UNIVERSITÀ DEGLI STUDI DI TRIESTE

Dipartimento di Ingegneria e Architettura

Materials and Systems for the Energy Transition

Energy management and optimization strategies

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Who came here by car?

WOULD YOU DRIVE A CAR WITHOUT…

… a dashboard?



WOULD YOU DRIVE A CAR WITHOUT…

… a dashboard?



Lack of feedback and information
→ no chance to know what is happening

↓

Monitoring

WOULD YOU DRIVE A CAR WITHOUT…

… a dashboard?



… a steering wheel?



Lack of feedback and information
→ no chance to know what is happening

↓

Monitoring

WOULD YOU DRIVE A CAR WITHOUT…

… a dashboard?



Lack of feedback and information
→ no chance to know what is happening

↓

Monitoring

… a steering wheel?



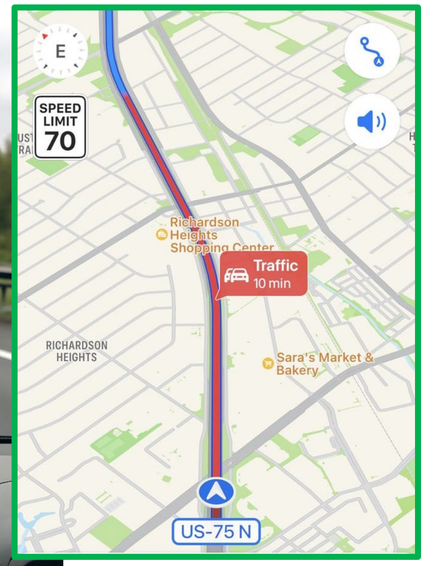
Lack of control
→ no chance to manage unwanted situations

↓

Control

WOULD YOU DRIVE TO A NEW PLACE WITHOUT A NAVIGATOR?

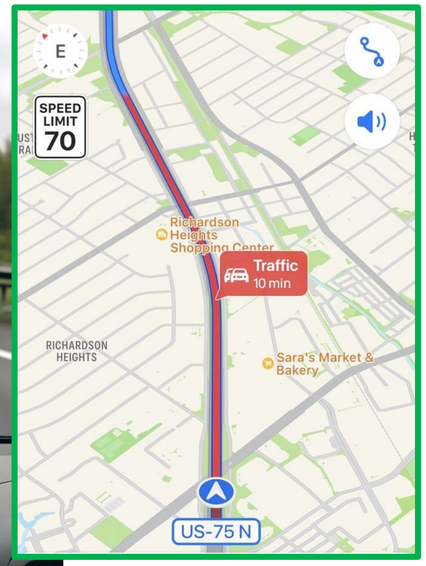






WOULD YOU DRIVE TO A NEW PLACE WITHOUT A NAVIGATOR?





Lack of traffic and total time predictions
→ no chance to change the route

↓

Forecasting

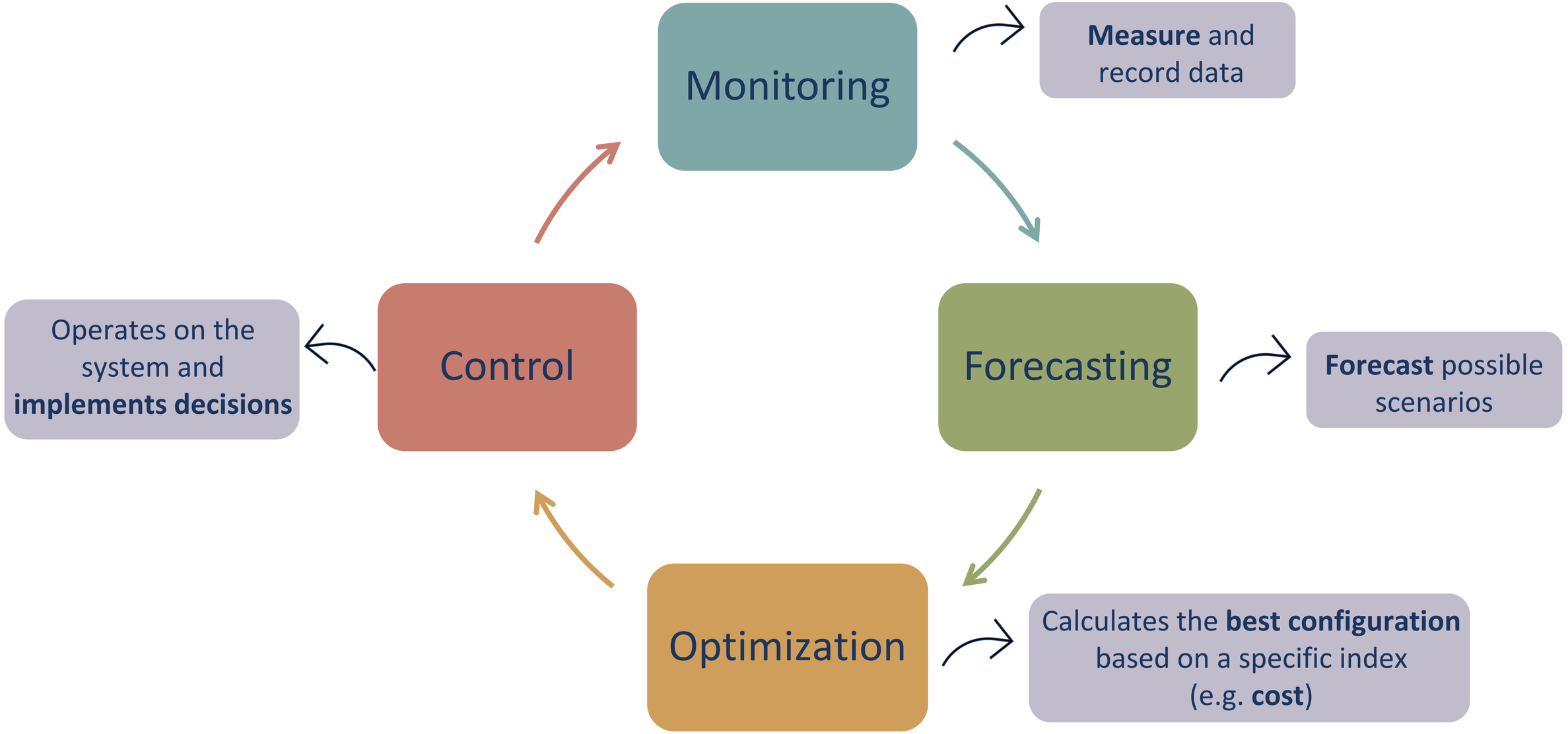


Lack of consumption management
(uphill hills, off-road routes, etc.) → no optimal route

↓

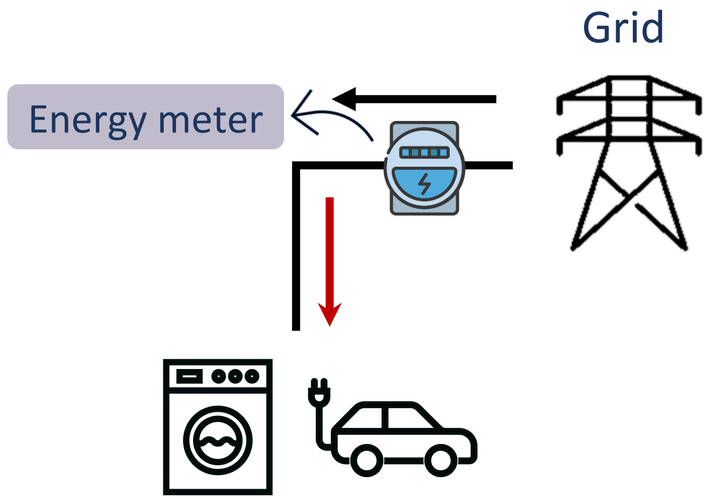
Optimization

MAIN FEATURES OF **ANY** MANAGEMENT (CONTROL) SYSTEM

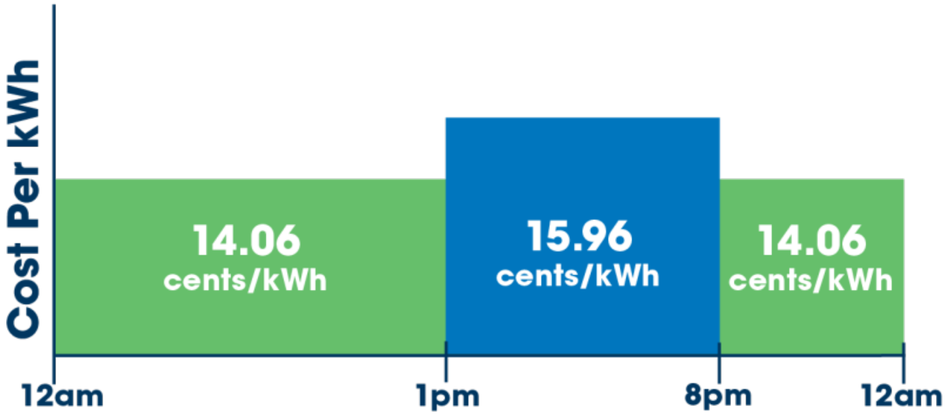


EVOLUTION OF ENERGY SYSTEM: MAIN COMPONENTS

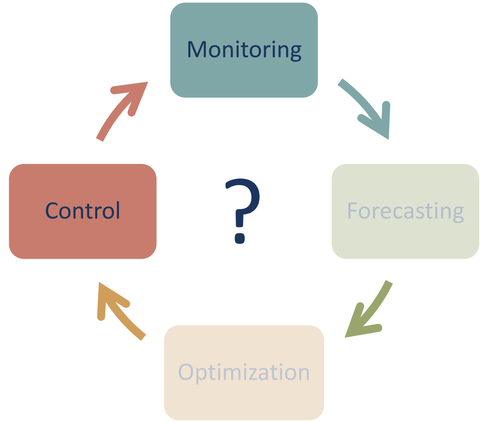
The **“control” action** is based on the loads utilization, typically relying on a specific index (the energy price, **changing in different time frames**) with the aim of minimizing the cost in the electricity bill.



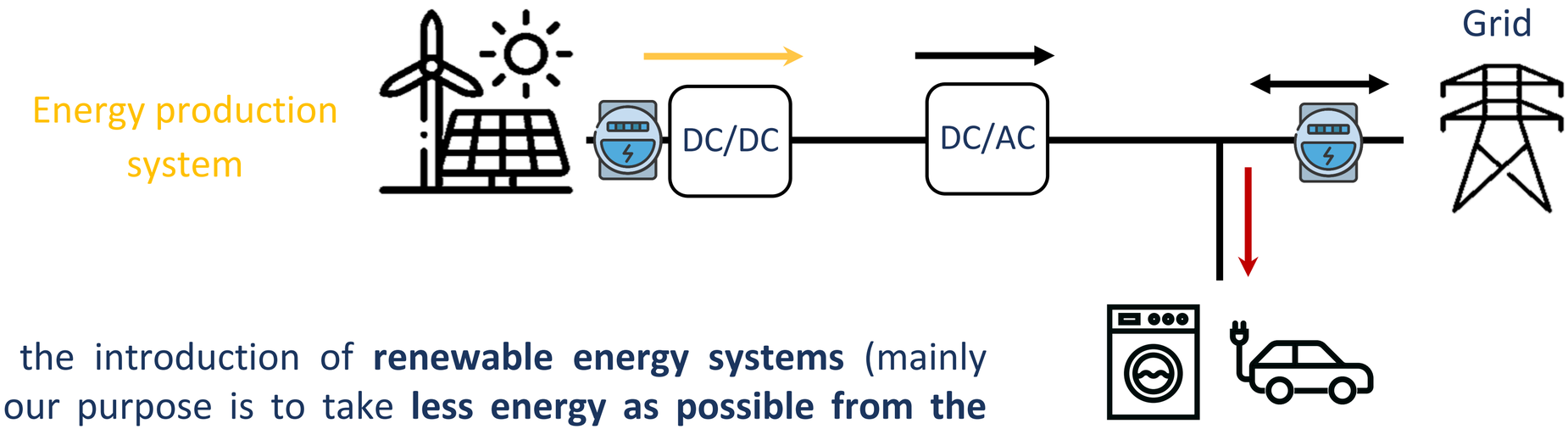
Time-Of-Use tariffs (TOU)





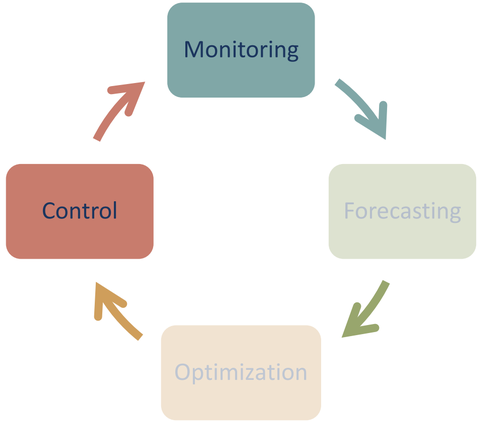


EVOLUTION OF ENERGY SYSTEM: MAIN COMPONENTS

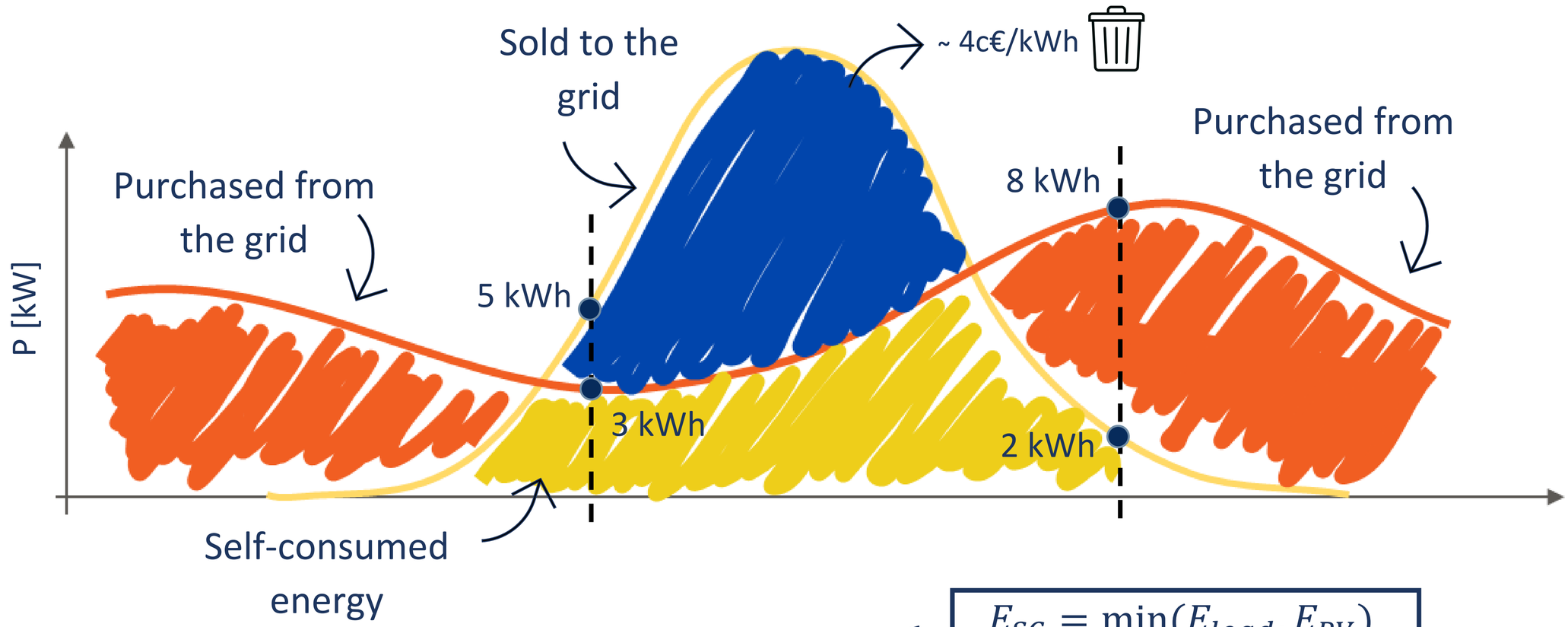


With the introduction of **renewable energy systems** (mainly PV), our purpose is to take **less energy as possible from the grid**, **self-consuming** most of the energy we produce locally.

- we **cannot control** PV production (it's based on the irradiance)
- we **can decide** when to use our loads (would be great when PV production is high)



EVOLUTION OF ENERGY SYSTEM: ENERGY FLOWS

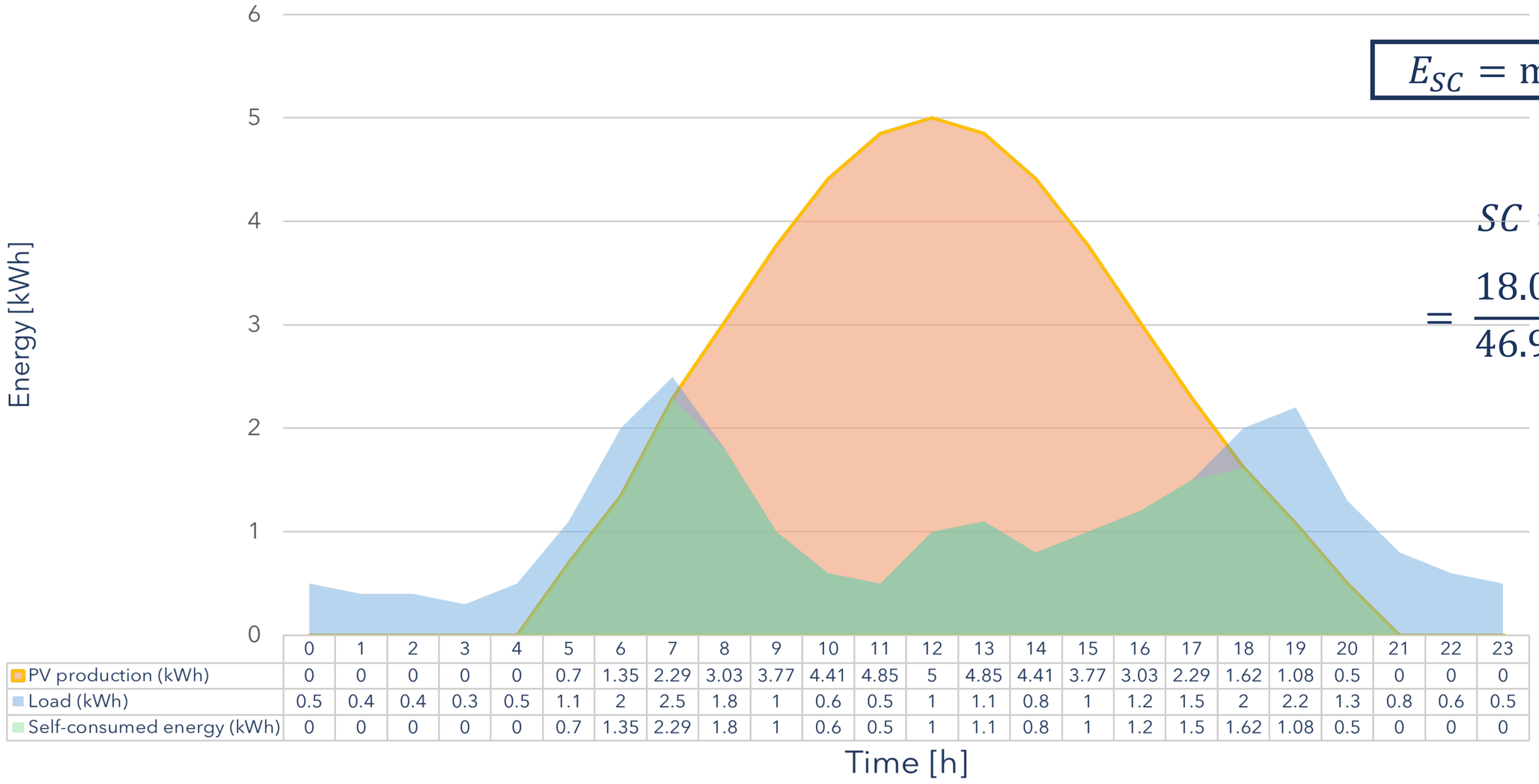


$$E_{SC} = \min(E_{load}, E_{PV})$$

From the self-consumed energy we can define an **energy indicator**

$$SC = \frac{E_{SC}}{E_{PV}} \cdot 100\ [\%]$$ **Self-consumption**

EVOLUTION OF ENERGY SYSTEM: ENERGY FLOWS

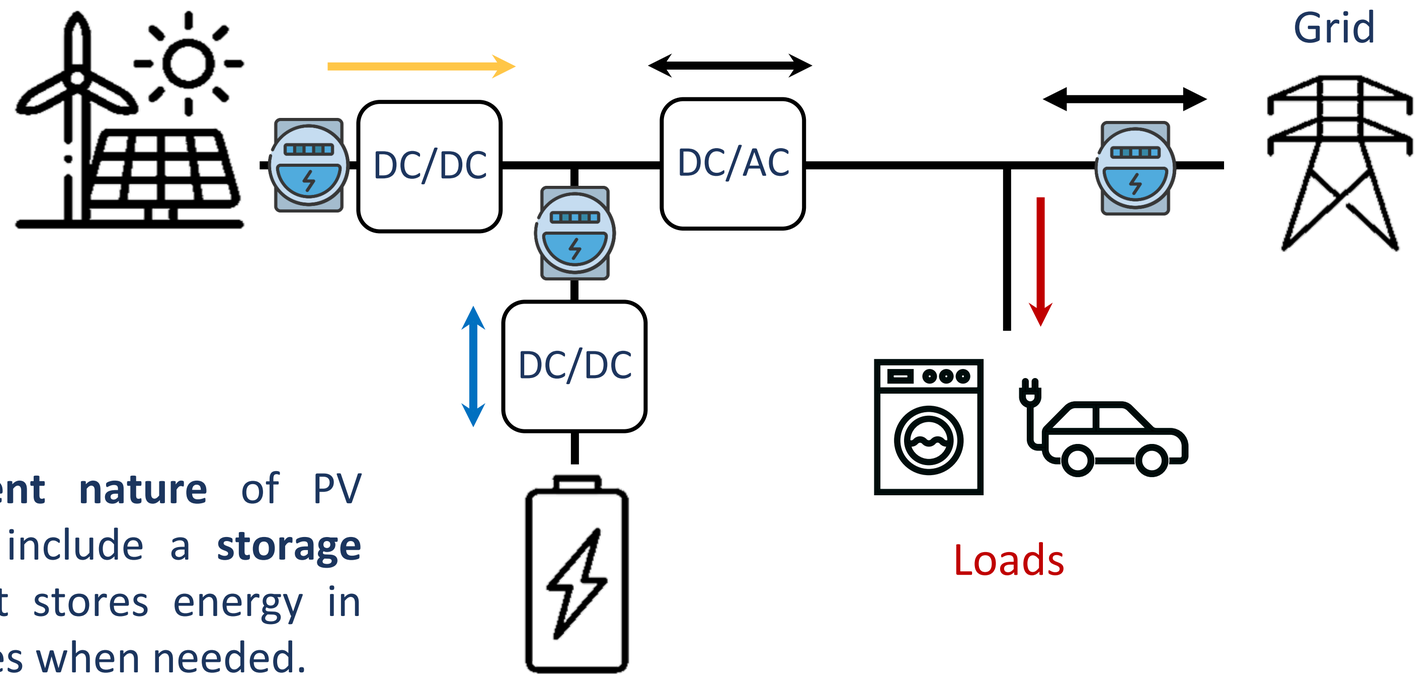


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
PV production (kWh)	0	0	0	0	0	0.7	1.35	2.29	3.03	3.77	4.41	4.85	5	4.85	4.41	3.77	3.03	2.29	1.62	1.08	0.5	0	0	0
Load (kWh)	0.5	0.4	0.4	0.3	0.5	1.1	2	2.5	1.8	1	0.6	0.5	1	1.1	0.8	1	1.2	1.5	2	2.2	1.3	0.8	0.6	0.5
Self-consumed energy (kWh)	0	0	0	0	0	0.7	1.35	2.29	1.8	1	0.6	0.5	1	1.1	0.8	1	1.2	1.5	1.62	1.08	0.5	0	0	0

$$E_{SC} = \min(E_{load}, E_{PV})$$

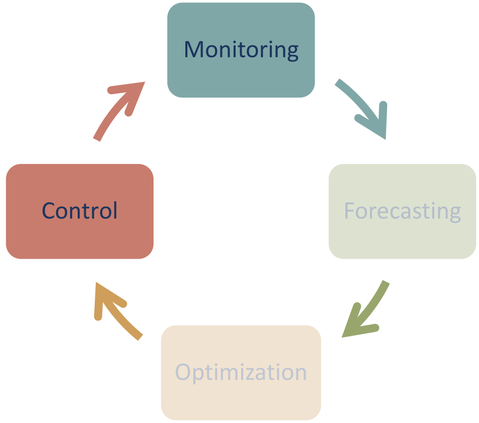
$$SC = \frac{E_{SC}}{E_{PV}} \cdot 100 = \frac{18.04}{46.95} \cdot 100 = 38.4\ \%$$

EVOLUTION OF ENERGY SYSTEM: MAIN COMPONENTS

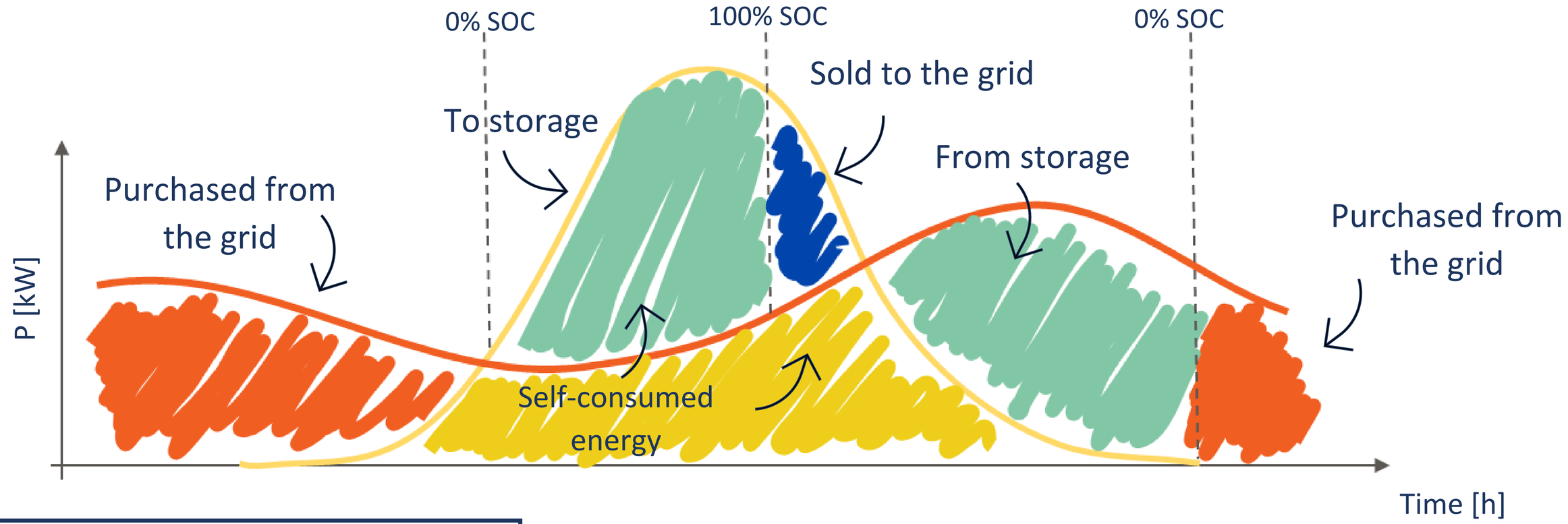


Because of the **intermittent nature** of PV production, it is useful to include a **storage system (e.g. batteries)** that stores energy in case of surplus and discharges when needed.

We now have a **new degree of freedom**: rather than controlling the loads (uncomfortable and not automatic), we can **control the charging and discharging power of our storage system**.



EVOLUTION OF ENERGY SYSTEM: ENERGY FLOWS



$$E_{SC} = \min(E_{load} + E_{charged}, E_{PV})$$

Increased!

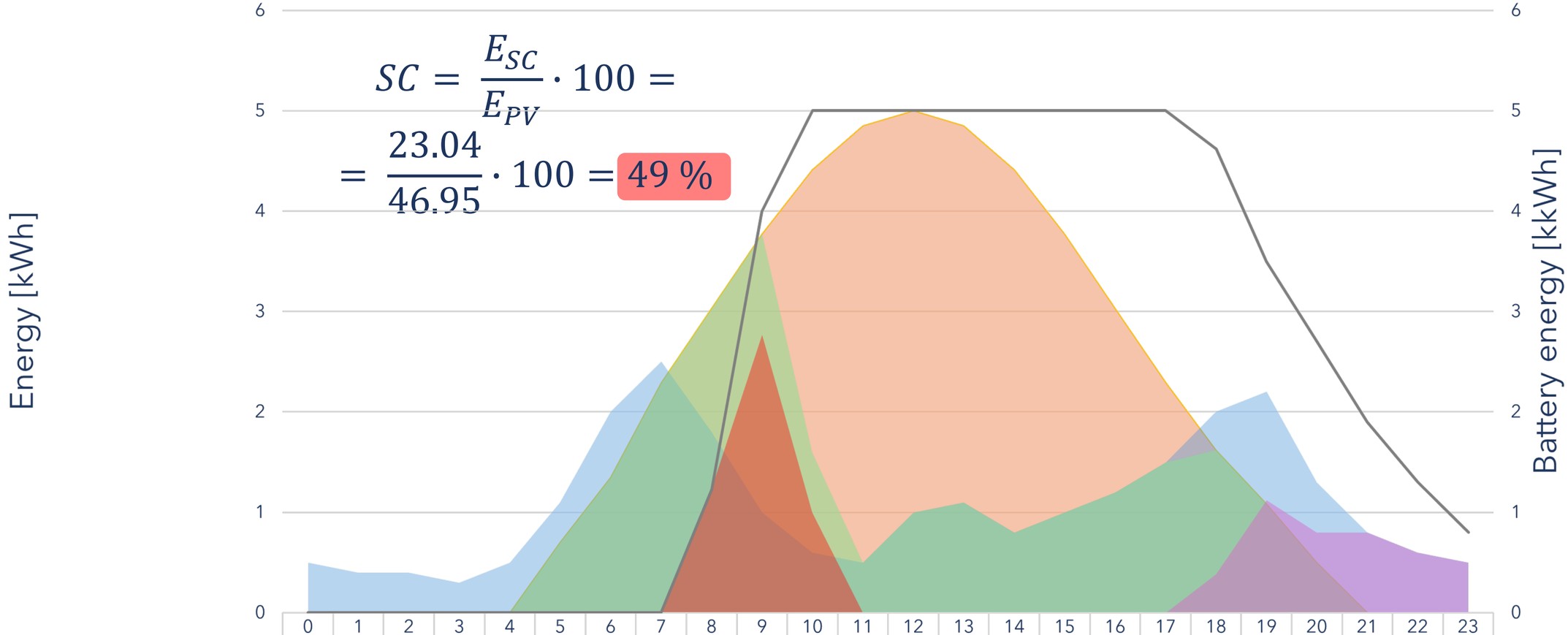
From the self-consumed energy we can define an **energy indicator**

$$SC = \frac{E_{SC}}{E_{PV}} \cdot 100\ [\%]$$

Self-consumption

EVOLUTION OF ENERGY SYSTEM: ENERGY FLOWS WITH 5 kWh BATTERY

$$SC = \frac{E_{SC}}{E_{PV}} \cdot 100 = \frac{23.04}{46.95} \cdot 100 = 49\ \%$$

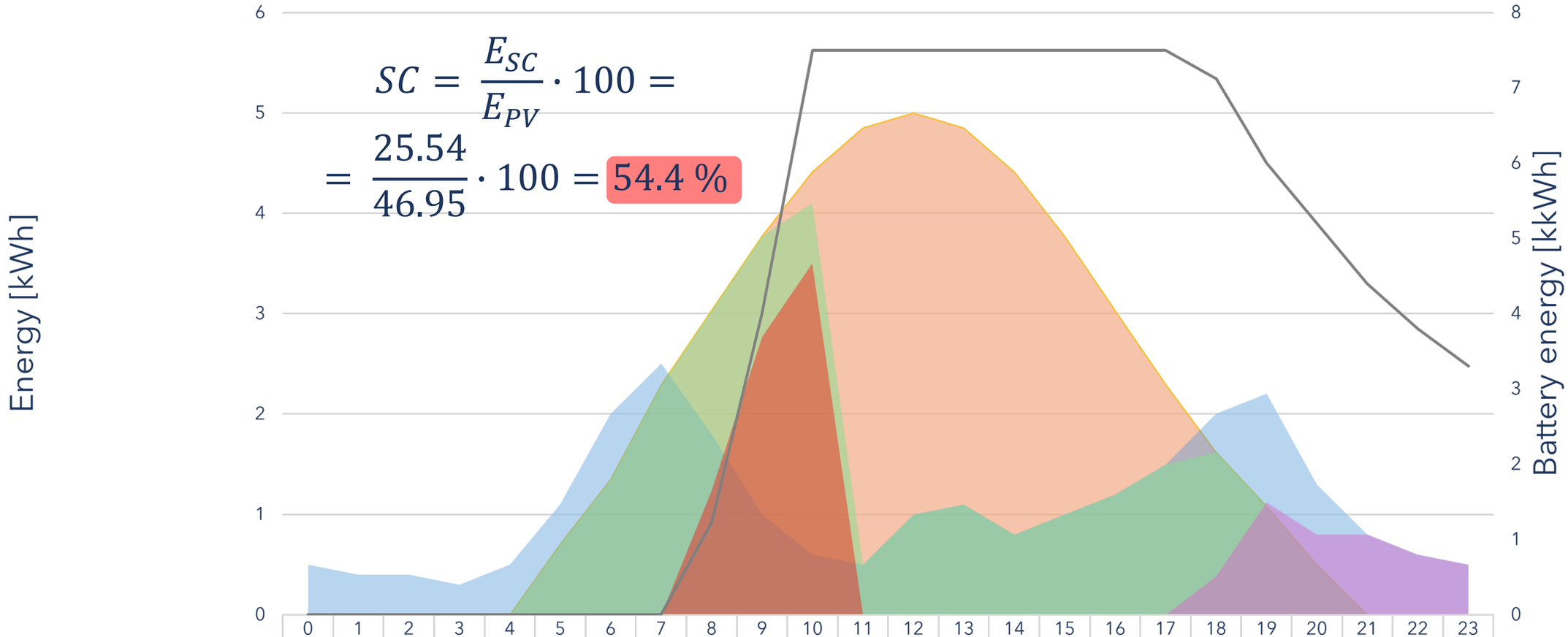


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
PV production (kWh)	0	0	0	0	0	0.7	1.35	2.29	3.03	3.77	4.41	4.85	5	4.85	4.41	3.77	3.03	2.29	1.62	1.08	0.5	0	0	0
Load (kWh)	0.5	0.4	0.4	0.3	0.5	1.1	2	2.5	1.8	1	0.6	0.5	1	1.1	0.8	1	1.2	1.5	2	2.2	1.3	0.8	0.6	0.5
Self-consumed energy (kWh)	0	0	0	0	0	0.7	1.35	2.29	3.03	3.77	1.6	0.5	1	1.1	0.8	1	1.2	1.5	1.62	1.08	0.5	0	0	0
Charged energy (kWh)	0	0	0	0	0	0	0	0	1.23	2.77	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Discharged energy (kWh)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.38	1.12	0.8	0.8	0.6	0.5
Battery energy (kWh)	0	0	0	0	0	0	0	0	1.23	4	5	5	5	5	5	5	5	5	4.62	3.5	2.7	1.9	1.3	0.8

Time [h]

EVOLUTION OF ENERGY SYSTEM: ENERGY FLOWS WITH 7.5 kWh BATTERY

$$SC = \frac{E_{SC}}{E_{PV}} \cdot 100 = \frac{25.54}{46.95} \cdot 100 = 54.4\ \%$$

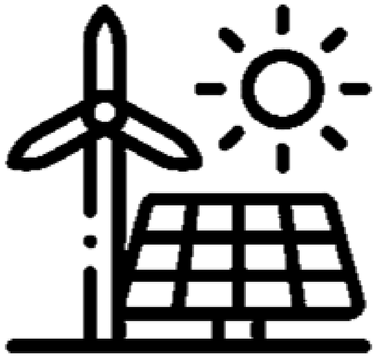


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
PV production (kWh)	0	0	0	0	0	0.7	1.35	2.29	3.03	3.77	4.41	4.85	5	4.85	4.41	3.77	3.03	2.29	1.62	1.08	0.5	0	0	0
Load (kWh)	0.5	0.4	0.4	0.3	0.5	1.1	2	2.5	1.8	1	0.6	0.5	1	1.1	0.8	1	1.2	1.5	2	2.2	1.3	0.8	0.6	0.5
Self-consumed energy (kWh)	0	0	0	0	0	0.7	1.35	2.29	3.03	3.77	4.1	0.5	1	1.1	0.8	1	1.2	1.5	1.62	1.08	0.5	0	0	0
Charged energy (kWh)	0	0	0	0	0	0	0	0	1.23	2.77	3.5	0	0	0	0	0	0	0	0	0	0	0	0	0
Discharged energy (kWh)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.38	1.12	0.8	0.8	0.6	0.5
Battery energy (kWh)	0	0	0	0	0	0	0	0	1.23	4	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.12	6	5.2	4.4	3.8	3.3

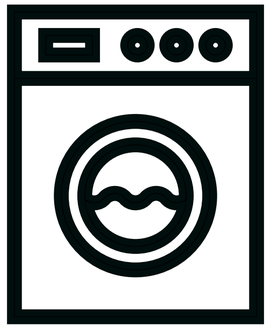
HOW CAN WE CONTROL THE BESS POWER?

Who are the key players? What do we need to **monitor**? What do we need to **control**?

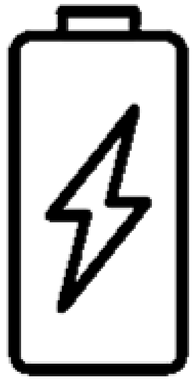
PV (max 10 kW)



Loads (max 3 kW)



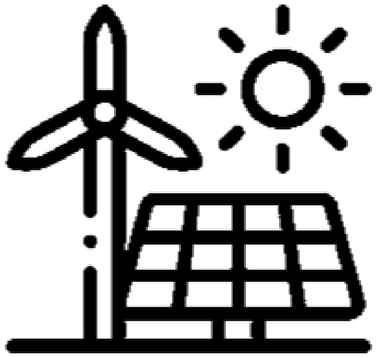
Battery (10 kWh)



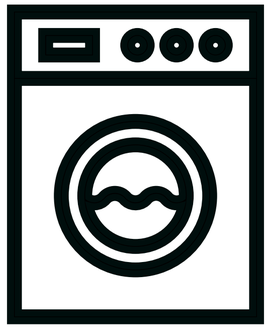
HOW CAN WE CONTROL THE BESS POWER?

Who are the key players? What do we need to **monitor**? What do we need to **control**?

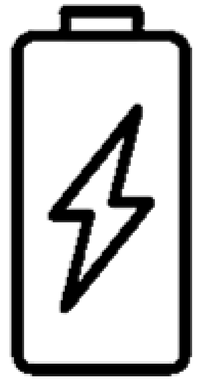
PV (max 10 kW)



Loads (max 3 kW)



Battery (10 kWh)

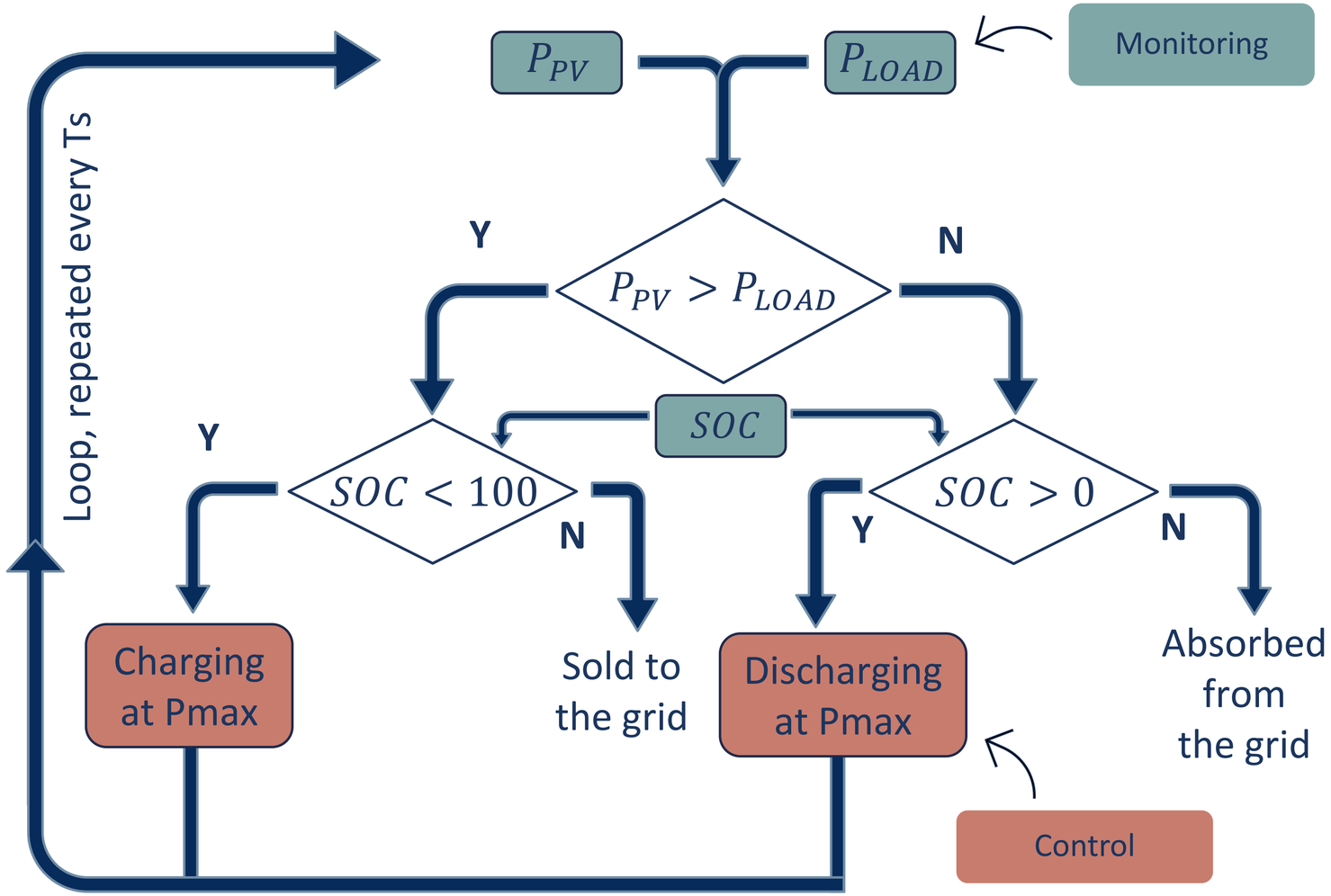


$$E_b(t) = E_b(t-1) + P_{battery}(t) \cdot \Delta t$$

$$SOC(t) = SOC(t-1) + \frac{P_{battery}(t)}{E_{b,tot}} \cdot \Delta t$$

HOW CAN WE CONTROL THE BESS POWER?

Basically, with a very basic control system, based on simple rules: a **rule-based EMS**




```c
#include <stdio.h>

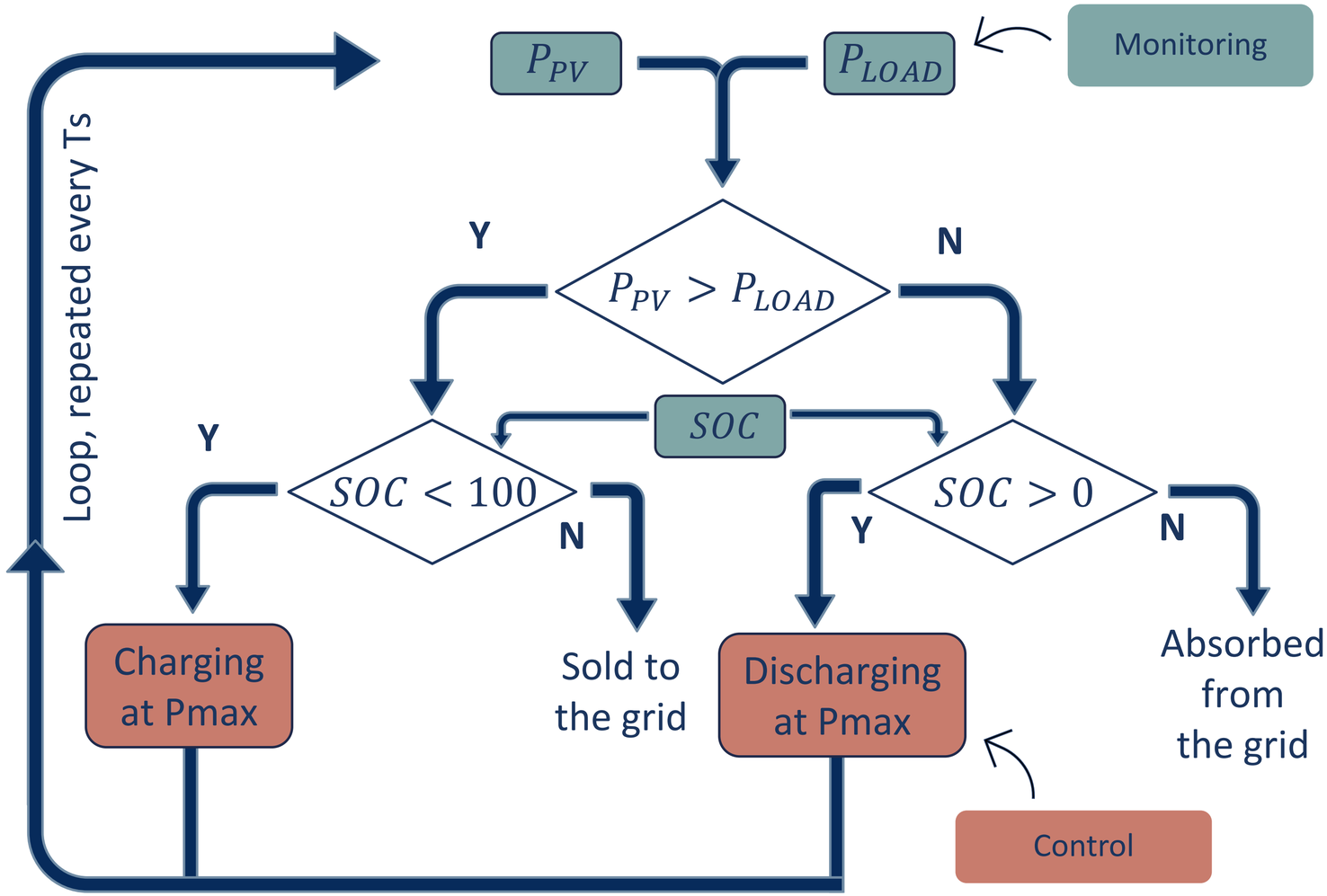
// Variable definition
float P_PV;       // PV power
float P_LOAD;     // Load power
int SOC;          // Battery State of Charge

// Main loop, repeated every Ts
void main() {
    P_PV = read(PV);       // kW
    P_LOAD = read(LOAD);   // kW
    SOC = read(SOC);       // %

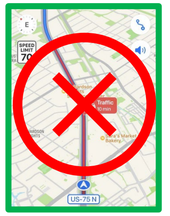
    if (P_PV > P_LOAD) {
        if (SOC < 100) {
            chg_cmd(Pmax);
        } else {
            // Nothing is done here... energy is sold!
        }
    } else {
        if (SOC > 0) {
            dischg_cmd(Pmax);
        } else {
            // Nothing is done here... energy is absorbed!
        }
    }
}
```

HOW CAN WE CONTROL THE BESS POWER?

Basically, with a very basic control system, based on simple rules: a **rule-based EMS**



In this EMS, we are only **monitoring (dashboard)** and **controlling (steering)**.







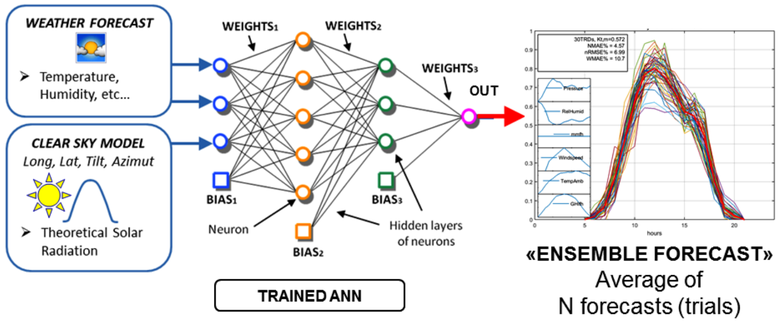
However, we have no chance to "*change the route*" (forecasting is missing) and no chance to *"calculate the optimal route"* (optimization is missing) based on forecasting.

What if we were able to know what happens in the future?

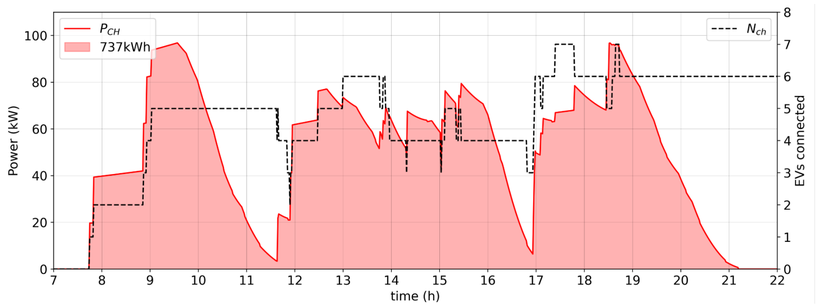
We could act in advance.

THE IMPORTANCE OF FORECASTING AND OPTIMIZATION

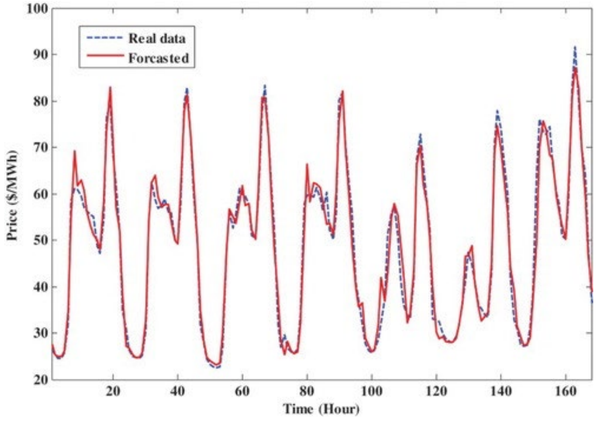
Scenario	PV production forecast	Load consumption forecast	Electricity price forecast
Forecasting	EMS predicts it will be cloudy tomorrow: photovoltaic production will be 40 percent below average.	The EMS predicts a consumption peak at 6 p.m. (e.g. **EV charging**).	EMS predicts a change in the electricity price
Optimization	The EMS can **charge the battery today** (while it is sunny) for tomorrow's needs.	The EMS can discharge the battery to **avoid exceeding contractual power limits**.	The EMS can charge the battery by taking energy from the grid when the **price is lower**



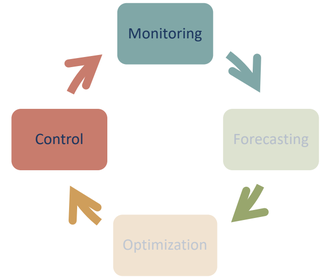
S. Leva, A. Dolara, F. Grimaccia, M. Mussetta, and E. Ogliari,
"Analysis and validation of 24 hours ahead neural network forecasting of photovoltaic output power,"
Mathematics and Computers in Simulation, 2015.

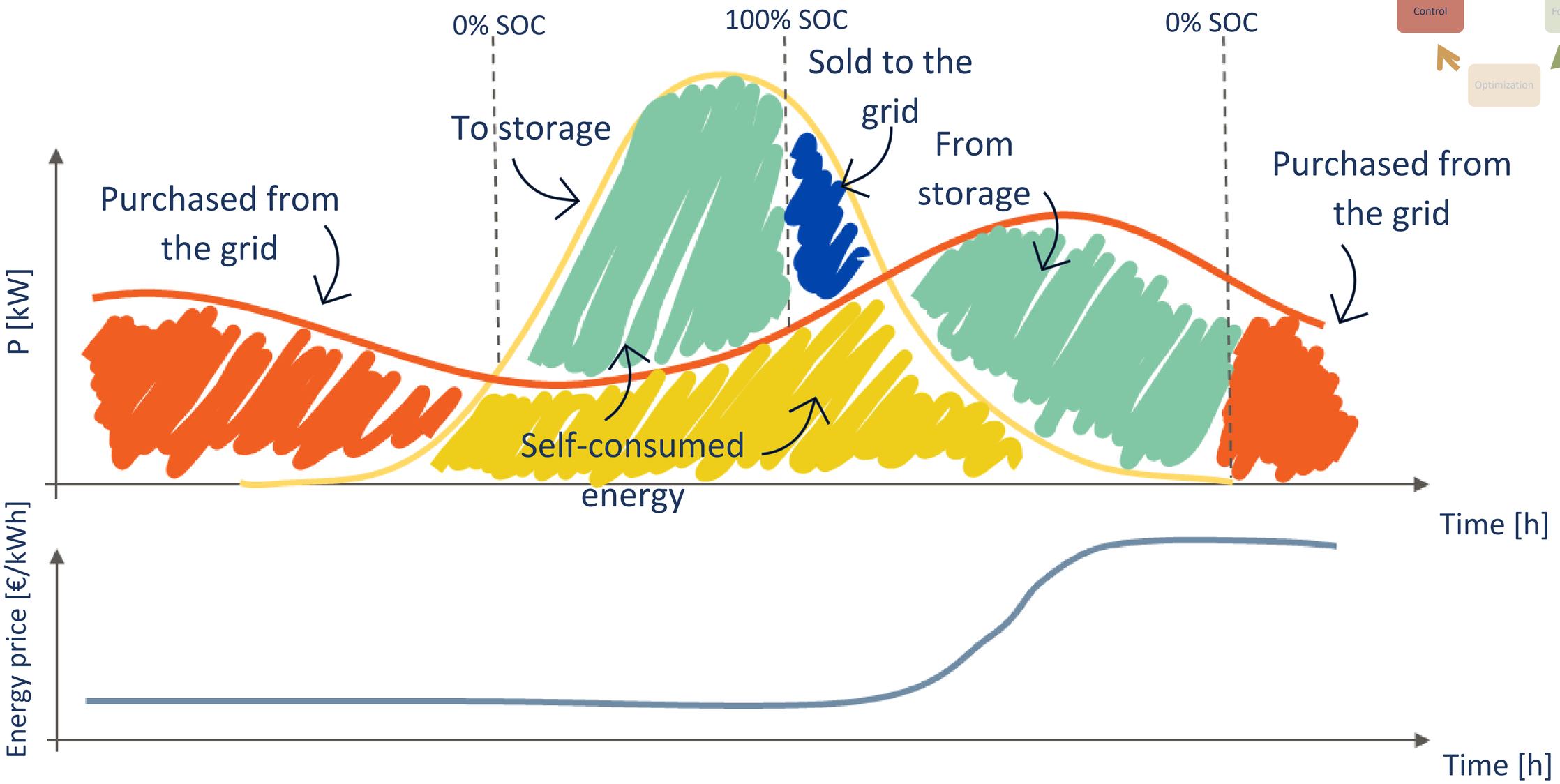


Lo Franco, F.; Cirimele, V.; Ricco, M.; Monteiro, V.; Afonso, J.L.; Grandi, G. Smart Charging for Electric Car-Sharing Fleets Based on Charging Duration Forecasting and Planning. *Sustainability* 2022, *14*, 12077. https://doi.org/10.3390/su141912077

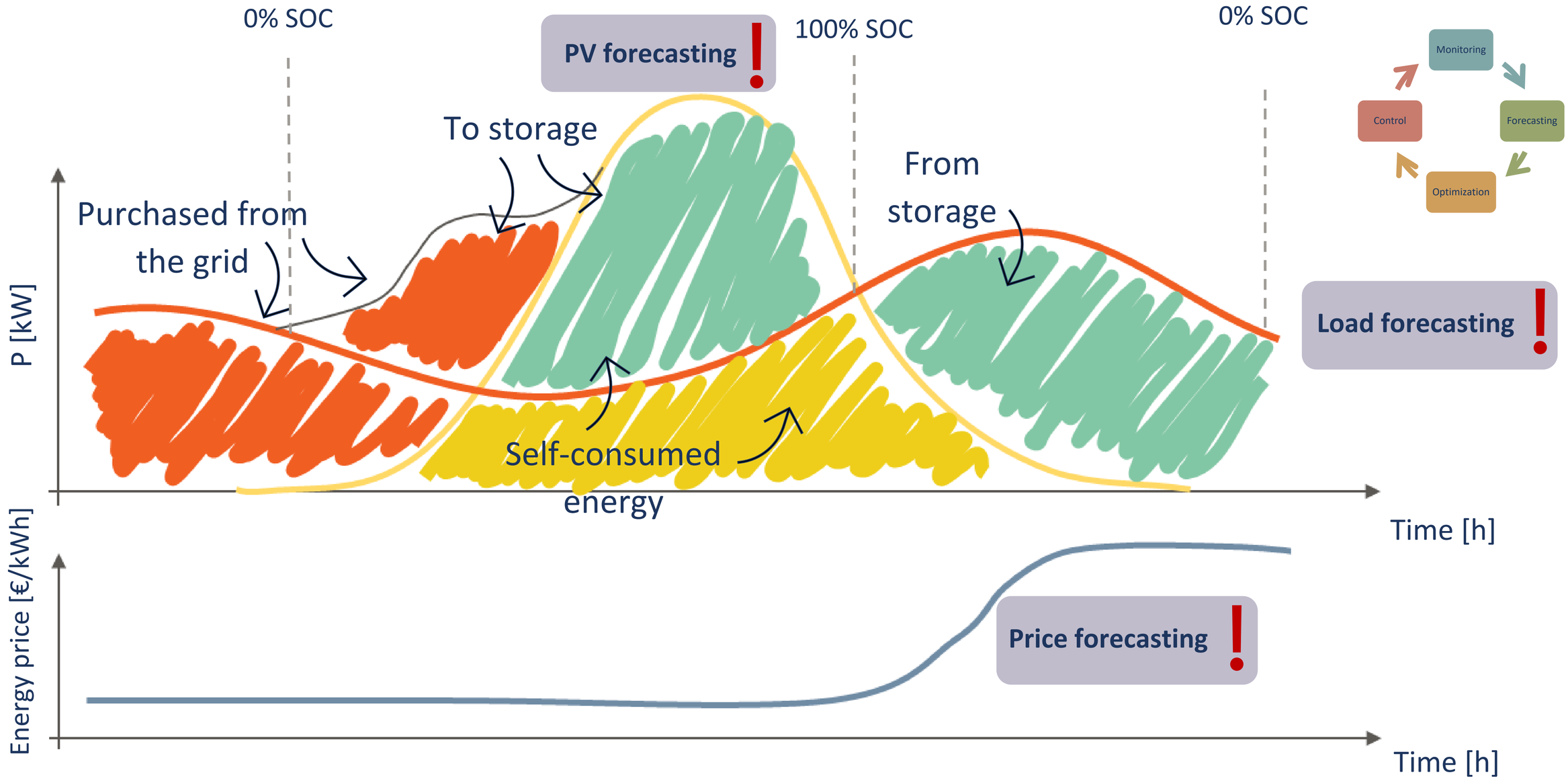


A TRIVIAL EXAMPLE: LET'S MINIMIZE TOTAL COST





A TRIVIAL EXAMPLE: OPTIMIZATION-BASED EMS TO MINIMIZE COSTS



Optimization algorithms

LINEAR PROGRAMMING (LP)

Linear programming (LP), also called **linear optimization**, is a method to achieve the best outcome (such as maximum profit or lowest cost) in a mathematical model whose requirements are represented by **linear** relationships.

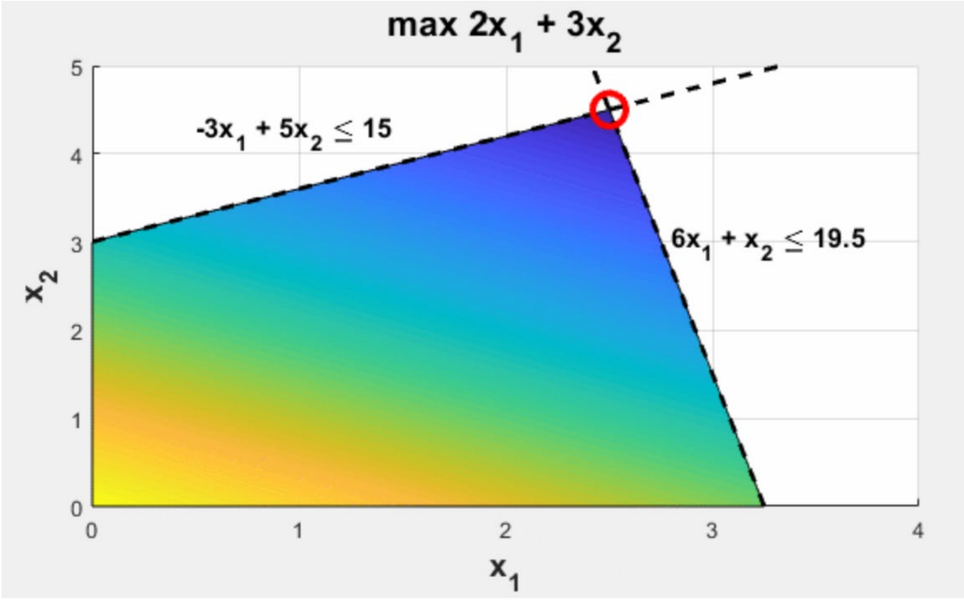
More formally, linear programming is a technique for the optimization of a **linear objective function**, subject to **linear** equality and **linear** inequality constraints.

Find a vector x

that max/minimizes $f(x)$

subject to

$$Ax \leq b \quad \text{(inequality constraint)}$$
$$A_{eq}x = b_{eq} \quad \text{(equality constraint)}$$
$$lb \leq x \leq ub \quad \text{(bound constraint)}$$



LINEAR PROGRAMMING (LP) - EXAMPLE

A company produce two products: Joops and Goops

- The capacity of your manufacturing unit is **525 hours per week**. It takes **five hours to produce one Joop**, and **three hours to produce one Goop**.
- Joops have a maximum demand of **only 100 per week**.
- Your suppliers provide raw materials needed to produce a **maximum of 75 Goops per week**.
- The profit per unit is:
  2.50€ for a Joop, and 2.00€ for a Goop

How many units of Joops and Goops should you produce each week to **maximize your profit**?

LINEAR PROGRAMMING (LP) - EXAMPLE

A company produce two products: Joops and Goops

- The capacity of your manufacturing unit is **525 hours per week**. It takes **five hours to produce one Joop**, and **three hours to produce one Goop**.

$$5J + 3G \leq 525$$

- Joops have a maximum demand of **only 100 per week**.

$$J \leq 100$$

- Your suppliers provide raw materials needed to produce a **maximum of 75 Goops per week**.

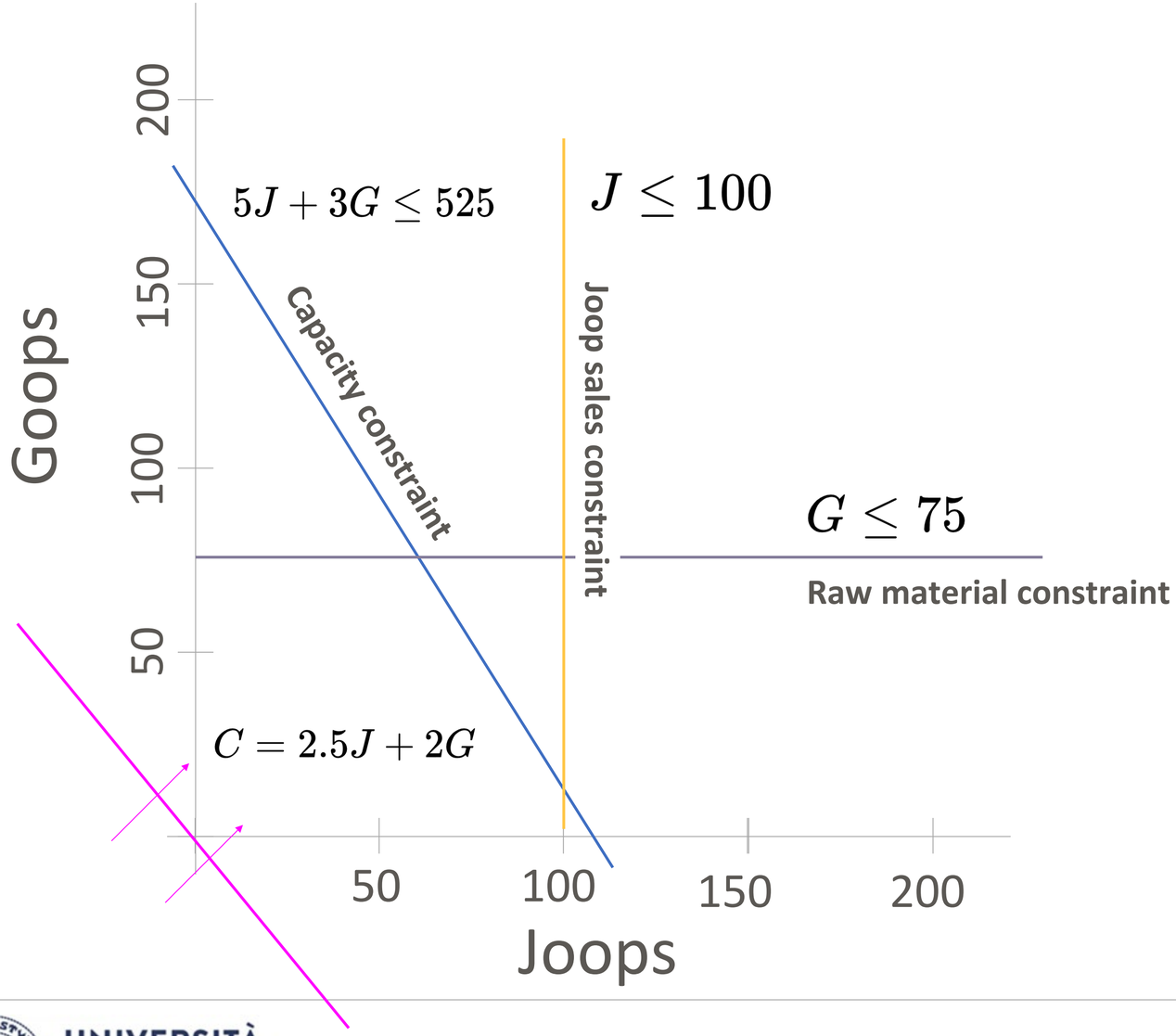
$$G \leq 75$$

- The profit per unit is:
  2.50€ for a Joop, and 2.00€ for a Goop

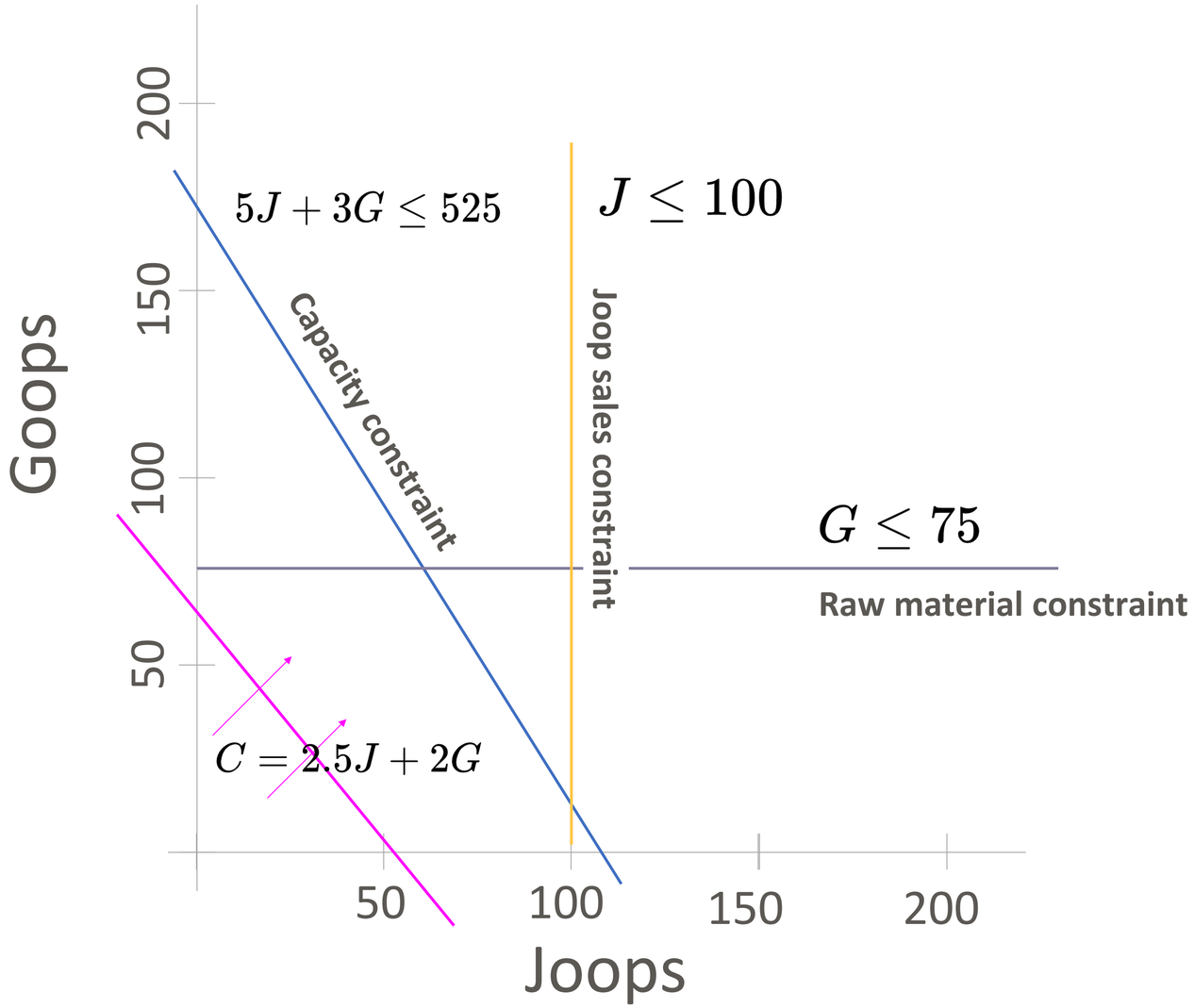
$$C = 2.5J + 2G$$

How many units of Joops and Goops should you produce each week to **maximize your profit**?

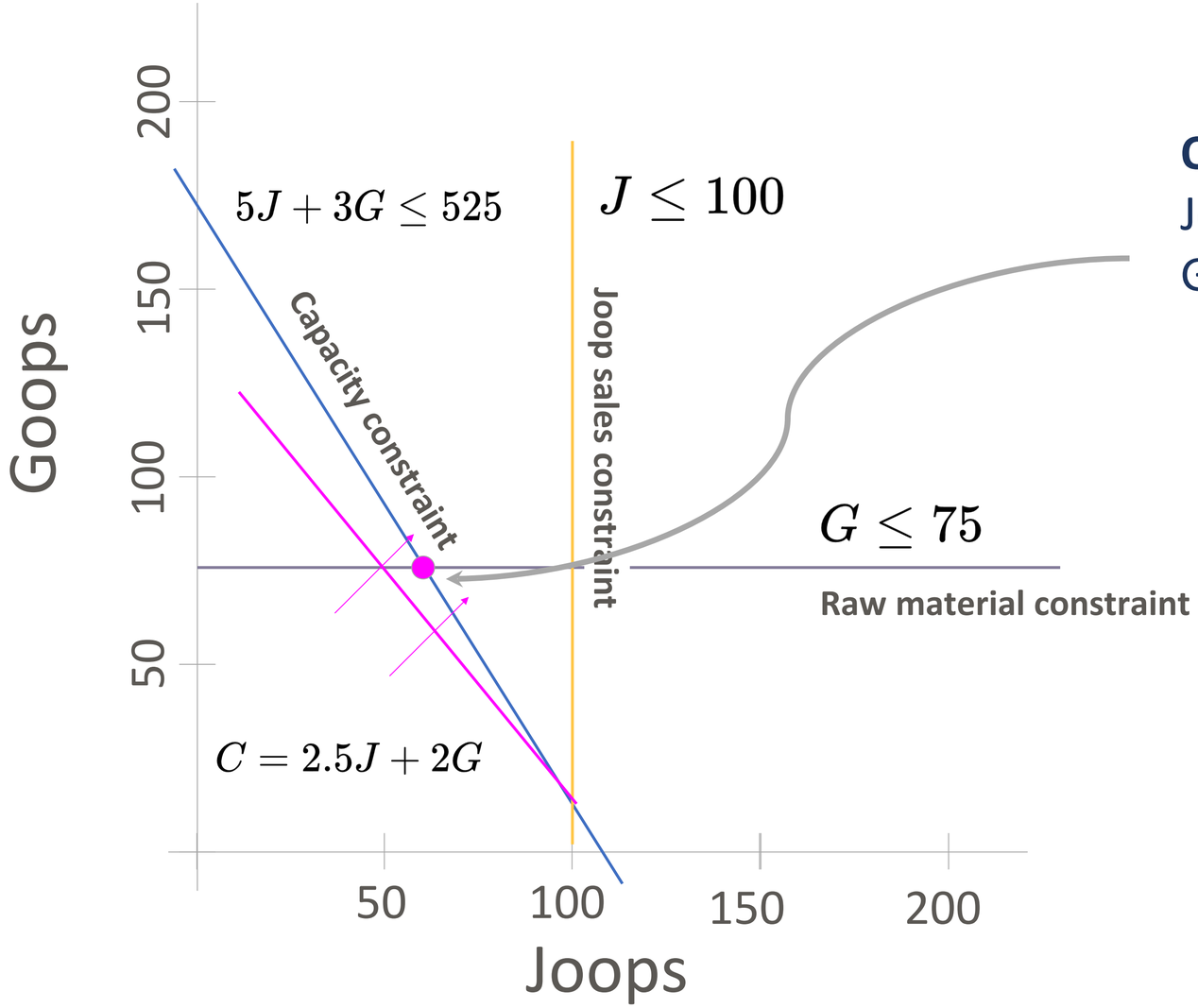
LINEAR PROGRAMMING (LP) - EXAMPLE



LINEAR PROGRAMMING (LP) - EXAMPLE



LINEAR PROGRAMMING (LP) - EXAMPLE



Optimal combination

Joops = 60

Goops = 75

QUADRATIC PROGRAMMING (QP) - EXAMPLE

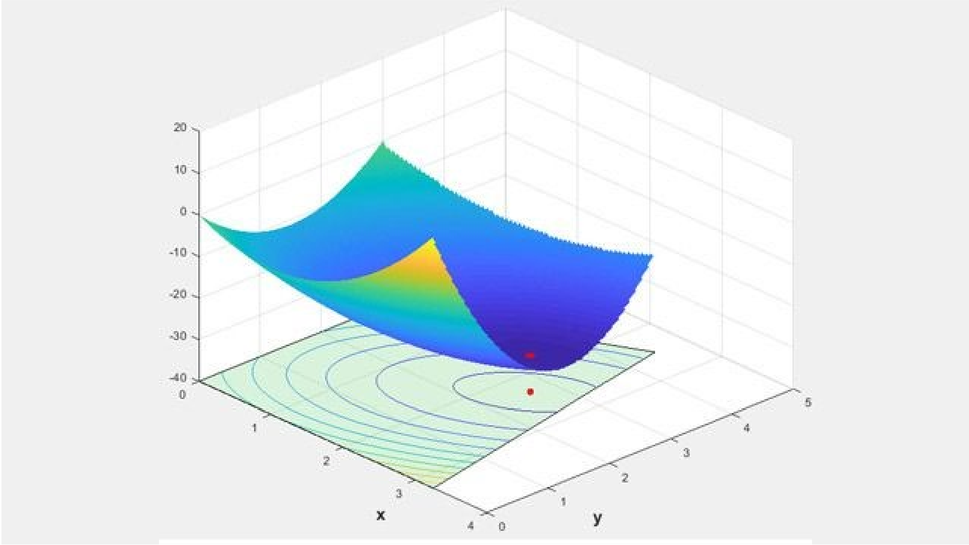
Quadratic programming (QP), also called **quadratic optimization**, is the process of solving certain mathematical optimization problems involving **quadratic functions**. Specifically, one seeks to optimize (minimize or maximize) a multivariate quadratic function subject to **linear constraints on the variables**. Quadratic programming is a type of nonlinear programming.

Find a vector x

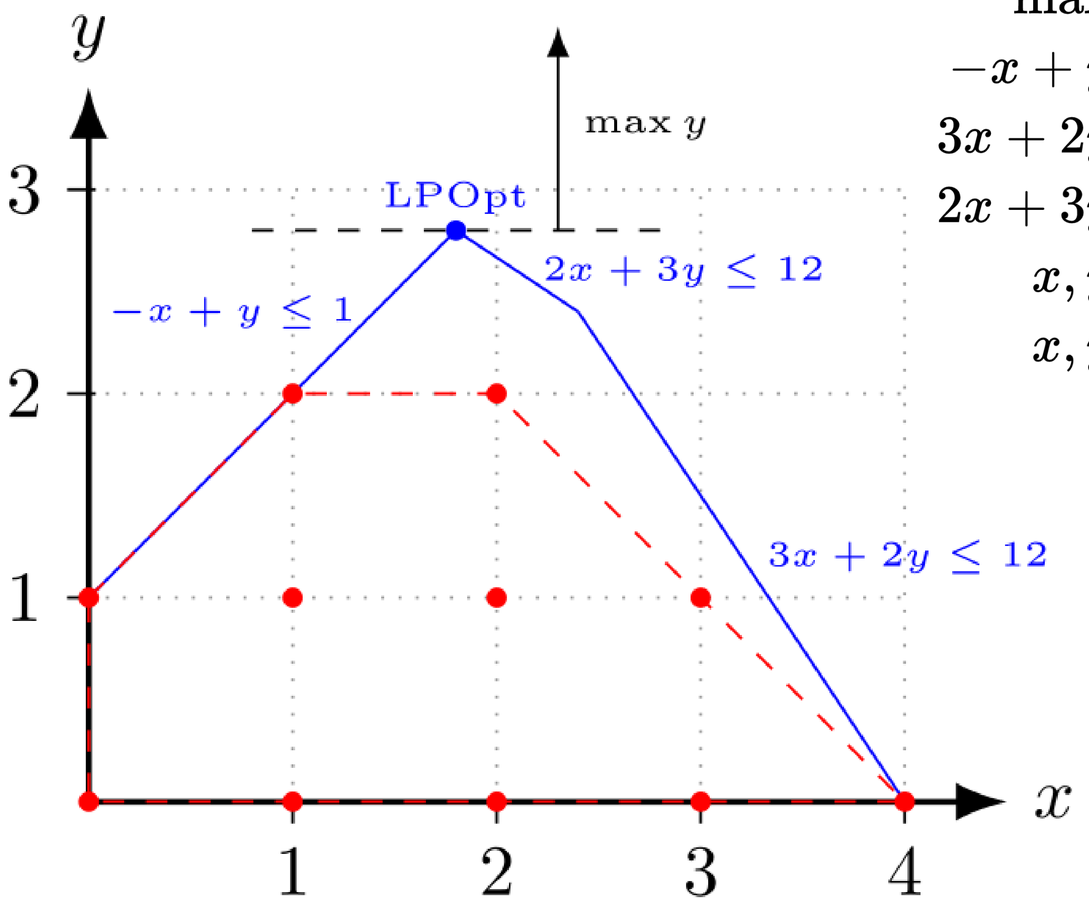
that max/minimizes $f\left(x^2\right)$

subject to

$$Ax \leq b \quad \text{(inequality constraint)}$$
$$A_{eq}x = b_{eq} \quad \text{(equality constraint)}$$
$$lb \leq x \leq ub \quad \text{(bound constraint)}$$



MIXED INTEGER PROGRAMMING (MIP)



$$\max y$$
$$-x + y \leq 1$$
$$3x + 2y \leq 12$$
$$2x + 3y \leq 12$$
$$x, y \geq 0$$
$$x, y \in \mathbb{Z}$$

If some of the decision variables are **discrete**, we call that problem a **Mixed Integer Problem (MIP).**

MIP models with a **quadratic objective** but without quadratic constraints are called Mixed Integer Quadratic Programming (MIQP) problems.

MIP models with **quadratic constraints** are called Mixed Integer Quadratically Constrained Programming (MIQCP) problems.

Models without any quadratic features are often referred to as **Mixed Integer Linear Programming (MILP) problems.**

NONLINEAR PROGRAMMING (NLP)

Nonlinear programming (NLP) is the process of solving an optimization problem where some of the constraints or the objective function are nonlinear (e.g. QP).

- EMS involves multiple conflicting objectives and are affected by many ***uncertainties and nonlinearities***.
- Limited by several *constraints*
- Linear Programming (LP) and Quadratic Programming (QP) are usually used for this type of optimization but these *are limited to simple and linear/quadratic objectives/constraints*.

Nonlinear Programming (NLP) and Mixed Integer Nonlinear Programming (MINLP) are used for more complicated problems.

These techniques have difficulties in handling the uncertain variables and require the involvement of large numbers of computational resources when dealing with the real world problems.

OTHER ALGORITHMS FOR OPTIMIZATION PROBLEMS

Two of the most popular and feasible **optimization heuristic algorithms** for the EMSs are:

- **PSO** - Particle Swarm Optimization
- **GA** - Genetic Algorithm
- **AC** – Ant Colony

is a technique designed to solve a problem **more quickly** when classic methods are too slow, in order to find an **approximate solution**

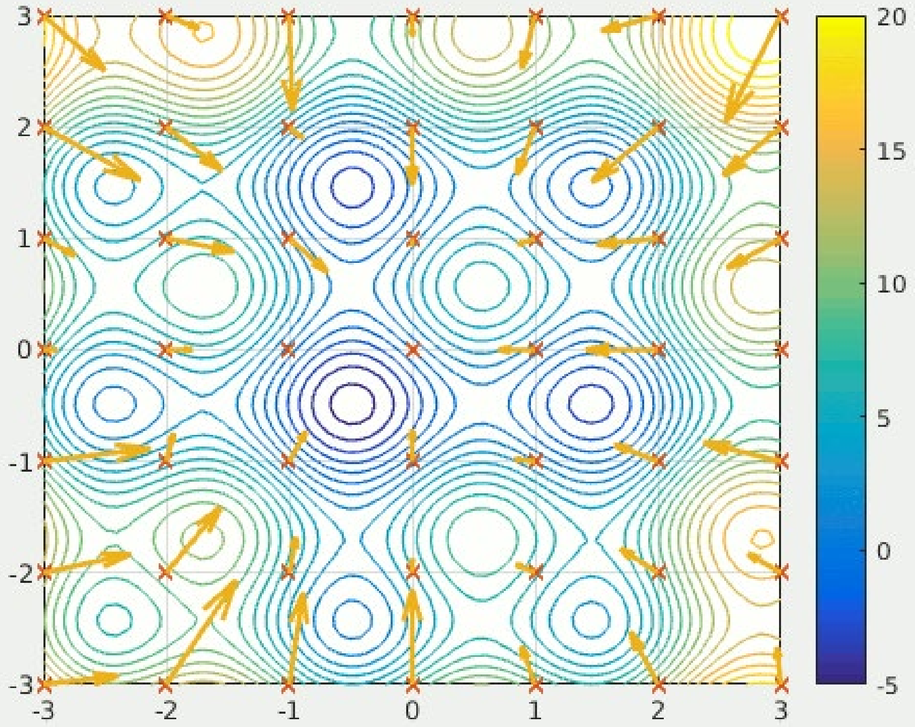
Artificial Intelligence (AI) provides alternative in solving complicated problems:

- **RL** - Reinforcement Learning

Predictive control:

- **MPC** - Model Predictive Control

PSO - PARTICLE SWARM OPTIMIZATION

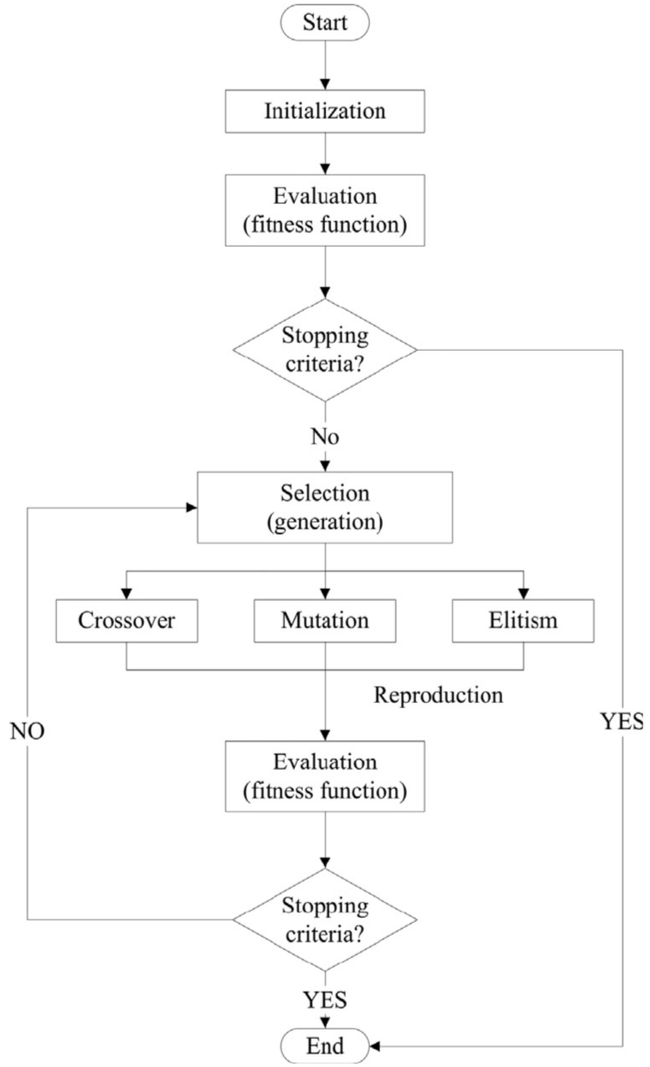


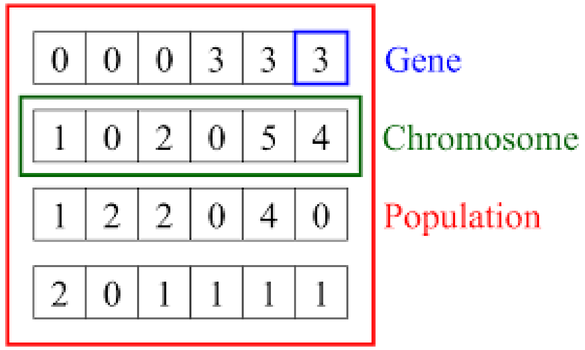
PSO works by ‘flying’ a population of co-operating potential solutions called particles through the multi-dimensional problem space in a specific velocity.

Each individual particle in the swarm is able to *interact with each other*. This enables them to adjust their moving velocity according to the movement patterns of its own and other particles.

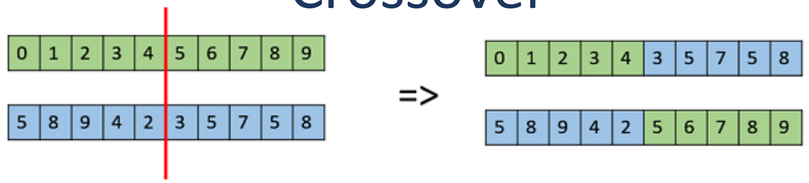
The random movement of the particle swarms helps to *prevent the solution to be trapped in the local minima*.

GA - GENETIC ALGORITHM

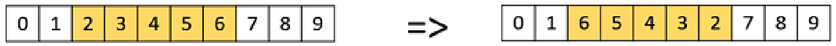




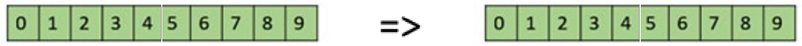
Crossover



Mutation



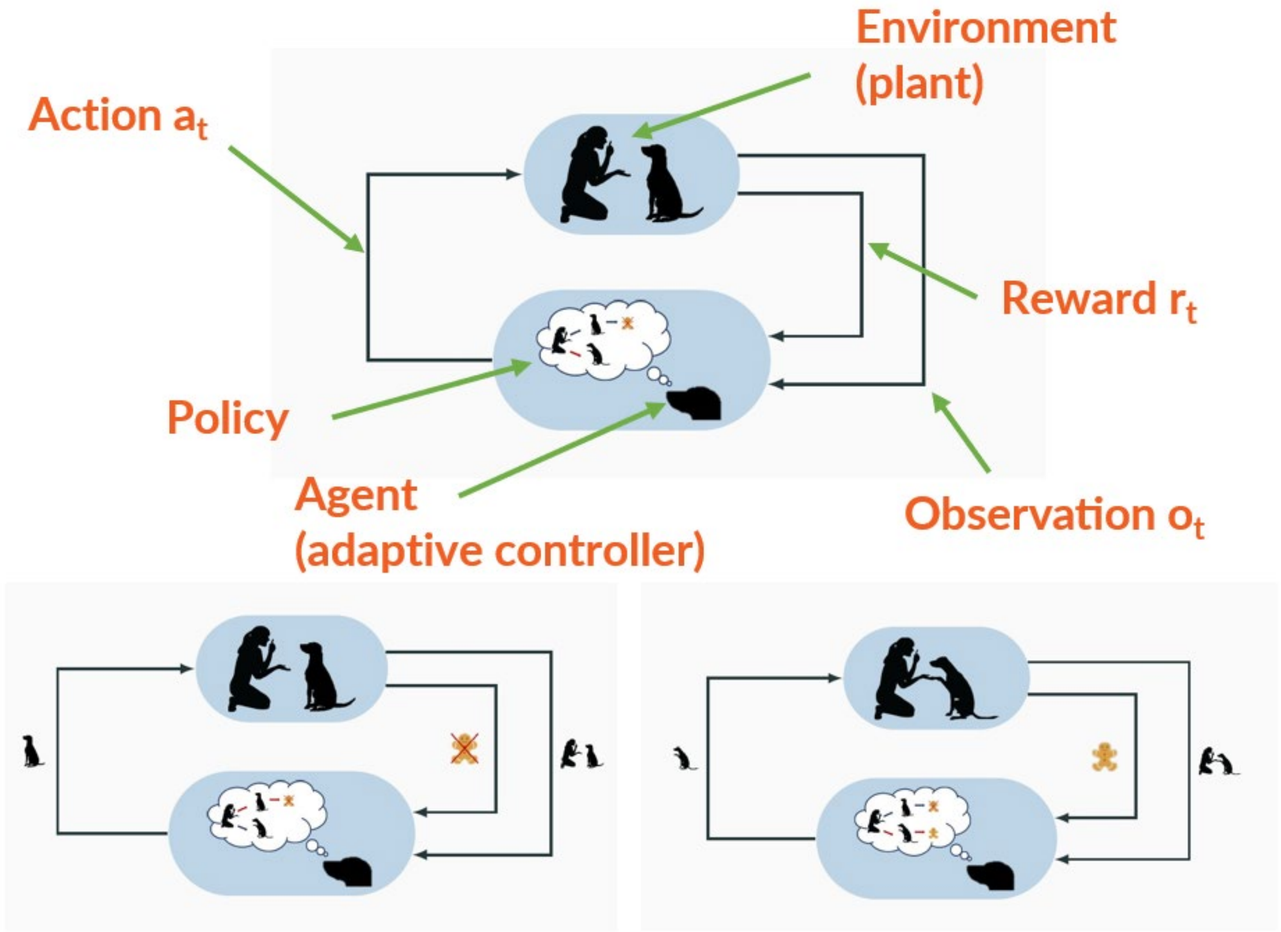
Elitism



The GA is inspired by the **principles of genetics and evolution**, and mimics the reproduction behavior observed in biological populations.

The GA employs the principal of "**survival of the fittest**" in its search process.

RL - REINFORCEMENT LEARNING



Reinforcement Learning (RL) is an agent-based AI algorithm in which the **agents** learn the **optimal set of actions**, i.e., the optimal policy through their interaction with the environment.

An agent interacts with an environment by making an **observation "o_t"** of the current state "s_t"of the environment and applying an action "a_t"which governs the environment into a new state "s_{t+1}". The action is selected based on a policy "π" such that $\mathbf{a_t=\pi(o_t)}$.

Additionally, the agent receives a **reward signal "r_t"** defined as a function of the state and the action

HOW CAN WE OPTIMIZE THE BESS POWER?

Input

1x24 **PV forecasting** P_{PV} ⟶

1x24 **Load forecasting** P_{load} ⟶

1x24 **Price forecasting** c_e ⟶

Prediction horizon (24h)

Optimizer

Cost function

$$C_t = \min\left(\sum_{t=1}^{24} P_{grid}(t) \cdot c_e(t) \cdot \Delta t\right)$$

Constraints

Power balance

$$P_{load}(t) + P_{PV}(t) + P_{grid}(t) + P_{battery}(t) = 0$$

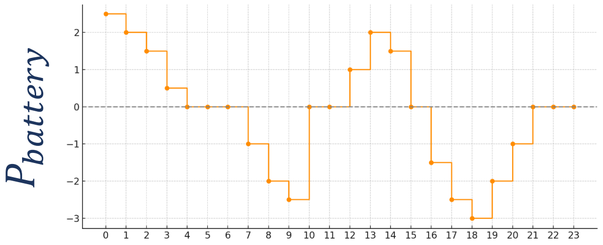
Battery model & limits

$$0 \leq E_b(t) \leq E_{b,max}$$

$$E_b(t) = E_b(t-1) + P_{battery}(t) \cdot \Delta t$$

$$P_{battery}(t) \leq P_{max}$$

Output



⟶ 1x24 **Optimal battery power vector** $P_{battery}$

We are asking the optimizer to try all possible combinations (**according to the constraints**) and for each one calculate the cost C_t:

the one with the lowest cost will be the optimal one!

HOW CAN WE OPTIMIZE THE BESS POWER?

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1x24 **Load forecasting** P_{load} ⟶

1x24 **Price forecasting** c_e ⟶

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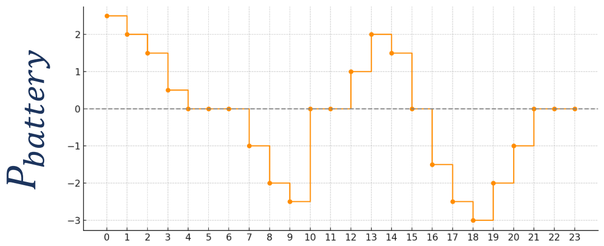
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$$P_{battery}(t) \leq P_{max}$$

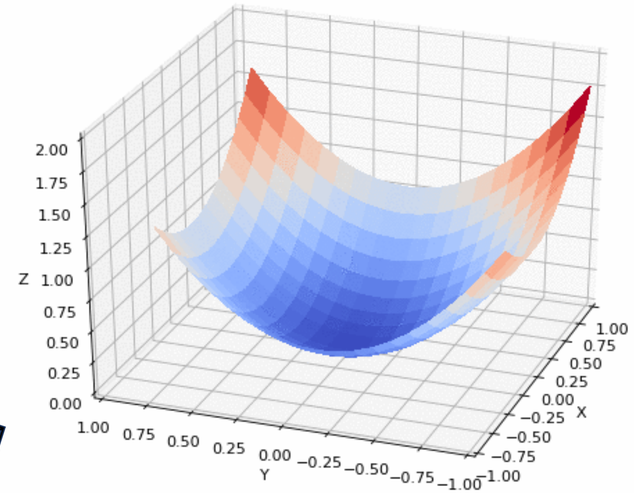
Output



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HOW CAN WE OPTIMIZE THE BESS POWER?

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1x24 **Price forecasting** c_e ⟶

Prediction horizon (24h)

Optimizer

Cost function

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Constraints

Power balance

$$P_{load}(t) + P_{PV}(t) + P_{grid}(t) + P_{battery}(t) = 0$$

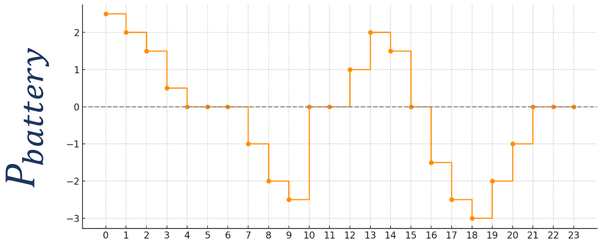
Battery model & limits

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Output



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the one with the lowest cost will be the optimal one!

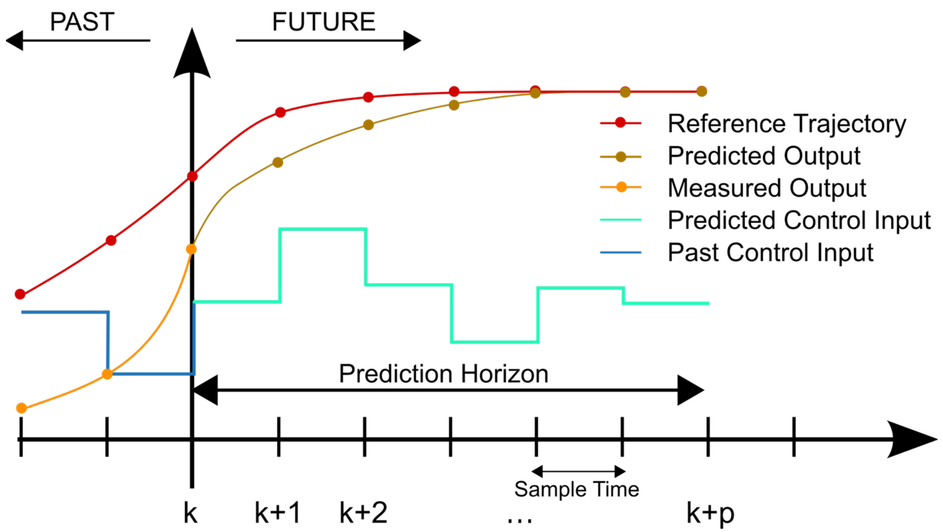
In this case, ***optimization is only done once***, based on the day's forecast.

What if (one or all) the forecasts changes?

It would be useful to **optimize more frequently** so as to take possible updates into account!

MPC – MODEL PREDICTIVE CONTROL

The main idea of MPC control is to **forecast the future performance of the controlled system** over a finite time horizon and compute an optimal control input that minimizes a previously defined functional cost.



The control input is determined by solving an optimal control problem at each sampling instant; then the **first value** of the optimal resulting input trajectory is applied to the system until the next sampling instant, at which **the horizon is shifted** and the **whole process is performed again**.



“ROLLING HORIZONS” (REAL-TIME OPTIMIZATION) EMS

t

Input

1x24 **PV forecasting** P_{PV} ⟶

1x24 **Load forecasting** P_{load} ⟶

1x24 **Price forecasting** c_e ⟶

Prediction horizon (24h)

Optimizer

Cost function

$$C_t = \min\left(\sum_{t=1}^{24} P_{grid}(t) \cdot c_e(t) \cdot \Delta t\right)$$

Constraints

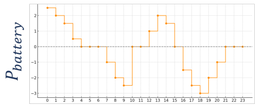
Power balance

$$P_{load}(t) + P_{PV}(t) + P_{grid}(t) + P_{battery}(t) = 0$$

Battery model & limits

$$0 \le SOC(t) \le SOC_{max}(t)$$
$$SOC(t) = SOC(0) + P_{battery}(t) \cdot \Delta t / E_b$$
$$P_{battery}(t) \le P_{max}$$

Output



⟶ 1x24 **Optimal battery power vector** $P_{battery}$

t+1

Input

1x24 **PV forecasting** P_{PV} ⟶

1x24 **Load forecasting** P_{load} ⟶

1x24 **Price forecasting** c_e ⟶

Prediction horizon (24h)

Optimizer

Cost function

$$C_t = \min\left(\sum_{t=1}^{24} P_{grid}(t) \cdot c_e(t) \cdot \Delta t\right)$$

Constraints

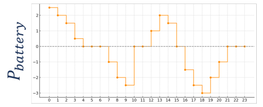
Power balance

$$P_{load}(t) + P_{PV}(t) + P_{grid}(t) + P_{battery}(t) = 0$$

Battery model & limits

$$0 \le SOC(t) \le SOC_{max}(t)$$
$$SOC(t) = SOC(0) + P_{battery}(t) \cdot \Delta t / E_b$$
$$P_{battery}(t) \le P_{max}$$

Output



⟶ 1x24 **Optimal battery power vector** $P_{battery}$

t+2

Input

1x24 **PV forecasting** P_{PV} ⟶

1x24 **Load forecasting** P_{load} ⟶

1x24 **Price forecasting** c_e ⟶

Prediction horizon (24h)

Optimizer

Cost function

$$C_t = \min\left(\sum_{t=1}^{24} P_{grid}(t) \cdot c_e(t) \cdot \Delta t\right)$$

Constraints

Power balance

$$P_{load}(t) + P_{PV}(t) + P_{grid}(t) + P_{battery}(t) = 0$$

Battery model & limits

$$0 \le SOC(t) \le SOC_{max}(t)$$
$$SOC(t) = SOC(0) + P_{battery}(t) \cdot \Delta t / E_b$$
$$P_{battery}(t) \le P_{max}$$

Output



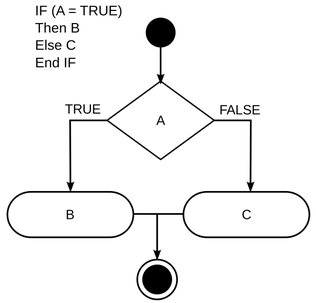
⟶ 1x24 **Optimal battery power vector** $P_{battery}$

Time

EMS CLASSIFICATION

EMS

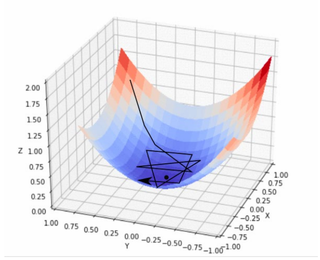
Rule-based



Pros:
- Simple, quick to implement.
- Reliable

Cons:
- Does not adapt to changing conditions
- Does not optimize for the long term.

Optimization-based

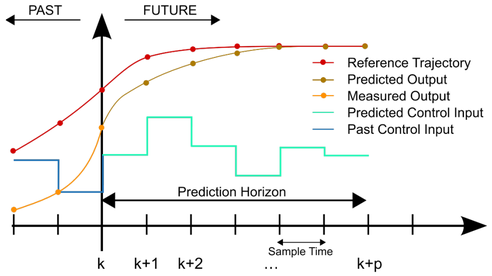


$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f(x) \\ \text{subject to} \quad & g_i(x) \leq 0, \quad i = 1, \ldots, m \\ & h_j(x) = 0, \quad j = 1, \ldots, p \end{aligned}$$

Pros:
- Mathematically defined

Cons:
- It adapts slowly to changing conditions
- It depends on good predictions.

Real-time optimization



Pros:
- Uncertainty management
- Real-time adaptation

Cons:
- Computationally complex
- Dependence on accurate models
- It depends on good predictions

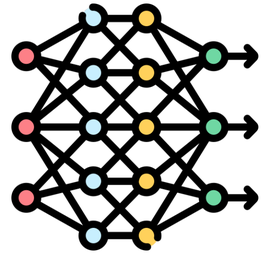
Metaheuristics



Pros:
- Suitable for problems that are nonlinear or not easily modeled.

Cons:
- Approximate or suboptimal solution

Artificial intelligence



Pros:
- High adaptability
- Continuous improvement

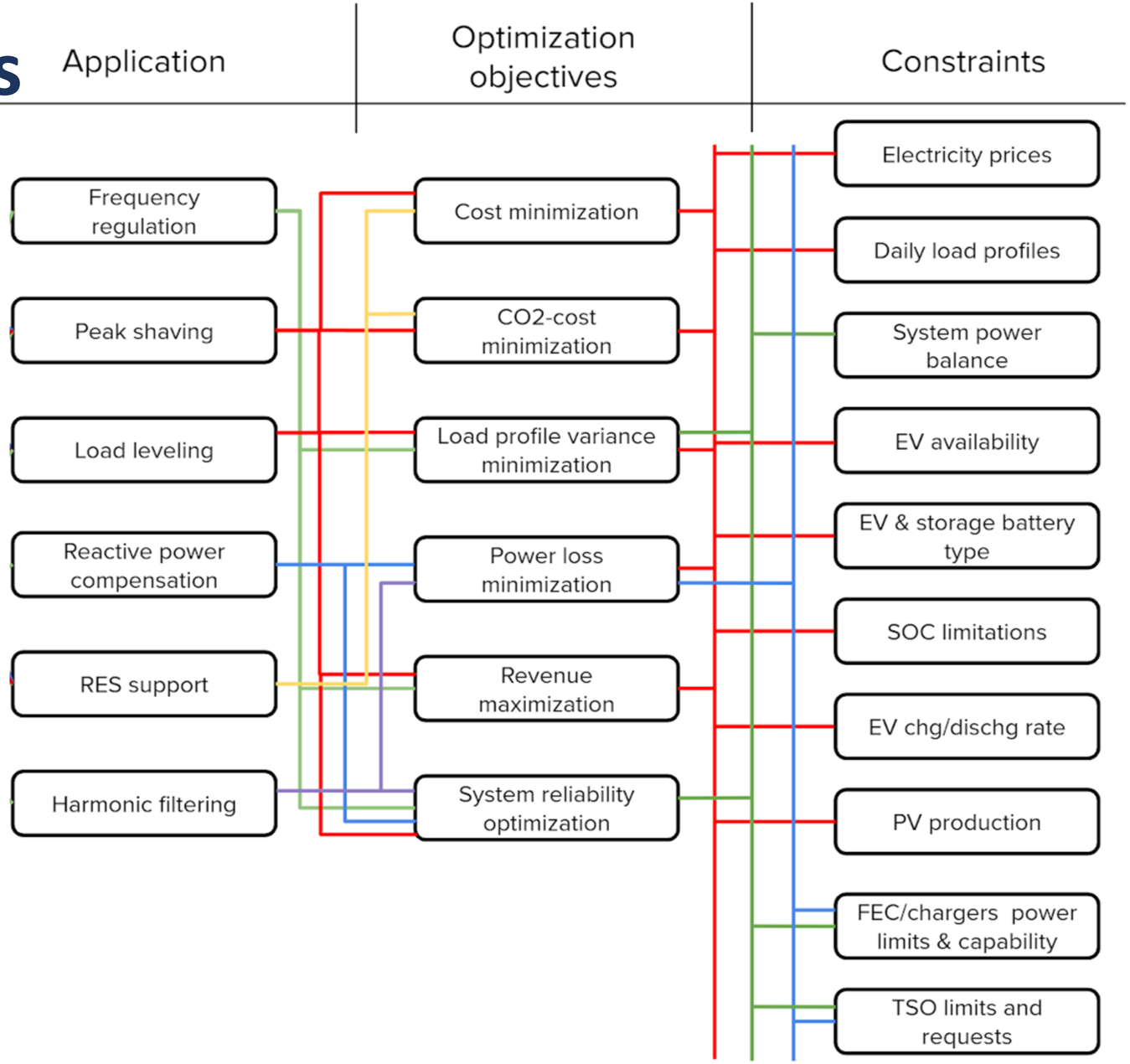
Cons:
- Requires a lot of data
- Complex training phase
- Not always interpretable

Applications and objectives

EMS may have **different applications** that change depending on the owner of the network (residential user or distributor/transmission system operator).

For each application, an **objective function** can be defined that is ***mathematically minimised or maximised*** by the EMS.

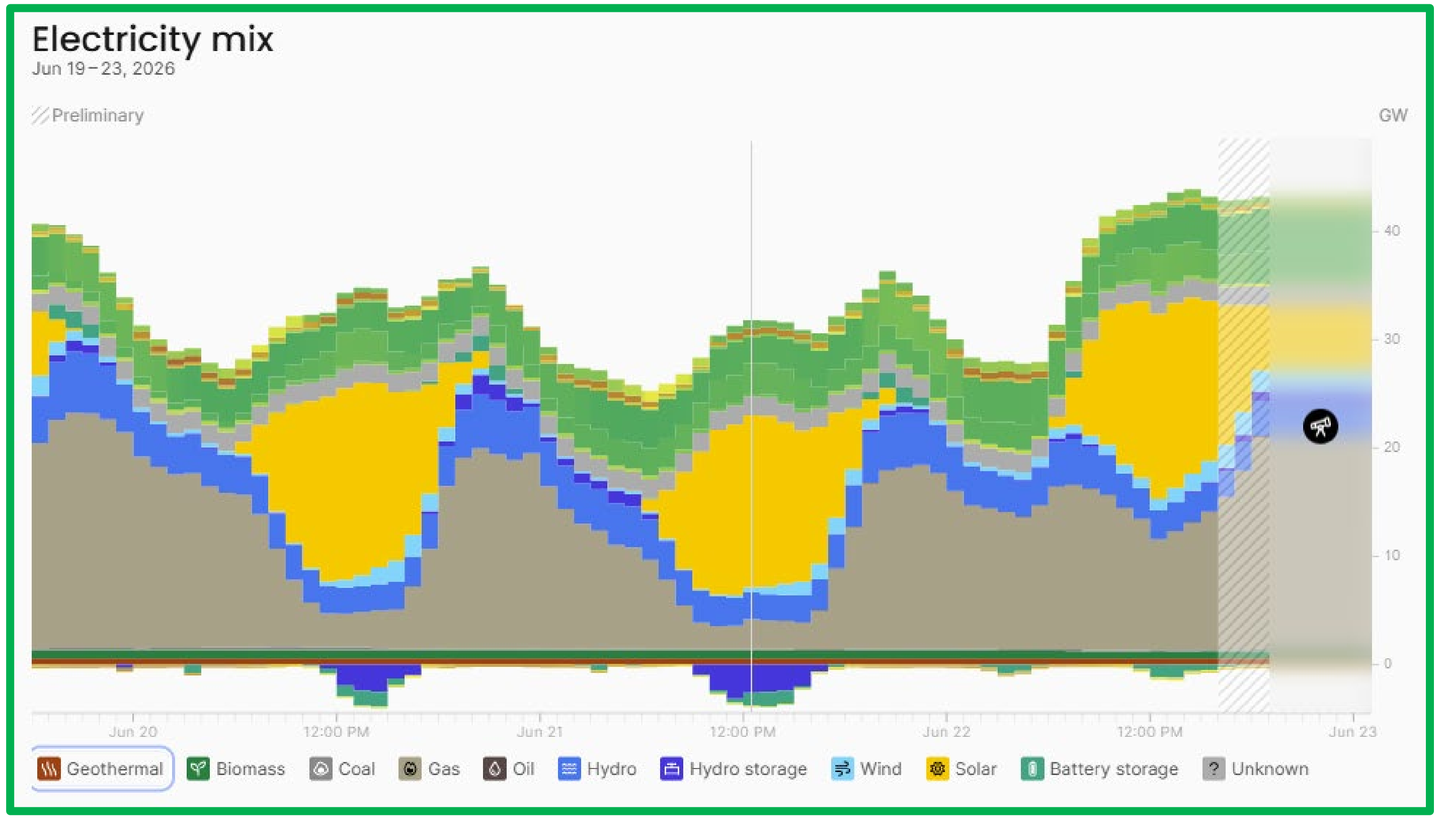
The EMS must respect **constraints** which are defined by the physical system (C-rate, frequency ranges, power balance, etc..) or specified by the user (EV availability, load utilization, etc..).



CARBON INTENSITY

Carbon intensity is a measure of **how clean our electricity is**.
It refers to how many grams of CO_2 are released to produce a unit [kWh] of electricity.

North Italy



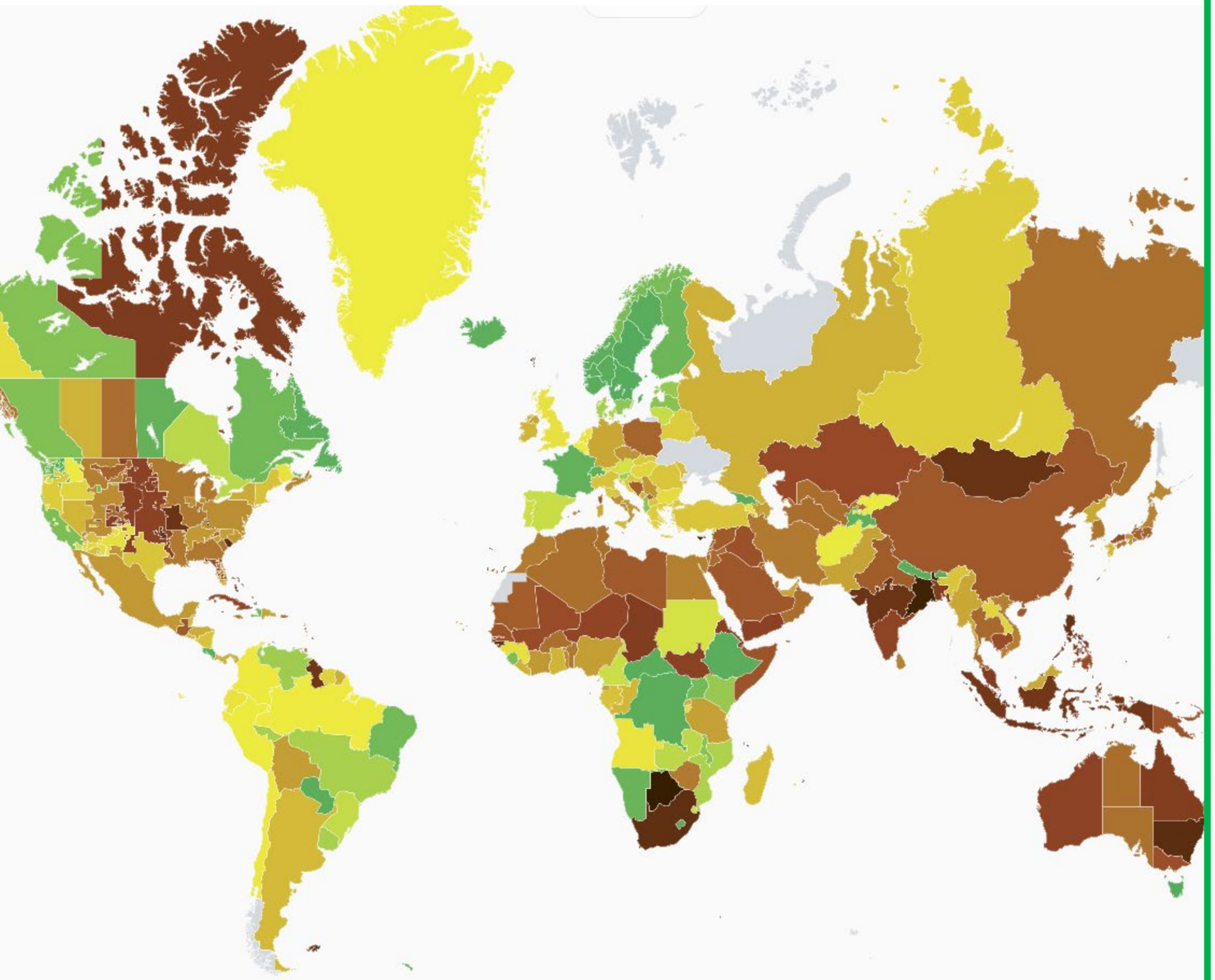
How much CO_2 for each production type?

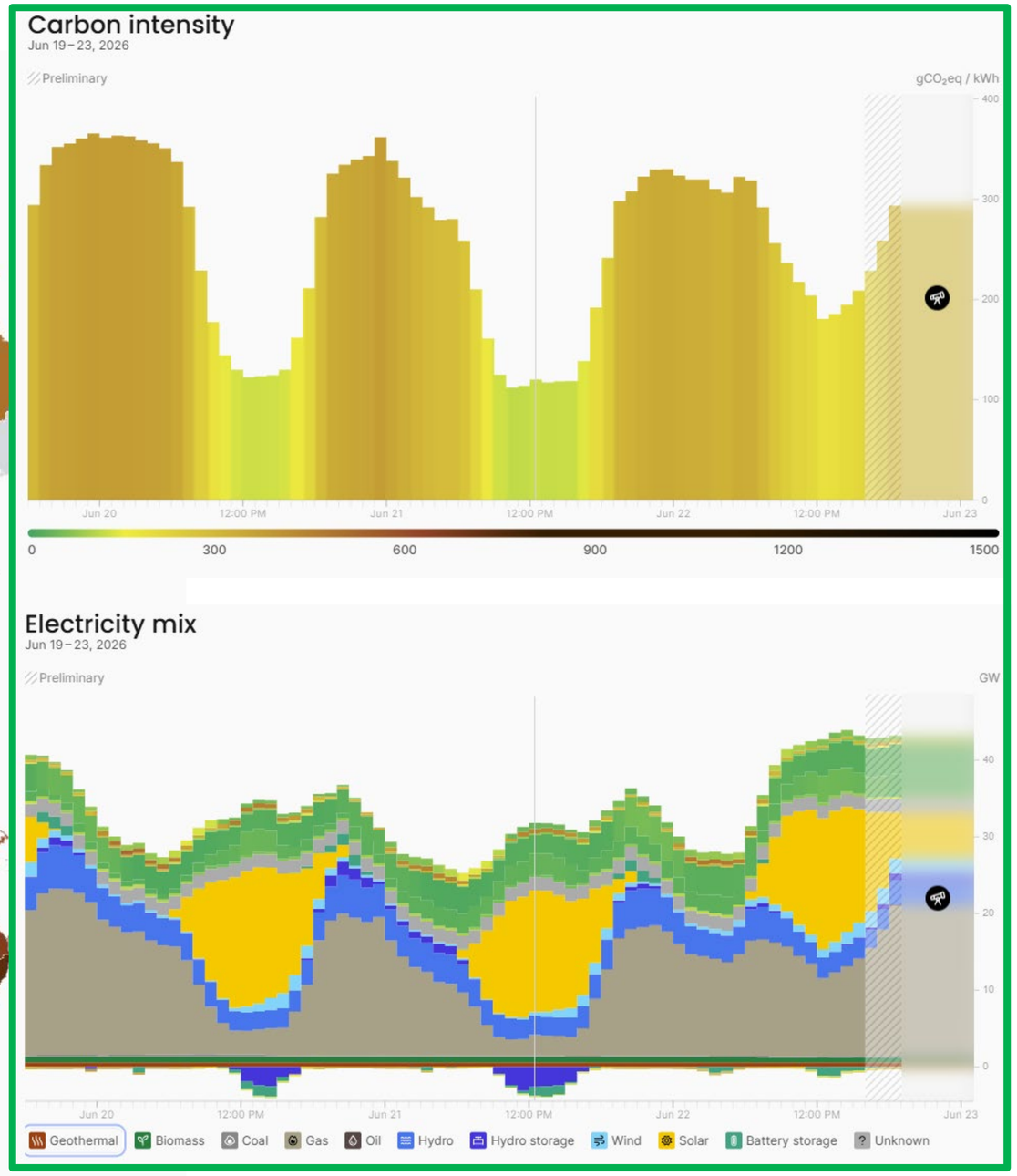
Emission factors $- EF_i$

- coal → 820 gCO2/kWh
- gas → 490 gCO2/kWh
- oil → 650 gCO2/kWh
- biomass → 230 gCO2/kWh
- photovoltaic → 48 gCO2/kWh
- wind → 12 gCO2/kWh
- hydro → 24 gCO2/kWh
- nuclear → 12 gCO2/kWh

$$CI = \sum_i \frac{E_i}{E_{tot}} \cdot EF_i \ \left[\frac{gCO_2}{kWh}\right]$$

IPCC Working Group III – Mitigation of Climate Change, Annex III: Technology - specific cost and performance parameters - Table A.III.2 (Emissions of selected electricity supply technologies (gCO 2eq/kWh))





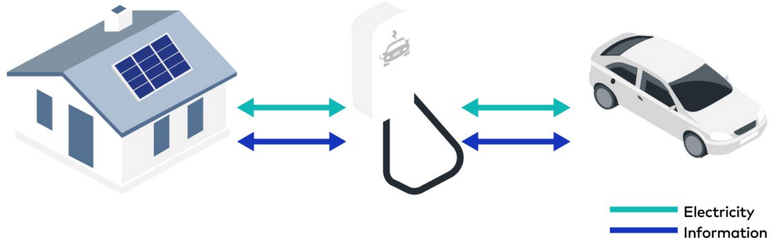
https://app.electricitymaps.com/map

VEHICLE TO ANYTHING: V2H, V2V, V2G…

V2H

V2H - Vehicle-to-Home is a technology that exploits the ***integration of an electric vehicle*** into a smart energy ***home***. The electric vehicle battery stores energy and intelligently feeds energy back to the household loads.

- ❑ Usually, V2H involves a single EV in a single home
- ❑ V2H can improve self-consumption thanks to EV storage and optimization strategies



V2V

V2V - Vehicle-to-vehicle is a technology that exploits an ***EV local community*** to create a suitable ***local power grid*** in order to exchange power between them.

- ❑ V2V involves multiple EVs.
- ❑ Optimization strategies must be performed to optimize power flows among EVs and with the grid.
- ❑ V2V can cooperate with larger renewable energies power generation according to the EV's number.



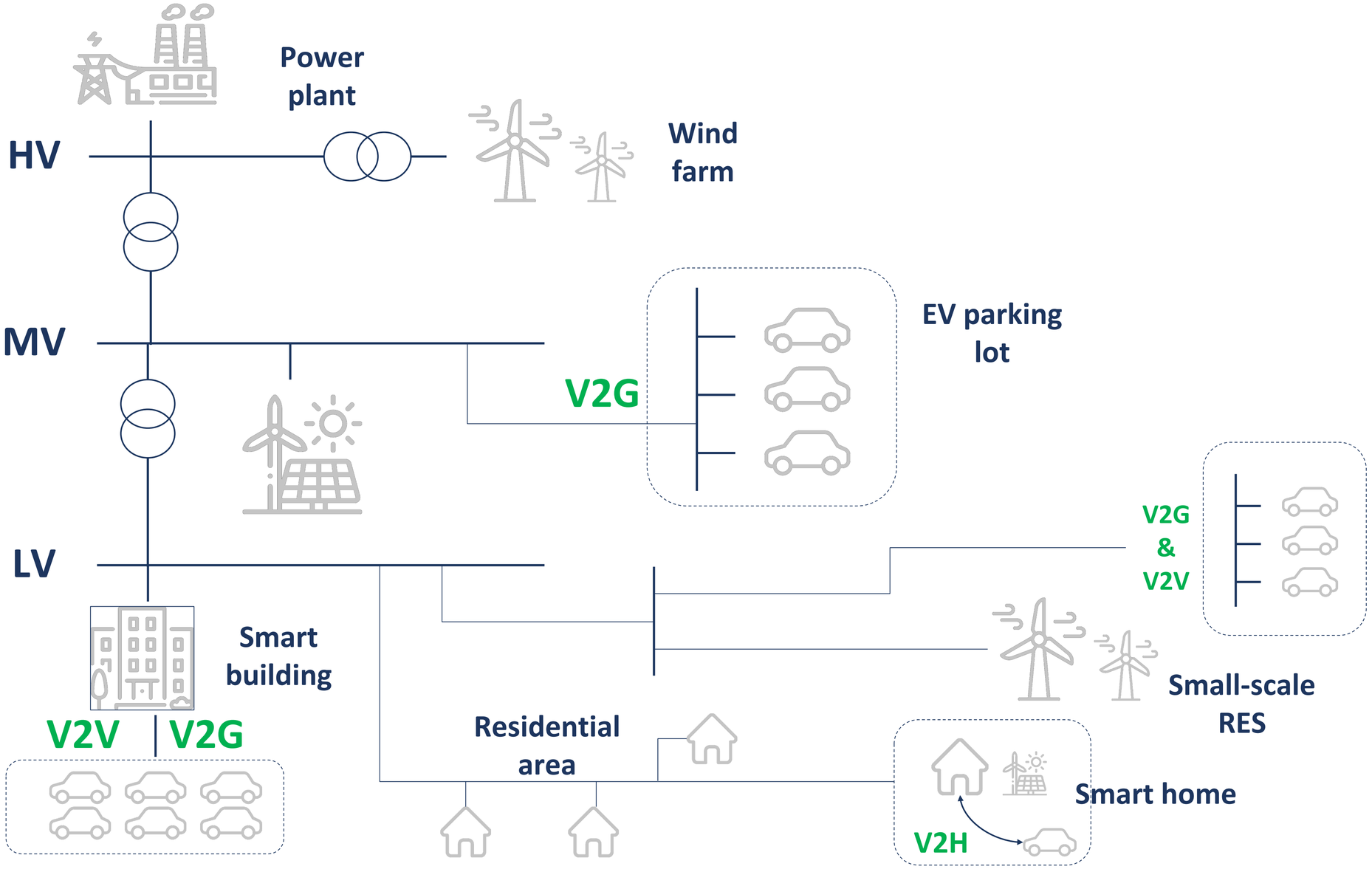
V2G

V2G - Vehicle-to-Grid is the integration of ***an electric vehicle*** into the ***public power grid***. By integrating a *large* number of EVs, the overall stability of the grid can be increased and services can be provided to the power grid itself.

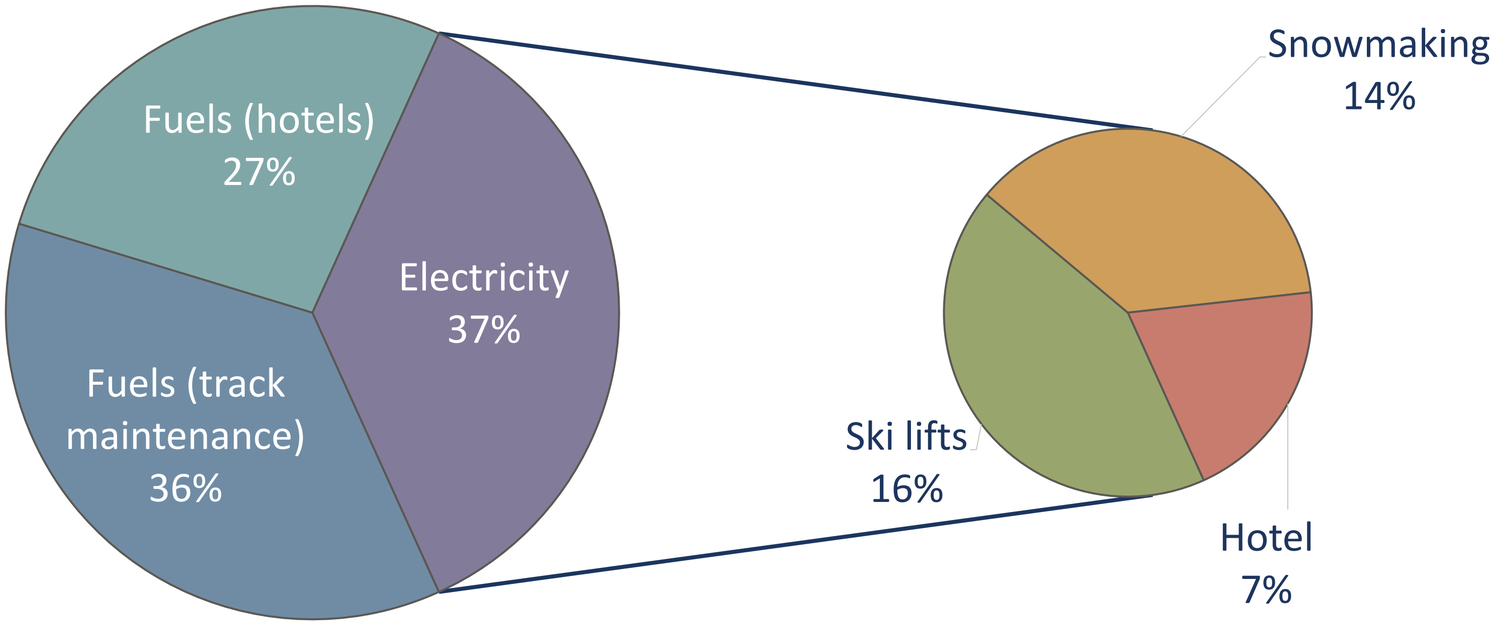
- ❑ V2G involves a large number of EVs
- ❑ V2G can further provide other "ancillary service"



VEHICLE TO ANYTHING



CASE STUDY N.1 – VEHICLE-TO-SKI: V2G ANALYSIS FOR A SKI RESORT

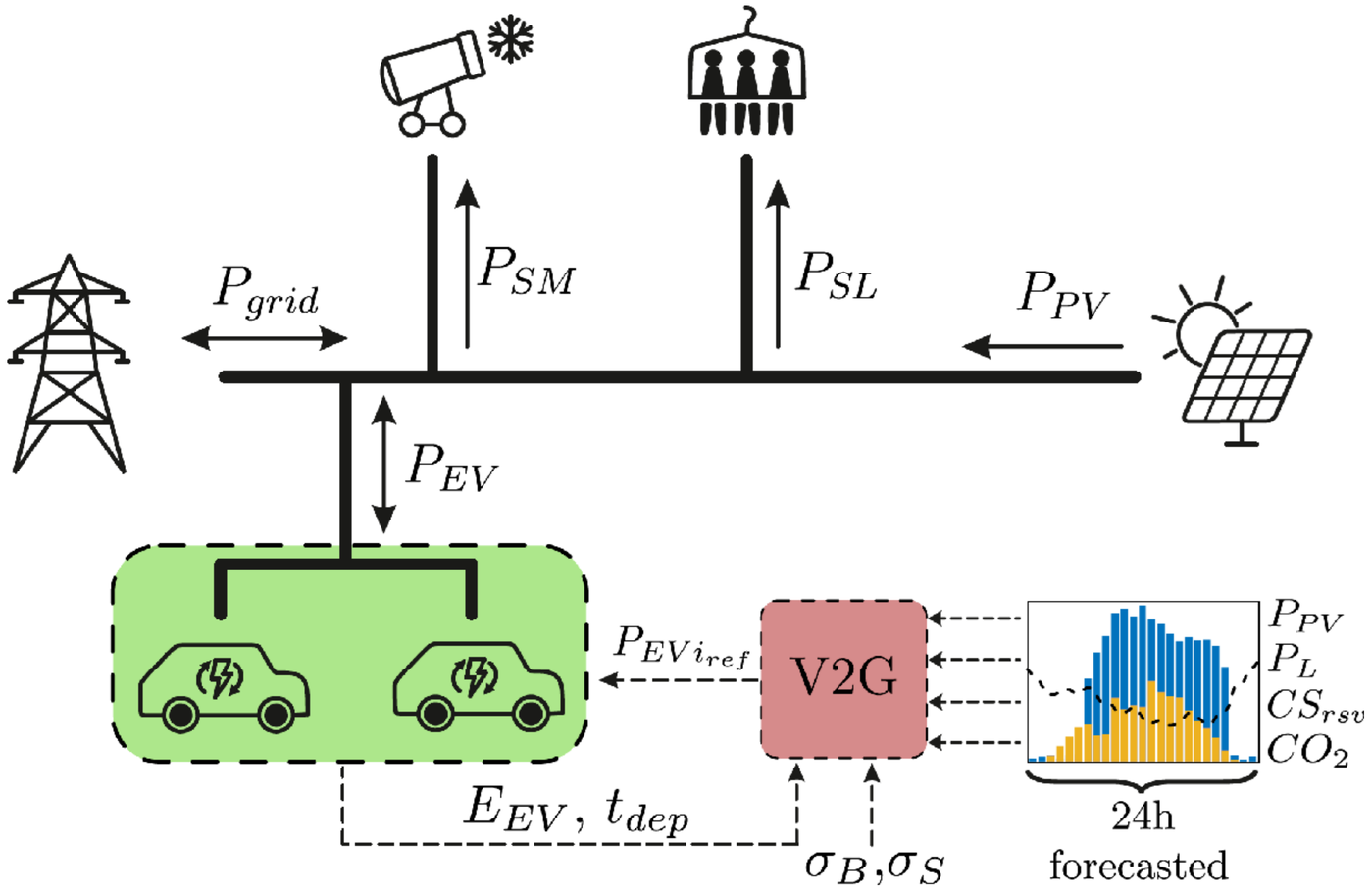


Electricity and (fossil) fuels are the basis for the operation of a ski resort.

Ski lifts and snowmaking on the slopes absorb most of the electricity

How can we reduce CO2 and costs resulting from electricity consumption?

CASE STUDY N.1 – VEHICLE-TO-SKI: V2G ANALYSIS FOR A SKI RESORT



Assumptions: installation of a PV system (e.g. on chairlift stations or on the ground)

Assumptions : skiers with electric cars and their diversification (daily and weekly)

Can we exploit vehicles to optimize costs and the environmental impact of the resort?

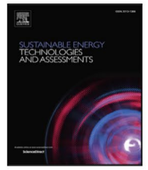
Vehicle-to-grid

CASE STUDY N.1 – VEHICLE-TO-SKI

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Vehicle-to-ski: A V2G optimization-based cost and environmental analysis for a ski resort

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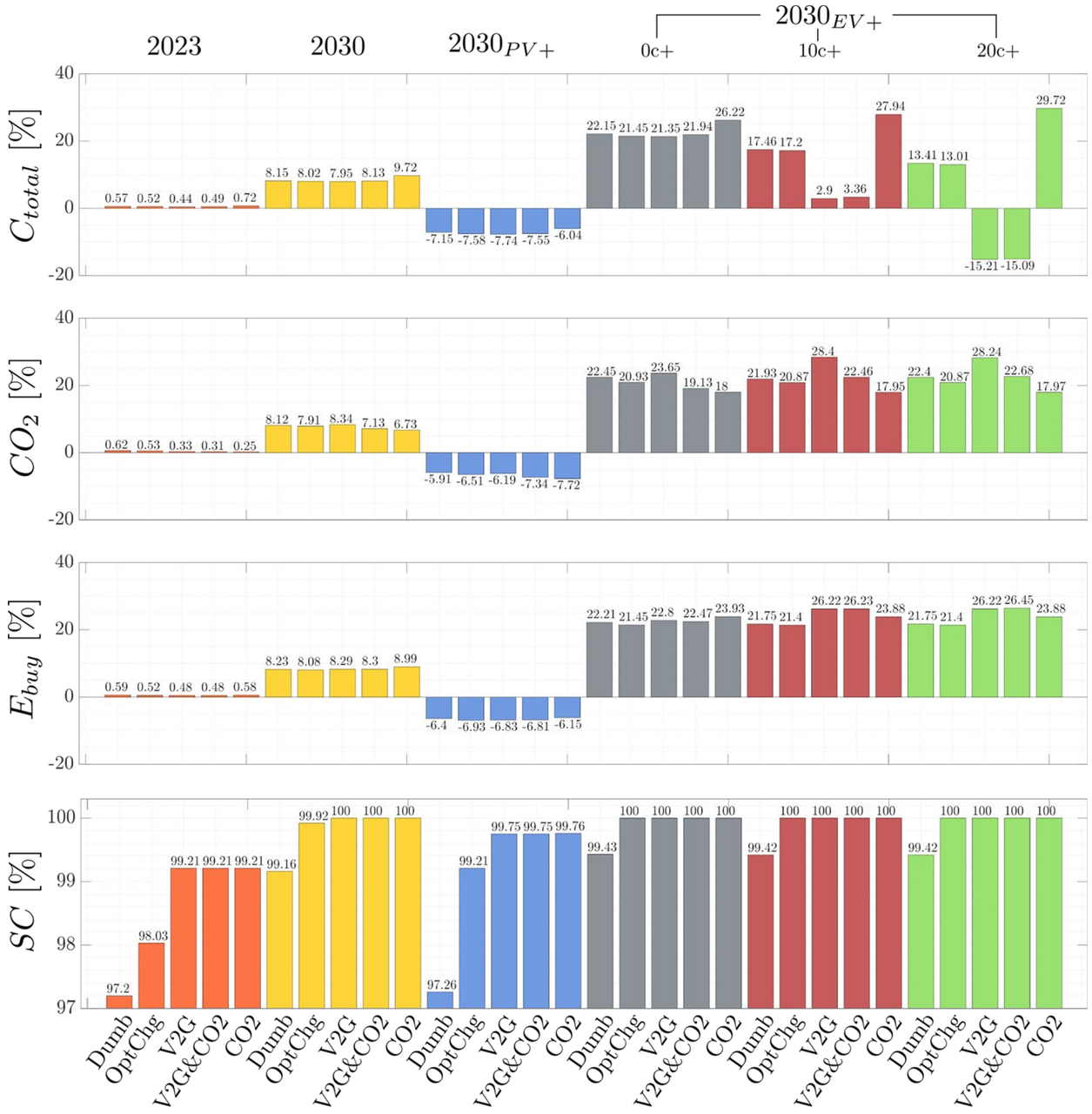
$$min\ f = \sum_{t=1}^{T} \alpha_1 \left(C_E(t) + C_{DEG}(t) \right) + \alpha_2 C_{CO2}(t)$$

$$E_{EV_i}(t) = \begin{cases} 0 \quad \text{(car not connected)} & \text{for } t < t^k_{i,arr} \\ E_{EV_{i,arr}} & \text{for } t = t^k_{i,arr} \\ E_{EV_i}(t-1) + \left(P^{chg}_{EV_i}(t-1)\eta_{EV} - \dfrac{P^{dis}_{EV_i}(t-1)}{\eta_{EV}} \right) \Delta t & \forall t \in [t^k_{i,arr} + 1, t^k_{i,dep}] \end{cases}$$

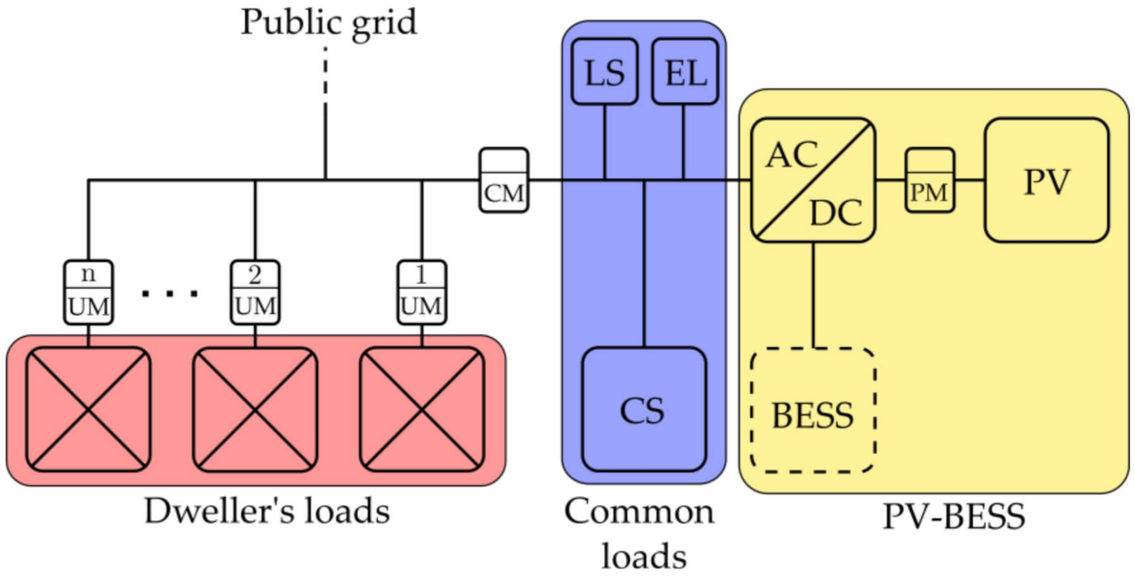
$$P_{PV}(t) + P_{grid}(t) - P_{SL}(t) + \sum_{i=1}^{EV_{con}} P_{EV_i}(t) - P_{SM}(t) - P_{AUX} = 0$$

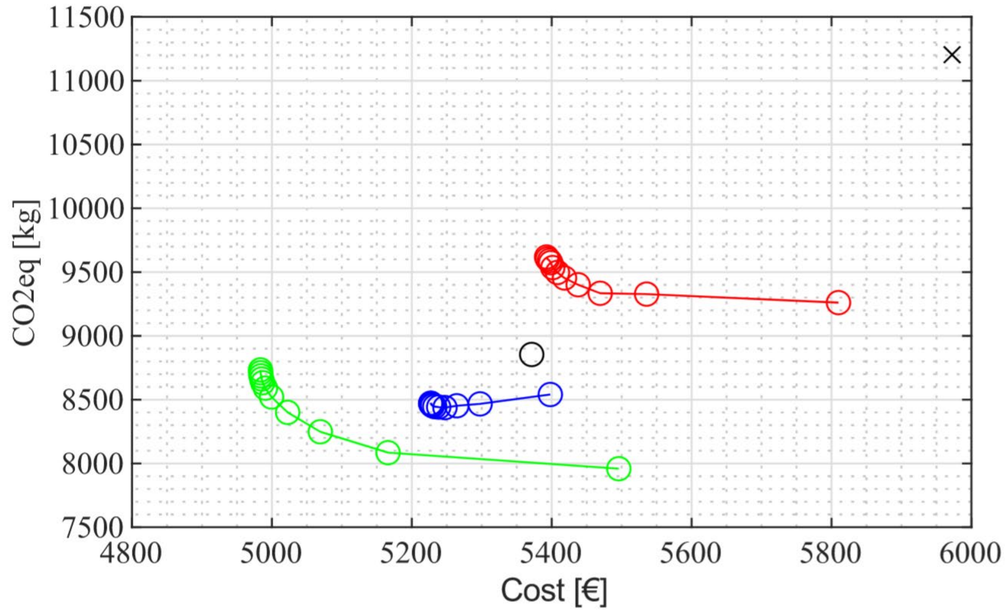
$$P_L(t) = P_{SL}(t) + P_{SM}(t) + P_{AUX}(t)$$

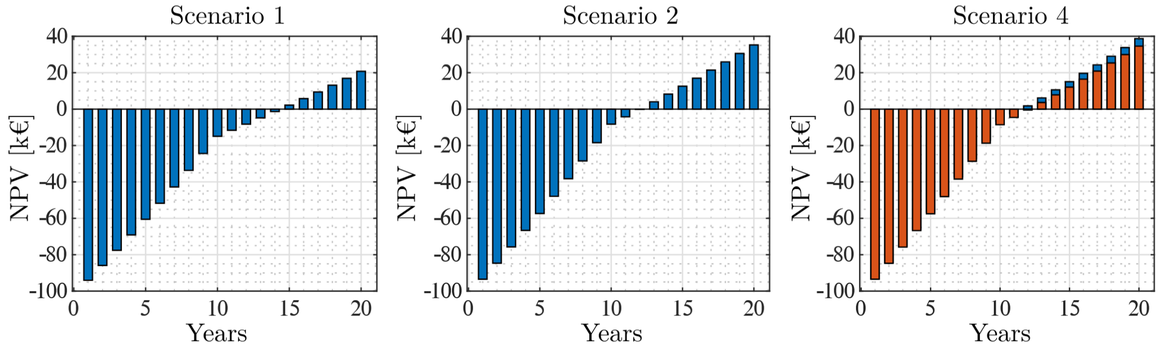
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CASE STUDY N.2 – RENEWABLE ENERGY COMMUNITIES







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Combined model predictive control and ANN-based forecasters for jointly acting renewable self-consumers: An environmental and economical evaluation

Simone Negri [a,*], Federico Giani [a], Nicola Blasuttigh [b], Alessandro Massi Pavan [b], Adel Mellit [c], Enrico Tironi [a]

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