



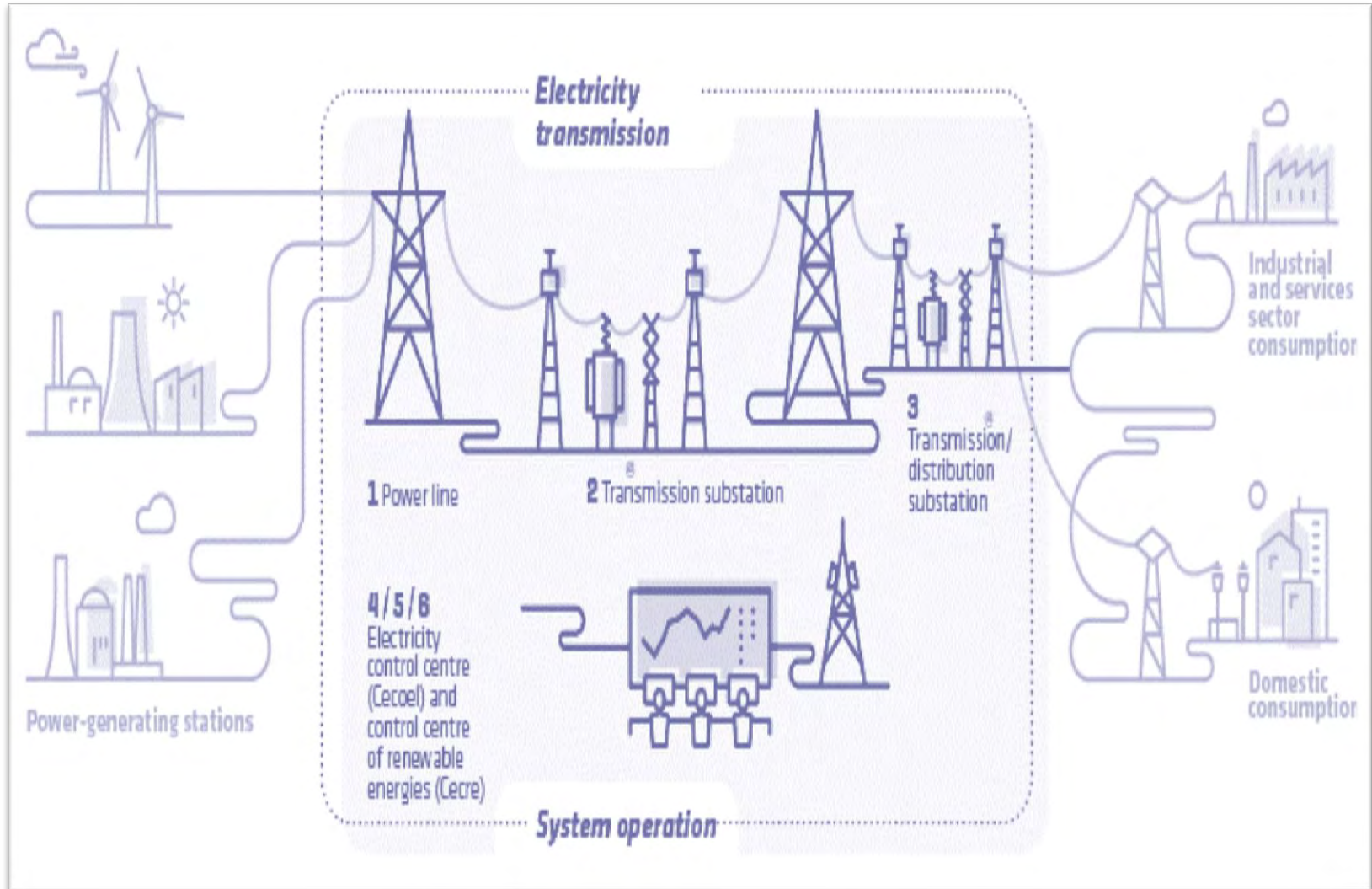
Le réseau
de transport
d'électricité

Grid operation-based outage maintenance planning

Ramón Álvarez-Valdés
Consuelo Parreño
Francisco Parreño



Electricity transmission system operator



POWER GENERATION

Nuclear

Wind

Off-shore wind

Fossil-fuelled

Photovoltaic solar

Hydro

IMPORT

ULTRA
HIGH VOLTAGE
lines

EXPORT

TRANSMISSION (RTE)

Substation

HIGH-VOLTAGE
Lines

Industrial
customers

HIGH-VOLTAGE
Lines

Railway
companies

Wind

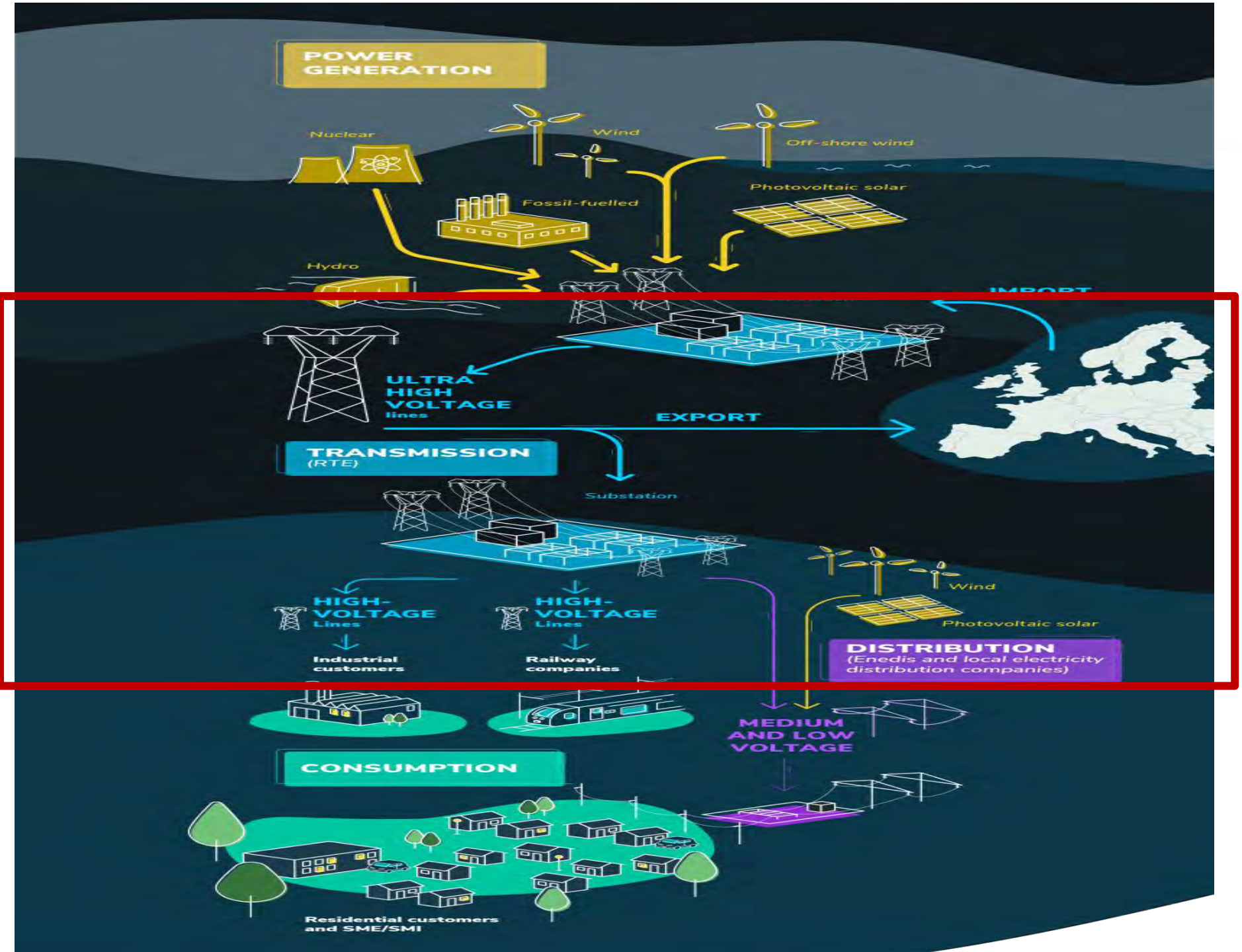
Photovoltaic solar

DISTRIBUTION
(Enedis and local electricity
distribution companies)

MEDIUM
AND LOW
VOLTAGE

CONSUMPTION

Residential customers
and SME/SMI



RTE: meeting the demand

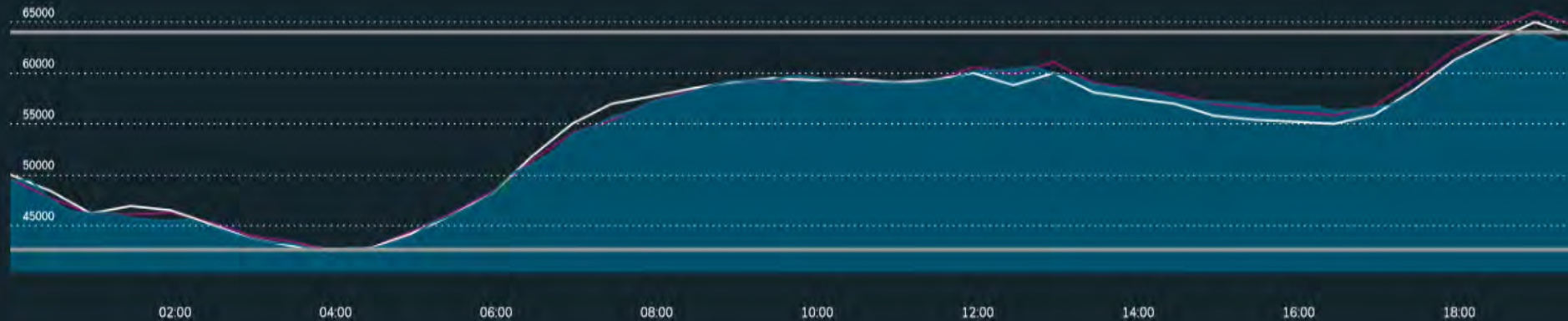
Rte

Real time electricity consumption in France

■ Actual power demand ● Day-ahead forecast ■ Intraday forecast

58545_{MW} **57800_{MW}** **58700_{MW}**

Real time data



LIVE

RTE key figures



106,047 km

of power lines, the
biggest grid in Europe



99.9994 %

power supply continuity



9,397

employees including 449
apprenticeships



4,729 M€

of revenue in 2020



35 M€

worth of investment
committed to R&D



87 %

customer satisfaction rate
in 2019

RTE maintenance



100 000 km

of overhead lines



5 000 km

of buried lines



280 000

electricity pylons



2783

substations



4 200

maintenance workers

RTE maintenance tasks

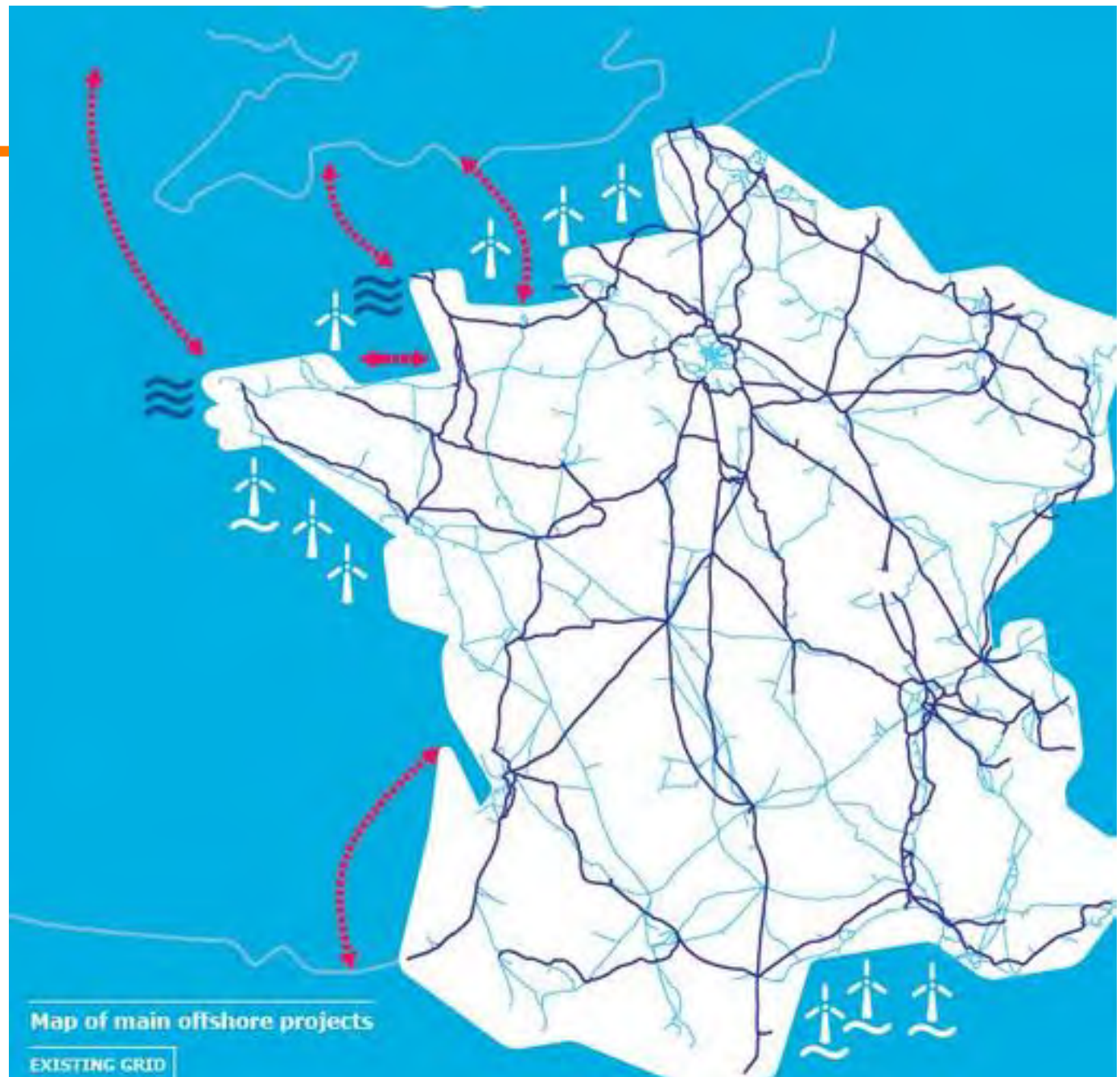


EST TRANSPORTÉE PAR LE RÉSEAU HAUTE
ET TRÈS HAUTE TENSION GÉRÉ PAR RTE.

RTE maintenance tasks



Network



Maintenance planning under uncertainty

The three- step approach of RTE:

- **RISK**

- Calculate the risk of each intervention under each scenario

- **PLAN**

- Assign interventions to periods minimizing a risk measure

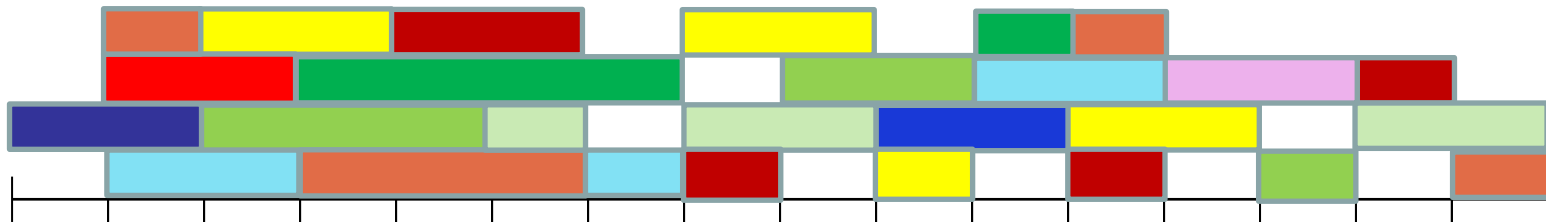
- **VALIDATE**

- Check is the plan is adequate

Planning the interventions

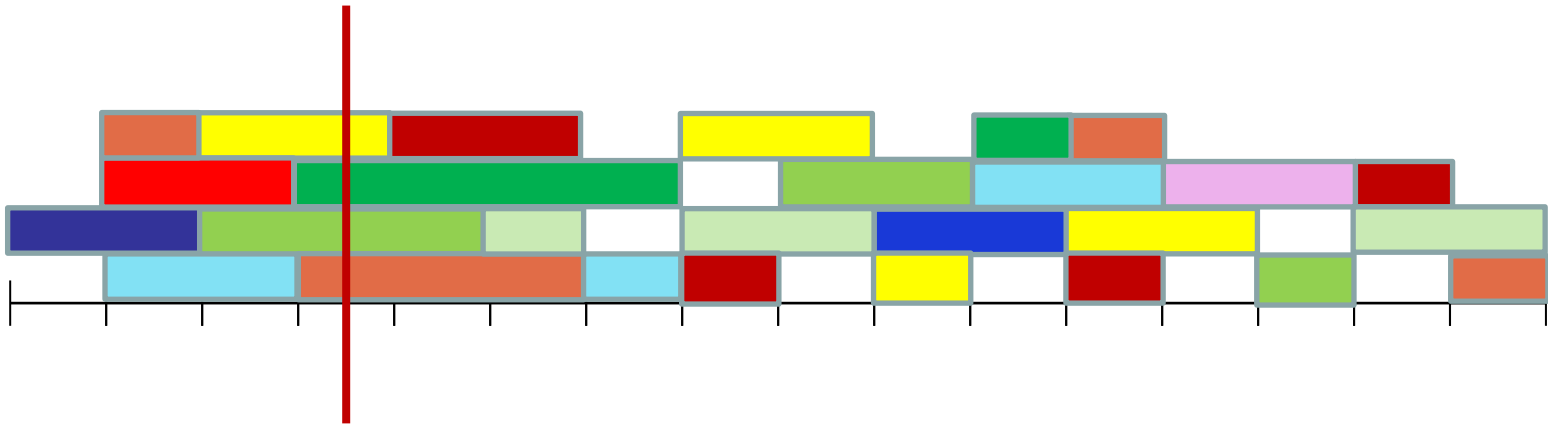
Interventions: tasks involving shutting down parts of the network

Assign interventions to periods in the planning horizon



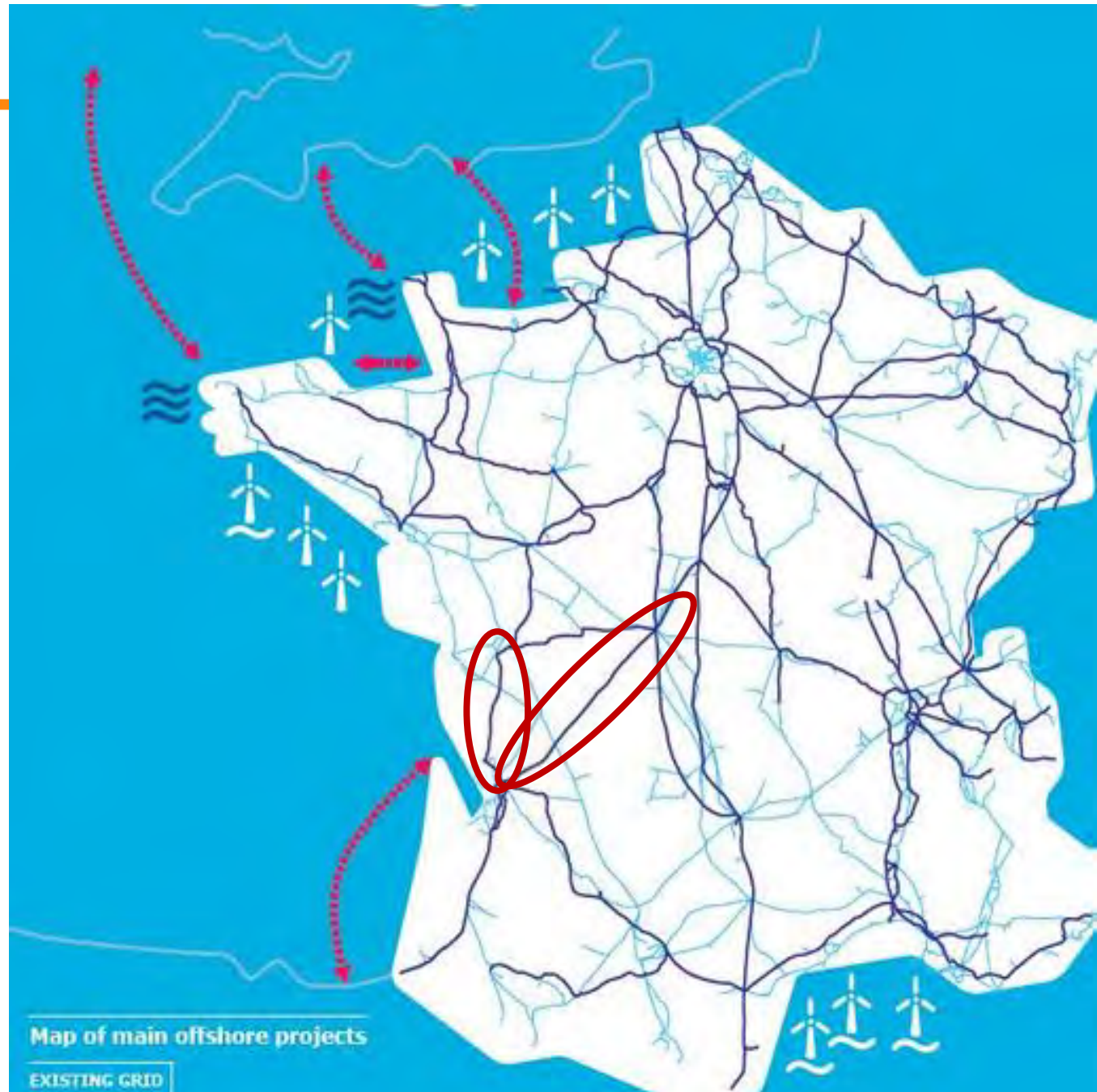
Constraints

- All interventions must be planned within the time horizon
- No-preemption: once started, the intervention cannot be interrupted
- Resource consumption: between the limits



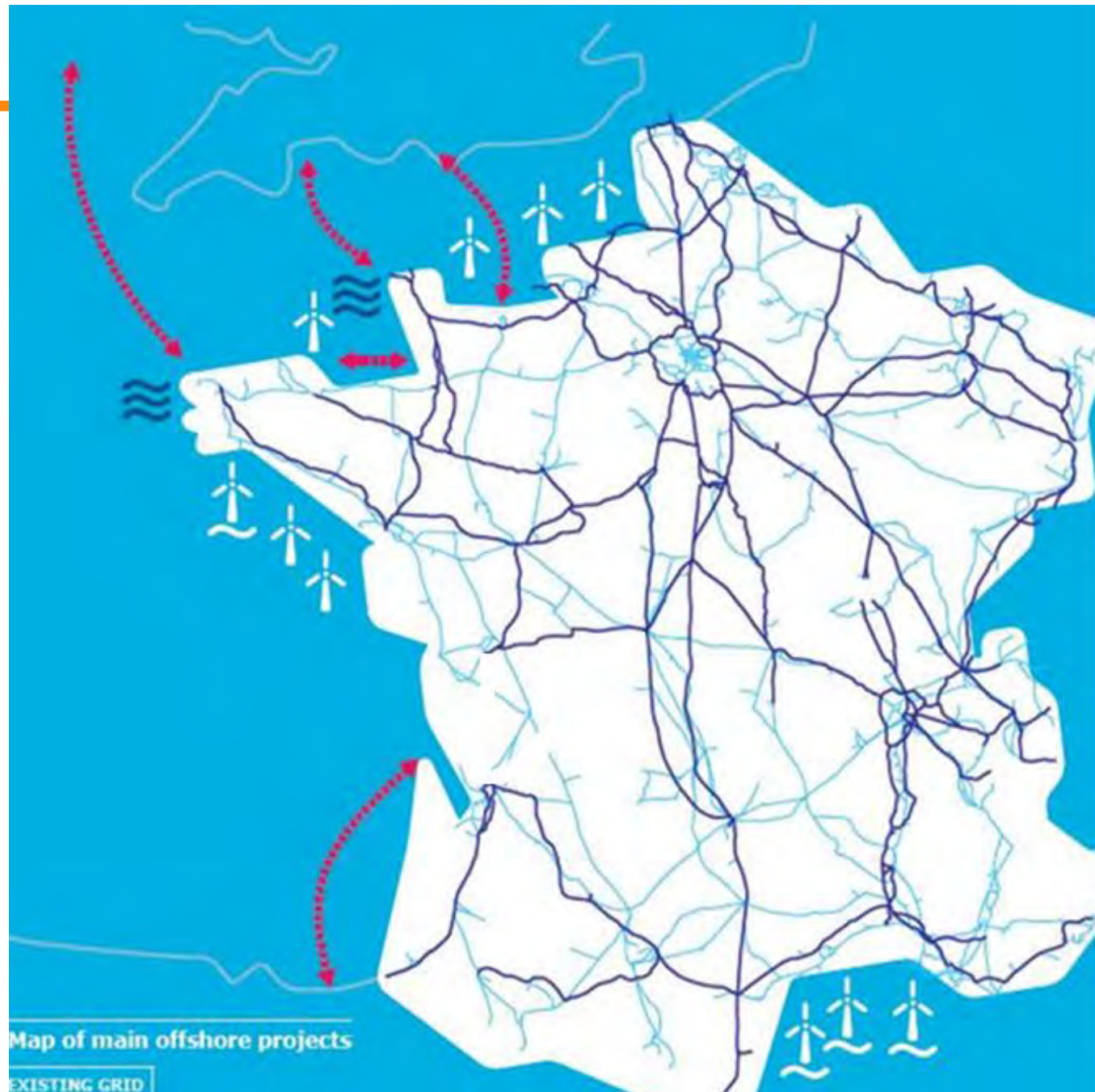
Exclusions

pairs of interventions
that cannot be done
simultaneously

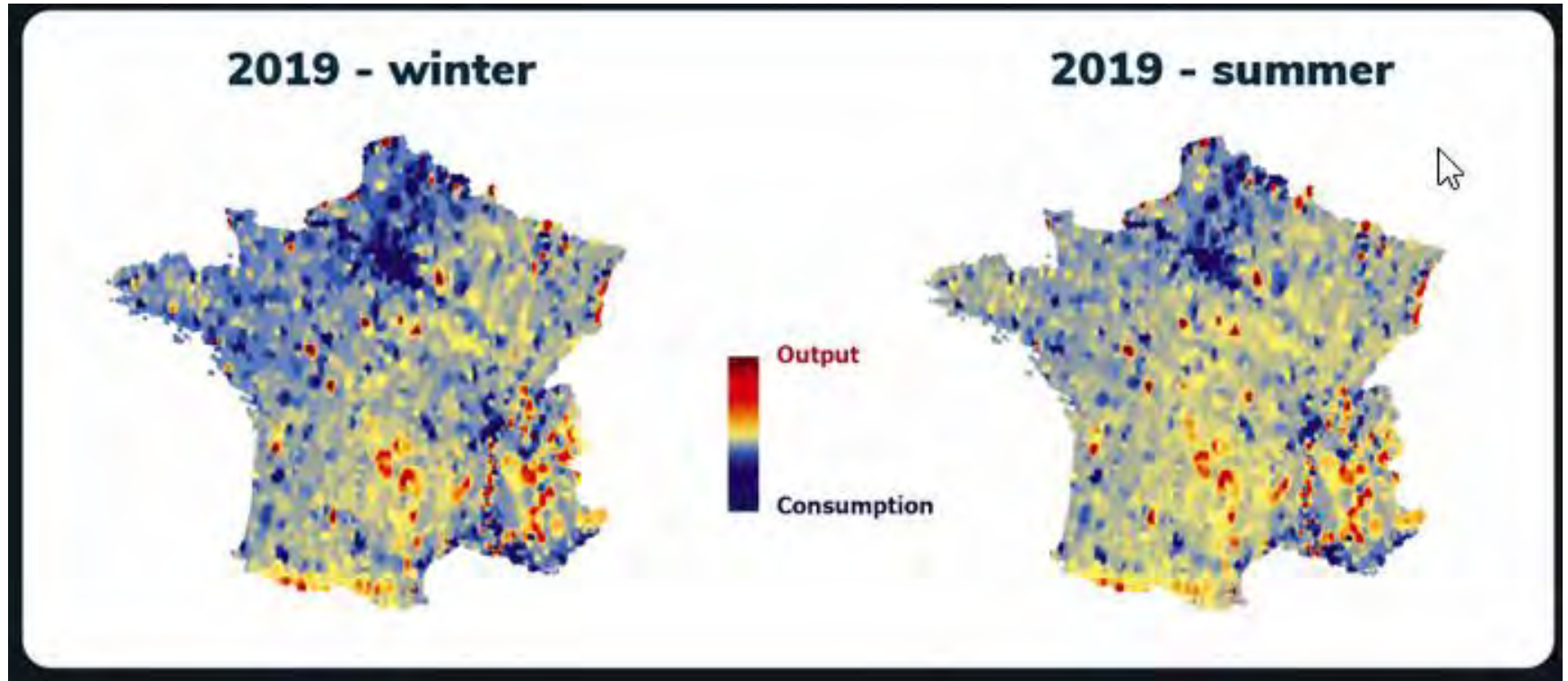


Exclusions

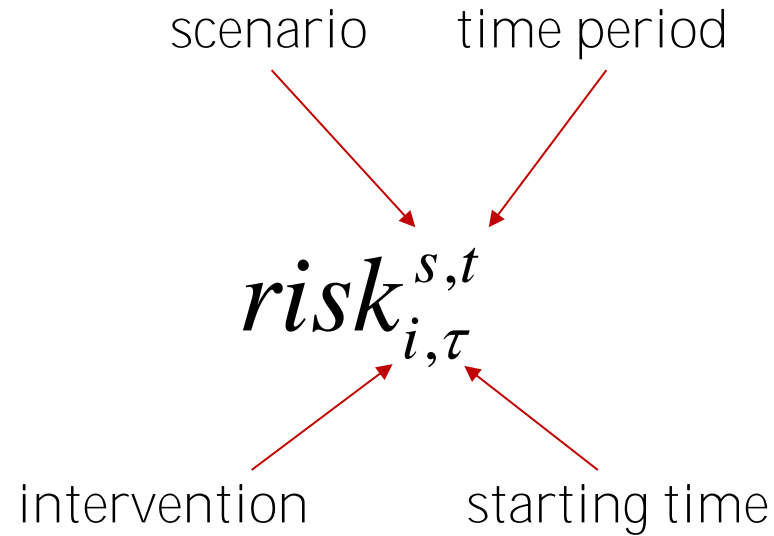
pairs of interventions
that cannot be done
simultaneously



Resources and exclusions depend on time



Measuring the risk



Mean risk cost

- Adding up all interventions in process at a given time t

$$risk^{s,t} = \sum_{i \in I_t} risk_{i,start_i}^{s,t}$$

- Taking the average over all the scenarios

$$\overline{risk}^t = \frac{1}{|S_t|} \sum_s risk^{s,t}$$

- Taking the average over all time periods: **Mean risk cost**

$$obj_1 = \frac{1}{T} \sum_t \overline{risk}^t$$

Expected excess

- Calculate the quantile of the risk distribution at a time t over the scenarios

$$Q_{\beta}^t = Q_{\beta} \left(\left\{ risk^{s,t} \right\}_{s \in S_t} \right) \quad (\text{for instance, } \beta = 90\%)$$

- Define the excess as the difference between quantile and average risks

$$Excess_{\beta}(t) = \max \left\{ 0, Q_{\beta}^t - risk^{s,t} \right\}$$

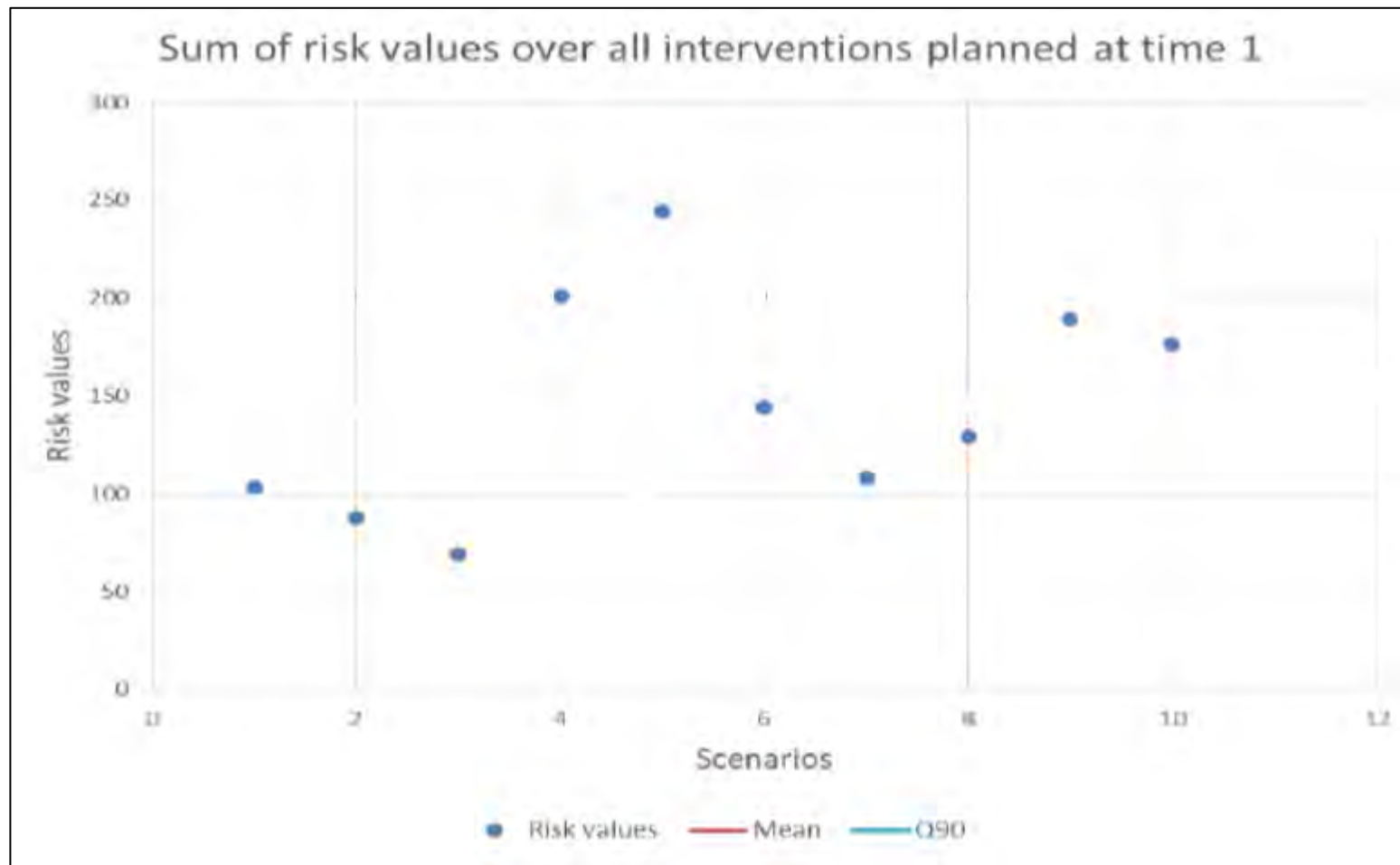
- Taking the average over all time periods: **Expected excess**

$$obj_2 = \frac{1}{T} \sum_t Excess_{\beta}(t)$$

(*quantile*: x is the smallest value such that $\Pr[X \leq x] \geq \beta$)

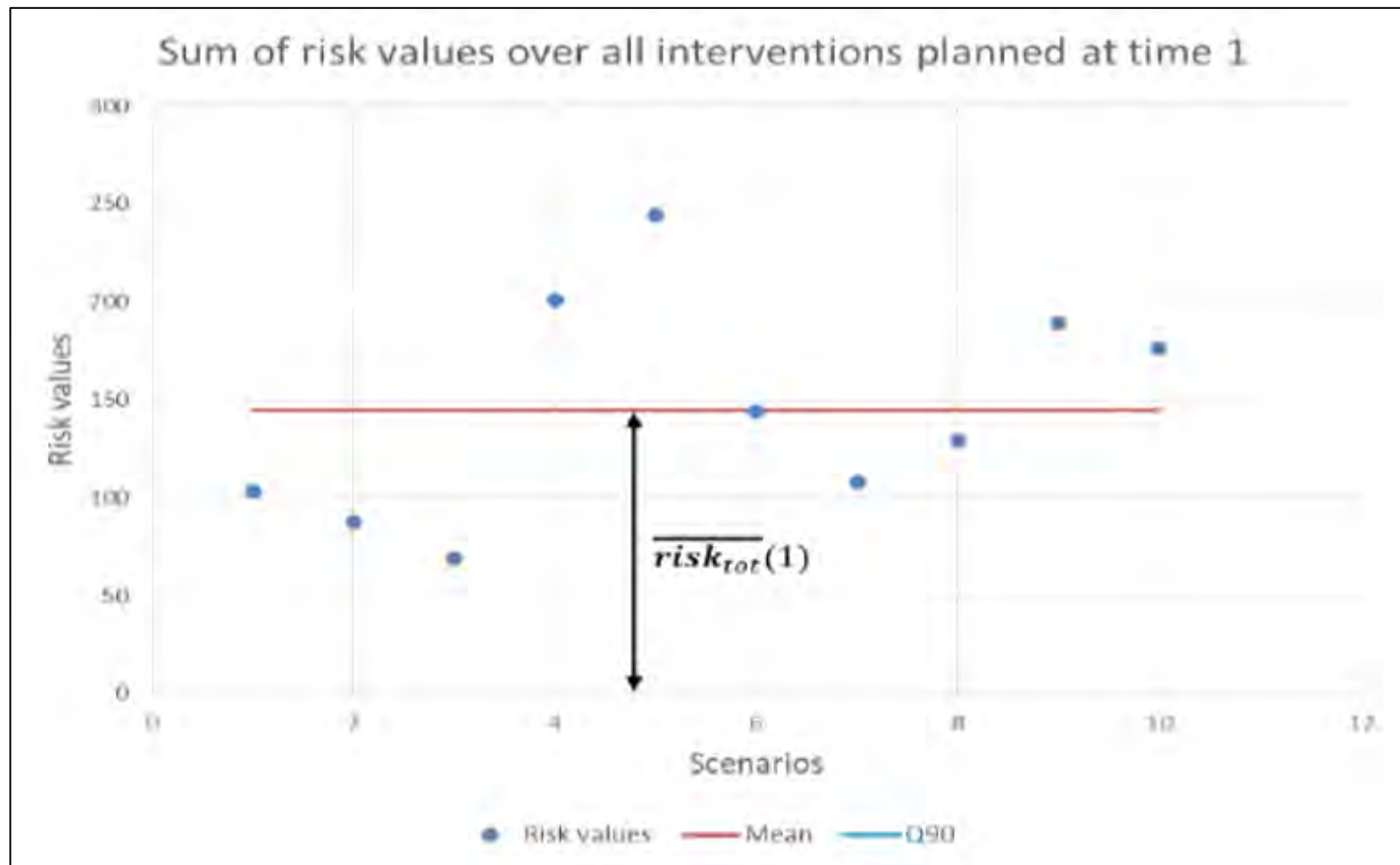
Explaining the excess

Time 1: 10 scenarios,
3 interventions whose risks are added for each scenario



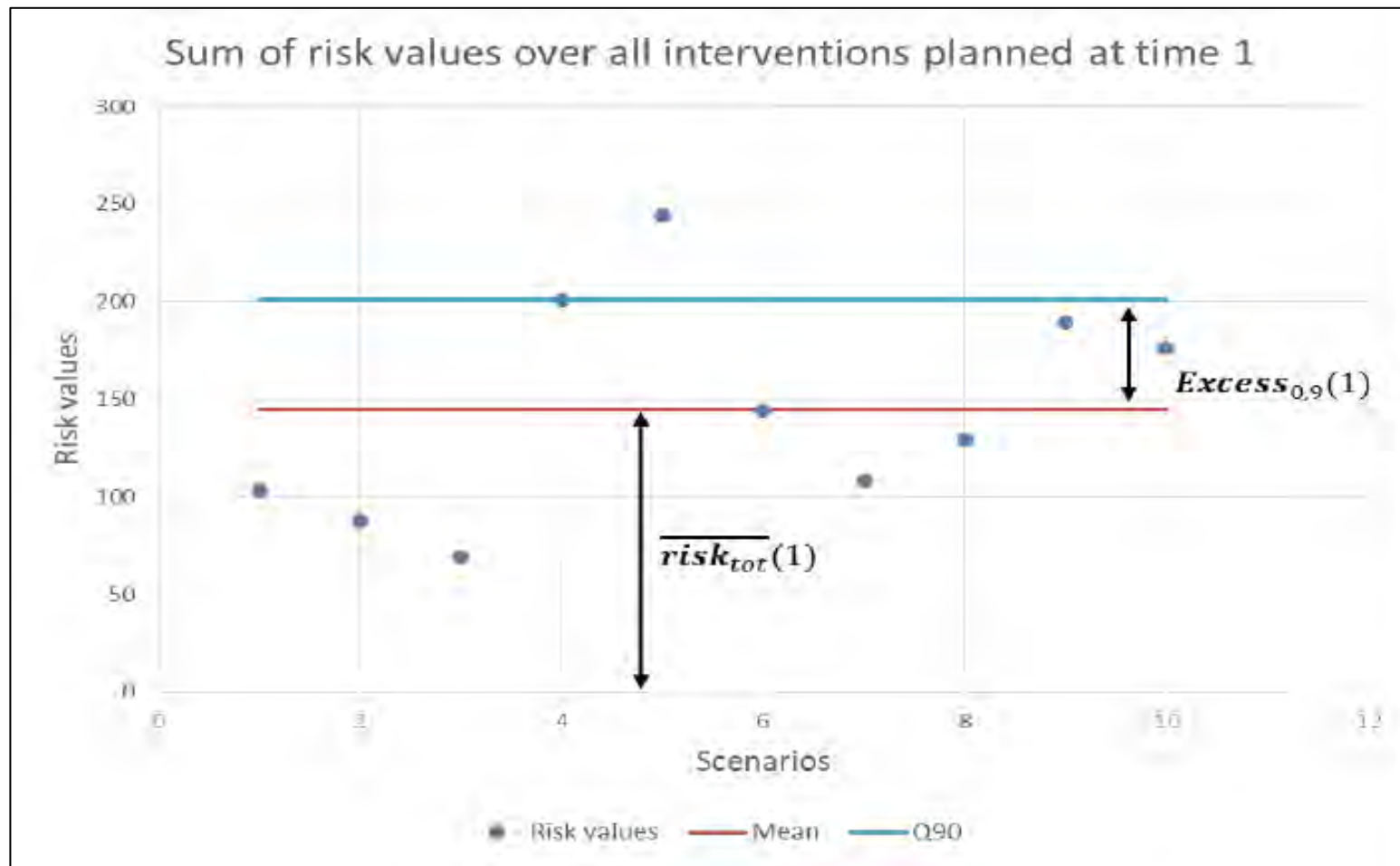
Explaining the excess

Time 1: 10 scenarios,
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Explaining the excess

Time 1: 10 scenarios,
3 interventions whose risks are added for each scenario



Combined objective function

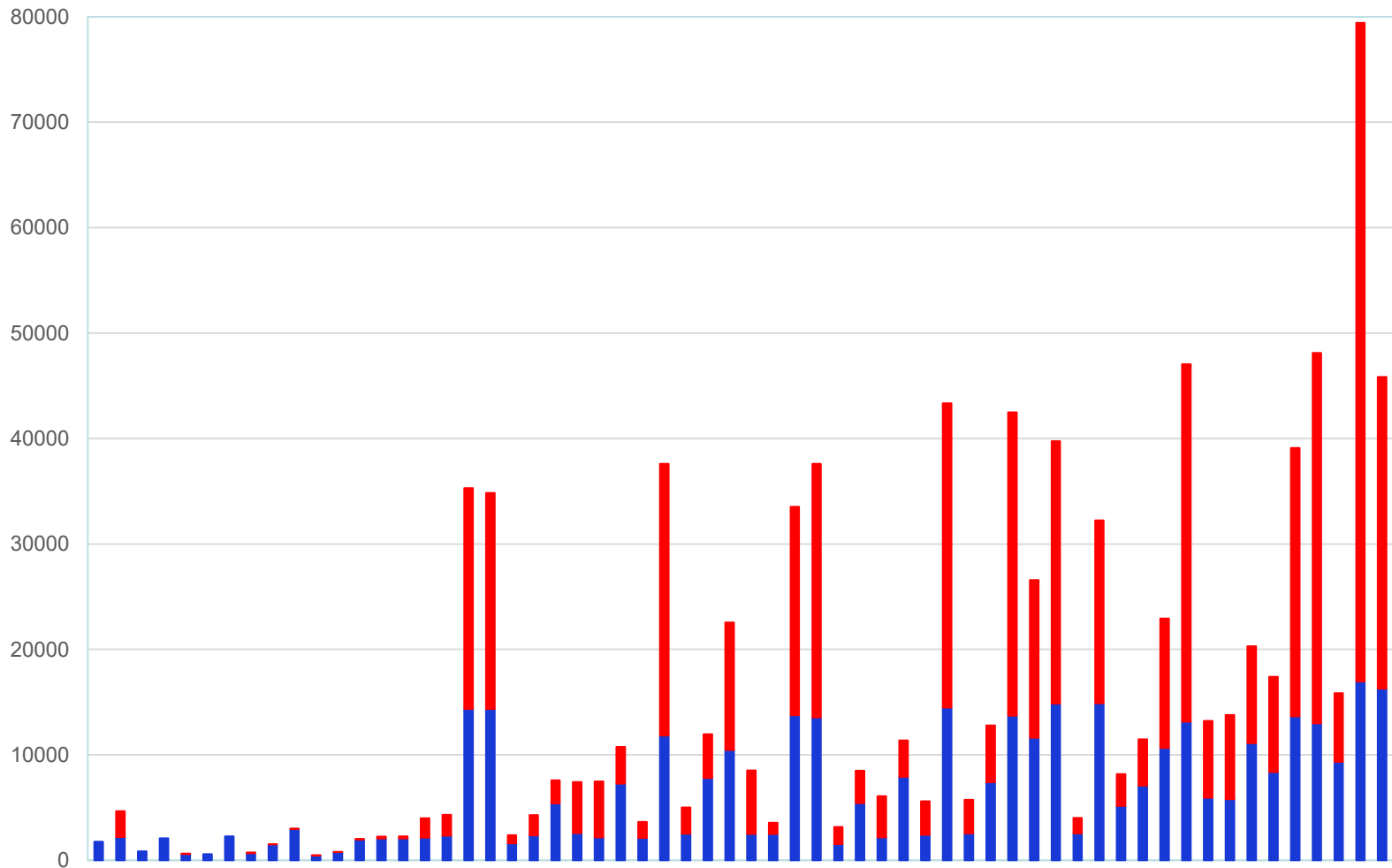
$$OBJ_{\beta} = \alpha \textcolor{red}{obj}_1 + (1 - \alpha) \textcolor{blue}{obj}_2$$

↑
relative weight

↑
mean risk

↑
excess
(risk variation)

Is the excess really important?



Algorithmic scheme

1. Obtaining an **initial solution** using a GRASP algorithm
2. Obtaining a **pool of good solutions** by using integer linear models
- 3. Improving** the solutions with a VND algorithm
- 4. Intensifying** the search in the neighbourhood of the best solutions

GRASP algorithm to obtain an initial solution

- **Constructive algorithm**

- Add one intervention at a time from the ordered list
 - Highest minimum risk
 - Highest regret (difference between lowest and second lowest risk)
 - Maximum percentage of resource consumption

- **Randomization**

- Sample Plus Greedy (select randomly a number of intervention and choose the first in the ordered list)

- **Improvement**

- VND algorithm

Model 1: considering only risk

$$x_{it} = \begin{cases} 1 & \text{if intervention } i \text{ starts at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Minimize } \sum_i \sum_t risk_{it} x_{it}$$

$$s.t. \quad \sum_t x_{it} = 1 \quad \forall i$$

$$l_t^c \leq \sum_i \sum_{\tau | \tau \leq i \leq \tau + d_{it} - 1} r_{i\tau}^{ct} x_{i\tau} \leq u_t^c \quad \forall c, \forall t$$

$$x_{it_1} + x_{jt_2} \leq 1 \quad \forall (i, j, t) \in Excl$$

$$\forall t_1 \mid t_1 \leq t \leq t_1 + d_{it_1} - 1$$

$$\forall t_2 \mid t_2 \leq t \leq t_2 + d_{it_2} - 1$$

$$(\text{where } risk_{it} = \sum_{s \in S_t} \sum_{\tau | \tau \leq t \leq \tau + d_{it} - 1} risk_{it}^{s\tau})$$

Model 2: adding individual quantiles

$$x_{it} = \begin{cases} 1 & \text{if intervention } i \text{ starts at time } t \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Minimize } \sum_i \sum_t (\alpha \mathbf{q}_{it} + (1-\alpha) \text{risk}_{it}) x_{it}$$

$$\text{s.t. } \sum_t x_{it} = 1 \quad \forall i$$

$$l_t^c \leq \sum_i \sum_{\tau | \tau \leq i \leq \tau + d_{it} - 1} r_{i\tau}^{ct} x_{i\tau} \leq u_t^c \quad \forall c, \forall t$$

$$x_{it_1} + x_{jt_2} \leq 1 \quad \forall (i, j, t) \in \text{Excl}$$

$$\forall t_1 \mid t_1 \leq t \leq t_1 + d_{it_1} - 1$$

$$\forall t_2 \mid t_2 \leq t \leq t_2 + d_{it_2} - 1$$

(where \mathbf{q}_{it} = sum of quantiles of risk distribution of intervention i
over the scenarios S_t in all times t in which i is in process)

Model 3: minimizing maximum risks

$$x_{it} = \begin{cases} 1 & \text{if intervention } i \text{ starts at time } t \\ 0 & \text{otherwise} \end{cases}$$

\mathbf{M}_t = maximum risk at time t

$$\text{Minimize } \sum_t (\alpha \mathbf{M}_t + (1-\alpha) \sum_i risk_{it} x_{it})$$

$$s.t. \quad \sum_t x_{it} = 1 \quad \forall i$$

$$l_t^c \leq \sum_i \sum_{\tau | \tau \leq i \leq \tau + d_{it} - 1} r_{it}^{ct} x_{it} \leq u_t^c \quad \forall c, \forall t$$

$$x_{it_1} + x_{jt_2} \leq 1 \quad \forall (i, j, t) \in Excl$$

$$\forall t_1 \mid t_1 \leq t \leq t_1 + d_{it_1} - 1$$

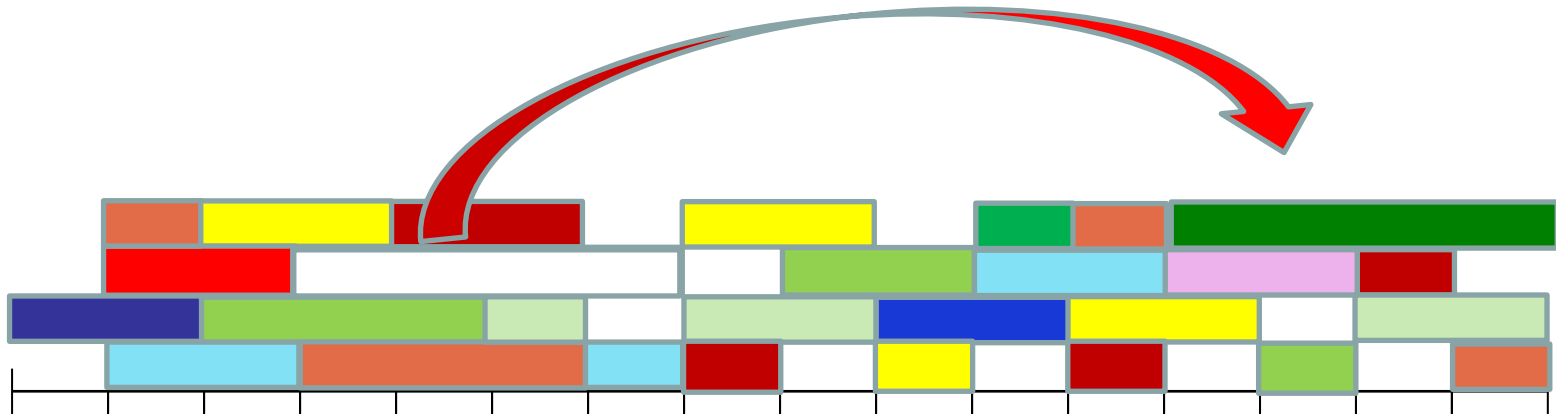
$$\forall t_2 \mid t_2 \leq t \leq t_2 + d_{it_2} - 1$$

$$\sum_i \sum_{\tau | \tau \leq i \leq \tau + d_{it} - 1} risk_{it} x_{it} \leq \mathbf{M}_t \quad \forall t$$

How to choose the right α ?

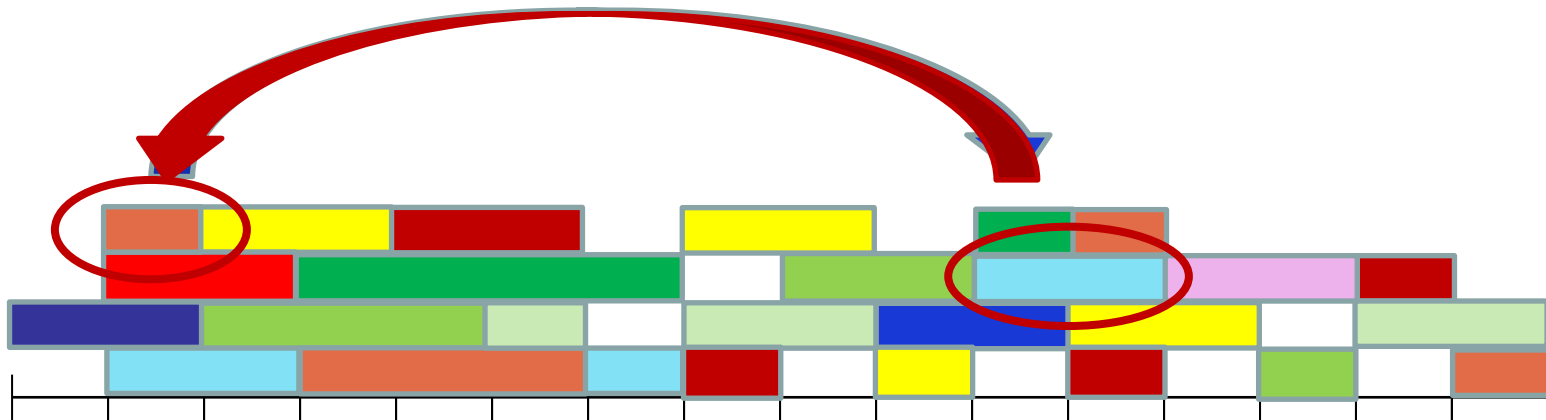
- In models 2 and 3, the best value of α is not easy to determine
- We follow an iterative procedure, covering values in the interval (0,1)
- The difficulty in obtaining feasible solutions by GRASP in the first phase is an indication of the hardness of the instance, and therefore of the number of times the model can be solved in a given time limit
- At each iteration, we solve the models with a different α , taking as initial solution the optimal solution of the previous iteration

VND: moving a single intervention

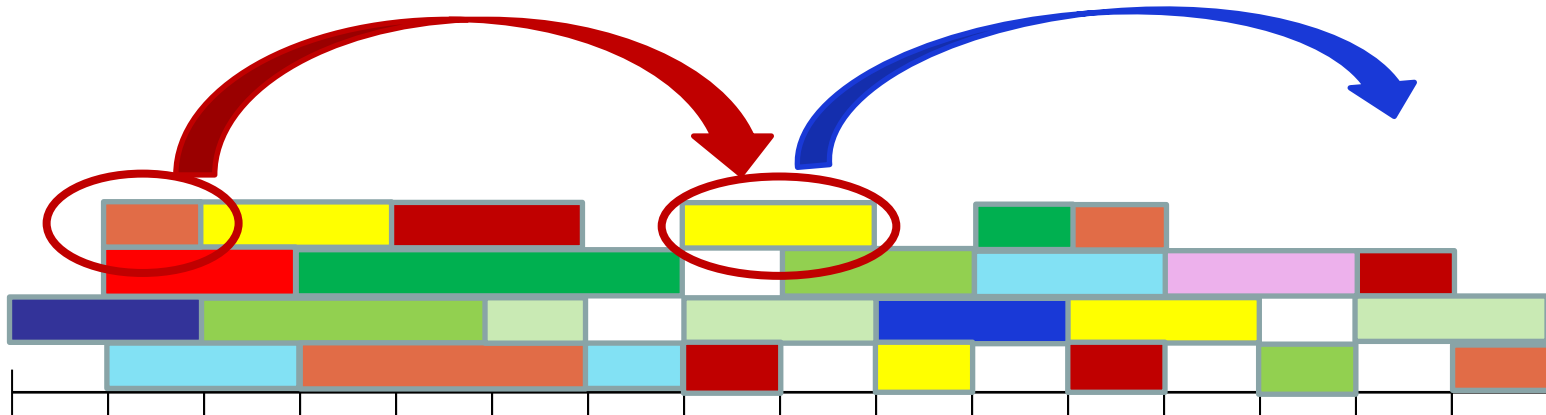


Ordered by: risk
excess

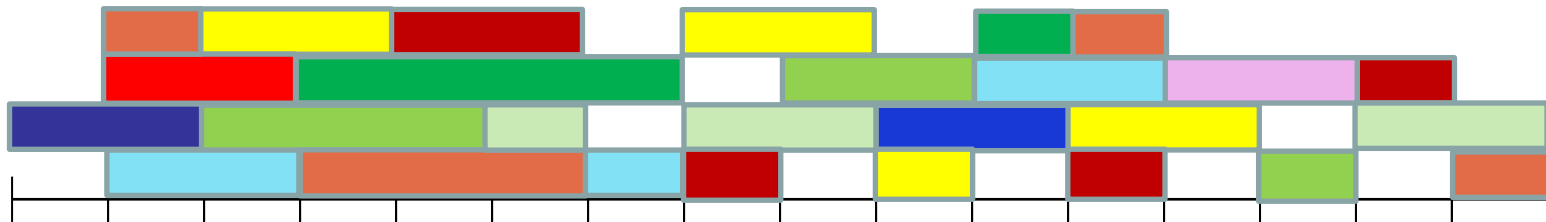
VND: exchanging pairs of interventions



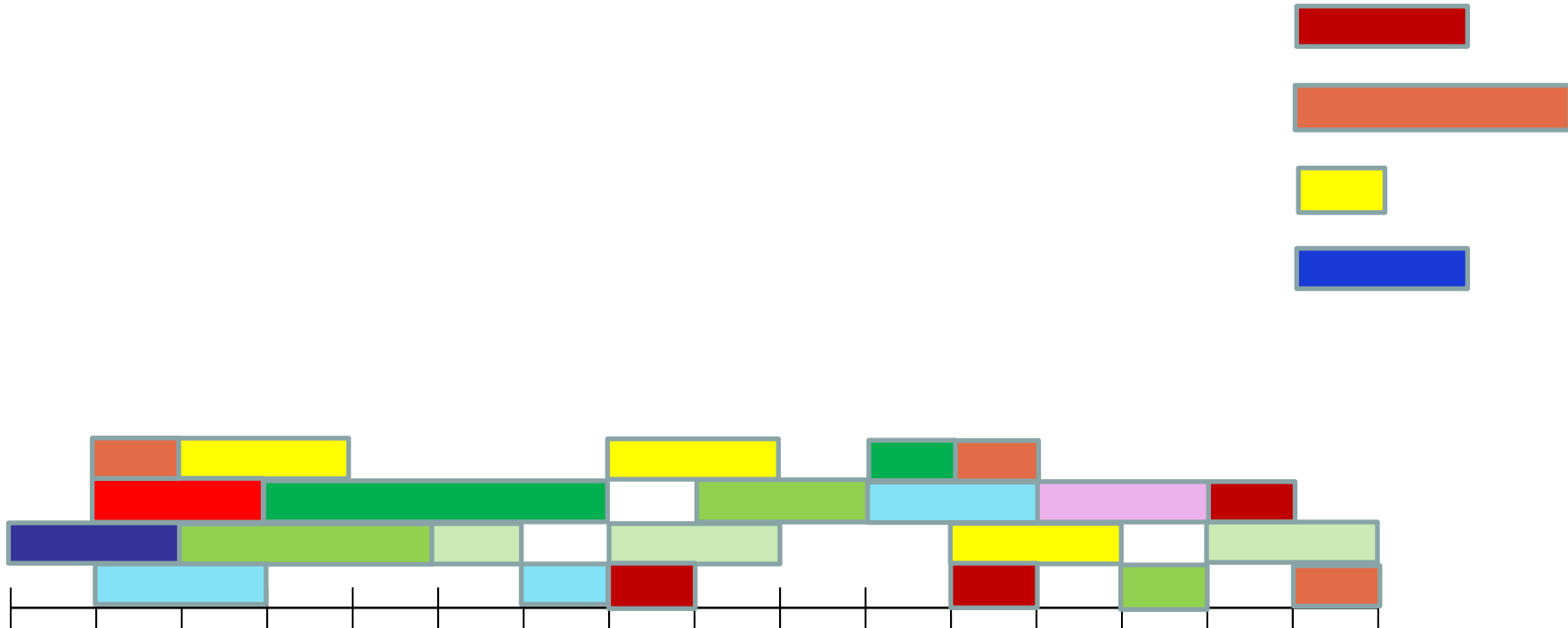
VND: simple ejection chains



VND: Ruin & build

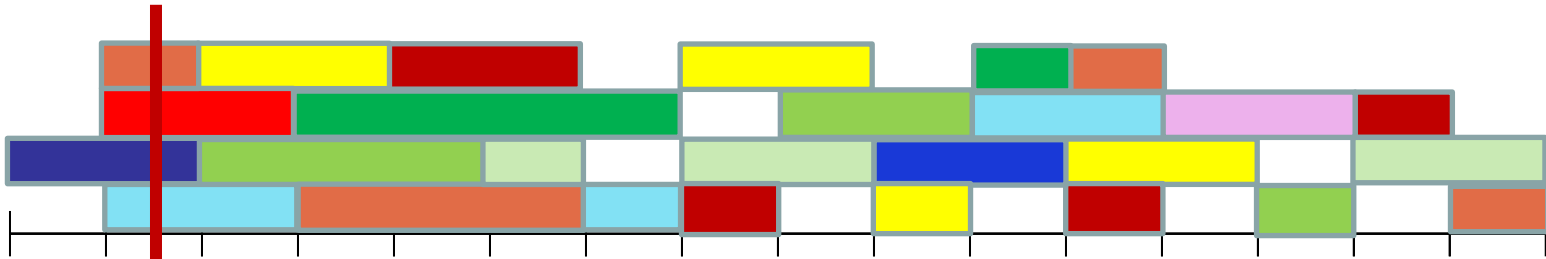


VND: Ruin & build

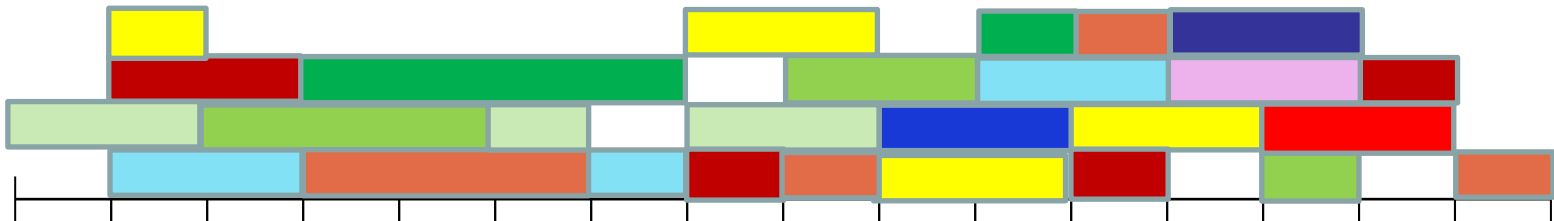


Path Relinking

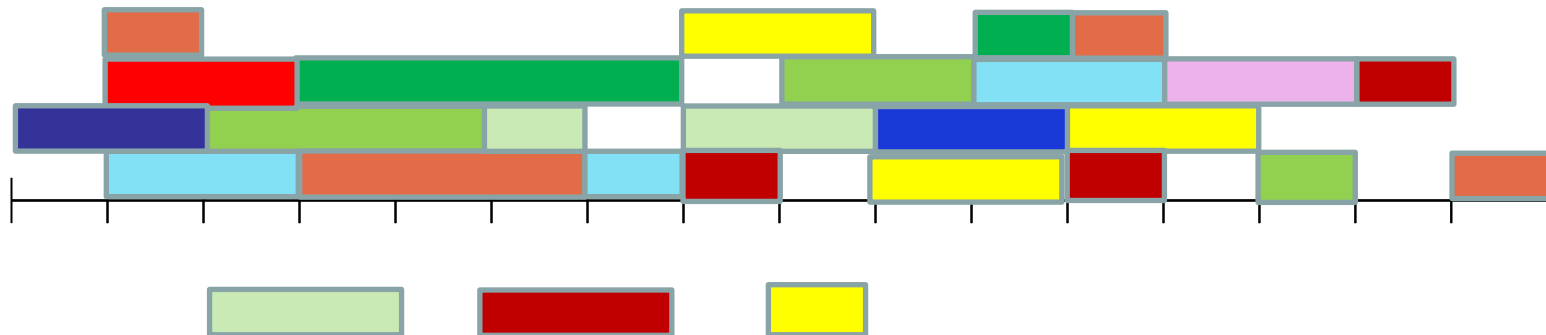
Target solution



Initial solution



Next step



RTE benchmarks

Dataset	Inst.	Periods	Interv.	Resour.	Scen.	Excl.	Feas.	Aver.
A	15	94	141	9	7038	127	15	76622
B	15	79	319	9	9462	394	12	8
C	15	106	380	9	10381	480	10	5
X	15	147	437	9	11514	553	1	0

Comparing the integer models

Are their objective functions good approximations to the real objective?

Model 1	Model 2	Model 3	BKS
7945	25989	43730	23504

Do they provide good solutions for the real problem?

Model 1	Model 2	Model 3	BKS
25635	23591	25303	23504

0.37%

Comparing with the best-known solutions

	900 seconds		5400 seconds	
	Our	BKS	Our	BKS
Average	23535	23513	23516	23504
% Distance	0.073		0.042	
New best	3		3	

Conclusions

- Large and challenging problem
- Excess: non-linear objective function
- Many local minima from which it is difficult to escape
- Integer model: pool of good solutions
- Improvement: VND, Path Relinking
- Competitive solutions and some new best solutions
- The validation phase will tell the practical value of the solutions

Thank you for your attention!

Any questions?

Ramón Alvarez-Valdés
Consuelo Parreño
Francisco Parreño

