Cycle Assessment) methodologies.

When we speak about LCC and LCA optimization we refer to optimization of the results and not of the methodologies.

Genetic algorithm has been selected because it has no problems with dealing with multi-objective optimization, instead linear programming cannot handle problems of this type. In addition genetic algorithm is more efficient than linear programming when the number of variables increases.

In this chapter we introduce the reasons and the main aspects of this work.

Firstly we explain the reasons that made us develop this work and why it may be interesting, then we make an overview of how the work was structured.

1.2 Reasons

In this work we want to apply a multi-objective optimization, based on genetic algorithm, of LCC and LCA, as previously mentioned.

The history of LCC and LCA methodologies starts in the 60s, while the history of genetic algorithm start in the 50s, these matters, taken individually, have already been extensively developed in the literature, so why have we developed this work?

In the next 2 sub-paragraph we explain the reasons of this work from the perspective of companies and of the existing literature.

1.2.1 Perspective of companies

As mentioned before in section 1.1, companies (particularly western companies) need new competitive leverages to survive in the global market. Two of these new tools are life cycle cost and environmental impacts, they are so interesting because of the impossibility to compete with the final cost of product of Far East companies.

We have access to the results of a questionnaire given to 3 western companies: Aker, Comau and Volkswagen. This questionnaire was submitted to the companies as part of an European project. The purpose is to understand how companies face development process. This is a complex environment, in which many actors collaborate and share their knowledge ,by using different methods and tools.

Development process is the phase where the majority of LCC (about 2/3s of the total) is fixed. (***Figure 1.1***) [Fol 95] [Yat 95] [Bla 91]

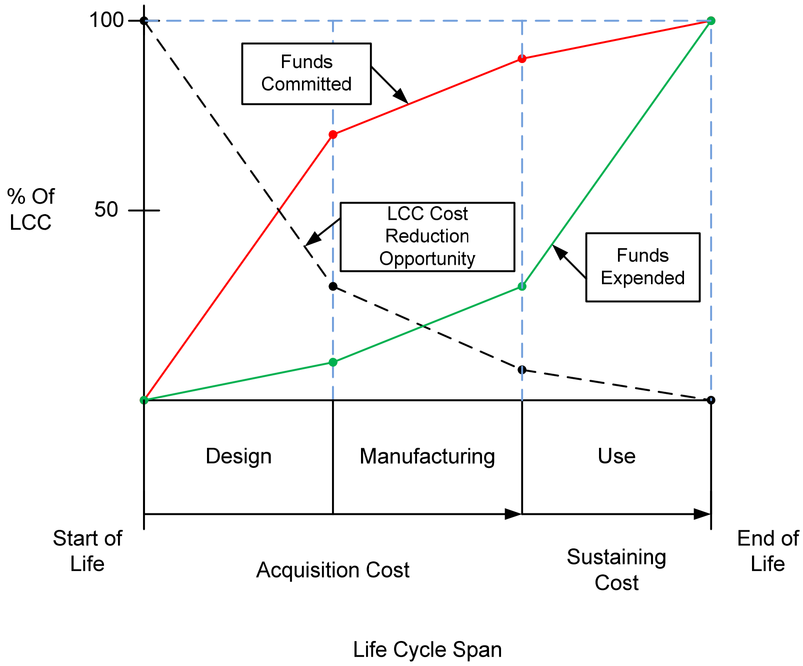


Figure 1.1 Funding Trends By Commitment And Expenditure [Bla 91]

It is possible to draw a similar graph for LCA, too.

Aker Solutions is a leading global oil services company that provides engineering services, technologies, product solutions and field-life solutions for the oil and gas industry. (Based in Norway)

Comau is a global supplier of industrial automation systems and services, mainly for the automotive manufacturing sector. (Based in Italy)

The Volkswagen Group is one of the world's leading automobile manufacturers and the largest carmaker in Europe. (Based in Germany)

From the questionnaire we have extracted what we needed for the purpose of this work.

From a question it is possible to analyze which are the main factors considered by the companies during their design/development processes. Typical factors have been defined from a literature analysis. We consider only the economics and environmental factors

As shown hereafter, in ***Table 1.1***, the economic and environmental factors are important or very important for all the companies.

So this work is based on existing needs of enterprises and our model ,that optimizes both LCC and LCA, can really help many companies.

How would you rate the company's consideration (i.e. factors used for evaluating alternative solutions) of the following factors/criteria during the design / development process?			
Factors	**Aker**	**Comau**	**VW**
Final Cost of the Product			
Costs along the Product Lifecycle			
ROI - Return of Investment			
Environmental aspects			

Legend	
Very Low	
Low	
High	
Very High	

Table 1.1 Importance of economics and environmental factors

Looking at the questionnaire, everything said above is correct and represents the reality of the companies. It's always considered important the final cost of the product ,because for the costumers is still significant (looking at the questionnaire it is the economic factor that companies consider more important , on average). Clearly the final cost has always to be kept under control, although it's difficult to compete with the Far East companies. Costs along the product life-cycle are also considered important, so these can be a new competitive leverage. Moreover talking with Comau's heads, they confirmed to us that life cycle cost and life cycle assessment can be used as competitive keys against lower acquisition costs of far-east competitors.

So the optimization of LCC and LCA can play a role on the competiveness of the company.

Also companies must respect the increasingly tight regulations (e.g. Kyoto protocol and ISO 14000). Our work can assist enterprises in respecting the regulations.

1.2.2 Perspective of literature

In this sub-paragraph we show what we found in the literature.

The literature of LCC and LCA is very wide. In the last years the number of papers is significantly increased, particularly the literature regards LCA.

However many of these works are not relevant, they treat briefly these methodologies; in fact many of these papers simply apply LCC or LCA, without adding anything new, in some of them there are not even calculations . Just few papers are innovative or, at least, complete.

This shows how this methodologies need to be further studied in-depth, because they are not accessible to the majority, although they are not a new concept (they were born in the 1960s).

So it is necessary to do an exhaustive search in the literature, in order to find the relevant papers.

The detailed state of the art is then discussed in chapter 3. We have analyzed 39 papers of LCC application and 40 papers of LCA application. These are the papers that we considered relevant.

Figure 1.2 and ***1.4*** show where LCC and LCA are applied, while ***Figure 1.3*** and ***1.5*** show the percentage of papers dedicated to a certain field of application.

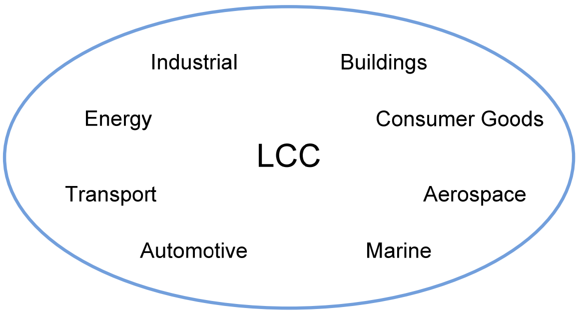


Figure 1.2 Field of application of LCC

For LCC methodology we have found 8 areas of application. Many of these fields are very interesting and we can observe how literature and reality converge. In fact, for example, in literature LCC was used in Automotive sector. In section 1.2.1 we can see how two companies of Automotive sector, Comau and Volskwagen, are very interested in costs along product life-cycle.

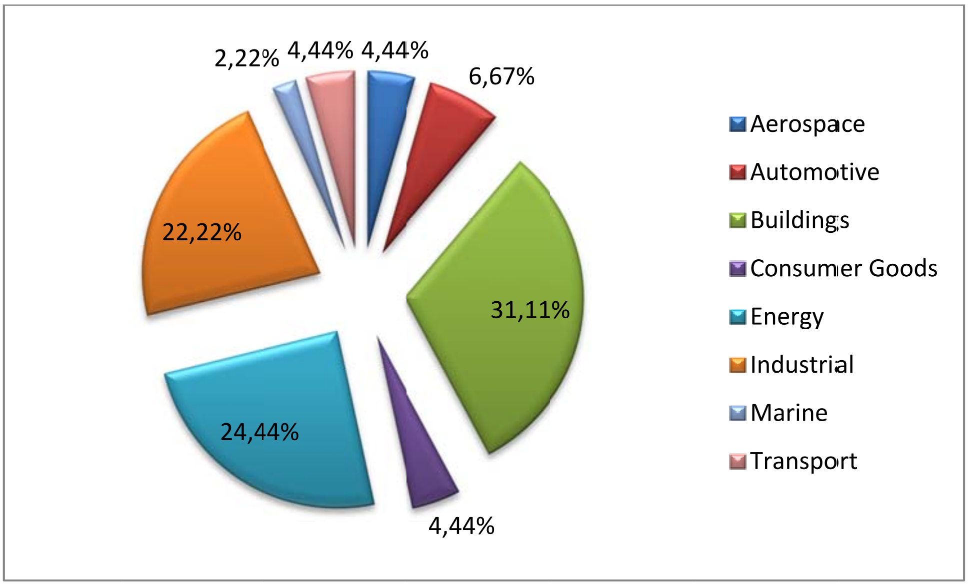


Figure 1.3Percentage of LCC papers dedicated to a certain field of application

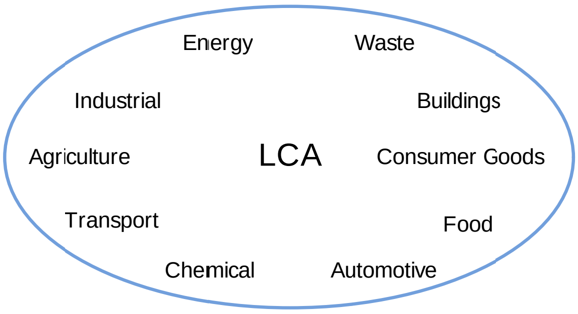


Figure 1.4 Field of application of LCA

For LCA methodology we have found 10 fields of application.

Compared to LCC, LCA also considers the primary sector (Agriculture and Food) and chemical sector. This is caused by very strict regulations, as RoHS (Restriction of use of certain Hazardous Substances) in chemical sector.

So our work is justified by the possibility to be applied in various field, different one from the other.

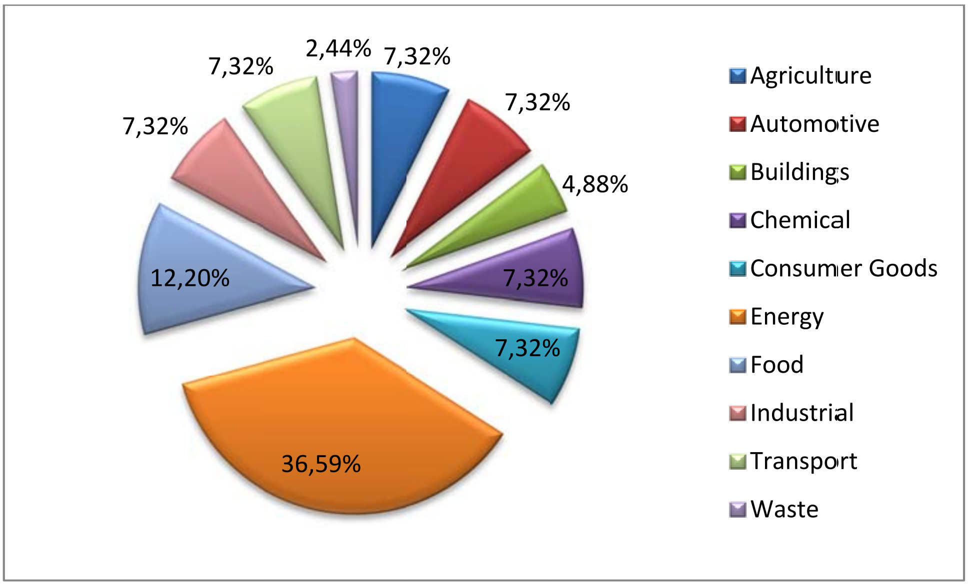


Figure 1.5 Percentage of LCA papers dedicated to a certain field of application

The second step , we want to do, is the analysis of the percentage of LCC or LCA optimization in the literature. ***Figure 1.6*** and ***Figure 1.7*** show graphically this analysis.

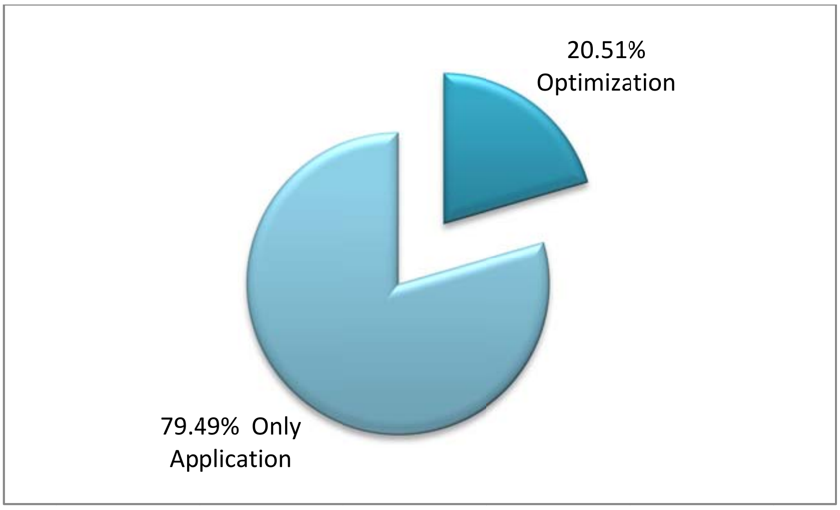


Figure 1.6 LCC Optimization percentage

As we can see, only about the 20% of papers presents a LCC optimization, while, for LCA optimization, only the 10% of papers shows an optimization.

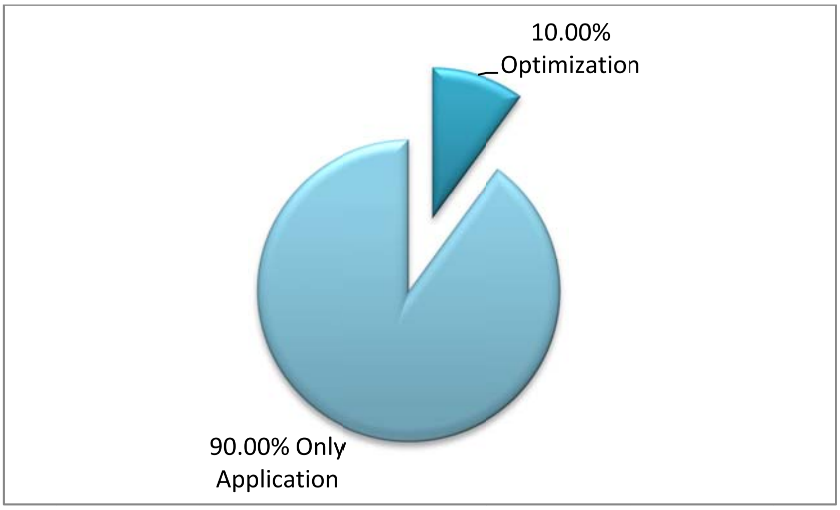


Figure 1.7 LCA Optimization percentage

Another analysis deepens which optimization methods are used. This is reported in ***Figure 1.8*** and ***Figure 1.9***.

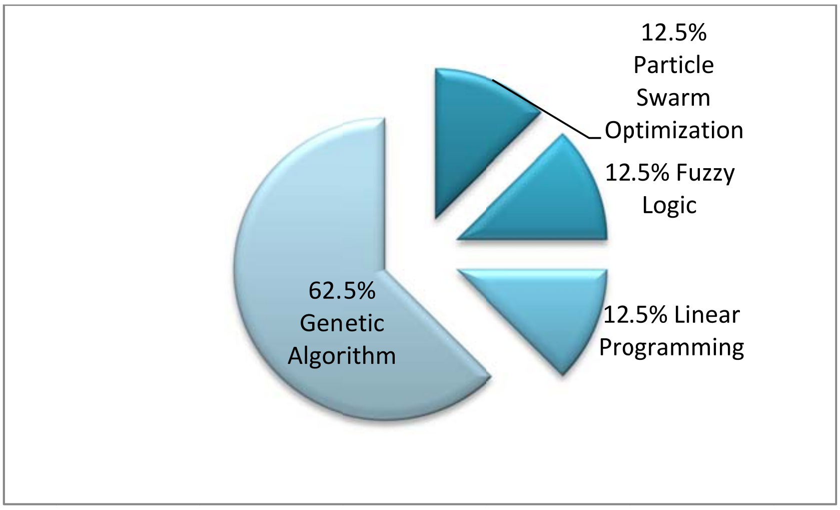


Figure 1.8 LCC optimization methods percentage

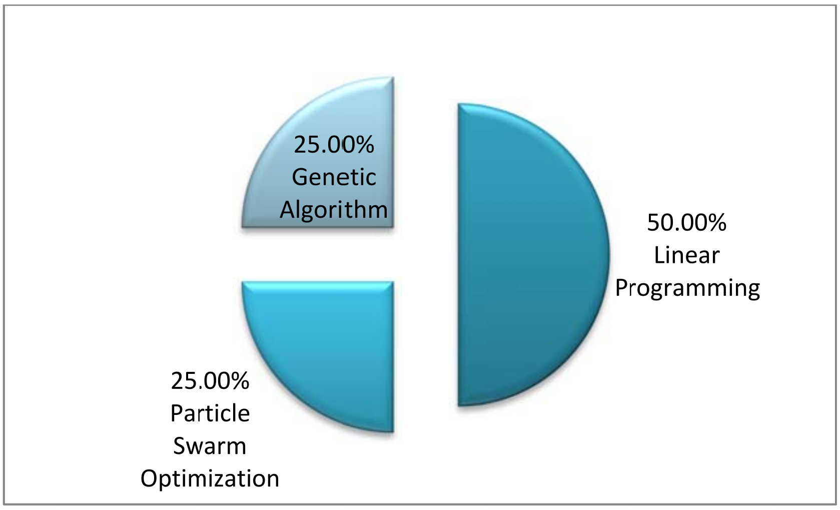


Figure 1.9 LCA optimization methods percentage

The comparison between the two methodologies shows their different evolution.
LCC has a major percentage of papers that talk about optimization than LCA.
Also, in LCC, the most percentage of optimization is composed by evolutionary algorithms (genetic algorithm and particle swarm optimization); instead in LCA linear programming and evolutionary algorithms have the same percentage.
In papers, that talk about LCA optimization, there isn't only environmental impact optimization, but also, for example, costs or production optimization.
Table 1.2 shows a summary of what we just mentioned.

	% of paper analyzed	% of evolutionary algorithms	Other optimization?
LCC optimization	20.51%	75%	No
LCA optimization	10.00%	50.00%	Yes (cost or production)

Table 1.2 Summary of paper analysis

The major problem of these papers is the lack of information regards models (objective functions and constraints) and used data. This makes any comparison or evaluation difficult.
From the paper analysis we can say that the route of LCC and LCA optimization is still open. Our work aims to continue and deepen this way.

1.3 Structure of the work

In this paragraph we explain the structure of our work, composed by 6 chapters, as graphically described in ***Figure 1.10***.

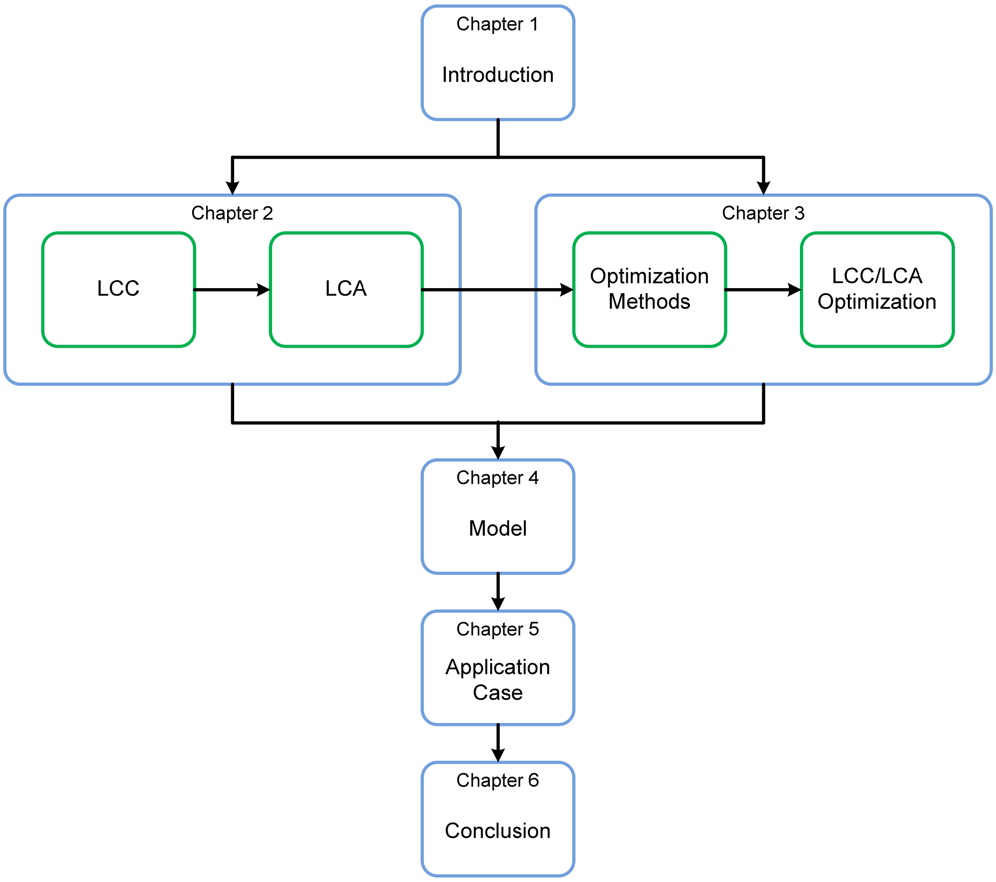


Figure 1.10 Structure of the work

Except Chapter 1, in which we introduce the reasons and the main aspects of the full work, all the other chapters are specifically focused on one of the stages of the performed project.

In Chapter 2, we explain the two methodologies whose results we want to optimize: Life Cycle Cost and Life Cycle Assessment. For both methodologies we did a deepen analysis.

In Chapter 3, we explain some methods to optimize LCA's and LCC's results.

We also analyze the state of the art of LCC and LCA optimization, showing some examples of LCC and LCA optimization.

In Chapter 4 we introduce a model to optimize product life-cycle costs and environmental impacts together. The model is developed with genetic algorithm and compared to linear programming. The three developed models (one with genetic algorithm, two with linear programming) are explained and then they are compared by using test cases with invented data. ***Figure 1.11*** shows better the structure of this chapter.

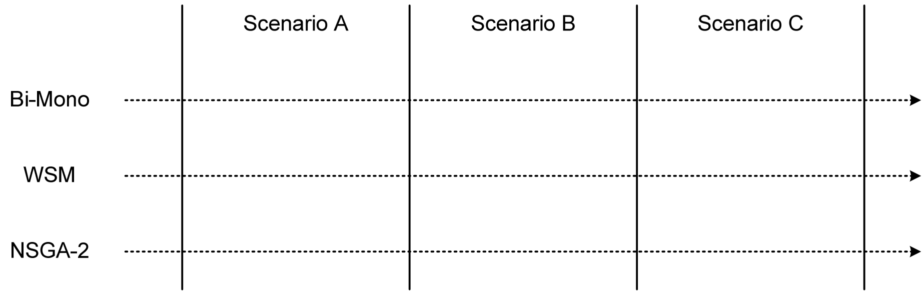


Figure 1.11 Structure of chapter 4

In Chapter 5 we apply the developed model to a real case: a fraction of Comau assembly line, studying two scenarios.

In Chapter 6, the final chapter, we illustrate benefits, criticisms and possible future developments of our work.

CHAPTER 2

Life Cycle Cost & Life Cycle Assessment

2.1 Introduction

In this chapter we explain the two methodologies whose results we want to optimize: Life Cycle Cost and Life Cycle Assessment. For both methodologies we did a deepen analysis.

It's important to emphasize that the procedures of Life Cycle Assessment are part of the ISO 14000 environmental management standards: in ISO 14040:2006 and 14044:2006 (ISO 14044 replaced earlier versions of ISO 14041 to ISO 14043).

2.2 Life Cycle Cost

Life cycle costs (LCC) are "cradle-to-grave" costs summarized as an economic model of evaluating alternatives for equipment and projects. Engineering details drive LCC cost numbers for the economic calculations. The economics of proposals drives the scenario selection process. Good engineering proposals without economic justification are often uneconomical. Good engineering with good economics provide business successes. The LCC economic model provides better assessment of long-term cost effectiveness of projects than can be obtained with only first costs decisions. [Bar 03]

2.2.1 Definitions

Some LCC definitions are:

- Life cycle cost is the total cost of ownership of machinery and equipment, including its cost of acquisition, operation, maintenance, conversion, and/or decommission; [Sae 99]
- LCC are summations of cost estimates from inception to disposal for both equipment and projects as determined by an analytical study and estimate of total costs experienced in annual time increments during the project life with consideration for the time value of money. The objective of LCC analysis is to choose the most cost effective approach from a series of alternatives to achieve the lowest long-term cost of ownership. LCC is an economic model over the project life span. Usually the cost of operation, maintenance, and disposal costs exceed all other first costs many times over. The best balance among cost elements is achieved when the total LCC is minimized. [Lan 96]

Businesses must summarize LCC results in net present value (NPV) format considering depreciation, taxes and the time value of money. Government organizations do not require inclusion of depreciation or taxes for LCC decisions but they must consider the time value of money. [Bar 03]

2.2.2 History of LCC

The history of life cycle costing began in the mid-1960s when a document entitled “Life Cycle Costing in Equipment Procurement” was published. In 1974, Florida became the first U.S. state to formally adopt the concept of life cycle costing and in 1978 the U.S.A Congress passed the National Energy Conservation Policy Act. According to this act every new federal government building should be life cycle cost effective. [Elm 06]

2.2.3 Use of LCC

LCC helps to change provincial perspectives for business issues with emphasis on enhancing economic competitiveness by working for the lowest long term cost of ownership which is not an easy answer to obtain. Consider these typical problems and conflicts observed in most companies:

1. Project Engineering wants to minimize capital costs as the only criteria;
2. Maintenance Engineering wants to minimize repair hours as the only criteria;
3. Production wants to maximize uptime hours as the only criteria;
4. Reliability Engineering wants to avoid failures as the only criteria;
5. Accounting wants to maximize project net present value as the only criteria;
6. Shareholders want to increase stockholder wealth as the only criteria.

Management is responsible for harmonizing these potential conflicts under the banner of operating for the lowest long term cost of ownership. LCC can be used as a management decision tool for harmonizing the never ending conflicts by focusing on facts, money, and time.

2.2.4 LCC Data and models

The basic tree for LCC starts with a very simple tree based on the costs for acquisition and the costs for sustaining the acquisition during its life. (***Figure 2.1***)

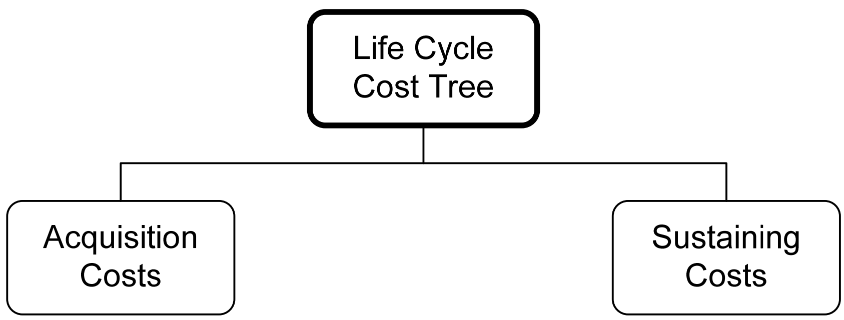


Figure 2.1 Top levels of LCC tree [Bar 96]

Acquisition and sustaining costs are not mutually exclusive. If you acquire equipment or processes, they always require extra costs to sustain the acquisition, and you can’t sustain without someone having acquired the item. Acquisition and sustaining costs are found by gathering the correct inputs, building the input database, evaluating the LCC and conducting sensitivity analysis to identify cost drivers.

Acquisition costs have several branches for the tree (***Figure 2.2***):

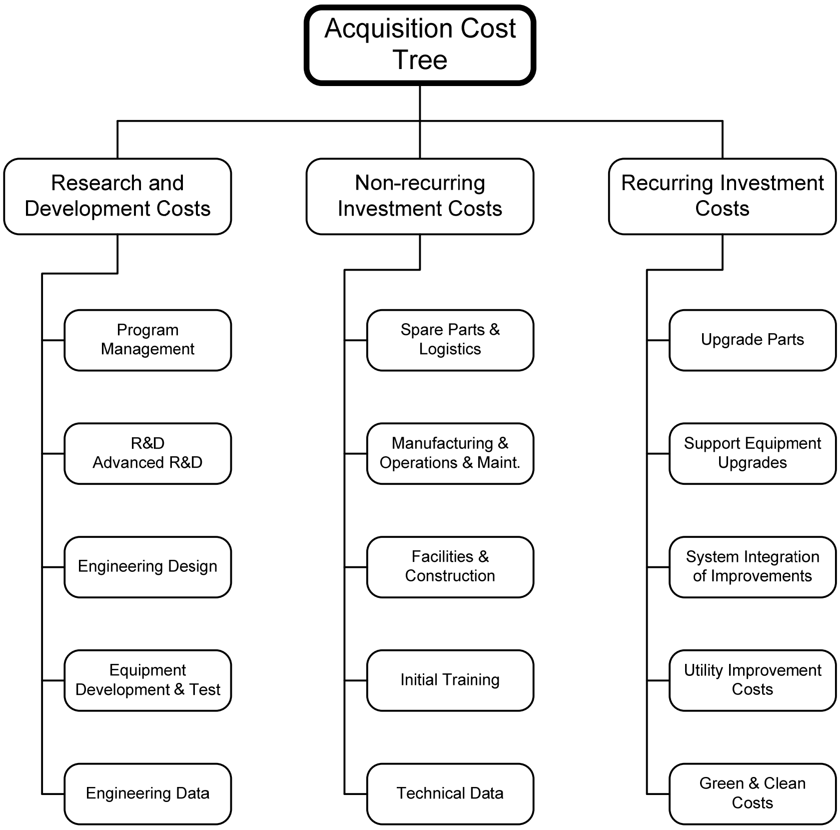


Figure 2.2 Acquisition Cost Tree [Bar 96]

Sustaining costs have several branches for the tree (***Figure 2.3***):

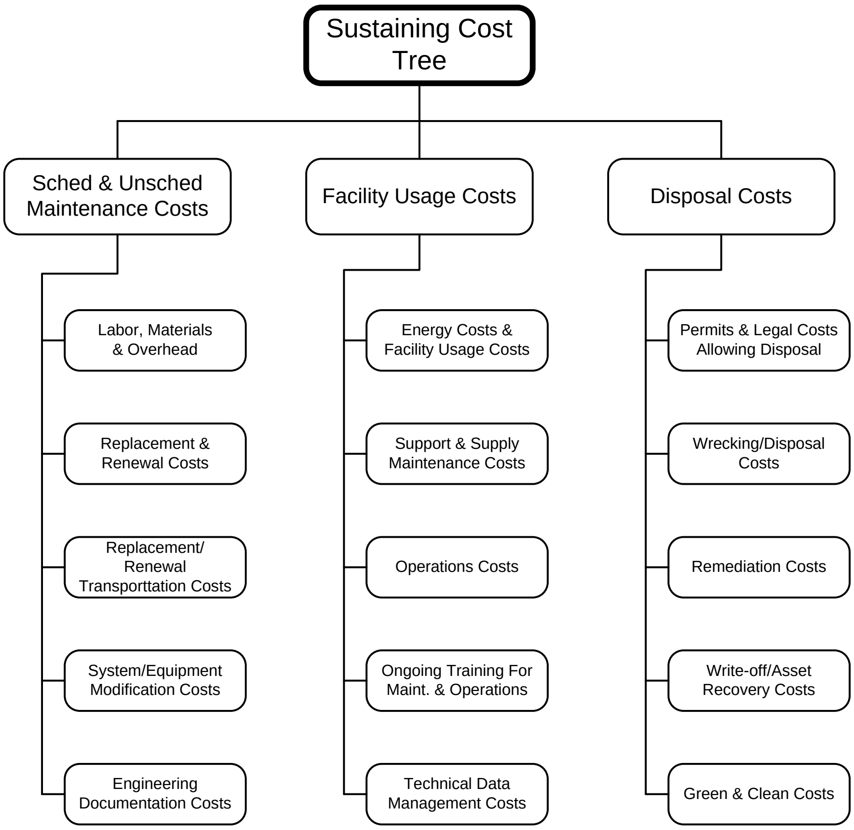


Figure 2.3 Sustaining Cost Tree [Bar 96]

What cost goes into each branch of the acquisition and sustaining branches? It all depends on the specific case and is generally driven by common sense. Include the appropriate cost elements and discard the elements which do not substantially influence LCC. [Bar 96] [Bar 03]

Consider these alternative LCC models as described by:

1) LCC = non-recurring costs + recurring costs;
2) LCC = initial price + warranty costs + repair, maintenance, and operating costs to end users;
3) LCC = manufacturer's cost + maintenance costs and downtime costs to end users. [Rah 91]

SAE also has a LCC model directed toward a manufacturing environment:

4) LCC = acquisition costs + operating costs + scheduled maintenance + unscheduled maintenance + conversion/decommission. (***Figure 2.4***) [Sae 93]

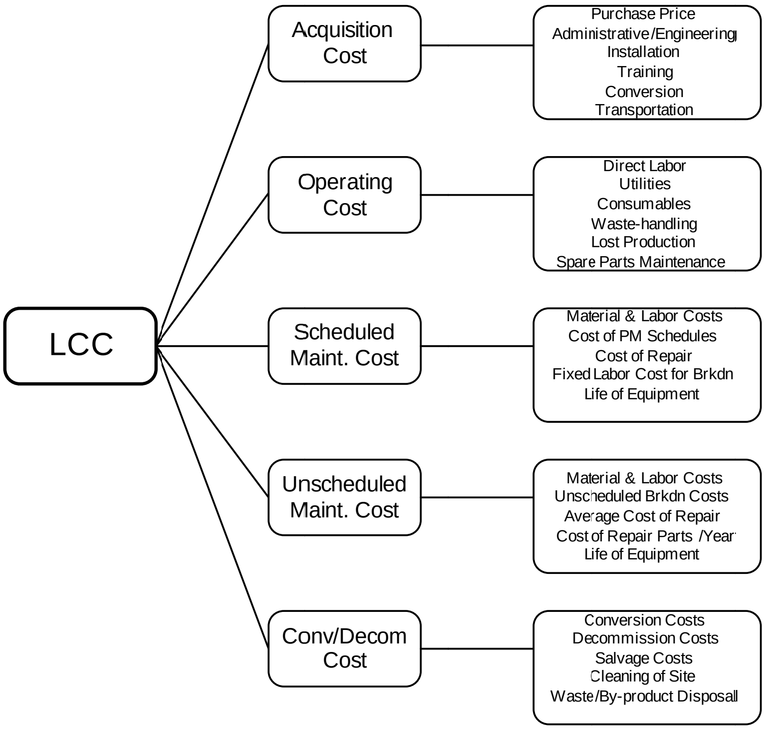


Figure 2.4 SAE Model of LCC [Sae 93]

2.2.5 Phases of a LCC

Figure 2.5 Phases of LCC

As shown in the attached diagram (***Figure 2.5***), Life Cycle Costing is a six-staged process. The first four stages comprise the Life Cost Planning phase with the last two stages incorporating the Life Cost Analysis phase. The six stages are:

- Stage 1: Plan LCC Analysis
- Stage 2: Select/Develop LCC Model
- Stage 3: Apply LCC Model
- Stage 4: Document and Review LCC Results
- Stage 5: Prepare Life Cost Analysis
- Stage 6: Implement and Monitor Life Cost Analysis

All stages may be performed iteratively as needed. Assumptions made at each stage should be rigorously documented to facilitate such iterations and to aid in interpretation of the results of the analysis.

Plan LCC analysis

The Life Cycle Costing process begins with development of a plan, which addresses the purpose, and scope of the analysis. The plan should:

- Define the analysis objectives in terms of outputs required to assist management decisions. Typical objectives are:
  - determination of the LCC for an asset in order to assist planning, contracting, budgeting or similar needs
  - evaluation of the impact of alternative courses of action on the LCC of an asset (such as design approaches, asset acquisition, support policies or alternative technologies)
  - identification of cost elements which act as cost drivers for the LCC of an asset in order to focus design, development, acquisition or asset support efforts.
- Delineate the scope of the analysis in terms of the asset(s) under study, the time period (life cycle phases) to be considered, the use environment and the operating and maintenance support scenario to be employed.
- Identify any underlying conditions, assumptions, limitations and constraints (such as minimum asset performance, availability requirements or maximum capital cost limitations) that might restrict the range of acceptable options to be evaluated.
- Identify alternative courses of action to be evaluated. The list of proposed alternatives may be refined as new options are identified or as existing options are found to violate the problem constraints.
- Provide an estimate of resources required and a reporting schedule for the analysis to ensure that the LCC results will be available to support the decision-making processes for which they are required.

The plan should be documented at the beginning of the Life Cycle Costing process to provide a focus for the rest of the work. Intended users of the analysis results should review the plan to ensure their needs have been correctly interpreted and clearly addressed.

Select LCC model

Stage 2 is the selection or development of an LCC model that will satisfy the objectives of the analysis.

The model should:

- create or adopt a cost breakdown structure (CBS) that identifies all relevant cost categories in all appropriate life cycle phases. Cost categories should continue to be broken down until a cost can be readily estimated for each individual cost element. Where available, an existing cost breakdown structure may provide a useful starting point for development of the LCC breakdown structure.
- identify those cost elements that will not have a significant impact on the overall LCC of the asset(s) under consideration or those that will not vary between alternatives. These elements may be eliminated from further consideration
- select a method (or methods) for estimating the cost associated with each cost element to be included in the model.
- determine the data required to develop these estimates, and identify sources for the data.
- identify any uncertainties that are likely to be associated with the estimation of each cost element.
- integrate the individual cost elements into a unified LCC model, which will provide the LCC outputs required to meet the analysis objectives.
- review the LCC model to ensure that it is adequate to address the objectives of the analysis.
- the LCC model including all assumptions should be documented to guide and support the subsequent phases of the analysis process.

Apply LCC model

Application of the LCC Model involves the following steps:

- obtain data and develop cost estimates and their timing for all the basic cost elements in the LCC model.
- validate the LCC model with available historical data if possible.
- obtain the LCC model results from each relevant combination of operating and support scenarios defined in the analysis plan.
- identify cost drivers by examining LCC model inputs and outputs to determine the cost elements that have the most significant impact on the LCC of the asset(s).
- quantify any differences (in performance, availability or other relevant constraints) among alternatives being studied, unless these differences are directly reflected in the LCC model outputs.
- categorize and summarize LCC model outputs according to any logical groupings, which may be relevant to users of the analysis results (eg. fixed or variable costs, recurring or non-recurring costs, acquisition or ownership costs, direct or indirect costs).
- conduct sensitivity analyses to examine the impact of variations to assumptions and cost element uncertainties on LCC model results. Particular attention should be focused on cost drivers, assumptions related to asset usage and different discount rates.
- review LCC outputs against the objectives defined in the analysis plan to ensure that all goals have been fulfilled and that sufficient information has been provided to support the required decision. If the objectives are not met, additional evaluations and modifications to the LCC model may be required.
- the LCC analysis (including all assumptions) should be documented to ensure that the results can be verified and readily replicated by another analyst if necessary.

Document and review result

The results of the LCC analysis should be documented to allow users to clearly understand both the outcomes and the implications of the analysis along with the limitations and uncertainties associated with the results. The report should contain the following:

- Executive Summary: a brief synopsis of the objectives, results, conclusions and recommendations of the analysis.
- Purpose and Scope: a statement of the analysis objective, asset description including a definition of intended asset use environment, operating and support scenarios, assumptions, constraints and alternative courses of action considered.
- LCC Model Description: a summary of the LCC model, including relevant assumptions, the LCC breakdown structure and cost elements along with the methods of estimation and integration.
- LCC Model Application: a presentation of the LCC model results including the identification of cost drivers, the results of sensitivity analyses and the output from any other related analyses.
- Discussion: discussion and interpretation of the results including identification of uncertainties or other issues which will guide decision makers and users in understanding and using the results.
- Conclusions and Recommendations: a presentation of conclusions related to the objectives of the analysis and a list of recommendations along with identification of any need for further work or revision of the analysis.

A formal review of the analysis process may be required to confirm the correctness and integrity of the results, conclusions and recommendations presented in the report. If such a requirement exists someone other than the original analysts should conduct the review (to ensure objectivity).

The following elements should be addressed in the review:

- the objectives and scope of the analysis to ensure that they have been appropriately stated and interpreted

- the model (including cost element definitions and assumptions) to ensure that it is adequate for the purpose of the analysis
- the model evaluation to ensure that the inputs have been accurately established, the model has been used correctly, the results (including those of sensitivity analysis) have been adequately evaluated and discussed and that the objectives of the analysis have been achieved
- all assumptions made during the analysis process to ensure that they are reasonable and that they have been adequately documented.

Prepare Life Cost analysis

The Life Cost Analysis is essentially a tool, which can be used to control and manage the ongoing costs of an asset or part thereof. It is based on the LCC Model developed and applied during the Life Cost Planning phase with one important difference: it uses data on nominal costs.

The preparation of the Life Cost Analysis involves review and development of the LCC Model as a "real-time" cost control mechanism. This will require changing the costing basis from discounted to nominal costs. Estimates of capital costs will be replaced by the actual prices paid. Changes may also be required to the cost breakdown structure and cost elements to reflect the asset components to be monitored and the level of detail required.

Targets are set for the operating costs and their frequency of occurrence based initially on the estimates used in the Life Cost Planning phase. These targets may change with time as more accurate data is obtained, either from the actual asset operating costs or from benchmarking with other similar assets.

Implement Life Cost Analysis

Implementation of the Life Cost Analysis involves the continuous monitoring of the actual performance of an asset during its operation and maintenance to identify areas in which cost savings may be made and to provide feedback for future life cost planning activities.

For example, it may be better to replace an expensive building component with a more efficient solution prior to the end of its useful life than to continue with a poor initial decision. [Nsw 04]

2.2.6 *Effectiveness*

One helpful tool for easing LCC calculations involving probabilities is the effectiveness equation which gives a figure-of-merit for judging the chances of producing the intended results. The effectiveness equation is described in several different formats where each element varies as a probability and the issue is finding a system effectiveness value which gives lowest long term cost of ownership:

System effectiveness = Effectiveness/LCC

Effectiveness is a measure of value received and effectiveness varies from 0 to 1:

Effectiveness = availability*reliability*maintainability*capability

=availability*reliability*performance (maintainability*capability)

=availability*dependability(reliability*maintainability)*capability

Availability

Availability deals with the duration of up-time for operations and is a measure of how often the system is alive and well. It is often expressed as (up-time)/(up-time + downtime) with many different variants.

Up-time refers to a capability to perform the task and downtime refers to not being able to perform the task. Also availability may be the product of many different terms such as:

$A = A_{hardware} * A_{software} * A_{humans} * A_{interfaces} * A_{process}$

Reliability

Reliability deals with reducing the frequency of failures over a time interval and is a measure of the probability for failure-free operation during a given interval, i.e., it is a measure of success for a failure free operation. It is often expressed as:

$R(t) = \exp(-t/MTBF) = \exp(-\lambda t)$

where λ is constant failure rate and MTBF is mean time between failure. MTBF measures the time between system failures and is easier to understand than a probability number. For exponentially distributed failure modes, MTBF is a basic figure-of-merit for reliability (and failure rate, λ, is the reciprocal of MTBF). Also reliability may be the product of many different reliability terms such as:

$R = R_{utilities} * R_{feed\text{-}plant} * R_{processing} * R_{packaging} * R_{shipping}$

Maintainability

Maintainability deals with duration of maintenance outages or how long it takes to achieve (ease and speed) the maintenance actions compared to a datum. The datum includes maintenance (all actions necessary for retaining an item in, or restoring an item to, a specified, good condition) is performed by personnel having specified skill levels, using prescribed procedures and resources, at each prescribed level of maintenance. Maintainability characteristics are usually determined by equipment design which set maintenance procedures and determine the length of repair times.

The key figure of merit for maintainability is often the mean time to repair (MTTR) and a limit for the maximum repair time. Qualitatively it refers to the ease with which hardware or software is restored to a functioning state. Quantitatively it has probabilities and is measured based on the total down time for maintenance including all time for: diagnosis, trouble shooting, tear-down, removal/replacement, active repair time, verification testing that the repair is adequate, delays for logistic movements, and administrative maintenance delays. It is often expressed as:

$M(t) = 1- \exp(-t/MTTR) = 1 - \exp(-\mu t)$

where μ is constant maintenance rate and MTTR is mean time to repair. MTTR is an arithmetic average of how fast the system is repaired and is easier to visualize than the probability value.

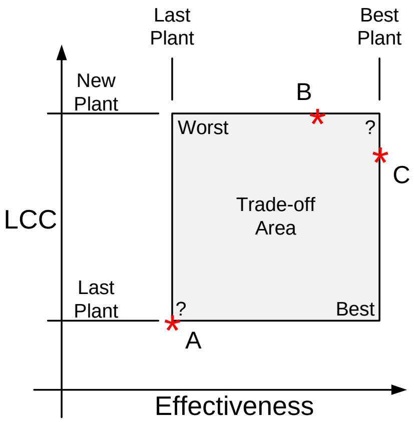
It is frequently expressed in exponential repair times rather than the more accurate but very cumbersome log-normal distributions of repair times describing maintenance times which are skewed to the right.

Capability

Capability deals with productive output compared to inherent productive output which is a measure of how well the production activity is performed compared to the datum. This index measure the systems capability to perform the intended function on a system basis. Often the term is the synonymous with productivity which is the product of efficiency multiplied by utilization. Efficiency measures the productive work output versus the work input. Utilization is the ratio of time spent on productive efforts to the total time consumed. [Bar 96]

System effectiveness

System effectiveness equations (Effectiveness/LCC) are helpful for understanding benchmarks, past, present, and future status as shown in ***Figure 2.6*** for understanding trade-off information.



Parameter	Last Plant	New Plant	Best Plant
Availability	0.95	0.95	0.98
Reliability	0.3	0.4	0.6
Maintanability	0.7	0.7	0.7
Capability	0.7	0.8	0.6
Effectiveness	0.14	0.22	0.25
LCC	80	100	95

Figure 2.6 Benchmark Data Shown In Trade-Off Format [Wei 96]

The lower right hand corner of ***Figure 2.6*** brings much joy and happiness often described as “bang for the buck”. The upper left hand corner brings much grief. The remaining two corners raise questions about worth and value. [Wei 96]

The system effectiveness equation is useful for trade-off studies as shown in the attached outcomes in ***Figure 2.7***. [Bre 85]

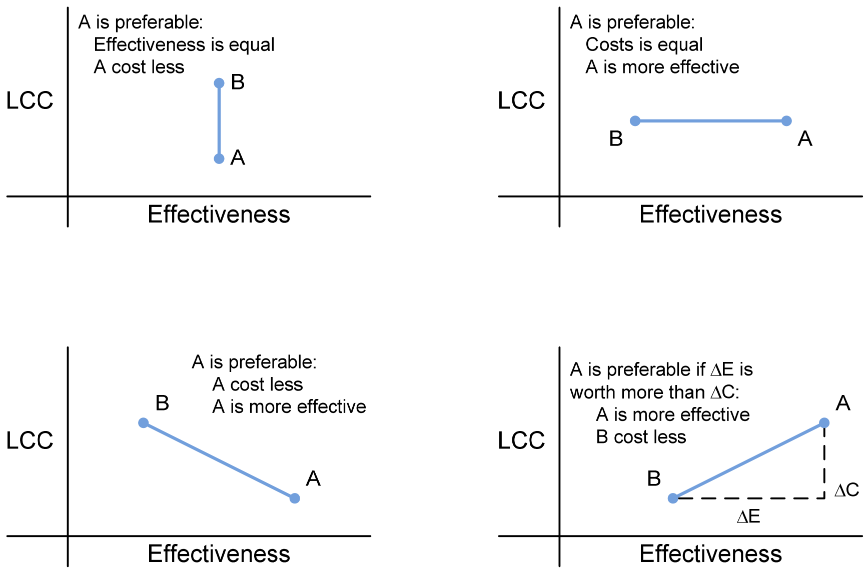


Figure 2.7 Some Possible Outcomes From Trade-Off Studies [Bre85]

System effectiveness equations have great impact on the LCC because so many decisions made in the early periods of a project carve the value of LCC into stone. About 2/3's of the total LCC are fixed during project conception [Fol 95] [Yat 95] even though expenditure of funds will flow at a later time, and the chance to influence LCC cost reductions grows smaller as shown in ***Figure 2.8***. [Bla 91]

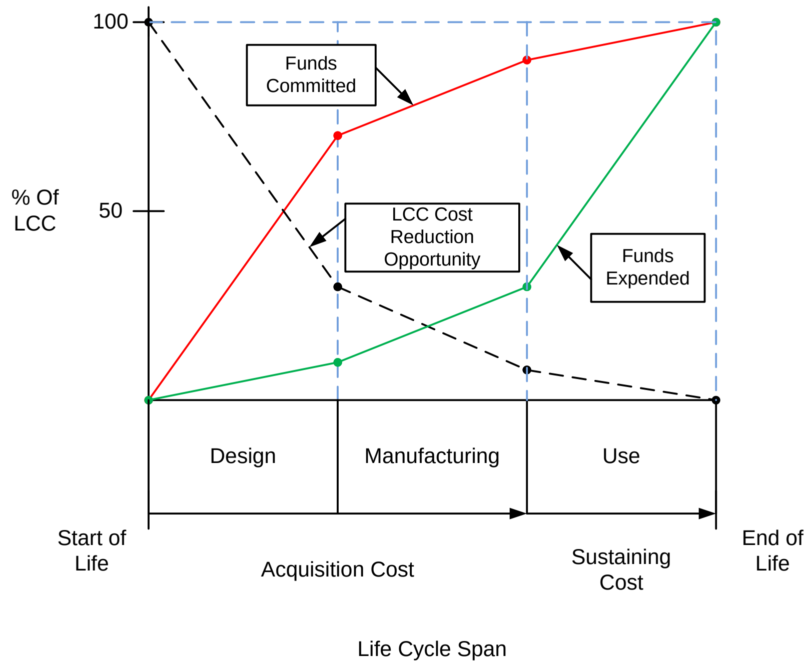


Figure 2.8 Funding Trends By Commitment And Expenditure [Bla 91]

2.3 Life Cycle Assessment

As environmental awareness increases, industries and businesses are assessing how their activities affect the environment. Society has become concerned about the issues of natural resource depletion and environmental degradation. Many businesses have responded to this awareness by providing "greener" products and using "greener" processes. The environmental performance of products and processes has become a key issue, which is why some companies are investigating ways to minimize their effects on the environment. Many companies have found it advantageous to explore ways of moving beyond compliance using pollution prevention strategies and environmental management systems to improve their environmental performance. One such tool is LCA. This concept considers the entire life cycle of a product. [Cur 96]

LCA is part of the ISO 14000 environmental management standards.

2.3.1 Definition

Life cycle assessment is a technique to assess environmental impacts associated with all the stages of a product's life from-cradle-to-grave. “Cradle-to-grave” begins with the gathering of raw materials from the earth to create the product and ends at the point when all materials are returned to the earth. LCA evaluates all stage of product’s life from the perspective that they are interdependent, meaning that one operation leads to the next. LCA enables the estimation of the cumulative environmental impacts resulting from all stages in the product life cycle, often including impacts not considered in more traditional analysis (e.g. raw material extraction, material transportation, etc.). By including the impacts throughout the product life cycle, LCA provides a comprehensive view of the environmental aspects of the product or process and a more accurate picture of the true environmental trade-offs in product and process selection. The term “life cycle” refers to the major activities in the course of the product’s life-span from its manufacture, use, and maintenance, to its final disposal, including the raw material acquisition required to manufacture the product.(***Figure 2.9***)

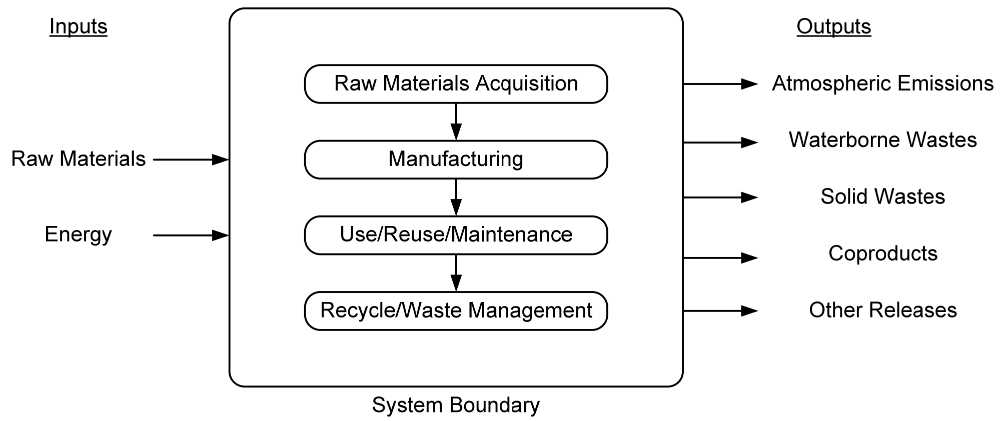


Figure 2.9 Possible life cycle stages that can be considered [Epa 93]

Specifically, LCA is a technique to assess the environmental aspects and potential impacts associated with a product, process, or service, by:

- Compiling an inventory of relevant energy and material inputs and environmental releases
- Evaluating the potential environmental impacts associated with identified inputs and releases
- Interpreting the results to help decision-makers make a more informed decision. [Sai 06]

2.3.2 History of LCA

Life Cycle Assessment (LCA) began in the 1960s in the USA, when concerns over the limitations of raw materials and energy resources sparked interest in finding ways to cumulatively account for energy use and to project future resource supplies and use.

In 1969, researchers initiated an internal study for The Coca-Cola Company that laid the foundation for the current methods of life cycle inventory analysis in the United States.

The study compared different beverage containers to determine which had the lowest releases to the environment and least affected the supply of natural resources. It quantified the raw materials and fuels used for each container, along with the environmental loadings from the manufacturing processes.

Interest in LCA waned from 1975 through the early 1980's, because environmental concerns shifted to issues of hazardous and household waste management.

But when solid waste became a worldwide issue in 1988, LCA again emerged as a tool for analyzing environmental problems.

By 1991, concerns over the inappropriate use by product manufacturers of LCAs to make broad marketing claims made it clear that uniform methods for conducting such assessments were needed. A consensus was also required on how this type of environmental comparison could be advertised non-deceptively. At the same time, pressure was growing from a number of environmental organizations to standardize LCA methodology. This led to the development of the LCA standards in the International Standards Organization (ISO) 14000 series (1997 through 2006).

In 2002, the United Nations Environment Programme (UNEP) joined forces with the Society of Environmental Toxicology and Chemistry (SETAC) to launch the Life Cycle Initiative as an international partnership.

The Initiative has three programs, which aim to put life cycle thinking into practice and improve the supporting tools through better data and indicators. They are the:

1. Life Cycle Management (LCM) program. Creates awareness and improves skills of decision-makers by producing information materials, establishing forums for sharing best practice, and carrying out training programs in all parts of the world.

2. Life Cycle Inventory (LCI) program. Improves global access to transparent, high quality life cycle data by hosting and facilitating expert groups whose work results in web-based information systems.

3. Life Cycle Impact Assessment (LCIA) program. Increases the quality and global reach of life cycle indicators by promoting the exchange of views among experts whose work results in a set of widely accepted recommendations. [Alc]

2.3.3 Benefits of LCA utilization

LCA can help decision-makers to select the product or process that results in the least impact to the environment. This information can be used with other factors, such as cost and performance data to select a product or process. LCA data identifies the transfer of environmental impacts from one media to another and/or from one life cycle stage to another. If an LCA were not performed, the transfer might not be recognized and properly included in the analysis because it is outside of the typical scope or focus of product selection processes.

This ability to track and document shifts in environmental impacts can help decision makers and managers fully characterize the environmental trade-offs associated with product or process alternatives.

By performing an LCA, analysts can:

- Develop a systematic evaluation of the environmental consequences associated with a given product.

- Analyze the environmental trade-offs associated with one or more specific products/processes to help gain stakeholder (state, community, etc.) acceptance for a planned action.
- Quantify environmental releases to air, water, and land in relation to each life cycle stage and/or major contributing process.
- Assist in identifying significant shifts in environmental impacts between life cycle stages and environmental media.
- Assess the human and ecological effects of material consumption and environmental releases to the local community, region, and world.
- Compare the health and ecological impacts between two or more rival products/processes or identify the impacts of a specific product or process.
- Identify impacts to one or more specific environmental areas of concern.

2.3.4 Limitations of conducting a LCA

Performing an LCA can be resource and time intensive. Depending upon how thorough an LCA the user wishes to conduct, gathering the data can be problematic, and the availability of data can greatly impact the accuracy of the final results. Therefore, it is important to weigh the availability of data, the time necessary to conduct the study, and the financial resources required against the projected benefits of the LCA.

LCA will not determine which product or process is the most cost effective or works the best. Therefore, the information developed in an LCA study should be used as one component of a more comprehensive decision process assessing the trade-offs with cost and performance.

2.3.5 Phases of a LCA

The LCA process is a systematic, phased approach and consists of four components: goal definition and scoping, inventory analysis, impact assessment and interpretation.(***Figure 2.10***)

This process is explain in ISO 14040 Environmental Management - Life Cycle Assessment - Principles and Framework.

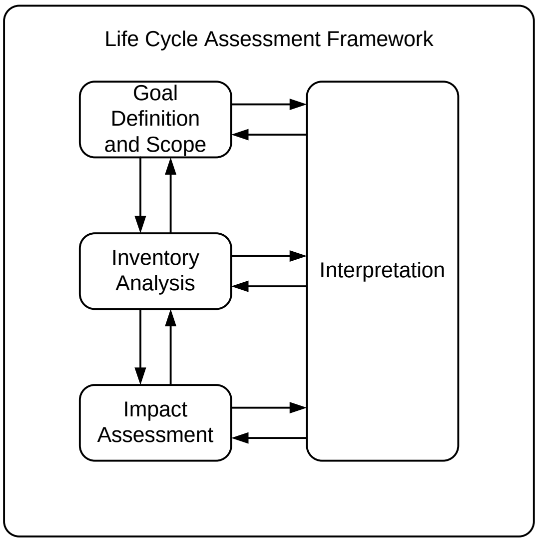


Figure 2.10 Phases of an LCA [Iso 97]

- Goal Definition and Scoping - Define and describe the product, process or activity. Establish the context in which the assessment is to be made and identify the boundaries and environmental effects to be reviewed for the assessment.
- Inventory Analysis - Identify and quantify energy, water and materials usage and environmental releases (e.g., air emissions, solid waste disposal, waste water discharges).
- Impact Assessment - Assess the potential human and ecological effects of energy, water, and material usage and the environmental releases identified in the inventory analysis.
- Interpretation - Evaluate the results of the inventory analysis and impact assessment to select the preferred product, process or service with a clear understanding of the uncertainty and the assumptions used to generate the results.

2.3.6 Goal definition and scoping

Goal definition and scoping is the phase of the LCA process that defines the purpose and method of including life cycle environmental impacts into the decision-making process. In this phase, the following items must be determined: the type of information that is needed to add value to the decision-making process, how accurate the results must be to add value, and how the results should be interpreted and displayed in order to be meaningful and usable.

The following six basic decisions should be made at the beginning of the LCA process to make effective use of time and resources:

1. Define the Goal(s) of the Project
2. Determine What Type of Information Is Needed to Inform the Decision-Makers
3. Determine the Required Specificity
4. Determine How the Data Should Be Organized and the Results Displayed
5. Define the Scope of the Study
6. Determine the Ground Rules for Performing the Work

Define the Goal(s) of the Project

LCA is a versatile tool for quantifying the overall (cradle-to-grave) environmental impacts from a product, process, or service. The primary goal is to choose the best product, process, or service with the least effect on human health and the environment. Conducting an LCA also can help guide the development of new products, processes, or activities toward a net reduction of resource requirements and emissions. There may also be secondary goals for performing an LCA, which would vary depending on the type of project.

Determine What Type of Information Is Needed to Inform the Decision-Makers

LCA can help answer a number of important questions. Identifying the questions that the decision-makers care about will help define the study parameters.

Determine the Required Specificity

At the outset of every study, the level of specificity must be decided. In some cases, this level will be obvious from the application or intended use of the information. In other instances, there may be several options to choose from, ranging from a completely generic study to one that is product-specific in every detail. Most studies fall somewhere in between.

An LCA can be envisioned as a set of linked activities that describe the creation, use, and ultimate disposal of the product or material of interest. At each life cycle stage, the analyst should begin by answering a series of questions: Is the product or system in the life cycle stage specific to one company or manufacturing operation? Or does the product or system represent common products or systems generally found in the marketplace and produced or used by a number of companies?

Such questions help determine whether data collected for the inventory should be specific to one company or manufacturing facility, or whether the data should be more general to represent common industrial practices.

Determine How the Data Should Be Organized and the Results Displayed

LCA practitioners define how data should be organized in terms of a functional unit that appropriately describes the function of the product or process being studied. Careful selection of the functional unit to measure and display the LCA results will improve the accuracy of the study and the usefulness of the results.

When an LCA is used to compare two or more products, the basis of comparison should be equivalent use, i.e., each system should be defined so that an equal amount of product or equivalent service is delivered to the consumer.

Define the Scope of the Study

An LCA includes all four stages of a product or process life cycle: raw material acquisition, manufacturing, use/reuse/maintenance, and recycle/waste management. To determine whether one or all of the stages should be included in the scope of the LCA, the following must be assessed: the goal of the study, the required accuracy of the results, and the available time and resources.

Raw Materials Acquisition

The life cycle of a product begins with the removal of raw materials and energy sources from the earth. For instance, the harvesting of trees or the mining of nonrenewable materials would be considered raw materials acquisition. Transportation of these materials from the point of acquisition to the point of processing is also included in this stage.

Manufacturing

During the manufacturing stage, raw materials are transformed into a product or package. The product or package is then delivered to the consumer. The manufacturing stage consists of three steps: materials manufacture (convert raw materials into a form that can be used to fabricate a finished product), product fabrication (take the manufactured material and processes it into a product that is ready to be filled or packaged), and filling/packaging/distribution (include all of the manufacturing and transportation activities that are necessary to fill, package, and distribute a finished product).

Use/Reuse/Maintenance

This stage involves the consumer's actual use, reuse, and maintenance of the product. Once the product is distributed to the consumer, all activities associated with the useful life of the product are included in this stage. This includes energy demands and environmental wastes from both product storage and consumption. The product or material may need to be reconditioned, repaired or serviced so that it will maintain its performance. When the consumer no longer needs the product, the product will be recycled or disposed.

Recycle/Waste Management

The recycle/waste management stage includes the energy requirements and environmental wastes associated with disposition of the product or material.

Determine the Ground Rules for Performing the Work

Prior to moving on to the inventory analysis phase it is important to define some of the logistical procedures for the project:

- Documenting Assumptions: all assumptions or decisions made throughout the entire project must be reported alongside the final results of the LCA project.
- Quality Assurance Procedures: quality assurance procedures are important to ensure that the goal and purpose for performing the LCA will be met at the conclusion of the project. The level of quality assurance procedures employed for the project depends on the available time and resources and how the results will be used.
- Reporting Requirements: defining "up front" how the final results should be documented and exactly what should be included in the final report helps to ensure that the final product meets the appropriate expectations. When reporting the final results, or results of a particular LCA phase, it is important to thoroughly describe the methodology used in the analysis.

The report should explicitly define the systems analyzed and the boundaries that were set.

2.3.7 Life Cycle Inventory

A life cycle inventory is a process of quantifying energy and raw material requirements, atmospheric emissions, waterborne emissions, solid wastes, and other releases for the entire life cycle of a product, process, or activity.

In the life cycle inventory phase of an LCA, all relevant data is collected and organized. Without an LCI, no basis exists to evaluate comparative environmental impacts or potential improvements. [Sai 06]

EPA's 1993 document, "Life-Cycle Assessment: Inventory Guidelines and Principles," and 1995 document, "Guidelines for Assessing the Quality of Life Cycle Inventory Analysis," provide the framework for performing an inventory analysis and assessing the quality of the data used and the results.

The two documents define the following four steps of a life cycle inventory:

1. Develop a flow diagram of the processes being evaluated.
2. Develop a data collection plan.
3. Collect data.
4. Evaluate and report results.

Develop a flow diagram of the processes being evaluated

A flow diagram is a tool to map the inputs and outputs to a process or system. The "system" or "system boundary" varies for every LCA project. The goal definition and scoping phase establishes initial boundaries that define what is to be included in a particular LCA; these are used as the system boundary for the flow diagram. Unit processes inside of the system boundary link together to form a complete life cycle picture of the required inputs and outputs (material and energy) to the system.(***Figure 2.11***)

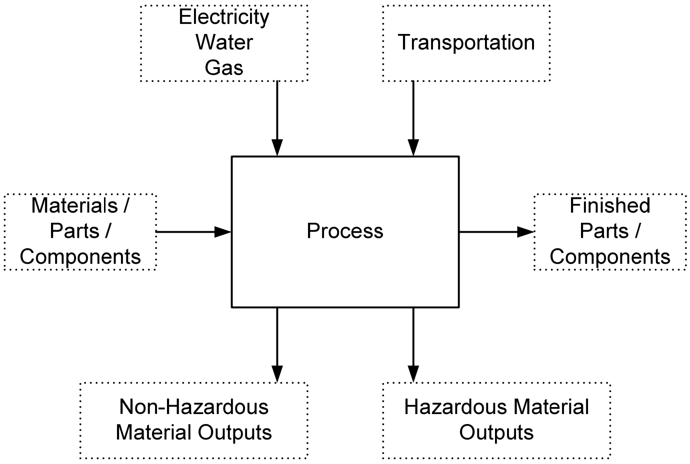


Figure 2.11 Generic Unit Process[Sai 06]

For a comparative study, it is important that both the baseline and alternatives use the same system boundary and are modeled to the same level of detail.

Develop a data collection plan

As part of the goal definition and scoping phase , the required accuracy of data was determined. When selecting sources for data to complete the life cycle inventory, an LCI data collection plan ensures that the quality and accuracy of data meet the expectations of the decision-makers.

Key elements of a data collection plan include the following:

1. Defining data quality goals
2. Identifying data sources and types
3. Identifying data quality indicators
4. Developing a data collection worksheet and checklist.

Defining data quality goals

Data quality goals provide a framework for balancing available time and resources against the quality of the data required to make a decision regarding overall environmental or human health impact. Data quality goals are closely linked to overall study goals and serve two primary purposes:

- Aid LCA practitioners in structuring an approach to data collection based on the data quality needed for the analysis.
- Serve as data quality performance criteria.

No pre-defined list of data quality goals exists for all LCA projects. The number and nature of data quality goals necessary depends on the level of accuracy required to inform the decision-makers involved in the process.

Identifying data sources and types

For each life cycle stage, unit process, or type of environmental release, specify the necessary data source and/or type required to provide sufficient accuracy and quality to meet the study's goals. Defining the required data sources and types prior to data collection helps to reduce costs and the time required to collect the data.

Examples of data sources include:

- Meter readings from equipment
- Equipment operating logs/journals
- Industry data reports, databases, or consultants
- Laboratory test results
- Government documents, reports, databases, and clearinghouses
- Other publicly available databases or clearinghouses
- Journals, papers, books, and patents
- Reference books
- Trade associations
- Related/previous life cycle inventory studies
- Equipment and process specifications
- Best engineering judgment.

Examples of data types include:

- Measured
- Modelled
- Sampled
- Non-site specific (i.e., surrogate data)
- Non-LCI data (i.e., data not intended for the purpose of use in an LCI)
- Vendor data.

Identify Data Quality Indicators

Data quality indicators are benchmarks to which the collected data can be measured to determine if data quality requirements have been met. Similar to data quality goals, there is no pre-defined list of data quality indicators for all LCIs. The selection of data quality indicators depends upon which ones are most appropriate and applicable to the specific data sources being evaluated. Examples of data quality indicators are precision, completeness, representativeness, consistency, and reproducibility.

Develop a Data Collection Spreadsheet

The next step is to develop a life cycle inventory spreadsheet that covers most of the decision areas in the performance of an inventory.

A spreadsheet can be prepared to guide data collection and validation and to enable construction of a database to store collected data electronically. The following eight general decision areas should be addressed in the inventory spreadsheet:

1. Purpose of the inventory
2. System boundaries
3. Geographic scope
4. Types of data used
5. Data collection procedures
6. Data quality measures
7. Computational spreadsheet construction
8. Presentation of results.

The spreadsheet is a valuable tool for ensuring completeness, accuracy, and consistency. It is especially important for large projects when several people collect data from multiple sources. The spreadsheet should be tailored to meet the needs of a specific LCI.

Collect Data

Data collection efforts involve a combination of research, site-visits and direct contact with experts, which generates large quantities of data. As an alternative, it may be more cost effective to buy a commercially available LCA software package. Prior to purchasing an LCA software package the decision-makers or LCA practitioner should insure that it will provide the level of data analysis required.

A second method to reduce data collection time and resources is to obtain non-site specific inventory data. Several organizations have developed databases specifically for LCA that contain some of the basic data commonly needed in constructing a life cycle inventory. Some of the databases are sold in conjunction with LCI data collection software; others are stand-alone resources.

Many companies with proprietary software also offer consulting services for LCA design. The use of commercial software risks losing transparency in the data. Often there is no record of assumptions or computational methods that were used. This may not be appropriate if the results are to be used in the public domain. Revisiting the goal statement is needed in order to determine if such data are appropriate.

Evaluate and report results

When writing a report to present the final results of the life-cycle inventory, it is important to thoroughly describe the methodology used in the analysis. The report should explicitly define the systems analyzed and the boundaries that were set. All assumptions made in performing the inventory should be clearly explained. The basis for comparison among systems should be given, and any equivalent usage ratios that were used should be explained.

Life-cycle inventory studies generate a great deal of information, often of a disparate nature. The analyst needs to select a presentation format and content that are consistent with the purpose of the study and that do not arbitrarily simplify the information solely for the sake of presenting it. In thinking about presentation of the results, it is useful to identify the various perspectives embodied in life-cycle inventory information. Two main types of format for presenting results are tabular and graphical. [Epa 86] [Epa 93] [Epa 95] [Sai 06]

2.3.8 Life Cycle Impact Assessment

The Life Cycle Impact Assessment (LCIA) phase of an LCA is the evaluation of potential human health and environmental impacts of the environmental resources and releases identified during the LCI. Impact assessment should address ecological and human health effects; it should also address resource depletion.

A life cycle impact assessment attempts to establish a linkage between the product or process and its potential environmental impacts.

An LCIA provides a systematic procedure for classifying and characterizing these types of environmental effects.

Although much can be learned about a process by considering the life cycle inventory data, an LCIA provides a more meaningful basis to make comparisons.

The results of an LCIA show the relative differences in potential environmental impacts for each option.

The following steps comprise a life cycle impact assessment:

1. Selection and Definition of Impact Categories - identifying relevant environmental impact categories (e.g., global warming, acidification, terrestrial toxicity).
2. Classification - assigning LCI results to the impact categories (e.g., classifying carbon dioxide emissions to global warming).
3. Characterization - modeling LCI impacts within impact categories using science-based conversion factors (e.g., modeling the potential impact of carbon dioxide and methane on global warming).
4. Normalization - expressing potential impacts in ways that can be compared (e.g. comparing the global warming impact of carbon dioxide and methane for the two options).
5. Grouping - sorting or ranking the indicators (e.g. sorting the indicators by location: local, regional, and global).
6. Weighting - emphasizing the most important potential impacts.
7. Evaluating and Reporting LCIA Results - gaining a better understanding of the reliability of the LCIA results. [Sai 06]

ISO developed a standard for conducting an impact assessment entitled ISO 14042, Life Cycle Impact Assessment, which states that the first three steps (impact category selection, classification, and characterization) are mandatory steps for an LCIA. Except for data evaluation (Step 7), the other steps are optional depending on the goal and scope of the study.

Selection and Definition of Impact Categories

The first step in an LCIA is to select the impact categories that will be considered as part of the overall LCA. This step should be completed as part of the initial goal and scope definition phase to guide the LCI data collection process and requires reconsideration following the data collection phase. The items identified in the LCI have potential human health and environmental impacts.

For an LCIA, impacts are defined as the consequences that could be caused by the input and output streams of a system on human health, plants and animals, or the future availability of natural resources.

Typically, LCIAs focus on the potential impacts to three main categories: human health, ecological health and resource depletion.

Classification

The purpose of classification is to organize and possibly combine the LCI results into impact categories.

For LCI items that contribute to only one impact category, the procedure is a straightforward assignment.

For LCI items that contribute to two or more different impact categories, a rule must be established for classification. There are two ways of assigning LCI results to multiple impact categories:

- Partition a representative portion of the LCI results to the impact categories to which they contribute. This is typically allowed in cases when the effects are dependent on each other.
- Assign all LCI results to all impact categories to which they contribute. This is typically allowed when the effects are independent of each other.

Characterization

Impact characterization uses science-based conversion factors, called characterization factors, to convert and combine the LCI results into representative indicators of impacts to human and ecological health.

Characterization factors also are commonly referred to as equivalency factors. Characterization provides a way to directly compare the LCI results within each impact category. In other words, characterization factors translate different inventory inputs into directly comparable impact indicators.

Impact indicators are typically characterized using the following equation:

Inventory Data × Characterization Factor = Impact Indicators

Normalization

Normalization is an LCIA tool used to express impact indicator data in a way that can be compared among impact categories. This procedure normalizes the indicator results by dividing by a selected reference value.

There are numerous methods of selecting a reference value, including:

- The total emissions or resource use for a given area that may be global, regional or local
- The total emissions or resource use for a given area on a per capita basis
- The ratio of one alternative to another (i.e., the baseline)
- The highest value among all options.

Grouping

Grouping assigns impact categories into one or more sets to better facilitate the interpretation of the results into specific areas of concern. Typically, grouping involves sorting or ranking indicators. The following are two possible ways to group LCIA data:

- Sort indicators by characteristics such as emissions (e.g., air and water emissions) or location (e.g., local, regional, or global).
- Sort indicators by a ranking system, such as high, low, or medium priority. Ranking is based on value choices.

Weighting

The weighting step (also referred to as valuation) of an LCIA assigns weights or relative values to the different impact categories based on their perceived importance or relevance. Weighting is important because the impact categories should also reflect study goals and stakeholder values. Because weighting is not a scientific process, it is vital that the weighting methodology is clearly explained and documented.

Although weighting is widely used in LCAs, the weighting stage is the least developed of the impact assessment steps and also is the one most likely to be challenged for integrity. In general, weighting includes the following activities:

- Identifying the underlying values of stakeholders
- Determining weights to place on impacts
- Applying weights to impact indicators.

Weighted data could possibly be combined across impact categories, but the weighting procedure must be explicitly documented.

Evaluating and Reporting LCIA Results

Now that the impact potential for each selected category has been calculated, the accuracy of the results must be verified. The accuracy must be sufficient to support the purposes for performing the LCA as defined in the goal and scope. When documenting the results of the life cycle impact assessment, thoroughly describe the methodology used in the analysis, define the systems analyzed and the boundaries that were set, and all assumptions made in performing the inventory analysis.

The LCIA, like all other assessment tools, has inherent limitations. Although the LCIA process follows a systematic procedure, there are many underlying assumptions and simplifications, as well subjective value choices.

Depending on the LCIA methodology selected, and/or the inventory data on which it is based, some of the key limitations may include:

- Lack of spatial resolution – e.g., a 4,000-gallon ammonia release is worse in a small stream than in a large river.

- Lack of temporal resolution – e.g., a five-ton release of particulate matter during a one month period is worse than the same release spread through the whole year.
- Inventory speciation – e.g., broad inventory listing such as "VOC" or "metals" do not provide enough information to accurately assess environmental impacts.
- Threshold and non-threshold impact – e.g., ten tons of contamination is not necessarily ten times worse than one ton of contamination.

[Sai 06] [Iso 98]

2.3.9 Life Cycle Interpretation

Life cycle interpretation is a systematic technique to identify, quantify, check, and evaluate information from the results of the LCI and the LCIA, and communicate them effectively. Life cycle interpretation is the last phase of the LCA process.

ISO has defined the following two objectives of life cycle interpretation:

1. Analyze results, reach conclusions, explain limitations, and provide recommendations based on the findings of the preceding phases of the LCA, and to report the results of the life cycle interpretation in a transparent manner.
2. Provide a readily understandable, complete, and consistent presentation of the results of an LCA study, in accordance with the goal and scope of the study.

Interpreting the results of an LCA is not as simple as two is better than three. In some cases, it may not be possible to state that one alternative is better than the others because of the uncertainty in the final results. This does not imply that efforts have been wasted. The LCA process will still provide decision-makers with a better understanding of the environmental and health impacts associated with each alternative, where they occur and the relative magnitude of each type of impact in comparison to each of the proposed alternatives included in the study. This information more fully reveals the pros and cons of each alternative.

The purpose of conducting an LCA is to better inform decision-makers by providing a particular type of information, with a life cycle perspective of environmental and human health impacts associated with each product or process. However, LCA does not take into account technical performance, cost, or political and social acceptance. Therefore, it is recommended that LCA be used in conjunction with these other parameters.

The guidance provided in this chapter is a summary of the information provided on life cycle interpretation from the ISO standard entitled "Environmental Management - Life Cycle Assessment - Life Cycle Interpretation," ISO 14043. Within the ISO standard, the following steps to conducting a life cycle interpretation are identified and discussed:

1. Identification of the Significant Issues Based on the LCI and LCIA.
2. Evaluation which Considers Completeness, Sensitivity, and Consistency Checks.
3. Conclusions, Recommendations, and reporting.

Identification of the Significant Issues Based on the LCI and LCIA.

The first step of the life cycle interpretation phase involves reviewing information from the first three phases of the LCA process in order to identify the data elements that contribute most to the results of both the LCI and LCIA for each product, process, or service, otherwise known as "significant issues."

The results of this effort are used to evaluate the completeness, sensitivity, and consistency of the LCA study.

Before determining which parts of the LCI and LCIA have the greatest influence on the results for each alternative, the previous phases of the LCA should be reviewed in a comprehensive manner.

Review the information collected and the presentations of results developed to determine if the goal and scope of the LCA study have been met. If they have, the significance of the results can then be determined.

Determining significant issues of a product system may be simple or complex. For assistance in identifying environmental issues and determining their significance, the following approaches are recommended:

- Contribution Analysis - the contribution of the life cycle stages or groups of processes are compared to the total result and examined for relevance.

- Dominance Analysis - statistical tools or other techniques, such as quantitative or qualitative ranking, are used to identify significant contributions to be examined for relevance.
- Anomaly Assessment - based on previous experience, unusual or surprising deviations from expected or normal results are observed and examined for relevance.

Significant issues can include:

- Inventory parameters like energy use, emissions, waste, etc.
- Impact category indicators like resource use, emissions, waste, etc.
- Essential contributions for life cycle stages to LCI or LCIA results such as individual unit processes or groups of processes

Evaluation which considers Completeness, Sensitivity, and Consistency of the Data.

The evaluation step of the interpretation phase establishes the confidence in and reliability of the results of the LCA. This is accomplished by completing the following tasks to ensure that products/processes are fairly compared:

1. Completeness Check - examining the completeness of the study.
2. Sensitivity Check - assessing the sensitivity of the significant data elements that influence the results most greatly.
3. Consistency Check - evaluating the consistency used to set system boundaries, collect data, make assumptions, and allocate data to impact categories for each alternative.

Conclusions, Recommendations, and reporting.

The objective of this step is to interpret the results of the life cycle impact assessment to determine which product/process has the overall least impact to human health and the environment, and/or to one or more specific areas of concern as defined by the goal and scope of the study.

Depending upon the scope of the LCA, the results of the impact assessment will return either a list of un-normalized and un-weighted impact indicators for each impact category for the alternatives, or it will return a single grouped, normalized, and weighted score for each alternative, or something in between, e.g., normalized but not weighted.

In the case where a score is calculated, the recommendation may be to accept the product/process with the lowest score. Or, it could be to investigate the reasons how the process could be modified to lower the score. However, do not forget the underlying assumptions that went into the analysis. [Sai 06] [Iso 98b]

2.4 Conclusion

In this chapter we deepen Life Cycle Cost and Life Cycle Assessment.

For LCC we explain:

- Definitions;
- History;
- Use;
- Data and models;
- Phases;
- Effectiveness (trade-off between LCC and performances).

For LCA we explain:

- Definition;
- History;
- Benefits and limitations;
- Phases (part of ISO 14000)
    - Goal definition and scoping;
    - Life cycle Inventory;
    - Life cycle impact assessment;
    - Life cycle interpretation.

CHAPTER 3

Optimization Methods and State of the Art of LCC and LCA

3.1 Introduction

In this chapter we explain some methods to optimize LCA and LCC. The chosen methods are: linear programming, dynamic programming, genetic algorithm and particle swarm optimization.

After this explanation we have analyzed the state of the art of LCC and LCA optimization, showing some examples of LCC and LCA optimization by the methods described.

3.2 Optimization Methods

Before digging any deeper into the matter, it is necessary to provide a classification of these algorithms as overview.

Figure 3.1 sketches a rough taxonomy of global optimization methods. Generally, optimization algorithms can be divided in two basic classes: deterministic and probabilistic algorithms. Deterministic algorithms are most often used if a clear relation between the characteristics of the possible solutions and their utility for a given problem exists. Then, the search space can efficiently be explored using for example a divide and conquer scheme. If the relation between a solution candidate and its "fitness" are not so obvious or too complicated, or the dimensionality of the search space is very high, it becomes harder to solve a problem deterministically. Trying it would possible result in exhaustive enumeration of the search space, which is not feasible even for relatively small problems.

Then, probabilistic algorithms come into play. An especially relevant family of probabilistic algorithms are the Monte Carlo - based approaches. They trade in guaranteed correctness of the solution for a shorter runtime. This does not mean that the results obtained using them are incorrect but they may just not be the global optima. On the other hand, a solution a little bit inferior to the best possible one is better than one which needs 10^{100} years to be found.

Heuristics used in global optimization are functions that help decide which one of a set of possible solutions is to be examined next. On one hand, deterministic algorithms usually employ heuristics in order to define the processing order of the solution candidates. A heuristic is a part of an optimization algorithm that uses the information currently gathered by the algorithm to help to decide which solution candidate should be tested next or how the next individual can be produced. Heuristics are usually problem class dependent. A meta-heuristic is a method for solving very general classes of problems. It combines objective functions or heuristics in an abstract and hopefully efficient way, usually without utilizing deeper insight into their structure. This combination is often performed stochastically by utilizing statistics obtained from samples from the search space or based on a model of some natural phenomenon or physical process. An important class of probabilistic Monte Carlo meta-heuristics is Evolutionary Computation. It encompasses all algorithms that are based on a set of multiple solution candidates (called population) which are iteratively refined. This field of optimization is also a class of Soft Computing as well as a part of the artificial intelligence area. Some of its most important members are evolutionary algorithms and Swarm Intelligence. Besides these nature-inspired and evolutionary approaches,

there exist also methods that copy physical processes like the before-mentioned Simulated Annealing, Parallel Tempering, and Raindrop Method, as well as techniques without direct real-world role model like Tabu Search and Random Optimization.

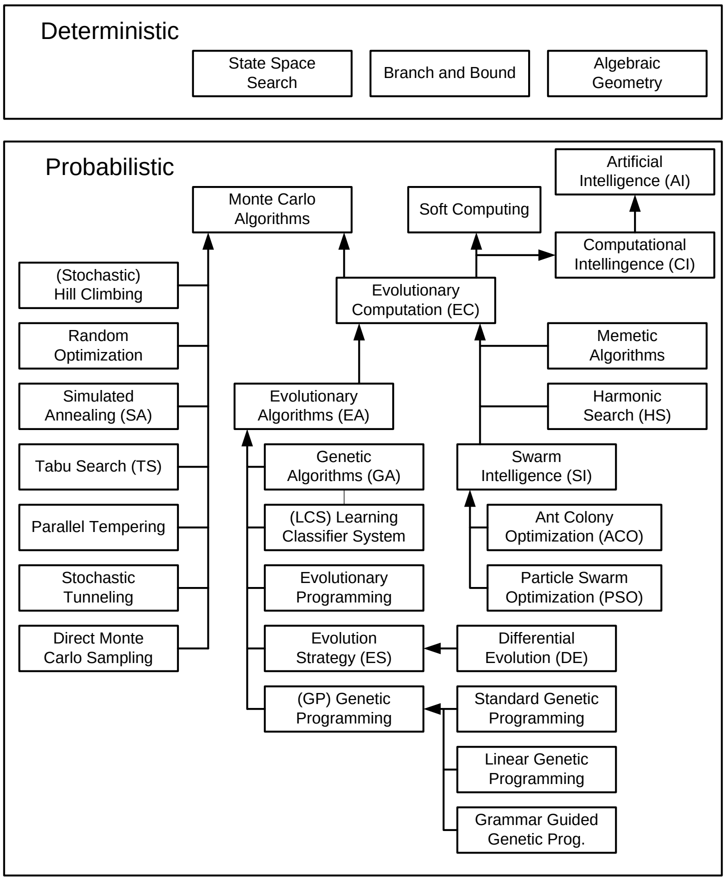


Figure 3.1 The taxonomy of global optimization algorithms [Wei 09]

Speed and precision are conflicting objectives, at least in terms of probabilistic algorithms. A general rule of thumb is that you can gain improvements in accuracy of optimization only by investing more time. [Wei 09]

Mathematical programming and heuristics are both common forms of optimization methods. Linear programming is a subset of mathematical programming but deemed important enough to be described separately.

Linear programming is a mathematical modelling technique designed to optimize the usage of limited resources. The usefulness of this technique is enhanced by the availability of highly efficient computer codes. A linear programming model consists of three basic elements:

- Decision variables that need to be determined.
- Objective (goal) that need to be optimized.
- Constraints that need to be satisfied.

Linear programming is particularly useful for large and medium scale problems in which there are many variables and many constraints to be considered. Therefore, the use of linear programming is often supported by computer software.

Methods based on heuristic approaches use standardized rules of thumb repeated many times in order to find a good enough solution to a problem. These types of models can be easier to apply than the mathematical programming methods. There are, one the other hand, no guarantees that the solutions found will be the optimal choices for solving the problem. [Nat 07]

3.2.1 Linear Programming

Linear programming was developed during World War II, when a system with which to maximize the efficiency of resources was of utmost importance. New war-related projects demanded attention and spread resources thin. "Programming" was a military term that referred to activities such as planning schedules efficiently or deploying men optimally. George Dantzig, a member of the U.S. Air Force, developed the Simplex method of optimization in 1947 in order to provide an efficient algorithm for solving programming problems that had linear structures. Since then, experts from a variety of fields, especially mathematics and economics, have developed the theory behind "linear programming" and explored its applications.

We can reduce the structure that characterizes linear programming problems into the following form:

Minimize $c_1 x_1 + c_2 x_2 + \cdots + c_n x_n = z$

Subject to $a_{11} x_1 + a_{12} x_2 + \cdots + a_{1n} x_n = b_1$

$a_{21} x_1 + a_{22} x_2 + \cdots + a_{2n} x_n = b_2$

.

.

.

$a_{m1} x_1 + a_{m2} x_2 + \cdots + a_{mn} x_n = b_m$

$x_1, x_2, \ldots, x_n \geq 0.$

In linear programming z, the expression being optimized, is called the objective function. The variables $x_1, x_2, \ldots, x_n$ are called decision variables, and their values are subject to $m+1$ constraints (every line ending with a b_i, plus the non-negativity constraint). A set of $x_1, x_2, \ldots, x_n$ satisfying all the constraints is called a feasible point and the set of all such points is called the feasible region. The solution of the linear program must be a point $(x_1, x_2, \ldots, x_n)$ in the feasible region, or else not all the constraints would be satisfied.

By applying some basic linear algebra, this problem becomes:

Minimize $\sum_{j=1}^{n} c_j x_j = z$

Subject to $\sum_{j=1}^{n} a_j x_j = b_j$

$x_j \geq 0 \quad j = 1, 2, \ldots, n$

or, more compactly,

Minimize $\mathbf{cx} = z$

Subject to $\mathbf{Ax} = \mathbf{b}$

$\mathbf{x} \geq 0$

Here **A** is an mxn matrix whose j^{th} column is $\boldsymbol{a}_j$. This matrix corresponds to the coefficients on $x_1, x_2, \ldots, x_n$ in the constraints of a linear programming problem. The vector **x** is a vector of solutions to the problem, **b** is the right-hand-side vector, and **c** is the cost coefficient vector. This more compact way of thinking about linear programming problems is useful especially in sensitivity analysis.

Several assumptions are implicit in linear programming problems. These assumptions are:

1. Proportionality: the contribution of any variable to the objective function or constraints is proportional to that variable. This implies no discounts or economies to scale.
2. Additivity: the contribution of any variable to the objective function or constraints is independent of the values of the other variables.
3. Divisibility: decision variables can be fractions. However, by using a special technique called integer programming, we can bypass this condition.

4. Certainty: this assumption is also called the deterministic assumption. This means that all parameters (all coefficients in the objective function and the constraints) are known with certainty. Realistically, however, coefficients and parameters are often the result of guess-work and approximation. The effect of changing these numbers can be determined with sensitivity analysis (Sensitivity analysis deals with the effect changing a parameter in a linear program has on the linear program's solution).

3.2.1.1 Simplex Method

Given the system $\mathbf{Ax}=\mathbf{b}$ and $\mathbf{x} \geq 0$ where $\mathbf{A}$ is an m×n matrix and $\mathbf{b}$ is a column vector with m entries. Suppose that rank($\mathbf{A}$, $\mathbf{b}$)=rank($\mathbf{A}$)=m.

After possibly rearranging the columns of $\mathbf{A}$, let $\mathbf{A} = [\mathbf{B}, \mathbf{N}]$ where $\mathbf{B}$ is an m×m invertible matrix and $\mathbf{N}$ is an m×(n−m) matrix. The solution $\mathbf{x} = \begin{bmatrix} x_B \\ X_N \end{bmatrix}$ to the equations $\mathbf{Ax} = \mathbf{b}$ where $\mathbf{x_B} = \mathbf{B}^{-1}\mathbf{b}$ and $\mathbf{x_N} = 0$ is called a basic solution of the system. If $\mathbf{x_B} \geq 0$ then x is called a basic feasible solution of the system. Here $\mathbf{B}$ is called the basic matrix and $\mathbf{N}$ is called the non-basic matrix. The components of $\mathbf{x_B}$ are called basic variables and the components of $\mathbf{x_N}$ are called non-basic variables. If $\mathbf{x_B} > 0$ then $\mathbf{x}$ is a non-degenerate basic solution, but if at least one component of $\mathbf{x_B}$ is zero then $\mathbf{x}$ is a degenerate basic solution.

The collection of extreme points corresponds to the collection of basic feasible solutions, and both are nonempty, provided that the feasible region is not empty.

If an optimal solution exists, then an optimal extreme point exists.

For every extreme point there corresponds a basis (not necessarily unique), and, conversely, for every basis there corresponds a (unique) extreme point. Moreover, if an extreme point has more than one basis representing it, then it is degenerate. Conversely, a degenerate extreme point has more than one set of basic variables representing it if and only if the system $\mathbf{Ax}=\mathbf{b}$ itself does not imply that the degenerate basic variables corresponding to an associated basis are identically zero.

With all of this information, we might think that the best way to solve a linear programming problem is to find all the extreme points of a system and see which one correctly minimizes (or maximizes) the problem. This is realistic (though still tedious) for small problems. The number of extreme points is $\left[{n \atop m}\right]$, where m is the rank of A and n is the number of variables. This number can be quite large. Also, this method does not indicate if the feasible region is unbounded or empty without first going through the whole set of extreme points. In short, this approach is not realistic. Instead, an ingenious algorithm known as the Simplex method, is the most common way to solve linear programs by hand, and is the basis for most computer software that solves linear programs.

The Simplex algorithm remedies the shortcomings of the aforementioned “brute force” approach. Instead of checking all of the extreme points in the region, the Simplex algorithm selects an extreme point at which to start. Then, each iteration of the algorithm takes the system to the adjacent extreme point with the best objective function value. These iterations are repeated until there are no more adjacent extreme points with better objective function values. That is when the system is at optimality. [Lew 08]

3.2.2 Dynamic Programming

The term *dynamic programming* was originally used in the 1940s by Richard Bellman to describe the process of solving problems where one needs to find the best decisions one after another. By 1953, he refined this to the modern meaning, referring specifically to nesting smaller decision problems inside larger decisions, and the field was thereafter recognized by the IEEE as a systems analysis and engineering topic. [Wik]

Dynamic Programming is a powerful technique that allows one to solve many different types of problems in time $O(n^2)$ or $O(n^3)$ for which a naive approach would take exponential time.

Dynamic Programming is a general approach to solving problems, much like “divide-and-conquer” except that the sub-problems will typically overlap.

What it wants to do is take the problem and somehow break it down into

a reasonable number of sub-problems (where “reasonable” might be something like n^2) in such a way that we can use optimal solutions to the smaller sub-problems to give us optimal solutions to the larger ones.

What kinds of problems can be solved using Dynamic Programming? One property these problems have is that if the optimal solution involves solving a sub-problem, then it uses the optimal solution to that sub-problem.

The other key property is that there should be only a polynomial number of different sub-problems. These two properties together allow to build the optimal solution to the final problem from optimal solutions to sub-problems.

In the top-down view of dynamic programming, the first property above corresponds to being able to write down a recursive procedure for the problem we want to solve. The second property corresponds to making sure that this recursive procedure makes only a polynomial number of different recursive calls. [Blu 09]

3.2.3 Evolutionary Algorithms

Evolutionary algorithms (EAs) are population-based metaheuristic optimization algorithms that use biology-inspired mechanisms like mutation, crossover, natural selection, and survival of the fittest in order to refine a set of solution candidates iteratively. The advantage of evolutionary algorithms compared to other optimization methods is their "black box" character that makes only few assumptions about the underlying objective functions. Furthermore, the definition of objective functions usually requires lesser insight to the structure of the problem space than the manual construction of an admissible heuristic.

EAs therefore perform consistently well in many different problem categories.

It can distinguish between single-objective and multi-objective evolutionary algorithms, where the latter means that we try to optimize multiple, possible conflicting criteria.

All evolutionary algorithms proceed in principle according to the scheme illustrated in ***Figure 3.2***:

1. Initially, a population Pop of individuals p with a random genome p.g is created.
2. The values of the objective functions $f \in F$ are computed for each solution candidate p.x in Pop. This evaluation may incorporate complicated simulations and calculations.

3. With the objective functions, the utility of the different features of the solution candidates have been determined and a fitness value v(p.x) can now be assigned to each of them. This fitness assignment process can, for instance, incorporate a prevalence comparator function cmp_F which uses the objective values to create an order amongst the individuals.
4. A subsequent selection process filters out the solution candidates with bad fitness and allows those with good fitness to enter the mating pool with a higher probability. Since fitness is subject to minimization in this context, the lower the v(p.x)-values are, the higher is the (relative) utility of the individual to whom they belong.
5. In the reproduction phase, offspring is created by varying or combining the genotypes p.g of the selected individuals p ∈ Mate by applying the search operations searchOp ∈ Op (which are called reproduction operations in the context of EAs). These offspring are then subsequently integrated into the population.
6. If the termination Criterion is met, the evolution stops here. Otherwise, the algorithm continues at step 2.

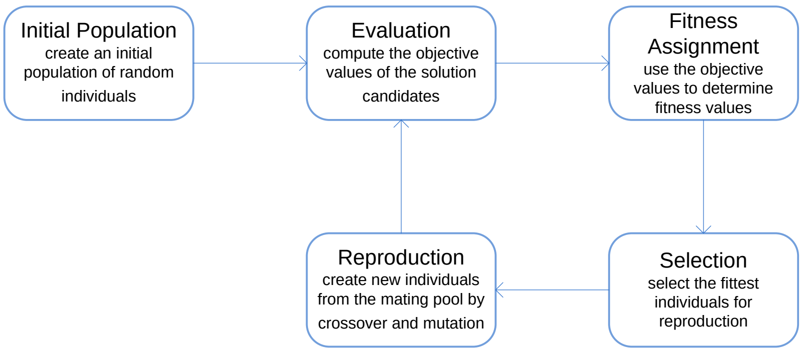


Figure 3.2 The basic cycle of evolutionary algorithms.[Wei 09]

There exist various way in which an evolutionary algorithm can process its population. Especially interesting is how the population Pop(t + 1) of the next iteration is formed as a combination of the current one Pop(t) and its offspring. If it only contains this offspring, we speak of extinctive selection.

3.2.4 Genetic Algorithm

Genetic algorithms (GAs) are a subclass of evolutionary algorithms where the elements of the search space G are binary strings ($G = B^*$) or arrays of other elementary types.

The roots of genetic algorithms go back to the mid-1950s, where biologists like Barricelli and the computer scientist Fraser began to apply computer-aided simulations in order to gain more insight into genetic processes and the natural evolution and selection. Bremermann and Bledsoe used evolutionary approaches based on binary string genomes for solving inequalities, for function optimization, and for determining the weights in neural networks in the early 1960s. At the end of that decade, important research on such search spaces was contributed by Bagley (who introduced the term genetic algorithm), Rosenberg, Cavicchio, Jr., and Frantz (all based on the ideas of Holland at the University of Michigan). As a result of Holland's work genetic algorithms as a new approach for problem solving could be formalized finally became widely recognized and popular. Today, there are many applications in science, economy, and research and development that can be tackled with genetic algorithms. Therefore, various forms of genetic algorithms have been developed to.

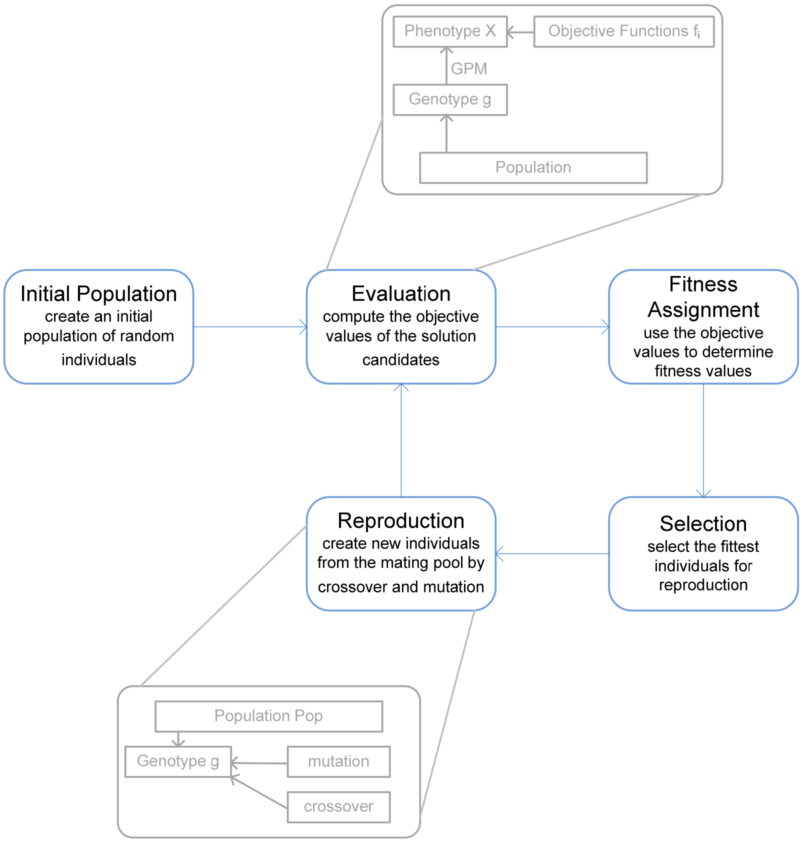


Figure 3.3 The basic cycle of genetic algorithms[Wei 09]

The search spaces G of genetic algorithms, for instance, are referred to genome and its elements are called genotypes. Genotypes in nature encompass the whole hereditary information of an organism encoded in the DNA. The DNA is a string of base pairs that encodes the phenotypical characteristics of the creature it belongs to. Like their natural prototypes, the genomes in genetic algorithms are strings, linear sequences of certain data types. (***Figure 3.3***)

Because of the linear structure, these genotypes are also often called chromosomes. In genetic algorithms, we most often use chromosomes which are strings of one and the same data type, for example bits or real numbers.

A string chromosome can either be a fixed-lengthtuple or a variable-length list.

In the first case, the loci i of the genes g_i are constant and, hence, the tuples may contain elements of different types G_i.

$G = \{\forall (g[1], g[2], .., g[n]) : g[i] \in G_i \ \ \forall i \in 1..n \}$

This is not given in variable-length string genomes. Here, the positions of the genes may shift when the reproduction operations are applied. Thus, all elements of such genotypes must have the same type G_T .

$G = \{\forall \text{ lists } g : g[i] \in G_T \ \forall\ 0 \le i < len(g)\}$

3.2.4.1 Fixed-Length String Chromosomes

Creation of fixed-length string individuals means simple to create a new tuple of the structure defined by the genome and initialize it with random values.

$create_{fl}() \equiv (g[1], g[2], .., g[n]) : g[i] = G_i[\lfloor random_u() * len(G_i) \rfloor]\ \forall\ i \in 1..n$

Mutation is an important method for preserving the diversity of the solution candidates by introducing small, random changes into them. In fixed-length string chromosomes, this can be achieved by randomly modifying the value (allele) of a gene. (***Figure 3.4***)

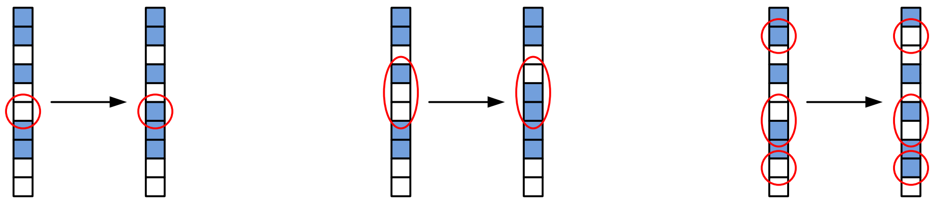


Figure 3.4 Value-altering mutation of string chromosomes[Wei 09]

The permutation operation is an alternative mutation method where the alleles of two genes are exchanged as sketched in ***Figure 3.5***. This, of course, makes only sense if all genes have similar data types. Permutation is, for instance, useful when solving problems that involve finding an optimal sequence of items.

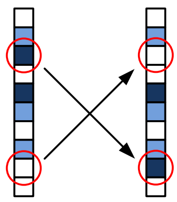


Figure 3.5 Permutation applied to a string chromosome[Wei 09]

Amongst all evolutionary algorithms, genetic algorithms have the recombination operation which probably comes closest to the natural paragon. ***Figure 3.6*** outlines the recombination of two string chromosomes, the so-called crossover, which is performed by swapping parts of two genotypes.

When performing single-point crossover (SPX), both parental chromosomes are split at a randomly determined crossover point. Subsequently, a new child genotype is created by appending the second part of the second parent to the first part of the first parent. In two-point crossover (TPX), both parental genotypes are split at two points and a new offspring is created by using parts number one and three from the first, and the middle part from the second parent chromosome. ***Figure 3.6*** also depicts the generalized form of this technique: the n-point crossover operation, also called multi-point crossover (MPX). For fixed-length strings, the crossover points for both parents are always identical.

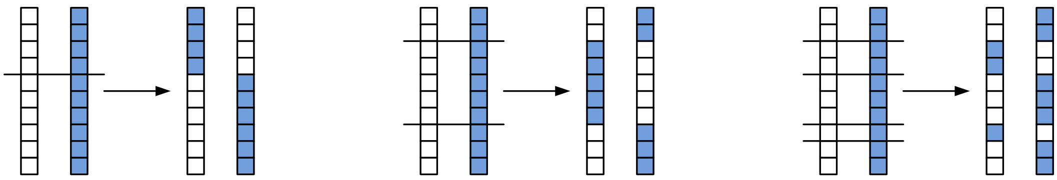


Figure 3.6 Crossover (recombination) operators for fixed-length string genomes[Wei 09]

3.2.4.2 Variable-Length String Chromosomes

Variable-length strings can be created by first randomly drawing a length l > 0 and then creating a list of that length filled with random elements.

If the string chromosomes are of variable length, the set of mutation operations can be extended by two additional methods. First, we could insert genes with randomly chosen alleles at any given position into a chromosome. Second, this operation can be reversed by deleting elements from the string. It should be noted that both, insertion and deletion, are also implicitly be performed by crossover. Recombining two identical strings with each other can, for example, lead to deletion of genes. The crossover of different strings may turn out as an insertion of new genes into an individual. (***Figure 3.7***)

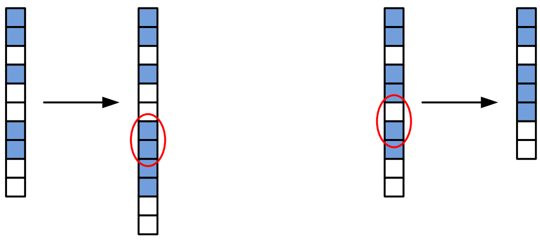


Figure 3.7 Search operators for variable-length strings[Wei 09]

For variable-length string chromosomes, the same crossover operations are available as for fixed-length strings except that the strings are no longer necessarily split at the same loci.

The lengths of the new strings resulting from such a cut and splice operation may differ from the lengths of the parents, as sketched in ***Figure 3.8***. A special case of this type of recombination is the homologous crossover, where only genes at the same loci are exchanged.

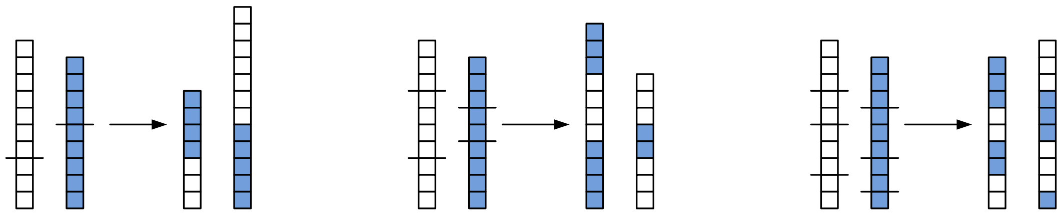


Figure 3.8 Crossover of variable-length string chromosomes[Wei 09]

3.2.5 Particle Swarm Optimization

Particle Swarm Optimization (PSO), developed by Eberhart and Kennedy in 1995, is a form of swarm intelligence in which the behavior of a biological social system like a flock of birds or a school of fish is simulated. When a swarm looks for food, its individuals will spread in the environment and move around independently. Each individual has a degree of freedom or randomness in its movements which enables it to find food accumulations. So, sooner or later, one of them will find something digestible and, being social, announces this to its neighbors. These can then approach the source of food, too. With Particle Swarm Optimization, a swarm of particles (individuals) in a n-dimensional search space G is simulated, where each particle p has a position $p.g \in G \subseteq R^n$ and a velocity $p.\mathbf{v} \in R^n$. The position p.g corresponds to the genotypes, and, in most cases, also to the solution candidates, i. e., p.x = p.g, since most often the problem space X is also the R^n and X = G. However, this is not necessarily the case and generally, we can introduce any form of genotype-phenotype mapping in Particle Swarm Optimization. The velocity vector p.**v** of an individual p determines in which direction the search will continue and if it has an explorative (high velocity) or an exploitive (low velocity) character.

In the initialization phase of Particle Swarm Optimization, the positions and velocities of all individuals are randomly initialized. In each step, first the velocity of a particle is updated and then its position. Therefore, each particle p has a memory holding its best position best(p) $\in$ G. In order to realize the social component, the particle furthermore knows a set of topological neighbors N(p). This set could be defined to contain adjacent particles within a specific perimeter, i. e., all individuals which are no further away from p.g than a given distance δ according to a certain distance measure dist. Using the Euclidian distance measure $dist_{eucl}$ we get:

$\forall$ p, q $\in$ Pop : q $\in$ N(p) $\Leftrightarrow$ $dist_{eucl}$ (p.g, q.g) $\leq \delta$

Each particle can communicate with its neighbors, so the best position found so far by any element in N(p) is known to all of them as best(N(p)). The best position ever visited by any individual in the population (which the optimization algorithm always keeps track of) is best(Pop).

The PSO algorithm may make use of either best(N(p)) or best(Pop) for adjusting the velocity of the particle p. If it relies on the global best position, the algorithm will converge fast but may find the global optimum less probably. If, on the other hand, neighborhood communication is used, the convergence speed drops but the global optimum is found more likely.

The search operation q = psoUpdate(p, Pop) applied in Particle Swarm Optimization creates a new particles q to replace an existing one (p) by incorporating its genotype p.g, its velocity p.**v**. We distinguish local updating and global updating , which additionally uses the data from the whole population Pop. psoUpdate thus fulfills one of these two equations, showing how the i^{th} components of the corresponding vectors are computed.

Global updating

$q.\mathbf{v}_i = p.\mathbf{v}_i + (random_u(0,\mathbf{c}_i) * (best(p).g_i - p.g_i)) + (random_u(0,\mathbf{d}_i) * (best(Pop).g_i - p.g_i))$

Local updating

$q.\mathbf{v}_i = p.\mathbf{v}_i + (random_u(0,\mathbf{c}_i) * (best(p).g_i - p.g_i)) + (random_u(0,\mathbf{d}_i) * (best(N(p)).g_i - p.g_i))$

$q.g_i = p.g_i + p.\mathbf{v}_i$

The learning rate vectors c and d have strong influence of the convergence speed of Particle Swarm Optimization. The search space G (and thus, also the values of p.g) is normally confined by minimum and maximum boundaries. For the absolute values of the velocity, normally maximum thresholds also exist. Thus, real implementations of "psoUpdate" have to check and refine their results before the utility of the solution candidates is evaluated. [Wei 09]

3.3 SOTA

In this chapter we want to show to what extent LCA and LCC optimization has been arrived. First of all we should underline that most of papers in literature tends to compare products or just to apply LCA and LCC methodologies rather than optimize them.

This is understandable because LCA and LCC methodologies require a large amount of data that not all optimization methods are capable of processing to extract a solution quickly. The best methods to reduce computational time are Evolutionary Algorithms, even if they are more complex to be applied than linear programming, for example. Moreover evolutionary algorithms and LCA and LCC methodologies are fairly recent topics so yet to be explored.

As regards the computational speed is well explained in a Gitzel's paper.

The author explains how to use the genetic algorithm to optimize LCC of an IT system (these considerations are possible also for LCA methodology).

Given the typical complexity of a LCC problem, brute force approaches can be ruled out for most realistic problem instances. To give a general impression, consider a DCS consisting of 10=n components which is supposed to run for 15=T years and whose components can either be replaced or kept installed in each year (which means d=2 decision possibilities). The resulting search space has a size of $(d^{T-1})^n = (2^{14})^{10} \approx 1.39*10^{42}$.

Even without the stochastic elements there are about $1.39*10^{42}$ possible life cycles. Under the assumption that 100 life cycles could be evaluated per second, it would still need $4.4*10^{23}$ years to process the complete search space.

Based on our problem-definition above, non-heuristical solutions also run into computational problems rather quickly. While most of them typically perform a lot better than brute-force approaches, the complexity (in terms of search space size) is still too high. For example, dynamic programming can be applied to discrete stochastic problems such as ours. However, the number of possible states in each period grows rapidly. To illustrate our case, consider a small system with 10 components that can fail individually.

Even without any decision branching, each state has 2^{10}=1024 exits. Early experiments we conducted in that direction where quickly dismissed. Generally speaking, the stochastic element adds a level of complexity that makes non-heuristics unappealing.

Heuristics hold more appeal for LCC, because the complexity can be reduced at the expense of the solution quality. While a heuristic gives us a valid solution (if it exists), this solution is not necessarily optimal. However, given the goal of LCC optimization, i.e. saving money through improved replacement decisions, any solution that costs less than the original plan is acceptable. The number of heuristics that could be applied to LCC is huge. [Git 08]

3.3.1 SOTA LCC

Before we show some papers in which some methods are used to optimize LCC, we want to show a survey table (***Table 3.1***). In this table there is a part of state of the art of LCC, exactly 39 papers or thesis. Only in 8 papers on 39 (about 20.5%) LCC is optimized. In the other papers (about 79.5%) LCC is not optimized (***Figure 3.9***). Optimization is by genetic algorithm for 62.5%, by particle swarm optimization for 12.5%, by linear programming for 12.5% and by fuzzy logic for 12.5% (***Figure 3.10***). So the genetic algorithms are the most used for LCC optimization. In the non-optimized papers LCC methodology is simply applied for about 64.5% (in many papers comparison and sensitivity and/or scenario analysis is also conducted). For about 19.4% LCC is calculated and compared by software (a faster and more analytical than simply application) (***Figure 3.11***). In the remaining 16.1% LCC is estimated (for 60% by artificial neural network, for 20% by regression model and for last 20% by Montecarlo simulation) (***Figure 3.12***).

Paper Code	Field of Application	Eventual method used	Brief Comments
AKT 06	Energy/Buildings		Application of LCC methodology and comparison with different scenarios
ARP 06	Buildings		Application of LCC methodology and comparison with different scenarios
BAQ 11	Energy		Application of LCC methodology and comparison with different scenarios and sensitivity analysis
BUT 10	Buildings		Application of LCC methodology, comparison and sensitivity analysis
CAN 02	Industrial		Application of LCC methodology, comparison and sensitivity analysis
CAT 09	Industrial/ Transport	Linear Programming	Optimization of LCC, but no explain on the replications
CHE 06	Automotive	Artificial Neural Network	Not optimization but only estimation of LCC
CIE 08	Industrial		Only application of LCC methodology
FLE 07	Industrial	Montecarlo Simulation	Not optimization but only estimation of LCC
FOL 10	Industrial		Application of LCC methodology, comparison and sensitivity analysis
FRA 06	Buildings	Genetic Algorithm	Optimization of LCC, but no data to test the model
GIT 08	Industrial	Genetic Algorithm	Optimization of LCC, but no data to test the model
GOE 07	Energy/ Automotive		Application of LCC methodology and comparison
GUS 02	Industrial	Software	LCC calculation, comparison and robustness but not LCC optimization
HEL 07	Automotive/ Transport		Application of LCC methodology and comparison with different scenarios
HEN 99	Industrial		Application of LCC methodology with statistical measurements
HIN 11	Industrial	Genetic Algorithm	Optimization of LCC, but no data and no explained model
HON 07	Buildings	Software	LCC calculation, comparison and robustness but not LCC optimization
JEO 02	Energy		Application of LCC methodology and comparison with different scenarios
KAV 11	Buildings	Genetic Algorithm (NSGA II)	Optimization of LCC, but no data and no constraints to test the model

Paper Code	Field of Application	Eventual method used	Brief Comments
KIM 09	Buildings	Software	LCC calculation, comparison and robustness but not LCC optimization
KUM 01	Marine		Application of LCC methodology and comparison with different scenarios
KUM 09	Energy/Buildings		Application of LCC methodology and comparison with different scenarios
LEE 09	Energy		Application of LCC methodology, comparison and sensitivity analysis
LIU 09	General	Regression Models	Not optimization but only estimation of LCC
MAR 11	Energy/Buildings		Application of LCC methodology and comparison with different scenarios and sensitivity analysis
MOR 11	Buildings		Application of LCC methodology as NPV, comparison and sensitivity analysis
OKA 09	Buildings	Genetic Algorithm (NSGA II)	Optimization of LCC, but no data to test the model
SAR 02	Buildings	Fuzzy Logic multicriteria(discrete)	Optimization of LCC, but no data to test the model
SEO 02	General	Artificial Neural Network	Not optimization but only estimation of LCC
SEO 06	Industrial	Artificial Neural Network	Not optimization but only estimation of LCC
SIL 11	Energy		Application of LCC methodology and comparison
SOR 11	Energy		Application of LCC methodology and comparison with different scenarios
VAL 08	Energy/Buildings	Software	LCC calculation, comparison and robustness but not LCC optimization
VEN 09	Energy/ Consumer Goods		Application of LCC methodology, comparison and sensitivity analysis
WAN 09	Consumer Goods	Particle Swarm Optimization	Optimization of LCC, but the model is not explain
WON 03	Buildings		Application of LCC methodology and comparison
WON 08	Aerospace	Software	LCC calculation, comparison and robustness but not LCC optimization
XU 08	Aerospace	Software	LCC calculation, comparison and robustness but not LCC optimization

Table 3.1 LCC survey

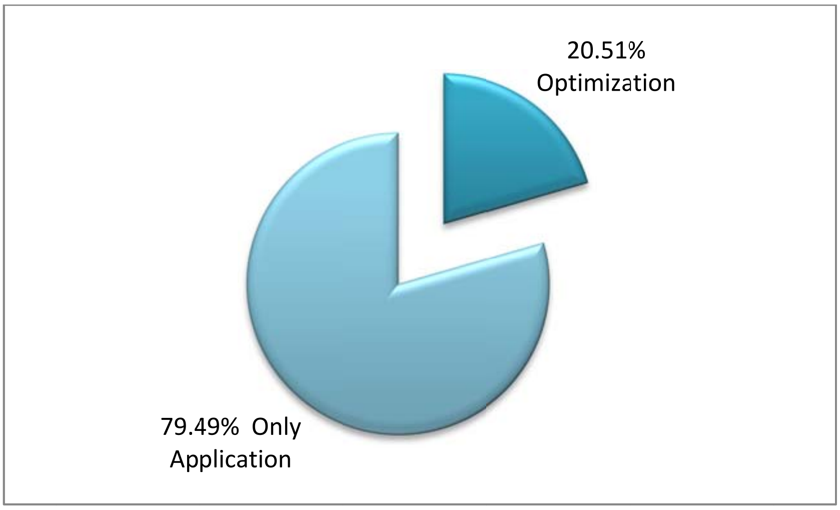


Figure 3.9 LCC Optimization percentage

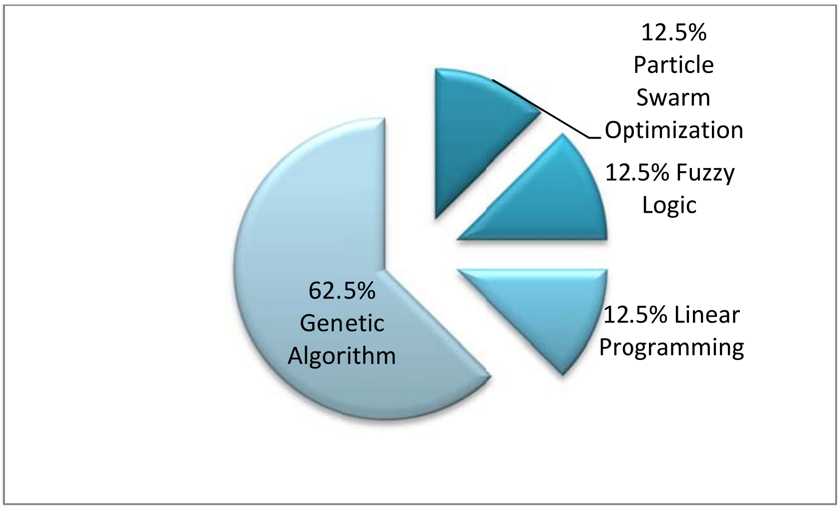


Figure 3.10 LCC optimization methods percentage

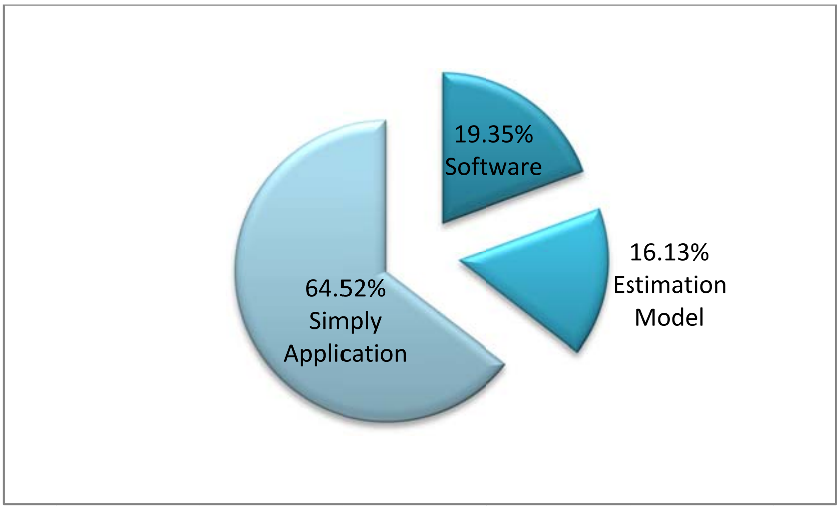


Figure 3.11 LCC not optimized percentage

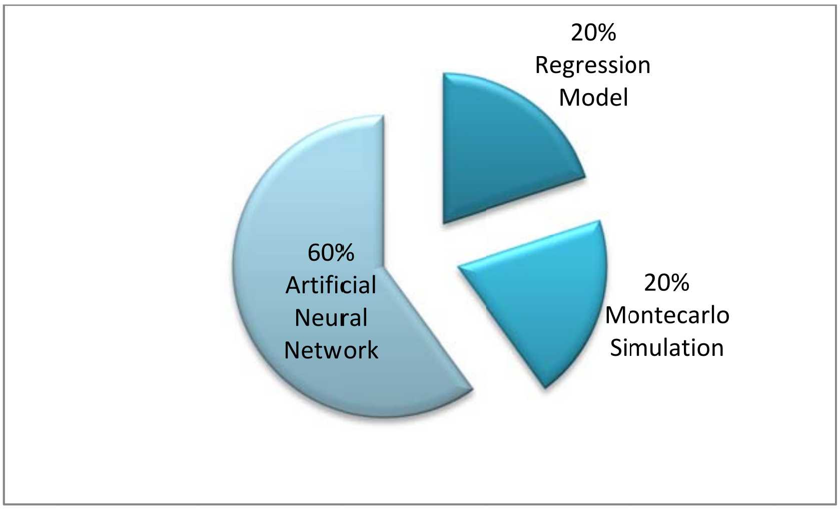


Figure 3.12 LCC estimation methods percentage

3.3.1.1 Linear Programming

The author (Cattaneo) show a methodology, based on a mixed integer linear programming model, to automatically determine the best design approach starting from a set of design alternatives is proposed for minimize LCC of a train's component.

The purpose is to use a hierarchal application strategy of the model, it starts from the train level and optimizes the selection of subgroups, then for each subgroup optimizes the choice of components.

Defined the hierarchal application strategy of the model, we need to explain the methodology to adequately perform the optimization within a given subgroup in the hierarchy. In fact, the results of a single execution are meaningless because of the uncertainty about the probability of failure so we need to make more repetitions of the model to the same subgroup. The different outputs have to be statistically characterized. R repetitions of optimization have to be performed and for each of these has to be changed the number of corrective maintenance for item, time and technology. The objective is to identify the optimal design configuration of the various options. Several experimental campaigns are performed to solve the model with different horizons of the life cycle to assess how the choices made by the model vary. For each component, the technology choices made by the model in different repetitions may differ due to different fault scenarios. So we choose the technology that appears in most of the repetitions. [Cat 09]

3.3.1.2 Genetic Algorithm

The authors' approach (Gitzel and Herbort) for life cycle cost optimization of control systems is to take the general problem description and apply the concepts of Genetic Algorithms. To run the optimization, the problem is first encoded in a form suitable for the genetic algorithm.

The algorithm returns an optimized variant to the life cycle, which is reconverted into a human-readable form. (***Figure 3.13***)

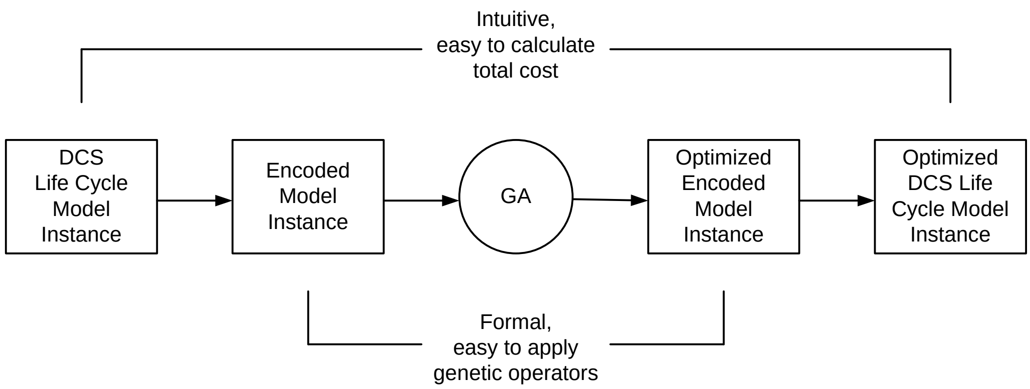


Figure 3.13 Flow of model instances within GA-based LCC optimization [Git 08]

In the context of this paper, the authors have looked at several different GA variants to solve the optimization problem. The algorithms vary in the aspects shown in ***Table 3.2***. The different options for each aspect are also shown.

Property	Variants
Encoding Length	Fixed Length, Variable Length
Encoding Data Type	Integer, Binary, Floating Point
Crossover operator	1-point, 2-point, BLX-α
Mutation operator	Standard, Non-uniform, Special

Table 3.2 Encoding Variants [Git 08]

The algorithm chosen for the optimization was carefully fine-tuned testing different combinations of the properties shown in *Table 3.2*. The different GA variants were applied to two different example systems. While system 1 was designed with a high optimization potential, system 2 was based on the IT level of a real-world water treatment plant. ***Table 3.3*** shows the GA variants analyzed in this context.

#	Genome Lenght	Data Type	Crossover Operator	Mutation Operator
1	Fixed	Integer	1-Point Crossover	Simple
2	Fixed	Integer	2-Point Crossover	Simple
3	Fixed	Binary	1-Point Crossover	Simple
4	Fixed	Binary	2-Point Crossover	Simple
5	Fixed	Floating	1-Point Crossover	Uniform
6	Fixed	Floating	1-Point Crossover	Non-Uniform
7	Fixed	Floating	2-Point Crossover	Uniform
8	Fixed	Floating	2-Point Crossover	Non-Uniform
9	Fixed	Floating	BLX-α Crossover	Uniform
10	Fixed	Floating	BLX-α Crossover	Non-Uniform
11	Dynamic	Integer	Mod. 1-Point Crossover	Special
12	Dynamic	Integer	Mod. 2-Point Crossover	Special

Table 3.3 Analyzed GA Variants [Git 08]

As a first step, they looked at all suggested configurations to figure out a general trend. The results are shown in ***Table 3.4***.

As can be seen, even for a simple system the dynamic length encodings are superior both in speed and quality of the results.

#	Cost after Optimization	Number of Generations Before Termination
1	57202	196
2	94916	174
3	126807	200
4	134937	77
5	56455	195
6	No valid solution	157
7	60925	53
8	60293	46
9	70073	176
10	148711	74
11	54170	25
12	54170	14

Table 3.4 Results for System 1 [Git 08]

The selected subset of the same GA variants was then applied to a more realistic example. The result in this case was less conclusive but still pointed to the variable length solutions (see ***Table 3.5***). These experiments led them to use combination 12 for our optimization algorithm. [Git 08]

#	Cost after optimization	Number of Generations Before Termination
1	2.33 Million	134
5	2.11 Million	199
7	2.26 Million	121
11	1.33 Million	190
12	1.46 Million	54

Table 3.5 Results for System 2 [Git 08]

3.3.1.3 Particle Swarm Optimization

To illustrate the application of PSO in product LCC optimization the authors (Wang et al.) use a case of personal computer. Assuming a personal computer is consisted by three main components: a motherboard, a hard drive, and a processor. The computer as a system operates only when all the three main subsystems function properly. Failure of any sub-system would cause a downtime and replacement, so as certain cost accordingly. However, components with high reliability have low service cost but high manufacturing cost. Therefore, finding a balanced choice is necessary. Moreover, the computer is to be designed for a lifetime of five years with reliability of 0.80 under 8 hrs/day service requirements. The downtime cost is estimated as Rs. 10/hr. The cited data includes MC (Manufacturing Cost) and SC (Service Cost) for each component with different reliability which is denoted here by Probability of survival of component i (P_i) and Life of component i (n_i). ***Table 3.6*** shows the exemplar. All the data are discrete: P_i ranges from 0.90 to 0.99, which is divided into ten degrees; lifetime n_i is in year arranged from 1 year to 5 year; P_i and n_i together indicate corresponding values of MC_i and SC_i. Thus, there are two variables for each component, and the dimension of this problem here is 2x3. The implementation is carried out with Matlab PSO Toolbox. 100 particles are chosen in initialization and 6 dimensions for each of them.

Then a 6x100 matrix is made up, in which the first two elements in every column randomly choose P_i and n_i in the domain of definition for Component 1, the middle two elements choose for Component 2 and the last two elements choose for Component 3 in the same way. Therefore, the value of objective function can be evaluated for each column.

P	Cost	Component 1				
		Life n_1 in Years				
		1	2	3	4	5
0.90	MC_i	4050	4100	4200	4500	5000
	SC_i	1000	870	800	750	700
0.91	MC_i	4700	5250	5750	6100	6500
	SC_i	900	850	725	650	600
0.92	MC_i	5000	5200	5800	6100	6200
	SC_i	850	775	650	550	500
0.93	MC_i	5200	5450	5700	6250	6550
	SC_i	800	750	675	650	610
0.94	MC_i	5300	5350	5600	5800	6250
	SC_i	770	740	625	610	490
0.95	MC_i	5400	5500	5700	5850	6300
	SC_i	650	610	575	520	440
0.96	MC_i	5600	5800	6100	6400	6800
	SC_i	600	580	540	500	410
0.97	MC_i	5700	5800	6100	6500	6800
	SC_i	550	520	400	390	380
0.98	MC_i	5900	6100	6300	6500	6900
	SC_i	510	490	480	450	360
0.99	MC_i	6100	6400	6600	6800	7100
	SC_i	480	450	410	380	320

Table 3.6 Cost data relevant to Component 1 [Wan 09]

Computational experiments are conducted with different algorithmic parameters w (inertial weight), c_1 and c_2 (acceleration coefficients) and number of fitness evaluations. The results are shown in ***Table 3.7***. Thereafter, best set of operating values are found and detailed in ***Table 3.8***. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). To find out the efficiency of PSO in this product LCC optimization problem, GA is employed in this case study to compare with PSO. ***Table 3.9*** represents the result obtained by GA and the results comparison between PSO and GA.

As it shows, PSO found a better result than GA: higher system reliability but lower LCC. [Wan 09]

Component 1		Component 2		Component 3		LCC
P_1	n_1	P_2	n_2	P_3	n_3	
0.95	2	0.99	4	0.99	5	428.42
0.97	3	0.99	1	0.99	1	363.33
0.99	5	0.98	3	0.99	2	376.09
0.98	1	0.99	1	0.99	1	342.94
0.99	1	0.99	5	0.98	2	394.32
0.98	4	0.98	4	0.99	4	413.26
0.97	3	0.99	2	0.99	4	386.80

Table 3.7 Experimental data for LCC optimization [Wan 09]

inertia weight		**acceleration coefficients**		**number of fitness evaluations**		
0.9		2.0	2.0	300		
Component 1		**Component 2**		**Component 3**		**LCC**
P_1	n_1	P_2	n_2	P_3	n_3	
0.99	1	0.99	1	0.99	1	329.66

Table 3.8 Details of algorithmic parameters and result [Wan 09]

		PSO	**GA**
Component 1	P_1	0.99	0.97
	n_1	1	4
Component 2	P_2	0.99	0.99
	n_2	1	1
Component 3	P_3	0.99	0.99
	n_3	1	1
Reliabilty	**R**	0.970	0.951
LCC		329.66	384.39

Table 3.9 Results for PSO and GA on LCC optimization [Wan 09]

3.3.2 SOTA LCA

As we did for LCC, we also want to show a survey table for LCA (***Table 3.10***). In this table there is a part of state of the art of LCA, exactly 40 papers or thesis. Here only in 4 papers on 40 (10%) LCA is optimized. In the other papers (90%) LCA is not optimized (***Figure 3.14***). This is less than the previous result on LCC (10% of LCA versus about 20.5% of LCC). So the state of the art of LCC is ahead of state of the art of LCA regarding optimization. Optimization is by genetic algorithm for 25%, by particle swarm optimization by 25% and by linear programming by 50% (***Figure 3.15***). Here, too, state of the art of LCC is more innovative than state of the art of LCA. In fact, LCC optimization by evolutionary algorithm is 75%, while LCA optimization by evolutionary algorithm is 50%. In the non-optimized papers LCA is simply applied for about 47.2% (as for LCC in many papers comparison and sensitivity and/or scenario analysis is also conducted). For about 2.8% LCA is estimated, while for 50% LCA is calculated and compared by software (much higher than LCC result, that was about 19.4%) (***Figure 3.16***). For LCA methodology software is very useful because it contains the principals LCA databases and allows a fast calculation and comparison. LCA is a methodology similar but more complex than LCC methodology; so it's clear why LCA software have a greater diffusion than LCC software. Exclusively in the papers where software is used, LCA calculation is by SimaPro for about 52.8%, by GaBi for about 19.4%, by LCAiT for about 16.7% and by DEAM and EIO-LCA software for about 5.55% respectively (***Figure 3.17***).

Paper Code	Field of Application	Eventual method used	Comments
ALL 07	Energy/Transport	GaBi Software	Application of LCA methodology and comparison with different scenarios
ARD 08	Energy		Only application of LCA methodology
AZA 95	Chemical	Linear Programming (LP)	Optimization of LCA, but the model is not explain
AZA 98	Chemical	Linear Programming (LP)	Optimization of LCA, but the model is not explain
BEC 10	Food	SimaPro Software + GaBi Software	Application of LCA methodology and comparison
BOV 07	Buildings	SimaPro Software	Application of LCA methodology and comparison with different scenarios
BRE 01	Agriculture		Application of LCA methodology and comparison
DAI 05	Transport	Hybrid (PLCA+EIOLCA) LCA model in software	Application of LCA (LCE also) methodology and comparison
DAS 11	Industrial	SimaPro Software	Application of LCA methodology and comparison with different scenarios
DAV 08	Food		Application of LCA methodology and comparison with different scenarios
DOB 11	Food		Application of LCA methodology and comparison with different scenarios
DUF 11	Energy	Genetic Algorithm (based on SPEA and SPEA2)	Optimization of LCA, but the model is not explain
EID 02	Food	LCAiT Software	Application of LCA methodology and comparison
EKM 11	Industrial		Application of LCA methodology and comparison with sensitivity analysis
GOR 02	Buildings		Application of LCA methodology and comparison with different scenarios
HAL 08	Energy	SimaPro Software	Application of LCA methodology and comparison

Paper Code	Field of Application	Eventual method used	Comments
HUS 07	Automotive		Application of LCA methodology and comparison
JUN 05	Energy		Application of LCA methodology and comparison with different scenarios
KIM 01	Consumer Goods	LCAiT Software	Application of LCA methodology with different scenarios
KIM 09	Chemical		Application of LCA methodology and comparison with sensitivity analysis
KOO 08	Energy	SimaPro Software	Application of LCA methodology and comparison with sensitivity analysis
KOR 05	Energy		Only application of LCA methodology
KOR 10	Energy	Particle Swarm Optimization	Optimization of LCA, but the model is not explain
LO 05	Waste		Application of LCA methodology and comparison
MAN 06	Energy		Application of LCA methodology and comparison
MCC 02	Transport		Application of LCA methodology and comparison with sensitivity analysis
MEY 11	Consumer Goods	SimaPro Software	Application of LCA methodology and comparison
MIL 06	Agriculture		Application of LCA methodology and comparison
MOB 10	Consumer Goods	GaBi Software	Application of LCA methodology and comparison with different scenarios
MUN 06	Energy	SimaPro Software	Application of LCA methodology and comparison
NTI 08	Agriculture	GaBi Software	Application of LCA methodology and comparison with different scenarios
PER 07	Energy	LCAiT Software	Application of LCA methodology with different scenarios
PHU 09	Energy		Only application of LCA methodology
PUR 09	Automotive	SimaPro Software	Application of LCA methodology and comparison
RAF 99	Energy		Application of LCA methodology and comparison

Paper Code	Field of Application	Eventual method used	Comments
RIB 07	Automotive	SimaPro Software	Application of LCA methodology and comparison with sensitivity analysis
SCH 10	Energy	SimaPro Software	Application of LCA methodology and comparison with different scenarios
SEO 07	Industrial	Artificial Neural Network	Not optimization but only estimation of LCA
SUW 11	Energy		Application of LCA methodology and comparison
ZUF 08	Food	DEAM Software	Application of LCA methodology and comparison

Table 3.10 LCA survey

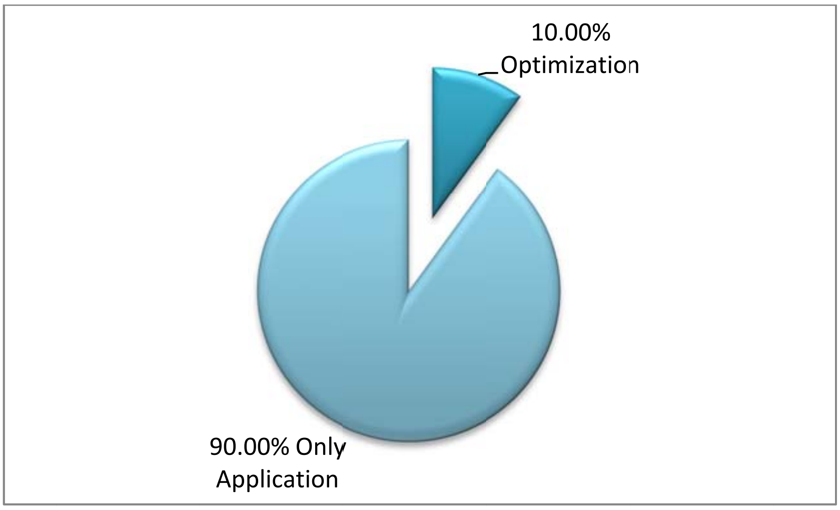


Figure 3.14 LCA optimization percentage

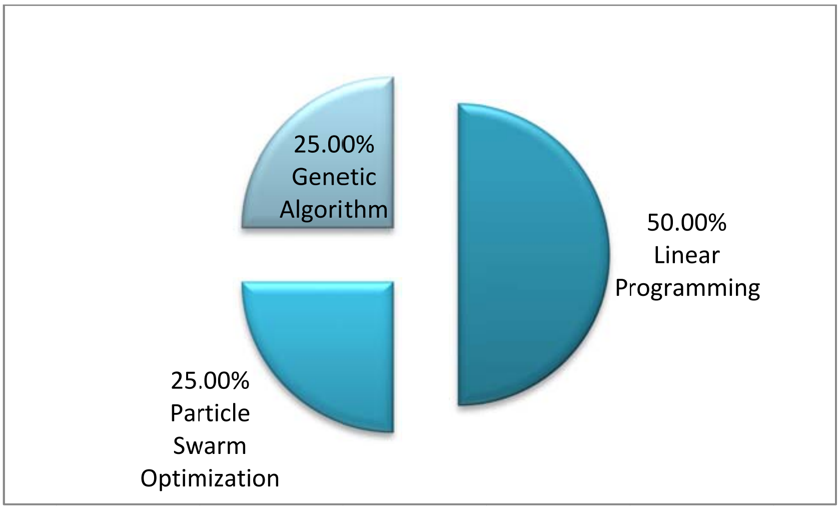


Figure 3.15 LCA optimization methods percentage

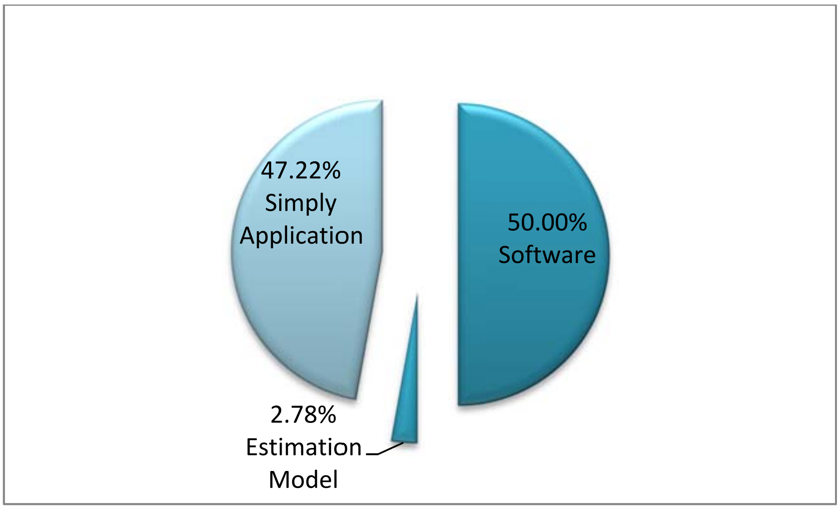


Figure 3.16 LCA not optimized percentage

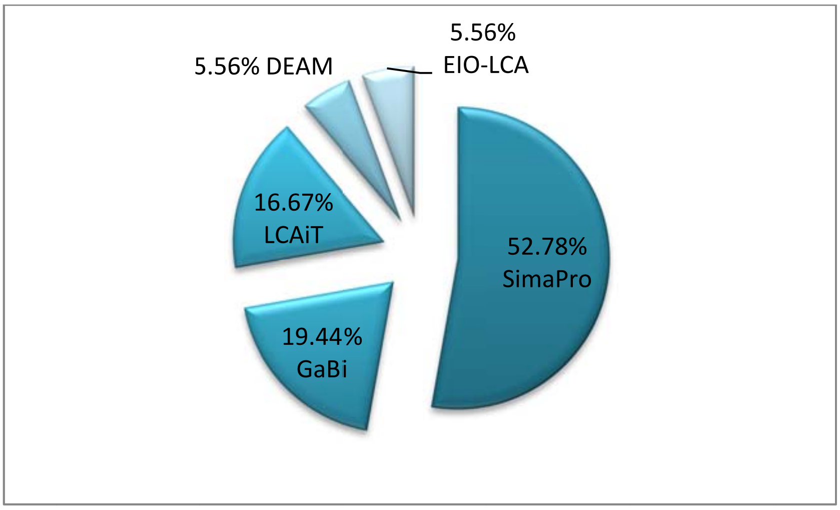


Figure 3.17 LCA software percentage

3.3.2.1 Linear Programming

The system considered by Azapagic and Clift is a chemical plant that produces 5 boron products. All activities, from extraction of raw materials to the production of the boron products and materials used, are included in the system described by the model. However, the use and disposal phases of the products are not considered making this essentially a “cradle-to-gate” study.

The main objective of performing a LCA of the system described above was to identify the possibilities for minimizing total environmental burdens and impacts from the system, while maximizing production subject to the product demand, and keeping the production costs at a minimum. The objective functions of the LP model, therefore, include environmental burdens and impacts, production costs and total production. The system is described by material balances, subject to products demand and raw material supply. Thirty-four environmental burdens and seven environmental impacts identified and quantified in the Inventory and Impact Assessment stages, are defined as objective functions.

The system considered in this paper is, therefore, optimized only on the environmental impact objective functions, and on the economic objective function, defined as the production costs. In addition, the system is also optimized on total production, defined by the mass outputs of each product in one year.

The system is first optimized on each objective to identify the feasible region and other functions are ignored. One of the functions is then arbitrarily chosen as an objective function and all other objectives are converted to constraints. A number of optimizations, in which the right-hand sides of the objectives-constraints are varied within the feasible region, are then performed to yield a range of non-inferior solutions. The results of the individual optimizations on functions compared to the existing operation of the system, are shown graphically in ***Figure 3.18*** and in ***Table 3.11***.

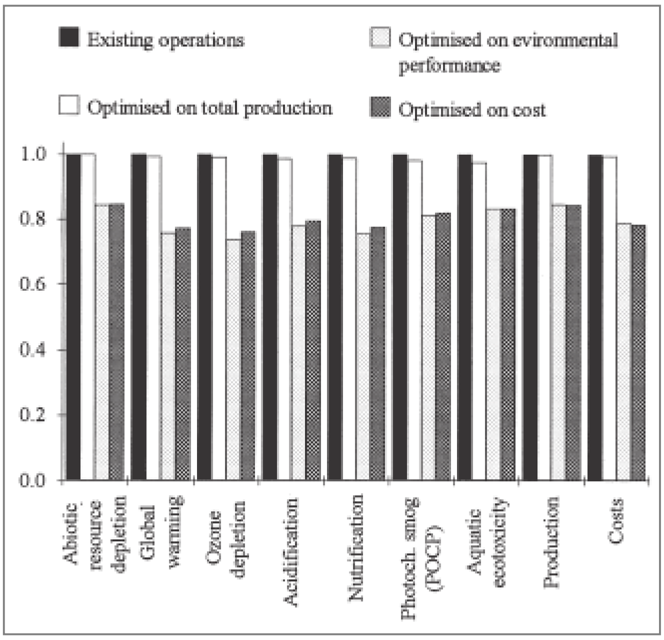


Figure 3.18 Comparison of results of individual optimizations [Aza 98]

Product	Existing operations	Optimized on: total production	Optimized on: environmental impacts	Optimized on: cost
5 mol	100	101.0	89.1	90.4
10 mol	100	102.2	48.0	30.8
Anhydrous borax	100	106.2	0.0	0.0
Anhydrous boric acid	100	98.9	0.0	0.0
Boric acid	100	102.1	93.5	93.5
Total	100	101.0	84.8	84.5

Table 3.11 Total production for single optimization problems [Aza 98]

The system is optimized first on total production, and the values of all other functions are calculated for the optimum production solution. This procedure is repeated for the environmental objectives and the costs, in turn. Optimization on the cost function gives almost the same results as the environmental optimization because of the properties of this system the products with the least environmental impacts have the least production costs. Again, this could be expected, because most of the environmental impacts from the process are related to energy consumption, which constitutes the main component of production costs in this system. Multi-Objective has, therefore, been performed on three objectives: total production (P), costs (C) and Global Warming Potential (GWP). The latter is arbitrarily chosen for the environmental optimization since, as already explained, optimization on one impact function optimizes the values of the others for this particular system. The non-inferior curves, showing trade-offs between cost and GWP functions, for constant values of the production, are shown in ***Figure 3.19***. To preserve the confidentiality of the data, the optimum values of the objectives have been normalized by dividing them by the optimum values obtained in the single objective optimizations, C* and GWP*.

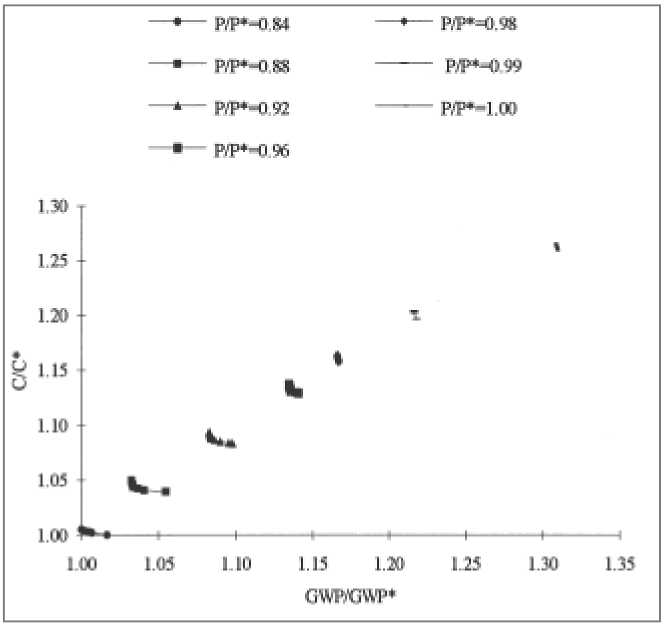


Figure 3.19 Non-inferior curves for costs and GWP for constant total production rate [Aza 98]

The figure shows that the cost objective function does not change significantly with GWP. The cost objective function can, therefore, be ignored, because optimization on GWP generates solutions that can be approximated as optimal with respect to production costs. The non-inferior curve obtained in the optimization on GWP and total production objectives is given in ***Figure 3.20***.

Selected solutions from the non-inferior curve are shown in ***Figure 3.21***. Points A and G represent optimum values of GWP and P, respectively, obtained in the single optimization problems; all other points are calculated by multi-objective optimization. At point A, GWP is at its minimum, but so is the production. By moving away from A along the non-inferior curve, both GWP and total production increase; at point G, production is at its maximum and the value of GWP increases by 24% relative to the solution at point A. [Aza 98]

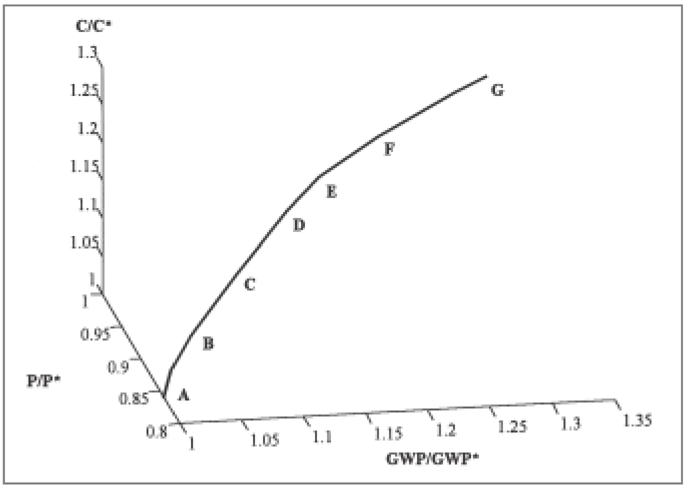


Figure 3.20 Non-inferior curve for multi-objective optimization. [Aza 98]

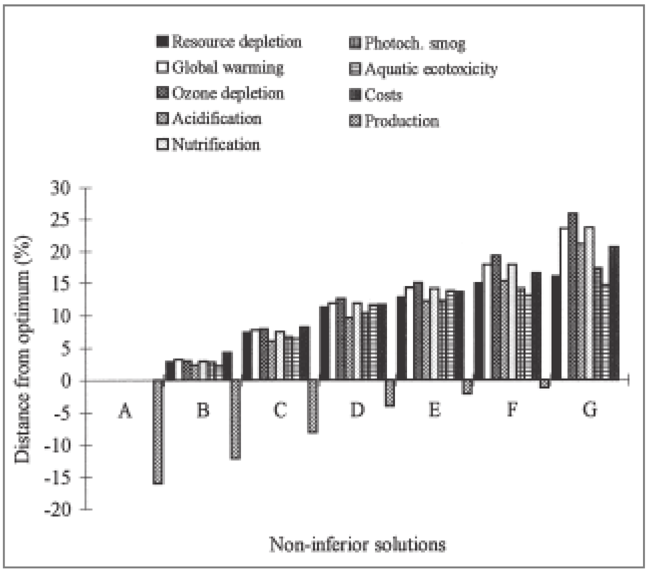


Figure 3.21 Graphical presentation of selected non-inferior solutions. [Aza 98]

3.3.2.2 *Genetic Algorithm*

The Strength Pareto Evolutionary Algorithm (SPEA) is applied , by Dufo-Lopez et al., to the multi-objective optimization of a stand-alone PV–wind–diesel system with batteries storage. (***Figure 3.22***)

The objectives to be minimized are the levelized cost of energy (LCOE) and the equivalent CO_2 life cycle emissions (LCE). The authors developed the Hybrid Optimization by Genetic Algorithms (HOGA) to serve as the design tool.

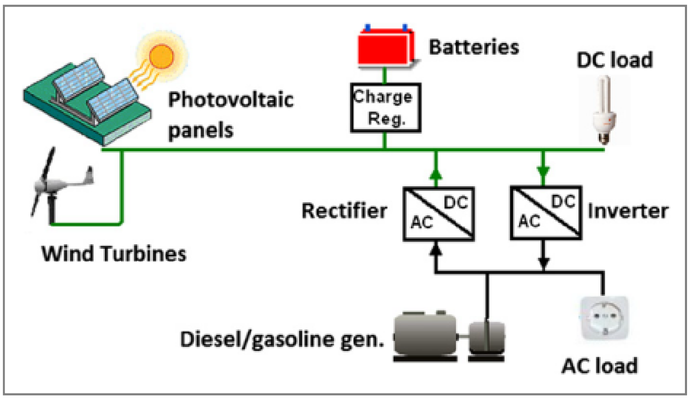


Figure 3.22 PV–wind–diesel-batteries hybrid system. [Duf 11]

The design is posed as an optimization problem with a solution that allows for the attainment of the configuration of the system that simultaneously minimizes both the LCOE and the LCE. For this task, HOGA uses Multi-Objective Evolutionary Algorithms (MOEAs), which have been applied in numerous research studies.

Some of the most important concepts that should be taken into account while applying MOEAs can be observed graphically. Fig. 3.22 shows a set of possible solutions to a multi-objective optimization problem of minimization considering two objectives (F_1 and F_2).

The solutions ‘‘a’’, ‘‘b’’, ‘‘c’’, ‘‘d’’, ‘‘e’’, and ‘‘f’’ are non-dominated solutions, as none of them has both lower F_1 and lower F_2 than any other of them. The non-dominated solutions are into the Pareto front. The solutions ‘‘1’’, ‘‘2’’, ‘‘3’’, and ‘‘4’’ are dominated solutions. For example, solution ‘‘1’’ is dominated by ‘‘b’’ and ‘‘c’’ (both ‘‘b’’ and ‘‘c’’ have lower F_1 and lower F_2 than ‘‘1’’), solution ‘‘4’’ is dominated by ‘‘b’’, ‘‘c’’, ‘‘d’’, ‘‘1’’, and ‘‘2’’, and so on. Therefore, the only solutions of interest are the non-dominated solutions.

At the end of the optimization process (when the last generation of the MOEA is evaluated), the non-dominated solutions of the Pareto front are the best considering, simultaneously, both objectives. This will be considered the ‘‘best Pareto front’’. (***Figure 3.23***)

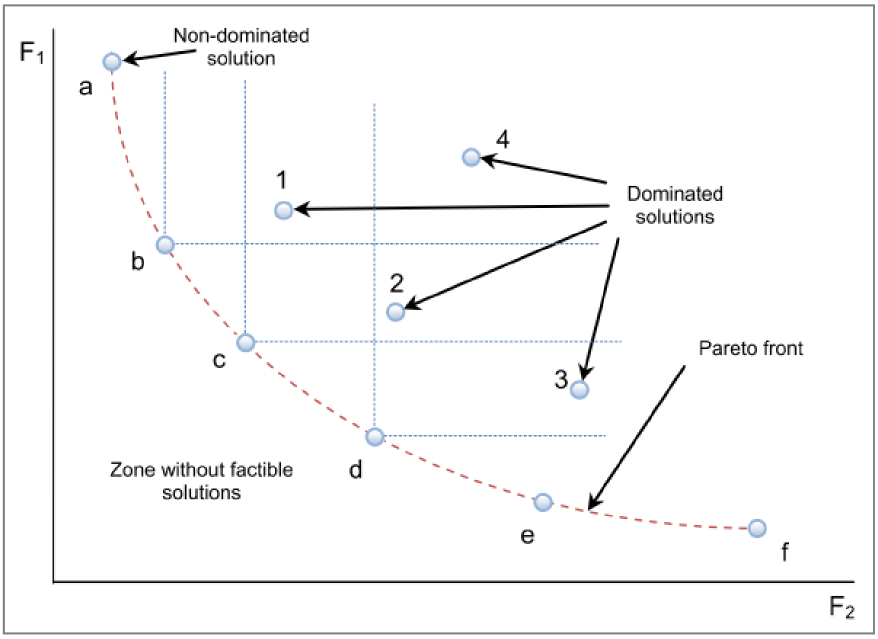


Figure 3.23 Pareto front of a MOEA [Duf 11]

The objectives F_1 and F_2 will be the equivalent CO_2 LCE and the LCOE, respectively. The MOEA is based on SPEA and SPEA2, which are not only the most efficient algorithms, but also the ones that give the best results.

The number of possible combinations of components and control strategies was 62,370 x 1296 = 81 million. HOGA can evaluate approximately 100 combinations per second, depending upon the speed of the computer. This implies that HOGA requires about 224 h (9.3 days) to optimize the hybrid system if the cases are examined using an enumerative technique. Because the solving time for the enumerative technique is unacceptable, HOGA uses evolutionary algorithms. Specifically, it utilizes two algorithms. The main algorithm is a MOEA based on SPEA and SPEA2, which searches the best combinations of components minimizing both costs and emissions. The design tool also uses a secondary algorithm, a genetic algorithm (GA) to find the best control strategy with the lowest costs for each combination of components. For each combination of components and control variables considered, HOGA simulates the performance of every hour of the year. If the whole unmet load of the year is higher than a percentage fixed by the user that combination of components is discarded. If not, HOGA calculates the LCOE and the LCE of the system. At the end of the optimization process, we obtained a set of possible solutions (best Pareto set) from which the designer could choose the solution that he/she preferred by considering the LCOE and LCE of each. [Duf 11]

3.3.2.3 Particle Swarm Optimization

The author (Kornelakis) studies a photovoltaic grid-connected systems (PVGCSs), used to supply the local electric grid with the total energy produced by PV modules. As shown in ***Figure 3.24*** a PVGCS is comprised of several DC/AC converters while every DC/AC converter's DC input is connected with a PV array which consists of a number of parallel branches of PV modules, while each branch includes several PV modules connected in series. The purpose of the proposed methodology is to suggest the optimal design parameters of a PVGCS such that the economic and environmental are both maximized.

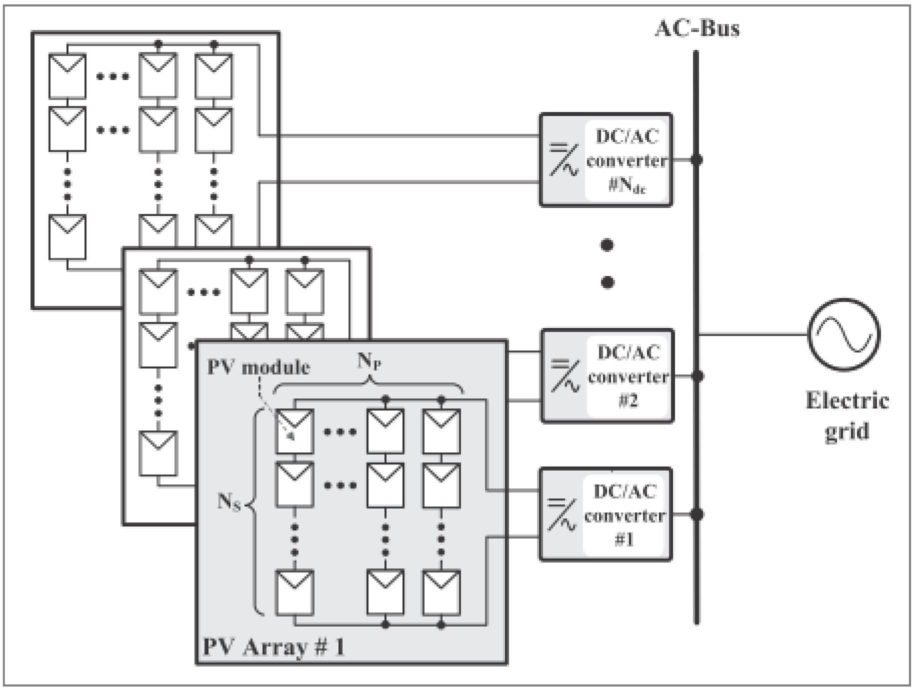


Figure 3.24 The block diagram of a generalized PVGCS [Kor 10]

An alternative PSO algorithm is proposed for the optimization of multi-objective problems. The proposed algorithm starts with the random initialization of the initial population. The repairing algorithm is applied for the correction of the initial particles that violate the problem's constraints. The repairing algorithm developed modifies the values of the decision variables of those particles such that all of constraints are fully satisfied. The constraints refer to the feasibility of the arrangement of the PV modules into the available land area, the distribution of the PV modules among the system's DC/AC converters and the values range of each decision variable and are examined through appropriate simulation algorithms. The feasible swarm is then evaluated by each objective function separately and the corresponding values are stored, while a global best solution $gbest_k$ arises for each one of the k objective functions. Afterwards, the $pbest_k$ vectors are being initialized for every single objective function. The algorithm's initialization process ends with the creation of the initial Pareto set with the non-dominated solutions inside the initial swarm. When the computations described above are completed, the iterative procedure starts with the application, initially, of the multi-objective PSO algorithm. We have six variants that are tested. The new population is, then, formed. After the application of a variant of the multi-objective PSO algorithm, the repairing algorithm is applied and every particle is evaluated according to each objective function, separately, while the $pbest_k$ vectors are being updated. At the end of each iteration, the Pareto set is being updated by adding new dominant solutions or removing previous Pareto solutions that are dominated by newly generated members of the current population. The population's size remains constant during the algorithm's execution, while the size of the Pareto set changes dynamically. After a specific predefined number of iterations, the proposed multi-objective algorithm gives the located Pareto front. In ***Figure 3.26*** the flowchart of the proposed multi-objective PSO algorithm is shown. In ***Figure 3.25*** the Pareto front calculated by the application of one of six variants of the algorithm is shown. [Kor 10]

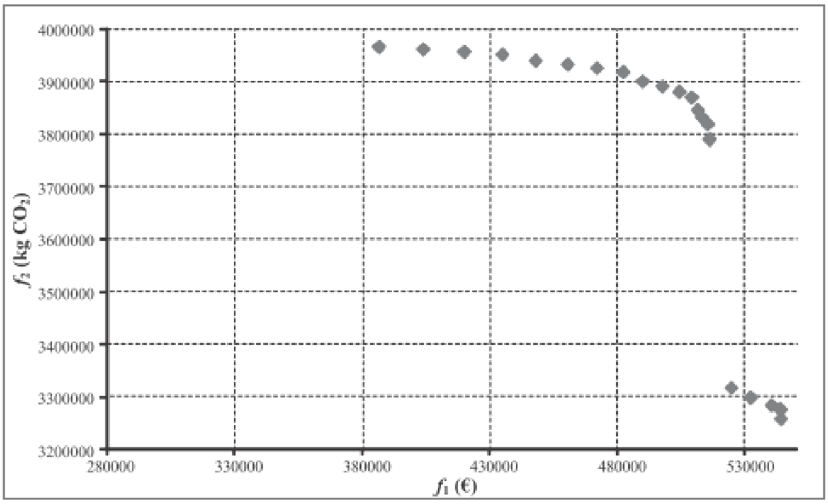


Figure 3.25 The Pareto front calculated by one of the six versions of the algorithm [Kor 10]

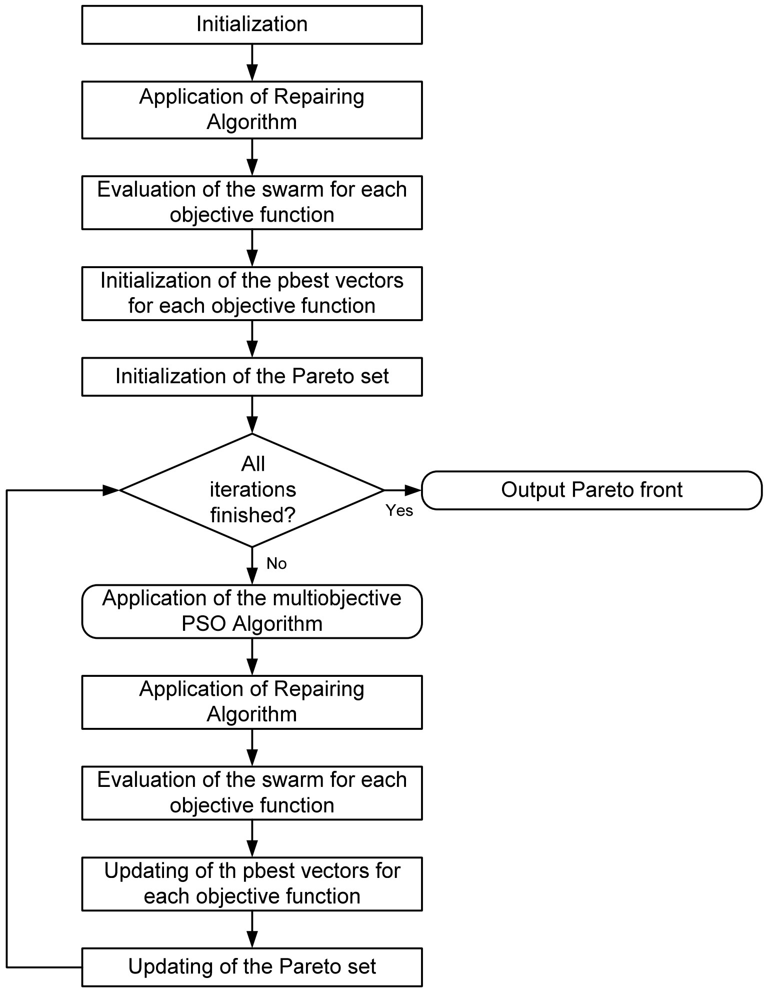


Figure 3.26 The flowchart of the proposed multiobjective PSO algorithm [Kor 10]

3.4 Conclusion

In this chapter we have explained linear programming, dynamic programming, genetic algorithm and particle swarm optimization. After this we have analyzed the state of the art of LCC and LCA optimization. Some examples have been shown. The major problem of this examples is the lack of information on models and data used. This makes difficult any comparison or evaluation.

CHAPTER 4

Model

4.1 Introduction

In this chapter we introduce a model to optimize product life-cycle costs and environmental impacts together. The model is developed with genetic algorithm and compared to linear programming. The three developed models (one with genetic algorithm, two with linear programming) are compared by using test cases with invented data.

4.2 Optimization Methods used

We use two optimization methods: linear programming and genetic algorithm.
Below we deepen how this methods have been applied.

4.2.1 Linear Programming

We use Weighted Sum Model and a model in which we turn the bi-objective problem into a single objective one, where an objective appears in the objective function, the other is displayed as a constraint.

4.2.1.1 Weighted Sum Model

The weighted sum model (WSM) is the best known and simplest multi-criteria decision analysis (MCDA) / multi-criteria decision making method for evaluating a number of alternatives in terms of a number of decision criteria. It is very important to state here that it is applicable only when all the data are expressed in exactly the same unit. If this is not the case, then the final result is equivalent to "adding apples and oranges."

In general, suppose that a given MCDA problem is defined on m alternatives and n decision criteria. Furthermore, let us assume that all the criteria are benefit criteria, that is, the higher the values are, the better it is. Next suppose that w_j denotes the relative weight of importance of the criterion C_j and a_{ij} is the performance value of alternative A_i when it is evaluated in terms of criterion C_j. Then, the total (i.e., when all the criteria are considered simultaneously) importance of alternative A_i, denoted as $A_i^{\text{WSM-score}}$, is defined as follows:

$A_i^{\text{WSM-score}} = \sum_{j=1}^{n} w_j a_{ij}$, for $i = 1, 2, 3, ..., m$.

For the maximization case, the best alternative is the one that yields the maximum total performance value.

For a simple numerical example suppose that a decision problem of this type is defined on three alternatives A_1, A_2, A_3 each described in terms of four criteria C_1, C_2, C_3 and C_4. Furthermore, let the numerical data for this problem be as in the following decision matrix (***Table 4.1***):

	C_1	C_2	C_3	C_4
Alternatives	0.20	0.15	0.40	0.25
A_1	25	20	15	30
A_2	10	30	20	30
A_3	30	10	30	10

Table 4.1 Decision Matrix [Wik 02]

For instance, the relative weight of the first criterion is equal to 0.20, the relative weight for the second criterion is 0.15 and so on. Similarly, the value of the first alternative (i.e., A_1) in terms of the first criterion is equal to 25, the value of the same alternative in terms of the second criterion is equal to 20 and so on.

When the previous formula is applied on these numerical data the WSM scores for the three alternatives are:

$A_1^{\text{WSM-score}} = 25 * 0.2 + 20 * 0.15 + 15 * 0.4 + 30 * 0.25 = 21.50$

Similarly, one gets:

$A_2^{\text{WSM-score}} = 22.00$.

$A_3^{\text{WSM-score}} = 20.00$.

Thus, the best alternative (in the maximization case) is alternative A_2 (because it has the maximum WSM score which is equal to 22.00). Furthermore, these numerical results imply the following ranking of these three alternatives: $A_2 > A_1 > A_3$. [Fis 67] [Tri 00] [Wik 02]

4.2.1.2 From bi-objective to single objective problem

We must optimize the problem in two objective (Life Cycle Cost and Life Cycle Assessment). Here we call the two objective *A* and *B*.

We have created this technique to solve this problem and to obtain a curve similar to Pareto curve.

Firstly we have solved a model with single objective *B*, finding the maximum (*Max*) and the minimum (*Min*) of the objective function.

Then we have divided this range (*Max – Min*) for a number of intervals *X* achieving a value equal to *Y*.

$$Y = \frac{(Max - Min)}{X}$$

So we have created values from *Max*, *Max – Y*, *Max – 2*Y*, ... to *Min*.

Finally we have solved the other objective (*A*) in a single objective problem, respecting the constraint derived from the previous resolution of *B*. The constraint is written as (equation of the constraint is expressed as *EQ.*):

- If *B* is to maximize, the constraint is: *EQ.>Min* for the first iteration; then *EQ.>Min + Y*,... until *EQ.>Max* for the last iteration.
- If *B* is to minimize, the constraint is: *EQ.<Max* for the first iteration; then *EQ.<Max – Y*,... until *EQ.<Min* for the last iteration.

In this way we have obtained a curve similar to Pareto curve.

A weakness of this strategy is that it can produce solutions that are not Pareto efficient.

4.2.2 Genetic Algorithm

Many types of multi-objective genetic algorithm exist in literature. We have decided to use Non Dominated Sorting Genetic Algorithm 2 (NSGA-2).

NSGA-2 is one of the most popular multi objective optimization algorithms with three special characteristics: fast non-dominated sorting approach, fast crowded distance estimation procedure and simple crowded comparison operator. [Deb 02]

Deb et al. simulated several test problems from previous study using NSGA-II optimization technique, and it is claimed that this technique outperformed PAES and SPEA in terms of finding a diverse set of solutions. [Kod 08] [Jia 09] [Mit 09] [Yus 11]

NSGA-2 has been demonstrated as one of the most efficient algorithms for multi-objective optimization on a number of benchmark problems. [Mur 09]

NSGA-2 is the second version of NSGA.

NSGA has been criticized mainly for:

1- $O(M\ N^3)$ computational complexity (where M is the number of objectives and N is the population size). This makes NSGA computationally expensive for large population sizes. This large complexity arises because of the complexity involved in the non-dominated sorting procedure in every generation.

2- Non-elitism approach. Rudolph and Zitzler et al. results show that elitism can speed up the performance of the GA significantly, which also can help preventing the loss of good solutions once they are found. [Rud 99] [Zit 00]

3- Need for specifying the sharing parameter σ_{share}: Traditional mechanisms of ensuring diversity in a population so as to get a wide variety of equivalent solutions have relied mostly on the concept of sharing. The main problem with sharing is that it requires the specification of a sharing parameter (σ_{share}).

Deb et al. proposed an improved version of NSGA, called NSGA-2.

NSGA-2 alleviates all the above three difficulties. Specifically, a fast non-dominated sorting approach with $O(M\ N^2)$ computational complexity with a selection operator that creates a mating pool by combining the parent and offspring populations and selecting the best (with respect to fitness and spread) N solutions.

From the simulation results on a number of difficult test problems, we find that NSGA-II outperforms two other contemporary MOEAs: Pareto-archived evolution strategy (PAES) and strength-Pareto EA (SPEA) in terms of finding a diverse set of solutions and in converging near the true Pareto-optimal set. [Deb 02]

Crowding distance approaches aim to obtain a uniform spread of solutions along the best-known Pareto front without using a fitness sharing parameter. For example, NSGA-II uses a crowding distance method as follows (***Figure 4.1***):

Step 1: Rank the population and identify non-dominated fronts $F_1, F_2, ..., F_R$. For each front $j = 1, ..., R$ repeat Steps 2 and 3.

Step 2: For each objective function k, sort the solutions in F_j in the ascending order. Let $l = |F_j|$ and $\mathbf{x}_{[i,k]}$ represent the ith solution in the sorted list with respect to the objective function k. Assign $cd_k(\mathbf{x}_{[1,k]}) = \infty$ and $cd_k(\mathbf{x}_{[l,k]}) = \infty$ and for $i = 2, ..., l-1$ assign

$$cd_k\left(\boldsymbol{x}_{[i,k]}\right) = \frac{z_k(\boldsymbol{x}_{[i+1,k]}) - z_k(\boldsymbol{x}^k_{[i-1,k]})}{z_k^{max} - z_k^{min}}.$$

Step 3: To find the total crowding distance $cd(\mathbf{x})$ of a solution $\mathbf{x}$, sum the solution's crowding distances with respect to each objective, i.e.,

$$cd(\boldsymbol{x}) = \sum_k cd_k(\boldsymbol{x}).$$

The main advantage of the crowding approach described above is that a measure of population density around a solution is computed without requiring a user-defined parameter such as σ_{share} or the kth closest neighbour. In NSGA-II, this crowding distance measure is used as a tie-breaker in a selection technique called the crowded tournament selection operator: Randomly select two solutions x and y; if the solutions are in the same non-dominated front, the solution with a higher crowding distance is the winner. Otherwise, the solution with the lowest rank is selected.

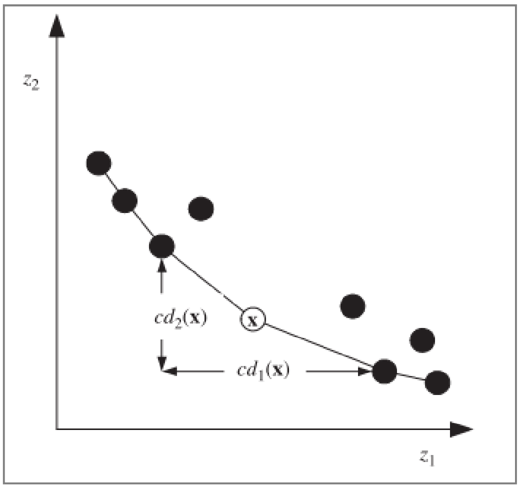


Figure 4.1 Crowding distance [Kon 06]

Elitism in the context of single-objective GA means that the best solution found so far during the search always survives to the next generation. In this respect, all non-dominated solutions discovered by a multi-objective GA are considered elite solutions. However, implementation of elitism in multi-objective optimization is not as straightforward as in single objective optimization mainly due to the large number of possible elitist solutions.

NSGA-II uses a fixed population size of N. In generation t, an offspring population Q_t of size N is created from parent population P_t and non-dominated fronts F_1, F_2, ..., F_R are identified in the combined population $P_t \cup Q_t$. The next population P_{t+1} is filled starting from solutions in F_1, then F_2, and so on as follows. Let k be the index of a non-dominated front F_k that $| F_1 \cup F_2 \cup ... \cup F_k | \leq N$ and $| F_1 \cup F_2 \cup ... \cup F_k \cup F_{k+1} | > N$. First, all solutions in fronts F_1, F_2, ..., F_k are copied to P_{t+1}, and then the least crowded (N - $| P_{t+1} |$) solutions in F_{k+1} are added to P_{t+1}. This approach makes sure that all non-dominated solutions (F_1) are included in the next population if $| F_1 | \leq N$, and the secondary selection based on crowding distance promotes diversity. The complete procedure of NSGA-2 is given below to demonstrate an implementation of elitism without using a secondary external population.

The procedure of NSGA-2 is:

- Create a random parent population P_0 of size N. Set $t = 0$.

- Apply crossover and mutation to P_0 to create offspring population Q_0 of size N.
- If the stopping criterion is satisfied, stop and return to P_t.
- Set $R_t = P_t \cup Q_t$.
- Using the fast non-dominated sorting algorithm, identify the non-dominated fronts F_1, F_2, ..., F_k in R_t.
- For $i = 1, ..., k$ do following steps:
  - Calculate crowding distance of the solutions in F_i.
  - Create P_{t+1} as follows:
    - Case 1: If $| P_{t+1} | + | F_i | \leq N$, then set $P_{t+1} = P_{t+1} \cup F_i$;
    - Case 2: If $| P_{t+1} | + | F_i | > N$, then add the least crowded $N - | P_{t+1} |$ solutions from F_i to P_{t+1}.
- Use binary tournament selection based on the crowding distance to select parents from P_{t+1}. Apply crossover and mutation to P_{t+1} to create offspring population Q_{t+1} of size N.
- Set $t = t+1$, and go to Step 3.

Note that when the combined parent and offspring population includes more N non-dominated solutions, NSGA-II becomes as a pure elitist genetic algorithm where only non-dominated solutions participate in crossover and selection.

The main advantage of maintaining non-dominated solutions in the population is straightforward implementation.

In this strategy, the population size is an important genetic algorithm parameter since no external archive is used to store discovered non-dominated solutions. [Deb 02] [Kon 06]

To realize the genetic algorithm NSGA-2 we use the software GANetXL (Savic et al.), an add-in for Microsoft Excel.

4.3 Tests' Scenarios

We have created three different scenarios to compare the three optimization methods, that we used.

Scenario A has a unique optimal solution. Scenario B has more optimal solutions arranged on a Pareto Front. Scenario C is equal to the second with the addition of a constraint. ***Table 4.2*** reports a summary of the characteristics of the Scenarios.

	Data Input	**Optimal Solutions**	**Constraint**
Scenario A	A	Unique	No
Scenario B	B	Pareto Front	No
Scenario C	B	Pareto Front	Yes (1)

Table 4.2 Summary of the characteristics of the Scenarios

Below there are the comparison between the three optimization methods.

4.3.1 Scenario A

We suppose to have a generic product composed of 10 subgroups. Each subgroup has two alternatives to be realized. Each alternative has this data input:

- *Cin*: initial cost;
- *Cmnt*: maintenance cost;
- *Cen*: energy cost;
- *Cmdpmn*: cost of manpower for maintenance;
- *BOL*: environmental impact in beginning of life;
- *MOL*: environmental impact in middle of life;
- *EOL*: environmental impact in end of life.

These data consider all the life cycle of the product so, for example, *Cmnt* is the maintenance cost during all the life cycle.

The units of measurement are a generic unit of cost for LCC and a generic unit of environmental impact for LCA.

LCC is calculated as:

$$LCC = \sum_{i=1}^{n} (Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$$

while LCA is calculated as:

$$LCA = \sum_{i=1}^{n} (BOL_i + MOL_i + EOL_i) * x_i$$

where x_i is a binary variable which assumes value 1 if the subgroup *i-th* is used to realize the product, otherwise it assumes value 0.

The two objectives are:

- Minimize the Life Cycle Cost (LCC);
- Minimize the Life Cycle Assessment (LCA).

In weighted sum model (WSM) the model is written as:

Minimize $\quad w * \frac{LCC}{LCC^*} + k * \frac{LCA}{LCA^*}$

Subject to $\quad LCC = \sum_{i=1}^{20}(Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

$LCA = \sum_{i=1}^{20}(BOL_i + MOL_i + EOL_i) * x_i$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5, \dots ,19$

$w + k = 1$

$w, k \geq 0$

$x_1, x_2, \dots , x_{20} \in (0,1)$

The two objectives are dimensionally different: LCC has a cost dimension while LCA has a environmental impact dimension. If we want to add LCA and LCC we must make LCA and LCC dimensionless. So firstly we solve a single objective problem, maximizing one time LCA and one time LCC. We obtain LCA^* and LCC^*. We put this values in objective function as shown above. So we make LCA and LCC dimensionless and we can sum them. Iteratively we change the values of *w* and *k*, respecting the constraint, to obtain the different solutions of the problem. We start from w=1 and k=0 to arrive at w=0 and k=1, passing through intermediate values as w=0.55 and k=0.45.

In the other linear programming method the model is written as:

Minimize $\quad LCC = \sum_{i=1}^{20}(Cin_i + Cmnt_i + Cen_i + Cmdpmn_i) * x_i$

Subject to $\quad \sum_{i=1}^{20}(BOL_i + MOL_i + EOL_i) * x_i \leq TV$

$x_i + x_{i+1} = 1 \qquad i = 1,3,5, \dots ,19$

$x_1, x_2, \dots , x_{20} \in (0,1)$

where *TV* is the Target Value, defined as described in Section 1.2.1.2.

In Multi-Objective Genetic Algorithm (we have used NSGA-2) there's a chromosome (which represent the generic product) composed of ten genes (which represent the subgroups). Each gene can assume only two values (for example gene 1 can be 1 or 2, gene 2 can be 3 or 4, ..., gene 10 can be 19 or 20). Genetic algorithm optimizes the two objective simultaneously creating a curve similar to Pareto front.

Here we have used a population size of 50, an one point crossover with a rate of 0.95 and a single mutation by gene with rate 0.05.

All the above-described is also valid for the other two scenarios.

In this scenario the data input are reported in ***Table 4.3***:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	5	10	-2
2	15	6	0	2	8	15	0
3	20	7	0	3	10	20	-6
4	25	8	0	4	15	25	-3
5	30	9	0	5	12	24	-5
6	35	10	0	6	15	28	-2
7	5	2	0	1	2	8	-1
8	10	3	0	2	4	13	3
9	20	4	10	7	10	20	5
10	25	5	11	8	15	25	10
11	50	12	5	11	20	29	-1
12	55	13	7	12	25	33	2
13	70	21	20	20	50	100	-15
14	75	22	25	21	60	130	-5
15	85	35	0	31	50	35	-15
16	90	36	0	32	60	45	-5
17	50	12	0	10	20	10	5
18	55	13	0	11	30	15	10
19	10	5	0	3	20	10	0
20	15	6	0	4	35	25	10

Table 4.3 Data Input for Scenario A

In this scenario the data are arranged, so that we obtain a unique solution reported in ***Table 4.4***.

Product Subgroups	1	3	5	7	9	11	13	15	17	19
Min LCC	589									
Min LCA	430									

Table 4.4 Solution of Scenario A

Every optimization methods reaches this solution.

4.3.2 Scenario B

In this scenario the models are equal to those of the previous scenario, while the data input changes. In ***Table 4.5*** we report the new Data Input:

	LCC				LCA		
Subgroup	**Cin**	**Cmnt**	**Cen**	**Cmdpmn**	**BOL**	**MOL**	**EOL**
1	10	5	0	1	10	18	2
2	15	6	0	2	8	15	0
3	20	7	0	3	18	28	9
4	25	8	0	4	15	25	-3
5	30	9	0	5	17	29	0
6	35	10	0	6	15	28	-2
7	5	2	0	1	6	14	4
8	10	3	0	2	4	13	3
9	20	4	10	7	19	27	12
10	25	5	11	8	15	25	10
11	50	12	5	11	28	35	4
12	55	13	7	12	25	33	2
13	70	21	20	20	65	145	0
14	75	22	25	21	60	130	-5
15	85	35	0	31	67	52	0
16	90	36	0	32	60	45	-5
17	50	12	0	10	34	18	12
18	55	13	0	11	30	15	10
19	10	5	0	3	40	27	12
20	15	6	0	4	35	25	10

Table 4.5 Data Input for Scenario B

In Scenario B there isn't a unique solution, but the solutions are distributed on a Pareto Curve. Here you can see the different behavior of the three optimization methods. In ***Table 4.6***, ***4.7*** and ***4.8*** we report the solutions found by WSM, Bi-Mono and genetic algorithm.

LCC	LCA	Subgroups
589	752	1 3 5 7 9 11 13 15 17 19
596	733	1 3 5 7 9 11 13 16 17 19
603	715	1 4 5 7 9 11 13 16 17 19
615	690	1 4 5 7 9 11 14 16 17 19
629	672	1 4 5 7 9 11 14 16 18 20
644	657	2 4 5 7 10 11 14 16 18 20
653	650	2 4 5 7 10 12 14 16 18 20
660	645	2 4 6 7 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.6 WSM solutions

LCC	LCA	Subgroups
589	752	1 3 5 7 9 11 13 15 17 19
596	745	2 3 5 7 9 11 13 15 17 19
596	734	1 4 5 7 9 11 13 15 17 19
601	727	1 3 5 7 9 11 14 15 17 19
603	724	1 3 5 7 9 11 13 16 18 19
603	715	1 4 5 7 9 11 13 16 17 19
608	709	1 4 5 7 9 11 14 15 17 19
610	706	1 4 5 7 9 11 13 16 18 19
615	701	2 3 5 7 9 11 14 16 17 19
615	690	1 4 5 7 9 11 14 16 17 19
622	685	1 4 6 7 9 11 14 16 17 19
629	677	1 4 5 8 9 11 14 16 17 20
629	674	2 4 5 7 9 11 14 16 17 20
636	668	1 4 5 8 9 11 14 16 18 20
643	661	2 4 5 8 9 11 14 16 18 20
644	657	2 4 5 7 10 11 14 16 18 20
651	652	2 4 6 7 10 11 14 16 18 20
660	646	2 4 5 8 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.7 Bi-Mono solutions

LCC	LCA	Subgroups
589	752	1 3 5 7 9 11 13 15 17 19
596	733	1 3 5 7 9 11 13 16 17 19
601	727	1 3 5 7 9 11 14 15 17 19
603	715	1 4 5 7 9 11 13 16 17 19
608	708	1 3 5 7 9 11 14 16 17 19
610	706	1 4 5 7 9 11 13 16 17 20
615	690	1 4 5 7 9 11 14 16 17 19
622	681	1 4 5 7 9 11 14 16 17 20
629	672	1 4 5 7 9 11 14 16 18 20
636	665	2 4 5 7 9 11 14 16 18 20
637	664	1 4 5 7 10 11 14 16 18 20
643	660	2 4 6 7 9 11 14 16 18 20
644	657	2 4 5 7 10 11 14 16 18 20
650	656	2 4 6 8 9 11 14 16 18 20
651	652	2 4 6 7 10 11 14 16 18 20
653	650	2 4 5 7 10 12 14 16 18 20
658	648	2 4 6 8 10 11 14 16 18 20
660	645	2 4 6 7 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.8 NSGA-2 solutions

A graphical comparison is reported in ***Figure 4.2***.

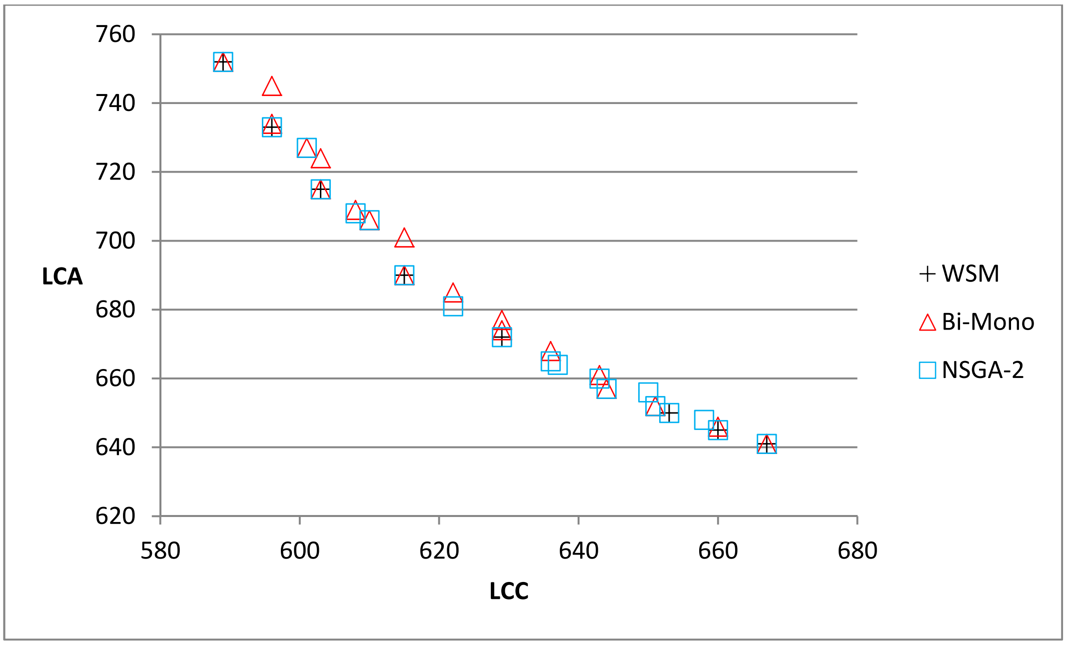


Figure 4.2 Graphical Comparison of the solutions

As you can see NSGA-2 provides a set of non dominated solutions more complete of the other two optimization methods. WSM find few non dominated solutions than NSGA-2. This is probably caused by chosen step (we have used a step of 0.05). This is the major disadvantage of WSM. The advantage is that WSM found solutions are surely on Pareto Curve. This allows a comparison between NSGA-2 solutions and WSM solutions: it's possible to observe from the graph that NSGA-2 solutions, corresponding to WSM solutions, are surely on Pareto Curve. Bi-Mono, instead, find a good number of solutions, but many of them are dominated.

4.3.3 Scenario C

In this scenario the data input and models are equal to the second scenario, with the addition of a column of values which must comply the following constraint, added in the models:

$$\sum_{i=1}^{20} g_i * x_i \leq G$$

where g_i is a generic value of the *i-th* subgroup and G is the threshold value.

The Data Input is reported in ***Table 4.9***.

	LCC				LCA			
Subgroup	Cin	Cmnt	Cen	Cmdpmn	BOL	MOL	EOL	g
1	10	5	0	1	10	18	2	20
2	15	6	0	2	8	15	0	15
3	20	7	0	3	18	28	9	35
4	25	8	0	4	15	25	-3	40
5	30	9	0	5	17	29	0	0
6	35	10	0	6	15	28	-2	0
7	5	2	0	1	6	14	4	0
8	10	3	0	2	4	13	3	0
9	20	4	10	7	19	27	12	30
10	25	5	11	8	15	25	10	20
11	50	12	5	11	28	35	4	25
12	55	13	7	12	25	33	2	15
13	70	21	20	20	65	145	0	40
14	75	22	25	21	60	130	-5	35
15	85	35	0	31	67	52	0	0
16	90	36	0	32	60	45	-5	0
17	50	12	0	10	34	18	12	0
18	55	13	0	11	30	15	10	0
19	10	5	0	3	40	27	12	25
20	15	6	0	4	35	25	10	20

Table 4.9 Data Input for Scenario C

In ***Table 4.10***, ***4.11*** and ***4.12*** we report the solutions found by WSM, Bi-Mono and genetic algorithm.

LCC	LCA	Subgroups
604	735	1 3 5 7 10 11 13 15 17 20
616	700	1 3 5 7 10 11 14 16 17 19
630	673	1 4 5 7 10 11 14 16 17 20
637	664	1 4 5 7 10 11 14 16 18 20
644	657	2 4 5 7 10 11 14 16 18 20
653	650	2 4 5 7 10 12 14 16 18 20
660	645	2 4 6 7 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.10 WSM solutions

LCC	LCA	Subgroups
604	735	1 3 5 7 10 11 13 15 17 20
609	719	1 3 5 7 10 11 14 15 17 19
611	716	1 3 5 7 10 11 13 16 17 20
615	711	2 3 5 7 9 11 14 15 17 20
616	700	1 3 5 7 10 11 14 16 17 19
622	692	2 3 5 7 9 11 14 16 17 20
629	683	2 3 5 7 9 11 14 16 18 20
630	673	1 4 5 7 10 11 14 16 17 20
637	666	2 4 5 7 10 11 14 16 17 20
644	660	1 4 5 8 10 11 14 16 18 20
651	653	2 4 5 8 10 11 14 16 18 20
660	646	2 4 5 8 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.11 Bi-Mono solutions

LCC	LCA	Subgroups
604	735	1 3 5 7 10 11 13 15 17 20
609	719	1 3 5 7 10 11 14 15 17 19
611	716	1 3 5 7 10 11 13 16 17 20
615	711	2 3 5 7 9 11 14 15 17 20
616	700	1 3 5 7 10 11 14 16 17 19
622	692	2 3 5 7 9 11 14 16 17 20
623	691	1 3 5 7 10 11 14 16 17 20
629	683	2 3 5 7 9 11 14 16 18 20
630	673	1 4 5 7 10 11 14 16 17 20
637	664	1 4 5 7 10 11 14 16 18 20
644	657	2 4 5 7 10 11 14 16 18 20
651	652	2 4 6 7 10 11 14 16 18 20
653	650	2 4 5 7 10 12 14 16 18 20
658	648	2 4 6 8 10 11 14 16 18 20
660	645	2 4 6 7 10 12 14 16 18 20
667	641	2 4 6 8 10 12 14 16 18 20

Table 4.12 NSGA-2 solutions

A graphical comparison is reported in ***Figure 4.3***.

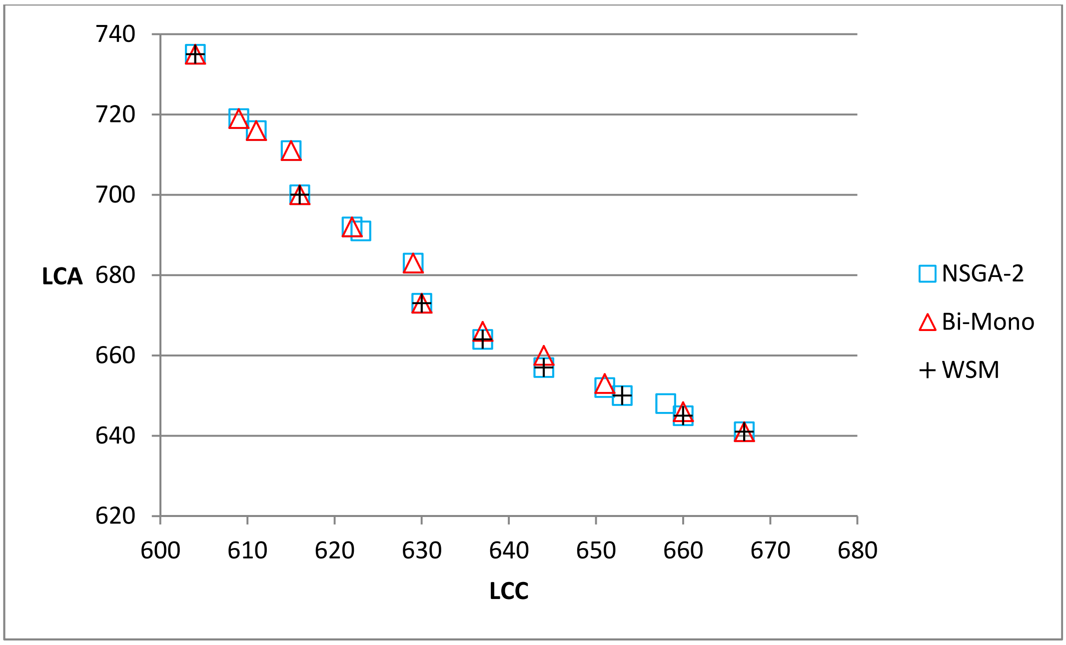


Figure 4.3 Graphical comparison of the solutions

The graphical comparison is very similar to the previous at scenario 2. NSGA-2 provides a major non dominated solutions than WSM. Bi-Mono, instead, provides some dominated solutions. So we can affirm that NSGA-2 is a robust and reliable optimization method.

4.4 Conclusion

In this chapter we compare three optimization methods: WSM, Bi-Mono and NSGA-2. The optimizations methods are tested on three scenario. (***Figure 4.4***)

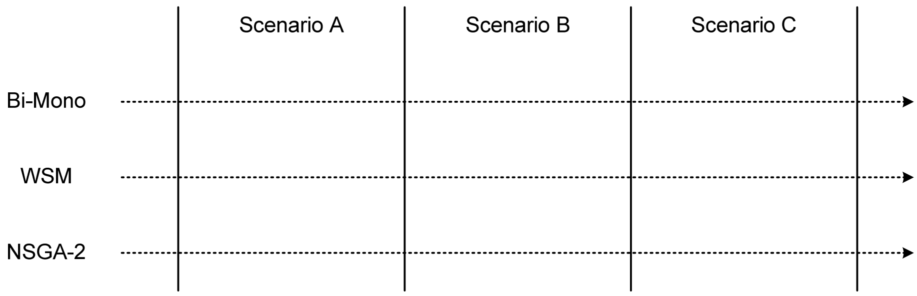


Figure 4.4 Structure of this chapter

The results of this analysis are:

- NSGA-2 provides a major number of non dominated solutions than the other two optimization methods;
- NSGA-2 is a robust and reliable optimization methods (it provides optimal solutions: we can say this by comparing NSGA-2 solutions with WSM solutions);
- WSM finds optimal solutions, but less than NSGA-2;
- Bi-Mono finds a good number of solution, but some of these are dominated.

Table 4.13 reports a summary of results of the tests.

	Number of solutions	**Optimal solutions**	**Dominated Solutions**
Bi-Mono	Medium	Low	Yes
NSGA-2	High	All (Should)	No
WSM	Low	All	No

Table 4.13 Summary of results of the tests

CHAPTER 5

Application Case: Comau

5.1 Introduction

In this chapter we apply the model, presented in chapter 4, to a real case: a fraction of an assembly line made by Comau.

Firstly we describe who is Comau and the fraction of assembly line studied. Then we describe used variables, constraints and alternatives. Finally we use the model to optimize the line and a scenario analysis is conducted.

5.2 Who is Comau

Comau is a global supplier of industrial automation systems and services mainly for the automotive manufacturing sector. With 23 locations in 13 countries, and more than 35 years of experience, Comau is now a global leader in this field. Over the years, by acquiring and integrating other companies, Comau broadened its presence all over the world, becoming the ideal partner for the automotive industry in developing solutions for all industrial production programs. Comau's utmost goal is customer satisfaction, anticipating needs and exceeding expectations. The continuous improvement of products, processes and services, through the application of the most advanced innovative technological solutions, allows Comau to contribute to its customers' competitive advantage. Comau is organized into 5 Business Units: Body Welding & Assembly, Powertrain Machining & Assembly, Robotics & Maintenance Services, Aerospace Production Systems and Adaptive Solutions. The offering of full service, from product engineering to production systems and maintenance services, together with a global organization, allows Comau to compete in the continuously evolving market. Comau provides integrated services to the manufacturing plants, from assistance to the production start-up phases, up to equipment and plant full maintenance activities. Comau is active in several industrial sectors, including automotive, aerospace, steel, petrochemical, foundries, heavy industry, public transportation and energy industry. To the automotive customers worldwide, Comau offers its proficiency as system integrator and its complete engineering solutions, from product development to manufacturing, from assistance to the production start-up phases, up to equipment and plant full maintenance activities.

5.2.1 LCC in Comau

For estimating life cycle cost, the life cycle phases for the product under consideration should be clearly defined to allow identification of various activities that involve costs over the various life cycle phases. The life cycle of equipment goes from the system concept definition up to the final disposal and it is divided in the following phases (***Figure 5.1***):

Figure 5.1 Phases of manufacturing Machinery and equipment Life Cycle

5.2.1.1 Phase 1 - Concept

The first phase is research and limited development or design, and it usually ends with a proposal. During this phase, user and supplier must work together in order to establish system requirements. Both team should provide machine operators, maintenance personnel and engineering personnel. Machinery mission and environmental requirements are defined during this phase, as well as goals for R&M and for Life Cycle Cost. Generally the selection of the product is here addressed, after market analysis devoted aimed to explore new product opportunities. Afterwards, the manufacturing technology is chosen and buy/make decision are taken. Finally the main cost drivers are defined and manufacturability and construction assessment are performed. The definition of the warranty incentive schemes is also carried out during this phase.

5.2.1.2 Phase 2 – Development/Design

In the development/design phase, the largest part of life cycle costs are determined, all the issues from the concept phase are incorporated, as well as safety issues, ergonomics, accessibility and maintenance aspects. R&M allocation requirements are here formalized, components and component suppliers are here selected according to the cost analysis.

Two main design reviews are planned in order to ensure that the planned design is able to meet all the requirements in the most cost-effective way, considering all variables and constrains with particular attention to maintainability. A first preliminary review precedes commitment to the final design approach, while a critical design review determines overall readiness for production prior to release of drawings to the manufacturing function.

At this phase the design must include suitable test plans, agreed by both the user and the supplier, in order to demonstrate compliance to requirements. Responsibility for data collection, analysis and reporting is negotiated.

5.2.1.3 Phase 3 – Build & Install

This phase consists in the manufacturing and assembly of the machining and equipment in the user plant. Issues that could affect the R&M must be communicated back to the design engineers. Several events that occur during the manufacturing phase require further comments:

- Maintenance procedures are here developed. A user representative should be involved in this process;
- Training of the operators starts in this phase;
- Machine acceptance testing, as agreed during the design phase should be performed before installation of the equipment;
- R&M data base collection begins during machine acceptance testing;
- Criticality during assembly of the machinery should be addressed during teardown;
- Many efforts should be taken in order to reduce the infant mortality failures that may occur during installation.

5.2.1.4 Phase 4 – Operation & Support

In this phase the equipment has been delivered and installed to the user, and it is fully operating. It represents the steady state part of the machining operation. Data collection and feedback are very important in order to facilitate the R&M analysis and to update the Life Cycle Cost calculations. Preventive maintenance should be performed periodically and all the data should be delivered to the supplier for the R&M update.

5.2.1.5 Phase 5 – Conversion and/or Decommissioning

This phase is the end of the expected machine life. If an increasing failure rate has been found, the machine may require decommissioning or maybe conversion to a new state. On the contrary, if the machine presents good conditions in the end of its life, the user could decide to sell it, or sell separate components of the equipment. This would not be a cost, but revenue for the user that should be considered in the Life Cycle Cost of the machine. No R&M activities are typically performed during this phase.

5.3 Application Case

The Comau industrial case focuses on a real assembly line, the Short block SDE (Small Diesel Engine) Assembly line, of which we consider a fraction.

The focus is on 5 locations: OP180, OP190, OP200, OP210 and OP220.

OP180 is a location for silicon coating, OP190 assemblies the base, in OP200 10 screws are filled in, OP210 fills in 10 another screws and pallets rotate in 180°, at the end there is OP220, in which the screwing in under base is done.

All of these locations can have automatic, semi-automatic or manual stations.

For these locations we have 6 alternatives: 3 automatic, 2 semi-automatic and 1 manual stations.

In particular, the focus will be on assembly line, because it is 100% of Comau machines and it presents manual, semi automatic and automatic stations. In fact, in automotive sector, the line can be commissioned from a company (for example Comau) but some stations of this line can be purchased from other supplier.

If in this analysis we chose a line with stations no Comau, difficult we would have conducted a complete analysis of LCC, due to lack of data.

5.3.1 Data

In this paragraph we explain all the data, that we have used to conduct the analysis. ***Table 5.1*** summarizes the time horizon and the units of measure used for costs and environmental impacts.

Time Horizon	Bank Rate (Discount Rate)	Unit of measure (costs)	Unit of measure (environmental impacts)
10 years	1.5%	Generic Unit Cost (invented)	Milli-points (Eco-Indicator 99)

Table 5.1 Summary

The unit of measure of costs has been camouflaged from euro to a generic unit cost, maintaining the proportion between the various costs. The unit of measure of environmental impacts is the milli-point, that is used in Eco-Indicator 99. Bank Rate assumed as a constant for all 10 years.

Here we list costs and environmental impacts we use for LCC and LCA analysis:

- Cin = initial cost, that is the acquisition cost of the station;
- Ce = electric energy cost. The equation to calculate it is:
  - $Ce = ehc(kwh) * nhy\left(\frac{h}{year}\right) * euc(\frac{cost}{kw})$ where e*hc* is the average hourly consumption, *nhy* is the number of hours per year of plant operation and e*uc* is the unit cost of electric energy;
- Cric = spare parts cost (1% of initial cost per year, for Comau);
- Cop = labor cost (on 1 manual or semi-automatic station we have 1 worker, on 1 automatic station we have 0.2 worker);
- Ccon = consumables cost (sum of cost of consumables as oil and grease, for example);
- Cair = air cost. The equation to calculate it is similar to that to calculate Ce, replacing e*hc* with the average hourly consumption of air and *euc* with the unit cost of air;
- Cmo = preventive maintenance cost. The equation is:

  - $Cmo = nhpm\left(\frac{h}{years}\right) * 1.5 * hmc\ (\frac{cost}{h})$ where $nhpm$ is number of hours per year for preventive maintenance and *hmc* is the hour maintainer cost. 1.5 is the average maintainers involved;
- Cmorip = corrective maintenance cost. The equation is:
  - $Cmorip = \frac{nhy(\frac{h}{years})}{MTBF(h)} * MTTR(h) * 1.5 * hmc(\frac{cost}{h})$ where nhy is the number of hours per year of plant operation, *MTBF* is the mean time between failure, *MTTR* is the mean time to repair and *hmc* is the hour maintainer cost. 1.5 is the average maintainers involved;
- EIst = environmental impact of the station. We know that Comau station are principally made of Steel Low Alloy, so the equation to calculate it is:
  - $EIst = mst(kg) * Isla(\frac{millipoints}{kg})$ where *mst* is the mass of the station and *Isla* is the tabular value of steel low alloy's environmental impact (Eco-Indicator 99);
- EIel = environmental impact of electric energy. The equation is similar to the previous:
  - $EIel = ehc(kwh) * nhy\left(\frac{h}{year}\right) * Iel(\frac{millipoints}{kwh})$ where e*hc* is the average hourly consumption, *nhy* is the number of hours per year of plant operation and *Iel* is the tabular value of electric energy's environmental impact (we considered Electricity LV Europe in Eco-Indicator 99);
- A = availability of the station. The equation is:
  - $A = MTBF(h)/(MTBF + MTTR)(h)$ where *MTBF* is the mean time between failure and *MTTR* is the mean time to repair.

Since the time horizon is 10 years and since LCC uses discounted costs, incurred costs over the years will be discounted by a certain Bank Rate (or Discount Rate), that we have set to the value of 1.5%.

So the equation to calculate incurred costs over the years is:

$C = {C_t}/{(1 + br)^t}$

where C is a generic discounted cost, C_t is a generic cost incurred in year t and br is the Bank Rate.

Table 5.2 shows when the costs and environmental impacts have been incurred during the years.

		Year										
		0	1	2	3	4	5	6	7	8	9	10
Costs	Cin	x										
	Ce	x	x	x	x	x	x	x	x	x	x	x
	Cric	x	x	x	x	x	x	x	x	x	x	x
	Cop	x	x	x	x	x	x	x	x	x	x	x
	Ccon	x	x	x	x	x	x	x	x	x	x	x
	Cair	x	x	x	x	x	x	x	x	x	x	x
	Cmo	x	x	x	x	x	x	x	x	x	x	x
	Cmorip	x	x	x	x	x	x	x	x	x	x	x
Environmental Impacts	EIst	x										
	EIel	x	x	x	x	x	x	x	x	x	x	x

Table 5.2 Costs and environmental impacts incurred over the years.

Before we describe the model and show the results of the analysis, it's better investigated the Eco-Indicator 99. In the next sub-paragraph we explain it.

5.3.1.1 Eco-Indicator 99

The standard Eco-indicator values can be regarded as dimensionless figures.

As a name we use the Eco-indicator point (Pt). In the Eco-indicator lists usually the unit milli-point (mPt) is used.

The absolute value of the points is not very relevant as the main purpose is to compare relative differences between products or components. The scale is chosen in such a way that the value of 1 Pt is representative for one thousandth of the yearly environmental load of one average European inhabitant.

In order to calculate the Eco-indicator score, three steps are needed:

1- Inventory of all relevant emissions, resource extractions and land-use in all processes that form the life cycle of a product. This is a standard procedure in Life Cycle Assessment (LCA).

2- Calculation of the damages these flows cause to Human Health, Ecosystem Quality and Resources.
3- Weighting of these three damage categories.

Of course it is very important to pay attention to the uncertainties in the methodology that is used to calculate the indicators. We distinguish two types:

1- Uncertainties about the correctness of the models used.
2- Data uncertainties.

The first type of uncertainties include value choices like the choice of the time horizon in the damage model, or the question whether we should include an effect even if the scientific proof that the effect exists is incomplete.

The data uncertainties refer to difficulties in measuring or predicting effects.

This type of uncertainties is relatively easy to handle and can be expressed as a range or a standard deviation. Uncertainties about the correctness of the model are very difficult to express as a range.

Uncertainties about the correctness of the model

In debates about the seriousness of environmental effects opinions are usually very diverse. This may have to do with differences in knowledge levels, but also fundamental differences in attitude and perspective play an important role. Some people would argue long time effects are more important than short term, while others could argue that on the long term environmental problems can be solved by technological developments and if the appropriate measures are taken. Another difference would be that some people would only be concerned about an issue if sufficient scientific proof is available, while others would argue that every possible effect should be taken seriously.

Such fundamentally different perspectives cannot be reconciled, and there is no way to determine if a perspective is right or wrong.

In Eco-Indicator 99 there are three perspectives, reported in ***Table 5.3***:

Perspective of Basishouding	*Time perspective*	*Manageability*	*Required level of evidence*
H (Hierarchist)	Balance between short and long term	Proper policy can avoid many problems	Inclusion based on consensus
I (Individualist)	Short time	Technology can avoid many problems	Only proven effects
E (Egalitarian)	Very long term	Problems can lead to catastrophes	All possible effects

Table 5.3 Perspectives [EI 99]

These "Archetypes" are taken from the Cultural Theory framework [Tho 90] [Hof 98], and is frequently used in social science.

Data uncertainties

Data uncertainties deal with completely different issues. For instance we are confronted with the uncertainty in the expected number of cancer cases when a group of people are exposed to a certain substance, or the uncertainty in the concentration of a certain mineral. In the methodology report the data uncertainties for almost all human health effects and for most ecosystem effects, as well as for the panel procedure are determined and described. Unfortunately uncertainties in the acidification, eutrophication and resources, as well as the uncertainties in the normalisation values are not available.

In considering uncertainties it is important to distinguish between the absolute and relative uncertainties. With the latter we mean the uncertainties in the differences between the indicators. This relative uncertainty is the most important for the practical application of the user who wants to compare materials or design options.

The relative uncertainty can be much smaller than the absolute uncertainty.

This is because these uncertainties are correlated and have the tendency to compensate each other.

Weighting

In Eco-Indicator 99 there are 4 types of weighting, described in ***Table 5.4***. These are the results of a questionnaire developed by Mettier [Met 99]

	Average	*Individualist*	*Egalitarian*	*Hierarchist*
Ecosystem Quality	40%	25%	50%	40%
Human Health	40%	55%	30%	30%
Resources	20%	20%	20%	30%

Table 5.4 Estimate of rounded weighting factors per cultural perspective

So you have to combine the weighting set with the perspective set.

In principle many combinations are possible, but the most relevant are:

1- The Hierarchist damage model and normalization with the Average weighting. (H,A)

2- The Egalitarian damage model and normalization with the Egalitarian weighting. (E,E)

3- The Individualist damage model and normalization with the Individualist weighting. (I,I)

In principle a fourth version can be made, using the Hierarchist damage model and the Hierarchist weighting (H,H). However, as the number of respondents in the panel was very low, and the standard deviation was very high, this weighting set is too unreliable. The Egalitarian and Individualist damage models can also be combined with the average weighting (E,A and I,A).

Hierarchist perspective with the Average weighting set (H,A) is the default version of the methodology. The other perspectives can be used in a robustness analysis. If the conclusions of your LCA (A is better than B) are the same for all perspectives, one may conclude that the result is independent of the perspectives, and thus independent of the time frame, the required evidence on the cause-effect chain or other subjective choices. [EI 99]

We use only (H,A) because it’s the only available combination that we have.

5.4 Model

The model for the Comau case is very simple and it was made under instructions from Comau.

The model has two objective function, one that minimizes the product life cycle costs and one that minimizes the environmental impacts during the whole life cycle.

The model has two types of constraints: the availability of the fraction of the assembly line must be greater than 0.95; all the locations must have a station, it's automatic, semi-automatic or manual.

Below we report the model written in analytical form:

$$\min \sum_{i=1}^{30} (Cin * x_i + Ce * x_i + Cric * x_i + Cop * x_i + Ccon * x_i + Cair * x_i + Cmo * x_i + Cmorip * x_i)$$

$$\min \sum_{i=1}^{30} (EIst * x_i + EIel * x_i)$$

Subject to

$$\sum_{i=1}^{6} A_i x_i * \sum_{i=7}^{12} A_i x_i * \sum_{i=13}^{18} A_i x_i * \sum_{i=19}^{24} A_i x_i * \sum_{i=25}^{30} A_i x_i \geq 0.95$$

$$\sum_{i=1}^{6} x_i = 1$$

$$\sum_{i=7}^{12} x_i = 1$$

$$\sum_{i=13}^{18} x_i = 1$$

$$\sum_{i=19}^{24} x_i = 1$$

$$\sum_{i=25}^{30} x_i = 1$$

$$x_i \in \{0,1\} \quad i = 1,2,\dots,30$$

where the various costs, environmental impacts and availabilities are described in section 5.3.1, x_i is a binary variable.

We have conducted two analysis: one in which the line is installed in Eastern Europe and one in which the line is installed in Western Europe.

5.5 Eastern Europe Scenario

In ***Table 5.5*** we report sustained costs and environmental impacts along the life-cycle.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	EI st	EI el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	1737.771	235.1102	191.1549	22.99992	723.5773	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	1737.771	153.3328	151.2883	18.39993	482.9982	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	8688.857	143.1106	17.37771	1.609994	45.99983	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	1737.771	245.3324	197.697	24.37991	793.1521	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	1737.771	275.999	199.7415	26.4499	848.8119	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	8688.857	214.6659	23.25547	2.75999	75.43972	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	1737.771	183.9993	162.7372	19.43493	538.198	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	8688.857	143.1106	15.75239	1.149996	45.99983	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	1737.771	204.4437	170.0154	21.04492	579.5979	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	1737.771	306.6655	205.6704	27.7149	904.4717	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	1737.771	137.9995	147.915	17.36494	393.5285	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	8688.857	178.8882	19.99459	1.954993	58.87978	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	8688.857	194.2215	21.67103	2.299992	64.39976	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	8688.857	153.3328	6.278466	1.954993	12.64995	77000	935550	0.99984

Table 5.5 Costs and environmental impacts for all alternatives

Type indicates if the station is automatic (aut), semi-automatic (saut) or manual (m).

The model described in section 5.4 is applied with the genetic algorithm (NSGA-2) and with the WSM (Weighted Sum Model) to verify the results obtained with genetic algorithm.

In ***Table 5.6*** we report the parameters of NSGA-2.

Population	100
Crossover	Simple Multi-point (rate = 0.9)
Selector	Crowded Tournament
Mutator	Simple by gene (rate = 0.15)
Generations	200

Table 5.6 Parameters of genetic algorithm

The results are reported in ***Figure 5.2*** and ***Table 5.7***.

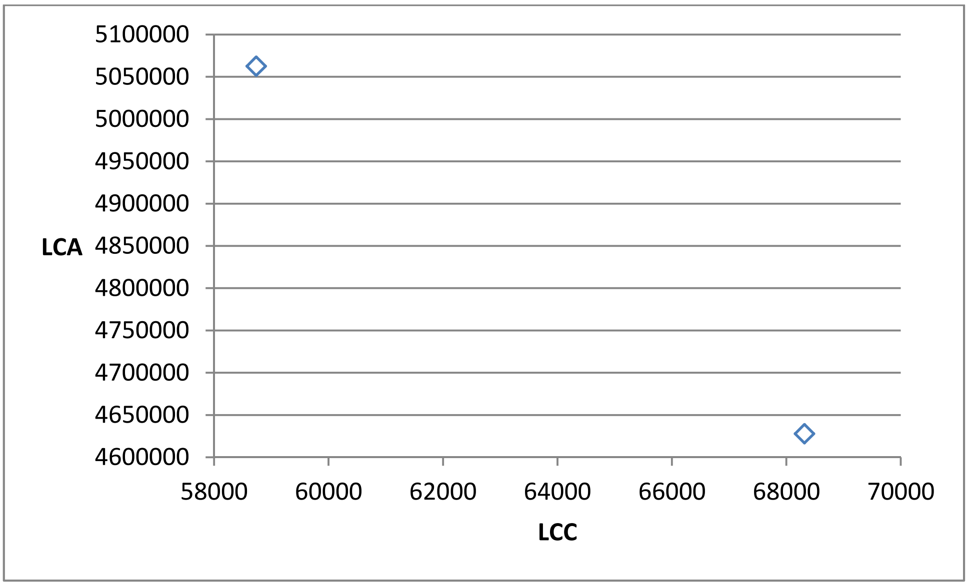


Figure 5.2 Results

Min LCC	*Min LCA*	*Stations*
58737.14	5062750	6(m) 12(m) 18(m) 24(m) 30(m)
68317.86	4627975	6(m) 12(m) 18(m) 23(saut) 30(m)

Table 5.7 Results

With the Weighted Sum Model we obtain the same results.

The results show that the best solution for LCC is the line with all manual stations.

To explain better why we obtain these results (principally for LCC analysis, because Comau is more interested to it than to LCA analysis) we show the weight of various costs (***Figure 5.3***, ***5.4***, ***5.5***) and the cumulative trend of life cycle cost

(***Figure 5.6***). We consider the average costs of an automatic, semiautomatic and manual station.

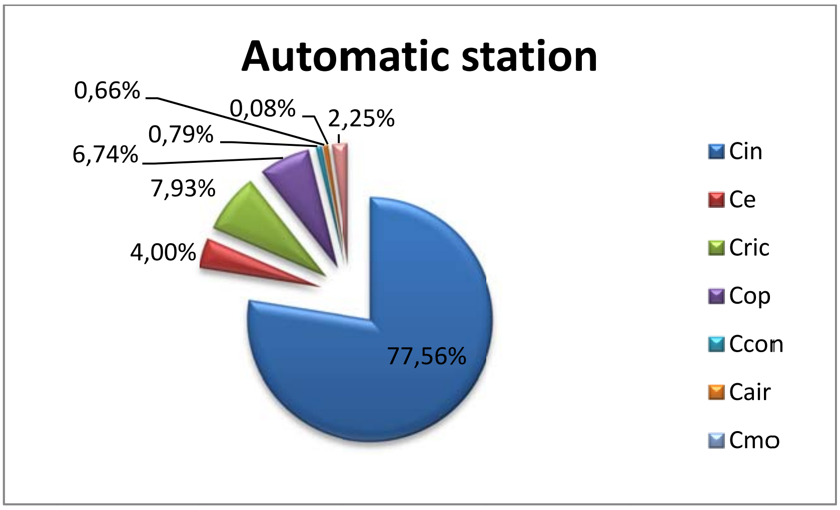


Figure 5.3 Weight of costs in automatic station

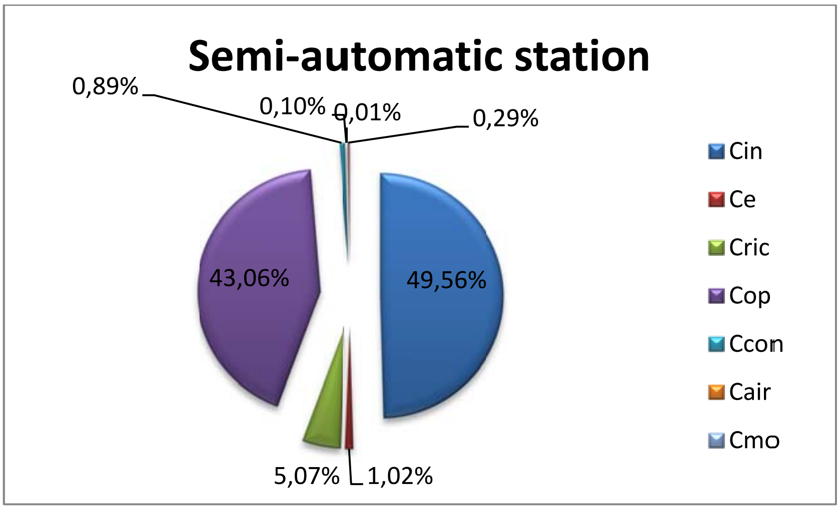


Figure 5.4 Weight of costs in semi-automatic station

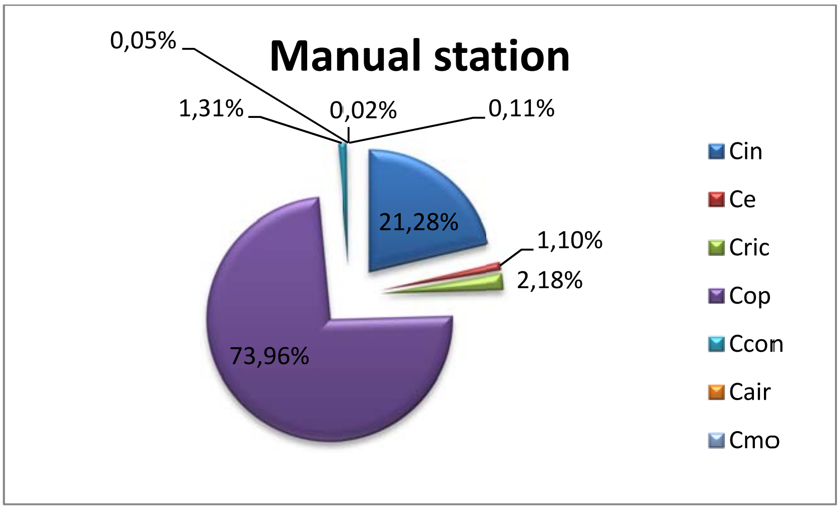


Figure 5.5 Weight of costs in manual station

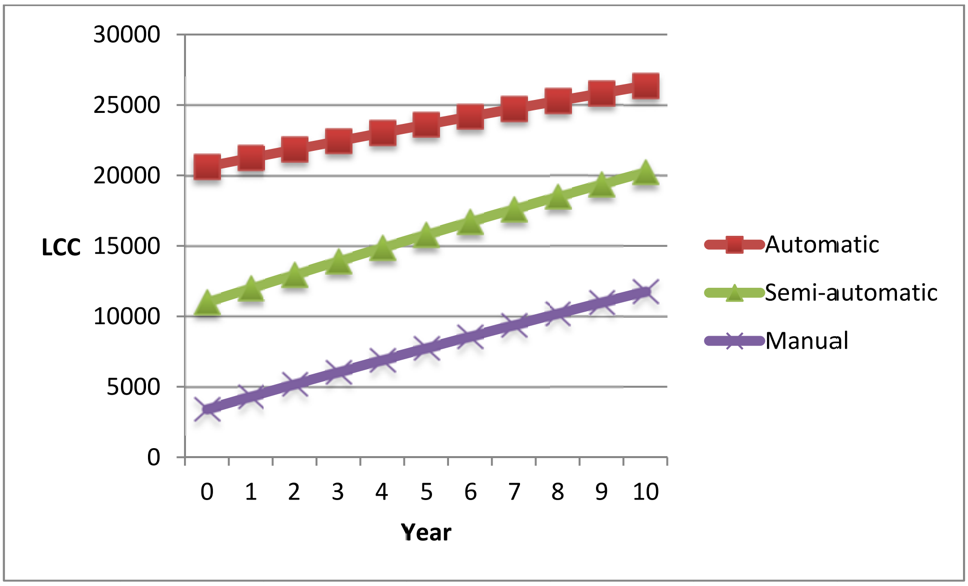


Figure 5.6 Cumulative trend of life cycle cost of station

We can observe that life cycle cost of manual station is less than automatic and semi-automatic. Automatic station is penalized by high initial cost.

So, if the constraint of availability is respect (and it is thus), the line with lower LCC will be composed of all manual stations. If instead we want to minimize LCA in location 4 we must use a semi-automatic station, even if the LCC increases by about 16%, against a reduction of LCA of about 8.5%.

To validate the results we asked to Comau if it is possible a solution with all manual stations. They have responded affirmatively, because cheap labor favors the installation of manual stations.

5.6 Western Europe Scenario

In ***Table 5.8*** we report sustained costs and environmental impacts along the life cycle. There are few differences compared to previous scenario (Eastern Europe), concentrated in labor cost (*Cop*) and in maintenance staff costs (*Cmo* and *Cmorip*). The differences are very large: in fact the labor and maintenance staff costs in Western Europe are three or four times respect to Eastern Europe.

Location	Type	Alternative	Cin	Ce	Cric	Cop	Ccon	Cair	Cmo	Cmorip	EI st	EI el	A
1 (OP 180)	aut	1	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	2	19000	1107.676	2146.659	6082.195	235.1102	191.1549	68.99975	2170.732	440000	8045730	0.99017
	aut	3	21500	901.5967	1891.104	6082.195	153.3328	151.2883	55.1998	1448.995	440000	6548850	0.99343
	saut	4	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	5	10500	154.5594	971.1075	30410.98	143.1106	17.37771	4.829982	137.9995	110000	1122660	0.99938
	m	6	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
2 (OP 190)	aut	7	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	8	18500	1210.716	2248.881	6082.195	245.3324	197.697	73.13973	2379.456	440000	8794170	0.98920
	aut	9	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	10	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	11	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	12	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
3 (OP 200)	aut	13	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	14	18000	1287.995	2432.88	6082.195	275.999	199.7415	79.34971	2546.436	440000	9355500	0.98844
	aut	15	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	16	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	17	9000	334.8788	1257.329	30410.98	214.6659	23.25547	8.279969	226.3192	110000	2432430	0.99898
	m	18	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
4 (OP 210)	aut	19	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	20	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	21	20500	953.1165	1972.882	6082.195	183.9993	162.7372	58.30479	1614.594	440000	6923070	0.99265
	saut	22	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	23	11500	64.39976	868.8857	30410.98	143.1106	15.75239	3.449987	137.9995	110000	467775	0.99938
	m	24	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984
5 (OP 220)	aut	25	20000	1030.396	2044.437	6082.195	204.4437	170.0154	63.13477	1738.794	440000	7484400	0.99208
	aut	26	17500	1365.275	2320.436	6082.195	306.6655	205.6704	83.14469	2713.415	440000	9916830	0.98768
	aut	27	22000	824.317	1758.216	6082.195	137.9995	147.915	52.09481	1180.586	440000	5987520	0.99461
	saut	28	10000	206.0792	1022.218	30410.98	178.8882	19.99459	5.864978	176.6393	110000	1496880	0.99920
	saut	29	9500	283.359	1103.996	30410.98	194.2215	21.67103	6.899975	193.1993	110000	2058210	0.99913
	m	30	2500	128.7995	255.5546	30410.98	153.3328	6.278466	5.864978	37.94986	77000	935550	0.99984

Table 5.8 Costs and environmental impacts for all alternatives

In this scenario we only use the genetic algorithm NSGA-2 (in chapter 4 and in the previous scenario we have seen the excellent performance and it has already been compared with other methods). The parameters we used are the same to those of the previous scenario (see ***Table 5.6***).

The results are reported in ***Figure 5.7*** and ***Table 5.9***. Since we obtain 59 along the curve similar to Pareto Front, we report in ***Table 5.9*** only 15 solutions (including those that minimize LCC and LCA).

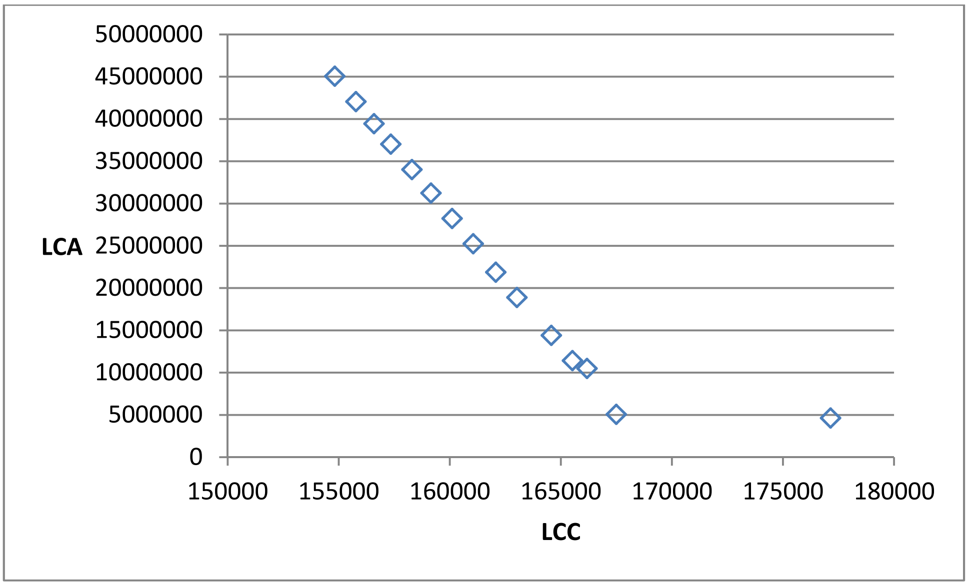


Figure 5.7 Results

Min LCC	*Min LCA*	*Stations*
154823	45048190	2(aut) 7(aut) 13(aut) 20(aut) 26(aut)
155774	42054430	2(aut) 9(aut) 13(aut) 20(aut) 25(aut)
156592.3	39446110	2(aut) 8(aut) 18(m) 20(aut) 26(aut)
157348.9	37013680	2(aut) 8(aut) 13(aut) 24(m) 26(aut)
158299.9	34019920	2(aut) 8(aut) 18(m) 21(aut) 25(aut)
159153.6	31224490	2(aut) 12(m) 18(m) 20(aut) 26(aut)
160104.7	28230730	2(aut) 9(aut) 18(m) 20(aut) 30(m)
161055.7	25236970	2(aut) 9(aut) 18(m) 21(aut) 30(m)
162075.6	21880210	2(aut) 12(m) 18(m) 20(aut) 30(m)
163026.6	18886450	2(aut) 12(m) 18(m) 21(aut) 30(m)
164571.8	14407030	6(m) 12(m) 18(m) 24(m) 26(aut)
165522.8	11413270	6(m) 12(m) 18(m) 21(aut) 30(m)
166178.3	10477720	6(m) 12(m) 18(m) 24(m) 27(aut)
167493.8	5062750	6(m) 12(m) 18(m) 24(m) 30(m)
177139.6	4627975	6(m) 12(m) 18(m) 23(saut) 30(m)

Table 5.9 Results

The best for LCC is the line with all automatic stations.

As done for previous scenario, we explain the results (principally for LCC) showing the weight of various costs (***Figure 5.8***, ***5.9***, ***5.10***) and the cumulative trend of life cycle cost (***Figure 5.11***).

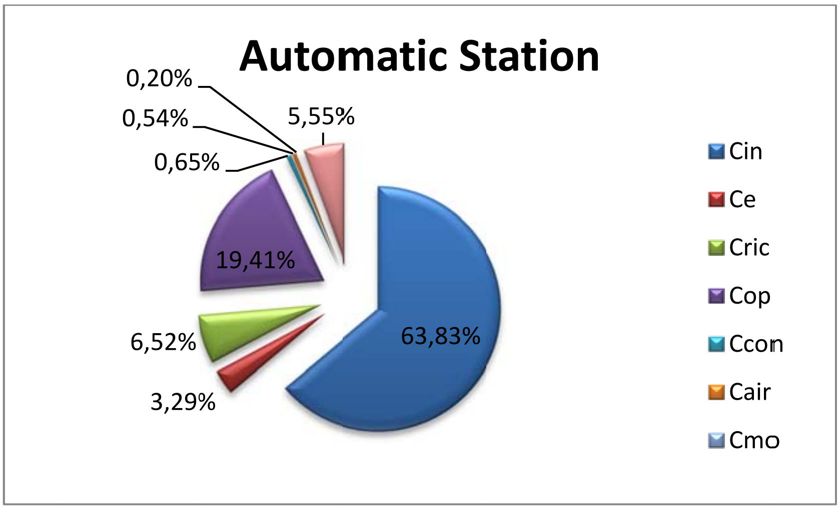


Figure 5.8 Weight of costs in automatic station

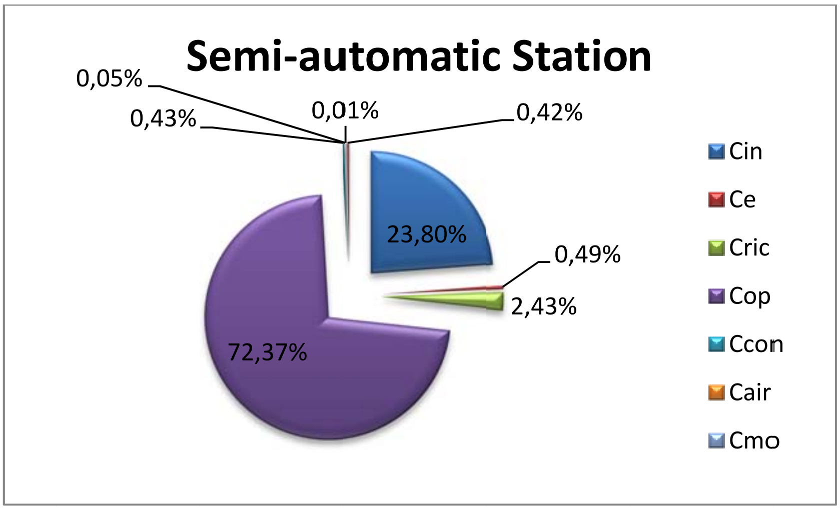


Figure 5.9 Weight of costs in semi-automatic station

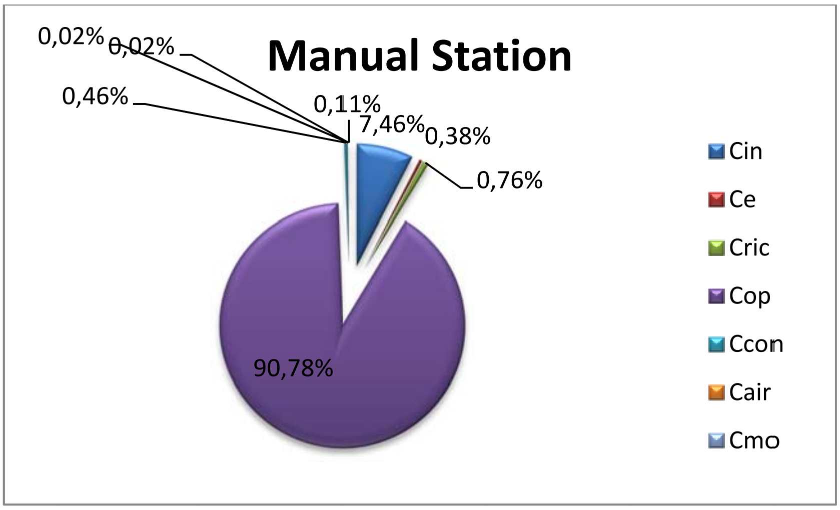


Figure 5.10 Weight of costs in manual station

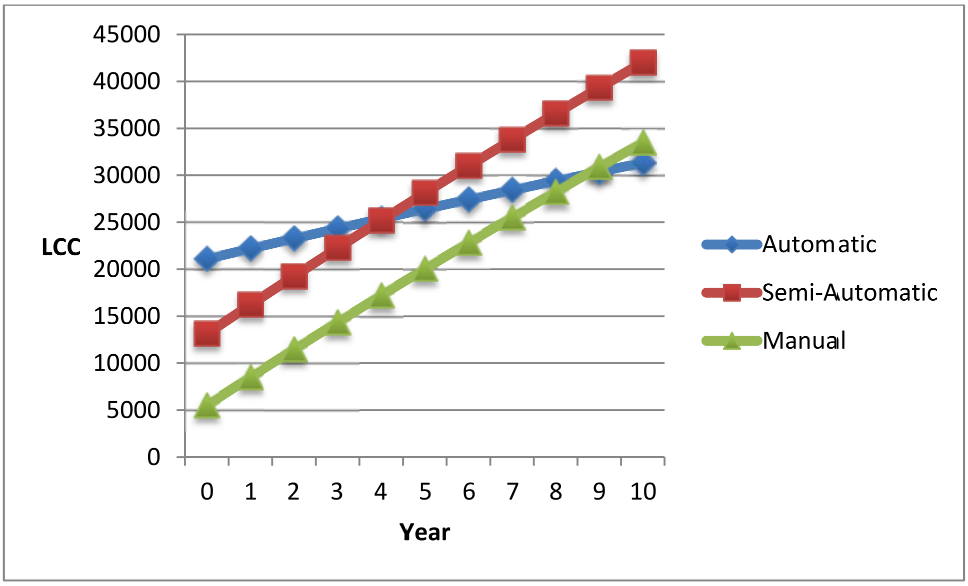


Figure 5.11 Cumulative trend of life cycle cost of station

Figure 5.11 is very interesting, because it shows how the automatic station, with the proceeding of the time, recovers the initial cost gap, thanks to lower costs for the operator: in fact 0.2 operator works on automatic station, while 1 operator works on automatic or manual station.

These results have been subjected to Comau, they have validated them.

So we showed how changing scenario, result are completely different.

Figure 5.11 shows how, if the time horizon is lower, manual stations are more cheap.

From the solution with LCC minimum (and LCA maximum) to solution with LCC maximum (and LCA minimum), LCC increases by about 14% against a LCA reduction of about 89.5%.

5.7 Conclusion

In this chapter we apply the model developed in Chapter 4 to a real case: a Comau assembly line. We have used two scenario: one, set in Easter Europe, where labor cost is low; the other, set in Western Europe, where labor cost is high.

The results obtained have been validated by Comau, so the model has worked well.

Surely Comau is more oriented to LCC than LCA: in fact LCC is already used while LCA has never been used.

So the LCA analysis is a bit poor: in fact, observing ***Figure 5.12***, the LCA analysis is limited only to inputs. This is due to lack of available data in the company.

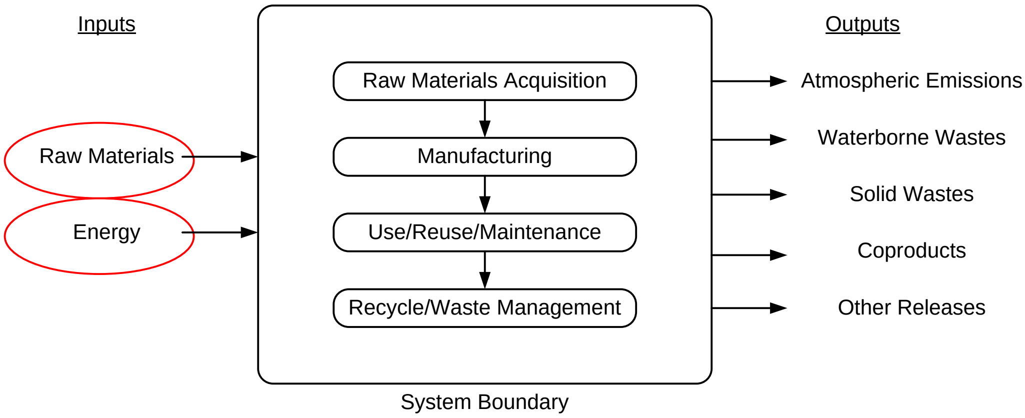


Figure 5.12 Possible life cycle stages that can be considered (items evaluated in the analysis are highlighted in red) [Epa 93]

LCC analysis, instead, was more complete and accurate, thanks to the presence of data.

In the concluding chapter we explain Comau uses and requests about the model developed.

CHAPTER 6

Conclusion

6.1 Introduction

In this chapter we conclude our work.

Firstly we make a brief overview on the work, explaining we did in each chapter.

After we explain benefits and criticism of our work.

In the end we present possible future developments.

6.2 Overview

The aim of our work is to develop a multi-objective optimization of product life-cycle costs and environmental impacts.

In the first chapter we explain the actual context and the reason, both from the perspective of companies and from the perspective of the literature.

In the second and third chapter we present Life Cycle Cost and Life Cycle Assessment (Chapter 2) and some methods to optimize LCC's and LCA's optimization results (Chapter 3). Also in Chapter 3, we analyze the state of the art of LCC and LCA optimization.

In the fourth chapter we introduce the model, based on genetic algorithm (and compared with linear programming), to optimize product life-cycle costs and environmental impacts.

In the fifth chapter we apply the model, developed in the Chapter 4, to a real case based on a fraction of Comau assembly line.

In this last chapter (Chapter 6), we explain benefits and criticism of our work and we present possible future developments.

6.3 Benefits and problems in the Comau application

The best way to understand if the model is useful or not is to subject it to the company of the real case.

So we asked to Comau about the usefulness of the developed model.

Firstly it's better to remember how Comau estimates LCC.

So we report the phases of manufacturing Machinery and equipment Life Cycle (***Figure 6.1***)

Figure 6.1 Phases of manufacturing Machinery and equipment Life Cycle

Phase 1 (Concept) is research and limited development or design, and it usually ends with a proposal. Comau tells us that the phase of proposal is a very long process. They think that this model can help them to offer a faster and more efficient proposal to the costumer faster and more efficient: in fact now all LCC calculation are hand-made with the help of a software such as Excel. So our model makes the preparation process of the proposal faster and more efficient than the existing one.

We also have to remember that the case is a fraction of assembly line (only 5 locations), while the entire assembly line is composed of about 100 locations, so the potential of the developed model is very high.

It also suggests the choice of the genetic algorithm.

The solutions obtained in the model must be tested in a simulator, in order to verify the respect of constraints imposed by the costumer.

To be more complete, our model should evaluate the performances (in this case, for example, the throughput), instead now with the existing process or with our model Comau spends considerable time in simulation.

In fact if we were able to include the performances by analytical formulas in the model, we could reduce the time dedicated to simulation.

This would be another great benefit.

Furthermore we should organize the database, so that the retrieval of data for the model would be immediate.

Figure 6.2 shows the time savings achievable.

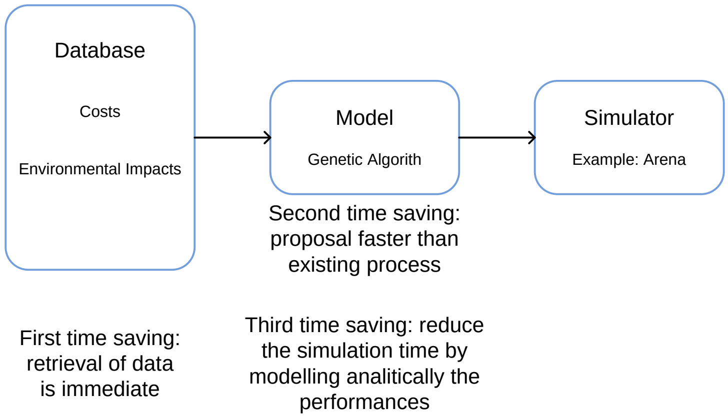


Figure 6.3 Time savings

A request asked us to Comau is to turn the environmental impacts into costs, transforming the optimization problem from bi-objective (to minimize the product life-cycle environmental impacts and costs) to single objective (to minimize the product life-cycle costs).

This would be possible using these equations:

$$min \sum_{i}^{n} LCC_i + \sum_{j}^{k} pc_j * eEI_j$$

$$EI_j - eEI_j \leq tvEI_j \qquad \forall j$$

where LCC_i is the life cycle cost of component *i-th*, pc_j is the penalty cost of *j-th* environmental impact, eEI_j is the excess of *j-th* environmental impact, EI_j is the *j-th* environmental impact and $tvEI_j$ is the threshold value of *j-th* environmental impact.

This surely minimizes the product life-cycle cost and it respects the environmental regulations, but this is a reactive approach.

Instead the aim of our work is to use a proactive approach to the environmental issues.

Table 6.1 summarizes benefits, criticisms and possible future developments encountered in the Comau case.

Benefits	*Criticisms*	*Possible Future Developments*
Reduce the time for the proposal	Performances are not evaluated	1- Evaluate performances in the model 2-Organize the database 3-Transform environmental impacts into cost

Table 6.1 Benefits, Criticisms and Possible Future Developments.

6.4 Our considerations

The aim of our work is to develop a multi-objective optimization of product life-cycle costs and environmental impacts.

With the test cases and real case we have succeeded.

Comau also found our work interesting, despite it has shown some weaknesses, which are now listed:

- LCA cannot to be well investigated due to lack of data;
- We cannot assess robustness of LCA due to lack of tabular values of the other perspectives;
- We haven't compared NSGA-2 with other multi-objective genetic algorithms or with other parameters value;
- Our model doesn't evaluate the performances.

The strengths of our work are:

- It was considered relevant by Comau;
- The comparison between linear programming and genetic algorithm;
- It is more complete than those in the literature (which lack of information);
- The analysis of reasons and of literature.

The main future developments are:

- System effectiveness equations of LCC and LCA (Effectiveness/LCC and Effectiveness/LCA) (see Chapter 2 section 2.2.6.5) and system performances equations (Performances/LCC and Performances/LCA);
- To deepen the use of LCA, using other databases in addition to Eco-Indicator 99.

ANNEX

SOTA LCC & LCA

SOTA LCC

#	Paper Code	Field of Application	Brief Description
1	AKT 06	Energy/Buildings	Comparison different air-conditioning systems in vary scenarios
2	ARP 06	Buildings	Comparison between different college dormitory in vary scenarios
3	BAQ 11	Energy	Comparison between Diesel and self-made straight vegetable oil in different scenarios with sensitivity analysis
4	BUT 10	Buildings	Comparison between exit stairs and occupant evacuation elevators with sensitivity analysis (Montecarlo simulation)
5	CAN 02	Industrial	Analysis, comparison and sensitivity analysis of electrical plants to the energy saving
6	CAT 09	Industrial/Transport	Optimization of LCC of a Train's component with linear programming model
7	CHE 06	Automotive	Estimation of cars' LCC with Back Propagation Artificial Neural Network, genetic algorithm and Levenberg-Marquardt for train ANN's weights
8	CIE 08	Industrial	Analysis of different pumping systems
9	FLE 07	Industrial	Estimation of machines' LCC with Montecarlo Simulation
10	FOL 10	Industrial	Comparison of different approaches in injection moulds with sensitivity analysis
11	FRA 06	Buildings	Multiobjective optimization of LCC and risk-based maintenance of civil infrastructure system with genetic algorithm, Montecarlo Simulation for consider the uncertainty
12	GIT 08	Industrial	Optimization of LCC of IT Systems in Process Industry Applications with genetic algorithm
13	GOE 07	Energy/Automotive	Comparison between different vehicles with vary fuels
14	GUS 02	Industrial	Software for calculation of LCC of Air Filters
15	HEL 07	Automotive/Transport	Comparison of car, citybus and intercity bus in different scenarios
16	HEN 99	Industrial	LCC of pumps with statistical measurements of failures
17	HIN 11	Industrial	Optimization of Substation Maintenance Strategy for LCC reduction using genetic Algorithm
18	HON 07	Buildings	Software for calculation of LCC of FRP bridge deck panels, Montecarlo simulation for uncertainty
19	JEO 02	Energy	Comparison between fuel cell and fuel cell hybrid vehicles in different scenarios
20	KAV 11	Buildings	Multiobjective optimization of LCC and initial costs (material weight) of large steel structures with genetic algorithm (NSGA II)
21	KIM 09	Buildings	Software for calculation of LCC of structures of light rail transit infrastructure, Montecarlo simulation for uncertainty
22	KUM 01	Marine	Comparison between 2 typologies of painting of ship in different scenarios
23	KUM 09	Energy/Buildings	Comparison of solar still with different scenarios
24	LEE 09	Energy	Comparison between Hydrogen and other fuels with sensitivity analysis
25	LIU 09	General	Estimation of LCC with Regression Models
26	MAR 11	Energy/Buildings	Comparison of different photovoltaic panel in vary scenarios with sensitivity analysis
27	MOR 11	Buildings	Comparison of residential buildings with sensitivity analysis, LCC is calculated as NPV
28	OKA 09	Buildings	Multiobjective optimization of structural maintenance considering LCC, redundancy and sistem reliability with genetic algorithm (NSGA II)
29	SAR 02	Buildings	LCC optimization for steel structures with Fuzzy Logic (Multiobjective)
30	SEO 02	General	Estimation of LCC with Artificial Neural Network
31	SEO 06	Industrial	Estimation of eletronic products' LCC with Artificial Neural Network, genetic algorithm for train ANN model (e.g. irrilevant factors, hidden nodes, weights, ecc.)
32	SIL 11	Energy	Comparison between different type of Biodiesel and Diesel (in LCC environmental cost too)
33	SOR 11	Energy	Comparison between ethanol and gasoline in different scenarios
34	VAL 08	Energy/Buildings	Software (simulation) for calculation of LCC (as Life Cycle Savings) of FRP based solar parabolic trough collector hot water generation system
35	VEN 09	Energy/Consumer Goods	Comparison of refrigerators in Brazil with sensitivity analysis
36	WAN 09	Consumer Goods	Optimization of LCC of Personal Computers with particle swarm optimization and comparison with genetic algorithm
37	WON 03	Buildings	Comparison between green roofs and conventional roofs
38	WON 08	Aerospace	Software based on discrete event simulation for calculation of LCC of Aero-engine maintenance
39	XU 08	Aerospace	Software for calculation of LCC of Aircraft systems

#	Paper Code	Eventual method used	Brief Comments
1	AKT 06		Application of LCC methodology and comparison with different scenarios
2	ARP 06		Application of LCC methodology and comparison with different scenarios
3	BAQ 11		Application of LCC methodology and comparison with different scenarios and sensitivity analysis
4	BUT 10		Application of LCC methodology, comparison and sensitivity analysis
5	CAN 02		Application of LCC methodology, comparison and sensitivity analysis
6	CAT 09	Linear Programming	Optimization of LCC, but no explain on the replications
7	CHE 06	Artificial Neural Network	Not optimization but only estimation of LCC
8	CIE 08		Only application of LCC methodology
9	FLE 07	Montecarlo Simulation	Not optimization but only estimation of LCC
10	FOL 10		Application of LCC methodology, comparison and sensitivity analysis
11	FRA 06	Genetic Algorithm	Optimization of LCC, but no data to test the model
12	GIT 08	Genetic Algorithm	Optimization of LCC, but no data to test the model
13	GOE 07		Application of LCC methodology and comparison
14	GUS 02	Software	LCC calculation,comparison and robustness but not LCC optimization
15	HEL 07		Application of LCC methodology and comparison with different scenarios
16	HEN 99		Application of LCC methodology with statistical measurements
17	HIN 11	Genetic Algorithm	Optimization of LCC, but no data and no explained model
18	HON 07	Software	LCC calculation,comparison and robustness but not LCC optimization
19	JEO 02		Application of LCC methodology and comparison with different scenarios
20	KAV 11	Genetic Algorithm (NSGA II)	Optimization of LCC, but no data and no constraints to test the model
21	KIM 09	Software	LCC calculation,comparison and robustness but not LCC optimization
22	KUM 01		Application of LCC methodology and comparison with different scenarios
23	KUM 09		Application of LCC methodology and comparison with different scenarios
24	LEE 09		Application of LCC methodology, comparison and sensitivity analysis
25	LIU 09	Regression Models	Not optimization but only estimation of LCC
26	MAR 11		Application of LCC methodology and comparison with different scenarios and sensitivity analysis
27	MOR 11		Application of LCC methodology as NPV, comparison and sensitivity analysis
28	OKA 09	Genetic Algorithm (NSGA II)	Optimization of LCC, but no data to test the model
29	SAR 02	Fuzzy Logic multicriteria(discrete)	Optimization of LCC, but no data to test the model
30	SEO 02	Artificial Neural Network	Not optimization but only estimation of LCC
31	SEO 06	Artificial Neural Network	Not optimization but only estimation of LCC
32	SIL 11		Application of LCC methodology and comparison
33	SOR 11		Application of LCC methodology and comparison with different scenarios
34	VAL 08	Software	LCC calculation,comparison and robustness but not LCC optimization
35	VEN 09		Application of LCC methodology, comparison and sensitivity analysis
36	WAN 09	Particle Swarm Optimization	Optimization of LCC, but the model is not explain
37	WON 03		Application of LCC methodology and comparison
38	WON 08	Software	LCC calculation,comparison and robustness but not LCC optimization
39	XU 08	Software	LCC calculation,comparison and robustness but not LCC optimization

SOTA LCA

#	Paper Code	Field of Application	Brief Description
1	ALL 07	Energy/Transport	Comparison of diesel, natural gas and hydrogen fuel cell with scenario analysis
2	ARD 08	Energy	LCA of an Italian wind farm
3	AZA 95	Chemical	Optimization of LCA of a thermoplastic plant by linear programming (LP)
4	AZA 98	Chemical	Multiobjective optimization of total production, cost and LCA of a chemical plant by linear programming (LP)
5	BEC 10	Food	Comparison of Italian citrus based products
6	BOV 07	Buildings	Comparison of refrigerants in refrigeration systems in different scenarios
7	BRE 01	Agriculture	Comparison of different nitrogen fertilisers
8	DAI 05	Transport	Comparison of motor bike and electric bike by hybrid model (PLCA and EIOLCA) (LCE also)
9	DAS 11	Industrial	Comparison of different carbon fiber-reinforced polymer composites in vary scenarios
10	DAV 08	Food	Comparison of two chicken meals in two scenarios
11	DOB 11	Food	Comparison of packaging systems in two scenarios
12	DUF 11	Energy	Multiobjective optimization of LCA (as Life Cycle Emissions) and cost of stand-alone PV-wind-diesel systems with batteries storage by HOGA (Hybrid Optimization by Genetic Algorithm) (based on SPEA and SPEA2)
13	EID 02	Food	Comparison of Industrial milk production due to the size and degree of automation of a dairy
14	EKM 11	Industrial	Comparison of oil hydraulic fluids with sensitivity analysis
15	GOR 02	Buildings	Comparison of different linoleums in vary scenarios
16	HAL 08	Energy	Comparison of fuels (fossil fuels and biofuels)
17	HUS 07	Automotive	Comparison of automobile technologies
18	JUN 05	Energy	Comparison of Photovoltaic plants in two scenarios and Wind Power plants
19	KIM 01	Consumer Goods	LCA of Color Computer Monitor with scenario analysis
20	KIM 09	Chemical	Comparison of enzymes production systems (uncertainty and sensitivity analysis with Monte Carlo)
21	KOO 08	Energy	Comparison of pulverized coal power plants with sensitivity analysis
22	KOR 05	Energy	LCA of Kerosene
23	KOR 10	Energy	Multiobjective optimization of LCA and NPV (Net Present Value) of photovoltaic grid-connected systems by MOPSO (Multiobjective Particle Swarm Optimization)
24	LO 05	Waste	Comparison of waste treatments. Uncertainty reduced by Bayesan Monte Carlo method
25	MAN 06	Energy	Comparison of mining methods
26	MCC 02	Transport	Comparison of electrics and internal combustion Vehicles (uncertainty and sensitivity analysis with Monte Carlo)
27	MEY 11	Consumer Goods	Comparison of socks
28	MIL 06	Agriculture	Comparison of apple production processes
29	MOB 10	Consumer Goods	Comparison of printed and tablet e-paper newspaper in two scenarios
30	MUN 06	Energy	Comparison of two solar-driven advanced oxidation processes
31	NTI 08	Agriculture	Comparison of Cocoa production process in different scenarios
32	PER 07	Energy	LCA of District Heat Distribution in two scenarios
33	PHU 09	Energy	LCA of natural gas power plants in Thailand
34	PUR 09	Automotive	Comparison of Australian automotive door skins
35	RAF 99	Energy	Comparison of electricity production from biomass and fossil fuel
36	RIB 07	Automotive	Comparison of a Multi-Material Car Component with sensitivity analysis
37	SCH 10	Energy	Comparison of rapeseed and palm oil in different scenarios
38	SEO 07	Industrial	Estimation of eletronic products' and automobiles' LCA with Artificial Neural Network, genetic algorithm for train ANN model (e.g. irrilevant factors, hidden nodes, weights, ecc.)
39	SUW 11	Energy	Comparison of mini-hydropower plants in Thailand
40	ZUF 08	Food	Comparison of industrial cooked dish methods

#	Paper Code	Eventual method used	Comments
1	ALL 07	GaBi Software	Application of LCA methodology and comparison with different scenarios
2	ARD 08		Only application of LCA methodology
3	AZA 95	Linear Programming (LP)	Optimization of LCA, but the model is not explain
4	AZA 98	Linear Programming (LP)	Optimization of LCA, but the model is not explain
5	BEC 10	SimaPro Software + GaBi Software	Application of LCA methodology and comparison
6	BOV 07	SimaPro Software	Application of LCA methodology and comparison with different scenarios
7	BRE 01		Application of LCA methodology and comparison
8	DAI 05	Hybrid (PLCA+EIOLCA) LCA model in software	Application of LCA (LCE also) methodology and comparison
9	DAS 11	SimaPro Software	Application of LCA methodology and comparison with different scenarios
10	DAV 08		Application of LCA methodology and comparison with different scenarios
11	DOB 11		Application of LCA methodology and comparison with different scenarios
12	DUF 11	Genetic Algorithm (based on SPEA and SPEA2)	Optimization of LCA, but the model is not explain
13	EID 02	LCAiT Software	Application of LCA methodology and comparison
14	EKM 11		Application of LCA methodology and comparison with sensitivity analysis
15	GOR 02		Application of LCA methodology and comparison with different scenarios
16	HAL 08	SimaPro Software	Application of LCA methodology and comparison
17	HUS 07		Application of LCA methodology and comparison
18	JUN 05		Application of LCA methodology and comparison with different scenarios
19	KIM 01	LCAiT Software	Application of LCA methodology with different scenarios
20	KIM 09		Application of LCA methodology and comparison with sensitivity analysis
21	KOO 08	SimaPro Software	Application of LCA methodology and comparison with sensitivity analysis
22	KOR 05		Only application of LCA methodology
23	KOR 10	Particle Swarm Optimization	Optimization of LCA, but the model is not explain
24	LO 05		Application of LCA methodology and comparison
25	MAN 06		Application of LCA methodology and comparison
26	MCC 02		Application of LCA methodology and comparison with sensitivity analysis
27	MEY 11	SimaPro Software	Application of LCA methodology and comparison
28	MIL 06		Application of LCA methodology and comparison
29	MOB 10	GaBi Software	Application of LCA methodology and comparison with different scenarios
30	MUN 06	SimaPro Software	Application of LCA methodology and comparison
31	NTI 08	GaBi Software	Application of LCA methodology and comparison with different scenarios
32	PER 07	LCAiT Software	Application of LCA methodology with different scenarios
33	PHU 09		Only application of LCA methodology
34	PUR 09	SimaPro Software	Application of LCA methodology and comparison
35	RAF 99		Application of LCA methodology and comparison
36	RIB 07	SimaPro Software	Application of LCA methodology and comparison with sensitivity analysis
37	SCH 10	SimaPro Software	Application of LCA methodology and comparison with different scenarios
38	SEO 07	Artificial Neural Network	Not optimization but only estimation of LCA
39	SUW 11		Application of LCA methodology and comparison
40	ZUF 08	DEAM Software	Application of LCA methodology and comparison

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