Multiple Objective Decision Analysis Multiple-Objective Optimization

Susana Barreiro

20, 22, 25 May 2020

- We have assumed so far that **linear programming** encompasses a **single overriding objective** (e.g. maximizing total profit / minimizing total cost).
- Most times this is not realistic since we frequently focus on a variety of objectives, e.g. forest management:
 - to maintain stable profit,
 - increase wood production,
 - diversify ecosystem services,
 - restrain the impact of pests /diseases,
 - minimize erosion,

Goal programming provides a way of achieving several objectives *simultaneously*.

representing some goals by constraints in effect gives them priority over the goal reflected in the objective function, because the objective function is optimized within the feasible region defined by the constraints

• ...

- Representing some goals by constraints in effect gives them priority over the goal reflected in the objective function, because the objective function is optimized within the feasible region defined by the constraints
- Deciding which goal should be selected as the objective function and which ones should be reflected by constraints is often arbitrary and difficult
- Goal programming attempts to overcome these limitations still while using linear programming, striving toward selected objectives simultaneously, treating them all in the same manner, although perhaps giving them different weights.

- Decision makers try to balance multiple objectives (e.g., cost, performance, reliability) none of which is obviously the best
- Multiple Objective Decision Analysis (MODA) is an operations research technique for evaluating a decision under multiple, sometimes competing and conflicting objectives or criteria.
- MODA provides a process that systematically identifies alternatives and the decision maker's objectives that serves as the measuring device for selecting the preferred alternative given the decision space.
- Multi-objective optimization leads to a set of optimal solutions because no solution can be considered better than any other regarding all the objectings. These solutions are known as Pareto-optimal solutions

Single objective

Selecting the eucalyptus clone with the highest volume production

Might lead to having:

- Frost sensitiveness
- Low re-sprouting ability
- Medium fiber quality
- Moderate resistance to defoliation
- Production cost

Multi-objective

We may want to optimize with the following objectives

- Volume production
- Frost resistance
- Re-sprouting ability
- Fiber quality
- Resistance to defoliation
- Production cost

Single objective

Selecting the eucalyptus clone with the highest volume production

Might lead to having:

- Frost sensitiveness
- Low re-sprouting ability
- Medium fiber quality
- Moderate resistance to defoliation
- Production cost

Multi-objective

We may want to optimize with the following objectives

- Volume production (obj. 1)
- Frost resistance (obj. 2)
- Re-sprouting ability (obj. 3)
- Fiber quality (obj. 4)
- Resistance to defoliation (obj. 5)
- Production cost (obj. 6)

Each solution will have 6 objective values indicating which



This poses several difficulties but the most significant is how we decide which solution is better than another?

Multi-objective

We may want to optimize with the following objectives

- Volume production (obj. 1)
- Frost resistance (obj. 2)
- Re-sprouting ability (obj. 3)
- Fiber quality (obj. 4)
- Resistance to defoliation (obj. 5)
- Production cost (obj. 6)

Multi-objective optimization problems with a number of equality and inequality constraints can be formulated as:

Minimize / Maximize $f_i(x)$ i = 1,..., N_{obi} – number of objective functions

Subject to:

a set of constraints

To simplify the solution process, in optimization problems with a number of objective functions, additional objective functions are usually handled as constraints

HOWEVER, the final solutions can be satisfying those constraints they cannot be called optimal with respect to all the objective functions.

How do we carry out multi-objective optimization for more than 2 variables?

We can use evolutionary optimization algorithms

- suitable to solve multi-objective optimization problems dealing with a set of possible solutions simultaneously.
- A single run enables finding several elements of the Pareto-optimal set
- Less susceptible to the shape or continuity of the Pareto-front dealing with discontinuous or concave Pareto fronts

There are **non-Pareto** and **Pareto** techniques for multi-objective optimization using evolutionary optimization (e.g. genetic algorithm, simulated annealing, PSO methods

Evolutionary Optimization Algorithms Non-Pareto techniques

- Approaches that do not incorporate directly the concept of **Pareto-optimum**
- Unable to reproduce certain portions of the Pareto front
- Efficient and easy to implement, but appropriate to handle only a few objectives

Pareto techniques

- Use of non-dominanted ranking and selection to move the population towards the Pareto front
- Require a ranking procedure and a technique to maintain diversity in the population

Assume we have a set of <u>feasible solutions</u> and <u>different objective functions</u>

The **Pareto-improvement** concept consists in moving from one feasible solution to another so that

- At least one objective function returns a better value
- And **no other** objective function becomes **worse**

When no further **Pareto-improvement** can be achieved the **Pareto-optimal** has been reached

Single objective obj. - volume production

Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clone	Clara	volume		Clana	volume
	(m ³ ha ⁻¹)		Cione	(m ³ ha ⁻¹)	
	А	130		А	130
	В	78		В	103
	С	109		С	109
	D	97		D	97
	E	115		Е	120

Clana	volume	frost		Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance		Cione	(m ³ ha ⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		Е	120	2.7

Let us plot the objective space:



Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

	volume	frost		Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance		Cione	(m ³ ha ⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		Е	120	2.7

Let us plot the objective space:



Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

	volume	frost		Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance		Cione	(m ³ ha ⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		Е	120	2.7

Let us plot the objective space:



Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clana	volume	frost	Clone		volume	frost
CIONE	(m ³ ha ⁻¹)	resitance			(m ³ ha ⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		E	120	2.7

Let us plot the objective space:



Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clana	volume	frost		Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance	Cione	(m ³ ha ⁻¹)	resitance	
Α	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		E	120	2.7

Let us plot the objective space:



We can get rid of solution C because it does not offer us anything solution E can not, thus we can say solution C is dominated by solution E

Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Classe	volume	frost		Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance	Cione		(m ^³ ha⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		Е	120	2.7

Let us plot the objective space:



We can get rid of solution C because it does not offer us anything solution A can not, thus we can say solution C is dominated by solution A

Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clana	volume	frost	Clone		volume	frost
cione	(m ³ ha ⁻¹)	resitance			(m ³ ha ⁻¹)	resitance
А	130	2.3		А	130	2.3
В	103	3.7		В	103	3.7
С	109	2		С	109	2
D	97	4.4		D	97	4.4
Е	120	2.7		Е	120	2.7

Let us plot the objective space:

After shading all the areas we can see that no solutions are inside the shaded area, thus all remaining solutions are non dominated



Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance
Α	130	2.3
В	103	3.7
D	97	4.4
E	120	2.7

Let us plot the objective space:

After shading all the areas we can see that no solutions are inside the shaded area, thus all remaining solutions are non dominated



So, which of these solutions is the best?

Multi-objective obj. 1 - volume production obj. 2 - Frost resistance

Clana	volume	frost	
Cione	(m ³ ha ⁻¹)	resitance	
А	130	2.3	
В	103	3.7	
D	97	4.4	
E	120	2.7	

Because no solution dominates another, no solution is completely better than the other UNLESS we have some additional information about the decision makers preferences... We may know he does not want frost resistance < 2.5

Let us plot the objective space:

After shading all the areas we can see that no solutions are inside the shaded area, thus all remaining solutions are non dominated



Multi-objective

Because no solution dominates another, no solution is completely better than the other UNLESS we have some additional information about the decision makers preferences... We may know he does not want frost resistance < 2.5

Clana	volume	frost
Cione	(m ³ ha ⁻¹)	resitance
А	130	2.3
В	103	3.7
D	97	4.4
E	120	2.7

There are several ways to reduce the number of solutions, but this still DOES NOT tell you which is best

So, which of these solutions is the best?

Challenges: Selecting the best solution,







How we visualize the objective space is not complicated for 2 variables, but for 3 it gets difficult to see which solutions are dominated and for 4...

Evolutionary Optimization Algorithms

Non-Pareto techniques

- Aggregating approaches
- Vector evaluated genetic algorithm (VEGA)
- Lexicographic ordering
- Target vector approaches

Pareto techniques

- Multi-objective genetic algorithm (MOGA)
- Non-dominated sorting genetic algorithm-II (NSGA-II)
- Multi-objective particle swarm optimization (MOPSO)
- Strength Pareto evolutionary algorithm (SPEA-II)

Evolutionary Optimization Algorithms

Non-Pareto techniques

- Aggregating approaches
- Vector evaluated genetic algorithm (VEGA)
- Lexicographic ordering
- Target vector approaches

Pareto techniques

- Multi-objective genetic algorithm (MOGA)
- Non-dominated sorting genetic algorithm-II (NSGA-II)
- Multi-objective particle swarm optimization (MOPSO)
- Strength Pareto evolutionary algorithm (SPEA-II)

Non-dominated sorting genetic algorithm-II (NSGA-II)

This method was proposed by Deb et al. in 2000

Key features:

- Emphasizes non-dominated sorting
- Uses a diversity preserving mechanism
- Performs crowding comparison
- Uses elitist principle: some parents go directly to the next generation based on the above mentioned conditions

Non-dominated sorting genetic algorithm-II (NSGA-II)

The algorithm uses an **evolutionary process** including selection, genetic crossover, and genetic mutation. (In the following example we will skip this part)

The population of solutions is sorted into a hierarchy of sub-populations based on the ordering of Pareto dominance.

Similarity between members of each sub-group is evaluated on the Paretofront

Similarity measures are used to promote a diverse front of non-dominated solutions.

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



A&B

A is <u>better</u> in terms of time, but B is better in terms of cost

THUS, A&B are a **non-dominated** set

Minimize Time & Minimize Cost

soil preparation	Time spent (hours)	Cost (100€)
A	2	7.5
В	3	6
C	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
I	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



A&B

A is <u>better</u> in terms of time, but B is <u>better</u> in terms of cost

THUS, A&B are a **non-dominated** set

A&C

A is <u>better</u> in terms of time, butC is <u>equally good</u> in terms of cost

THUS, A dominates C

... (see Excel)

Minimize Time & Minimize Cost

soil preparation	Time spent (hours)	Cost (100€)
A	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
I	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



A dominates C B dominates C, E, G, H, I D dominates E, G, H, I F dominates G, H, I

THUS

A, B, D, F form a non-dominated set

A, B, D, F form the Pareto-optimal front

Minimize Time & Minimize Cost

soil preparation	Time spent (hours)	Cost (100€)
A	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



The line is the Pareto-optimal front and the solutions in it are called the Pareto-optimal

Solutions along the line are non-dominated

All **Pareto-optimal** solutions are non-dominated

soil preparation	Time spent (hours)	Cost (100€)
А	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



If we repeat the comparison procedure leaving A, B, D and F out we conclude C, E and G form a **nondominated** set

Pareto-opt	imal front	2 Rank 2

Pareto-optimal front 1 Rank 1

soil preparation	Time spent (hours)	Cost (100€)
А	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
H	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) non-dominated sorting



Pareto-optimal f	Front 3 Rank 3
------------------	----------------

	Pareto-opti	mal front	2 Ran	k 2
--	-------------	-----------	-------	-----

Pareto-optimal front 1 Rank 1

When selecting Rank 1 has priority over 2 and 2 over 3, etc

soil preparation	Time spent (hours)	Cost (100€)
А	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) Population diversity and crowding



How to choose solutions in the same Pareto-optimal front ?

If we had to **choose 3 out of 4**, which would we choose?

We have to ensure population diversity so choosing solutions along the font will serve the purpose

A and F being at the extremes will be chosen, but we have to decide among B and D

soil preparation	Time spent (hours)	Cost (100€)
А	2	7.5
В	3	6
С	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Pareto-optimal front 1 Rank 1

Non-dominated sorting genetic algorithm-II (NSGA-II) Population diversity and crowd distance (CD)



1) Sort all the solutions in the Pareto front in ascending order for each objective $(f_m(x_{i+1}) > f_m(x_{i-1}))$ and compute CD:

$$CD_{im} = \frac{(f_m(x_{i+1}) - f_m(x_{i-1}))}{(f_m(x_{max}) - f_m(x_{min}))}$$

2) Repeat the process for each objective, the distance will result of the sum of the CD for all options/solutions

Pareto-optimal front 1

$$CD_i = \sum_{m=1}^M CD_{im}$$

3) Given 2 solutions, the one preferred is the one with the highest CD value

Where m is the number of objectives, I is the number of options/solutions in the Pareto-optimal front and f_m the values of each objective under each option

Non-dominated sorting genetic algorithm-II (NSGA-II) Population diversity and crowd distance (CD)



Pareto-optimal front 1

$$CD_{im} = \frac{\left(f_m(x_{i+1}) - f_m(x_{i-1})\right)}{\left(f_m(x_{max}) - f_m(x_{min})\right)}$$
$$(f_m(x_{i+1}) > f_m(x_{i-1}))$$

decide among B and D

Let us look at the crowding distance for B



 $CD_B (Cost) = (7.5 - 5) / (7.5 - 4.5) = 2.5/3 = 0.83$ $CD_B (Time) = (4 - 2) / (6 - 2) = 2/4 = 0.5$ $CD_B (Cost + Time) = 0.83 + 0.5 = 1.33$

soil preparation	Time spent (hours)	Cost (100€)
A	2	7.5
В	3	6
C	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) Population diversity and crowd distance (CD)



Pareto-optimal front 1

$$CD_{im} = \frac{\left(f_m(x_{i+1}) - f_m(x_{i-1})\right)}{\left(f_m(x_{max}) - f_m(x_{min})\right)}$$
$$(f_m(x_{i+1}) > f_m(x_{i-1}))$$

decide among B and D

Let us look at the crowding distance



$$CD_{D}$$
 (Cost) = (6 -4.5) / (7.5 -4.5) = 1.5/3 = 0.5
 CD_{D} (Time) = (5 -3) / (6 -2) = 2/4 = 0.5
 CD_{D} (Cost + Time) = 1.00

soil preparation	Time spent (hours)	Cost (100€)
A	2	7.5
В	3	6
C	3	7.5
D	4	5
E	4	6.5
F	5	4.5
G	5	6
Н	5	7
	6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II) Population diversity and crowd distance (CD)



Pareto-optimal front 1

decide among B and D

Let us look at the crowding distance

 $CD_B (Cost) = (7.5 - 5) / (7.5 - 4.5) = 2.5/3 = 0.83$ $CD_B (Time) = (4 - 2) / (6 - 2) = 2/4 = 0.5$ $CD_B (Cost + Time) = 0.83 + 0.5 = 1.33$

 CD_{D} (Cost) = (6 -4.5) / (7.5 -4.5) = 1.5/3 = 0.5 CD_{D} (Time) = (5 -3) / (6 -2) = 2/4 = 0.5 CD_{D} (Cost + Time) = 1.00

 $CD_A = CD_F = infinity$

 $CD_B = 1.33$, $CD_A = CD_F = infinity$

р	soil reparation	Time spent (hours)	Cost (100€)
	А	2	7.5
	В	3	6
	С	3	7.5
	D	4	5
	Е	4	6.5
	F	5	4.5
	G	5	6
	Н	5	7
		6	6.5

Non-dominated sorting genetic algorithm-II (NSGA-II)

- NSGA is an **extension** of the Genetic Algorithm for multiple objective function optimization.
- <u>Genetic algorithms</u> provide an alternative approach to optimization in the case of more complex problems:

- advantages - works well for problems with chaotic or ill-defined behavior and also those problems with local maxima or minima that would, perhaps, trap a conventional search algorithm; fitting several loops simultaneously

- disadvantages - its random nature may not always find the absolute optimum solution, but offers a greater chance of quickly finding a relatively good one.

Non-dominated sorting genetic algorithm-II (NSGA-II)

- NSGA is an **extension** of the Genetic Algorithm for multiple objective function optimization.
- <u>Genetic algorithms</u> provide an alternative approach to optimization in the case of more complex problems:

Requires

and

o a

optimum

natively good one.

- advantages - works well for problems with char also those problems with local maxima or minim conventional search algorithm; fitting several loo

implementation - disadvantages - its random nature may not always solution, but offers a greater chance of quickly findi

Addressing Multicriteria Forest Management With Pareto Frontier Methods: An Application in Portugal

Jose G. Borges, Jordi Garcia-Gonzalo, Vladimir Bushenkov, Marc E. McDill, Susete Marques, and Manuela M. Oliveira

The practice of multicriteria forest management planning is often complicated by the need to explicit a priori goals and preferences aims at describing an approach that may take advantage of a posteriori preference modeling to facilitate the specification of objectives in a typical forest management planning framework. The goal is to provide information about nondominated points i (FSCS) so that decisionmakers may take advantage of trade-off information. The emphasis is on demonstrating the potential o decisions when three or more criteria are considered. The approach combines the use of mathematical programming and interactiv how the estimation refinement method may be used to approximate the Pareto frontier of a typical model I linear programmin feasible goals method/interactive decision maps method may be used to retrieve a solution selected by stakeholders from interact frontier. Results are discussed for a large-scale test application encompassing over 1 million ha of cork and holm oak forest e

Keywords: forest management planning, cork oak, multiple criteria decisionmaking, Pareto frontier methods

The approach combines the use of mathematical programming and interactive decision maps techniques

(...)

The feasible goals method/interactive decision maps (FGM/IDM) technique is used to provide interactive and animated visualization of the Pareto frontier generated by the ERM

Conclusion: FGM/IDM technique may be used to develop and display the Pareto frontier in the case of problems with more than three forest management planning objectives

How do we carry out multi-objective optimization for more than 2 variables?

We can also use Multi Objective Linear Programming (MOLP)

Tradeoffs concept

Part of the challenge is in expressing the value trade-offs among the objectives.

These trade-offs indicate which objectives are relatively more important to the decision maker.

Which 2 objectives does a decision maker prefer: "decrease production costs" or "increase product quality"?

- Does he prefer them equally?
- Is one more important?
- How much more important is it?

Incorporating trade-offs into the decision-making process is valuable because it ensures decisions integrate the decision maker's values

Multi Objective Linear Programming

• Take the following example:

Untreated pulp and paper mill effluents are very toxic to most aquatic life, treatment can reduce toxicity but at a cost. Increasing profit usually leads to the production of more toxic waste. Ideally the mill managers will wish to maximize profit reducing toxic waste production.

The decision maker has to decide the most desirable level of trade-offs between profit and waste



Each point on the curve corresponds to a possible level of profit and the minimum amount of waste that must be produced to achieve it

Multi Objective Linear Programming

• Take the following example:

Untreated pulp and paper mill effluents are very toxic to most aquatic life, treatment can reduce toxicity but at a cost. Increasing profit usually leads to the production of more toxic waste. Ideally the mill managers will wish to maximize profit reducing toxic waste production.

The decision maker has to decide the most desirable level of trade-offs between profit and waste



Each point on the curve corresponds to a possible level of profit and the minimum amount of waste that must be produced to achieve it

Multi Objective Linear Programming



Decision makers should only want to consider decision alternatives that are non-dominanted.

MOLP guarantees the decisions presented to the decision maker are non-dominanted.

MOLP can be viewed as special types of GP problems where appart of solving the problem, we must also determine target values for each goal or objective.

Thus solving these problems also requires we use the minimization and maximization objectives described in previous classes.

Multi Objective Linear Programming

• Some ideas to form goal function:

Objective 1: Maximize profit (OF1) Objective 2: Minimize toxic waste production (OF2)

1st Goal Form:

Goal function = Max (OF1) and add OF2 as constraint

Produced hazards <= Max allowable

Multi Objective Linear Programming

• Some ideas to form goal function:

Objective 1: Maximize profit (OF1) Objective 2: Minimize toxic waste production (OF2)

2nd Goal Form:

Goal function = Max (OF1/OF2) or Goal function = Min (OF2/OF1)

Multi Objective Linear Programming

• Some ideas to form goal function:

Objective 1: Maximize profit (OF1) Objective 2: Minimize toxic waste production (OF2)

Absolut values are used to avoid the existence of big positive deviation in one OF to cancel big negative deviation in the other

3rd Goal Form (weighted normalized method):

Goal function = Min (W1 * abs (Actual OF1- Optimum OF1) / Optimum OF1) + W2 * abs (Actual OF2- Optimum OF2) / Optimum OF2)

Multi Objective Linear Programming

• Example:

Objective 1: Maximize profit (OF1) Objective 2: Minimize toxic waste production (OF2)

<u>3rd</u> Goal Form (weighted normalized method):

Goal function = Min (W1 * abs (Actual OF1- Optimum OF1) / Optimum OF1) + W2 * abs (Actual OF2- Optimum OF2) / Optimum OF2)

• Exercise 1

Blackstone Mining Company operates 2 coal mines Wythe and Giles. The manager is anticipating a demand increase for coal in the coming year and he wants to schedule extra shifts of workers to the mines. Each extra shift has an extra cost of 40000/month at Wythe and 32000/month at Giles.

The extraction methods lead to the production of toxic water. Running an extra shift at Wythe leads to the production of 800 gallons and 1250 gallons at Giles.

Despite safety guidelines are followed 0.2 life threatening accidents are expected at Wythe and 0.45

		Coal production month by a shift workers (ton)	duction a / a shift of rs (ton)	Increase in demand	Determine the number of extra shifts at each of the mines that
		Wythe	Giles	_	
	production of high-level coal	12	4	48	minimizes costs, toxic waste
	production of medium -level coal	4	4	28	production and life threatening accidents
	production of low -level coal	10	20	100	