XXXV Cycle - PhD Programs

Study and implementation of compact modeling techniques for the energy analysis and optimization of complex systems

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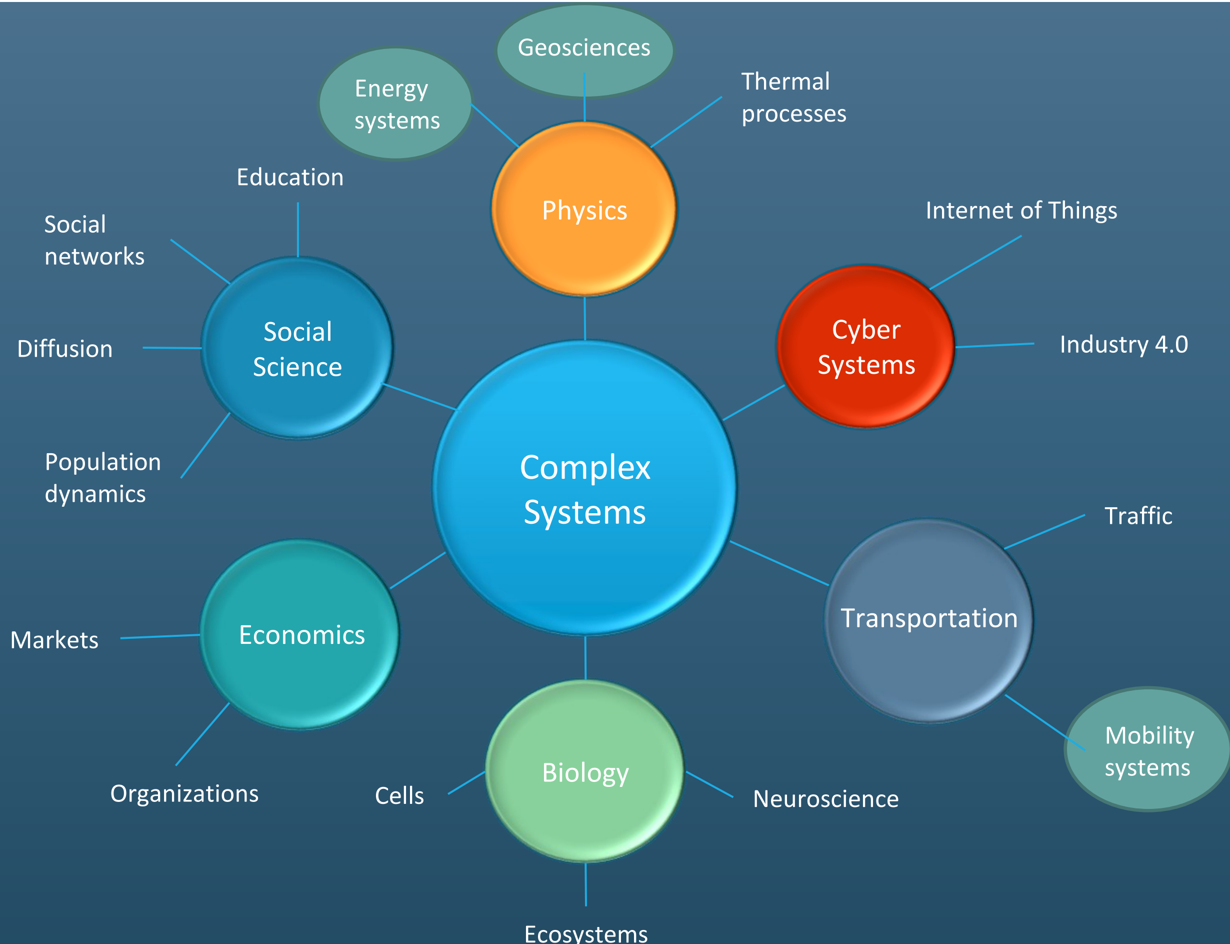
Outline

- Introduction
  - Modeling complex systems: state of the art
- Motivation
- Methodology for compact modeling
  - New and adapted models
- Research activities
  - Battery energy
  - Energy optimization for e-vehicles (EVs)
  - Solar energy
- Conclusions and future work

A world of complex systems



CS modeling: state of the art

Mathematical models

- They are usually based on ODE and PDE since the interactions of the individual elements generally exhibit nonlinear properties
- Reduced-order models are generally less accurate
- Nowadays, we have Artificial Neural Networks (ANNs)

Computational models

- Tools for modeling and simulating:
  - *System Dynamics (e.g.,* Vensim, PowerSim, Stella)
  - *Agent-Based Models (e.g.,* NetLogo, AnyLogic, Repast)

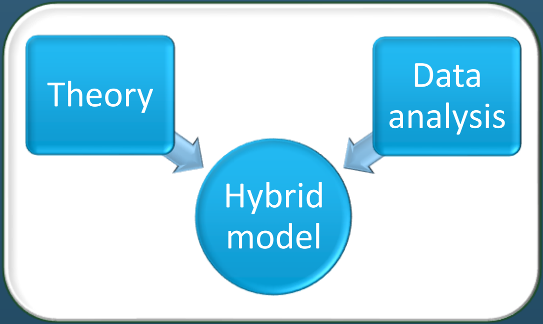
> “A good model is simple, valid, and robust.”
>
> *H. Sayama, Introduction to the Modeling and Analysis of Complex Systems, 2015*

Motivation and approach

Expanding the number of users who have access to the analysis of a complex system

- The most challenging goal is the development of a methodology for generating compact models

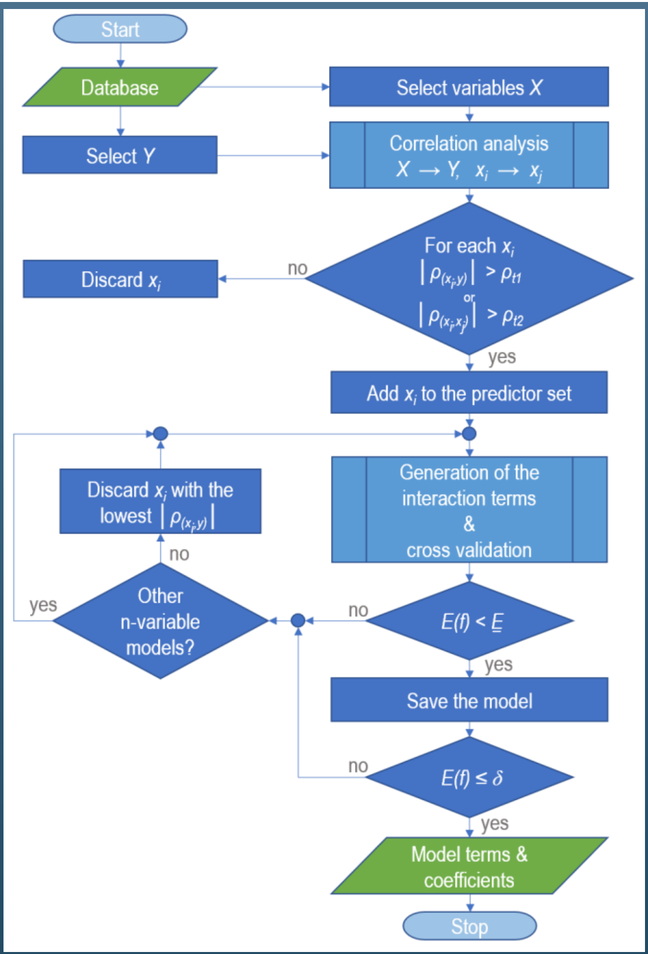
- Two different basic modeling approaches:
  - Improving existing models
  - Developing new models



Methodology: flow chart

- Correlation analysis
  - x_i vs. y
  - x_i vs. x_j
- Select variables as predictors

	x_1	x_2	x_3	x_4	y
x_1	1.0000	-0.2942	-0.6477	-0.7054	-0.6900
x_2	-0.2942	1.0000	0.4899	0.0162	0.1193
x_3	-0.6477	0.4899	1.0000	0.1410	0.3146
x_4	-0.7054	0.0162	0.1410	1.0000	0.8937
y	-0.6900	0.1193	0.3146	0.8937	1.0000



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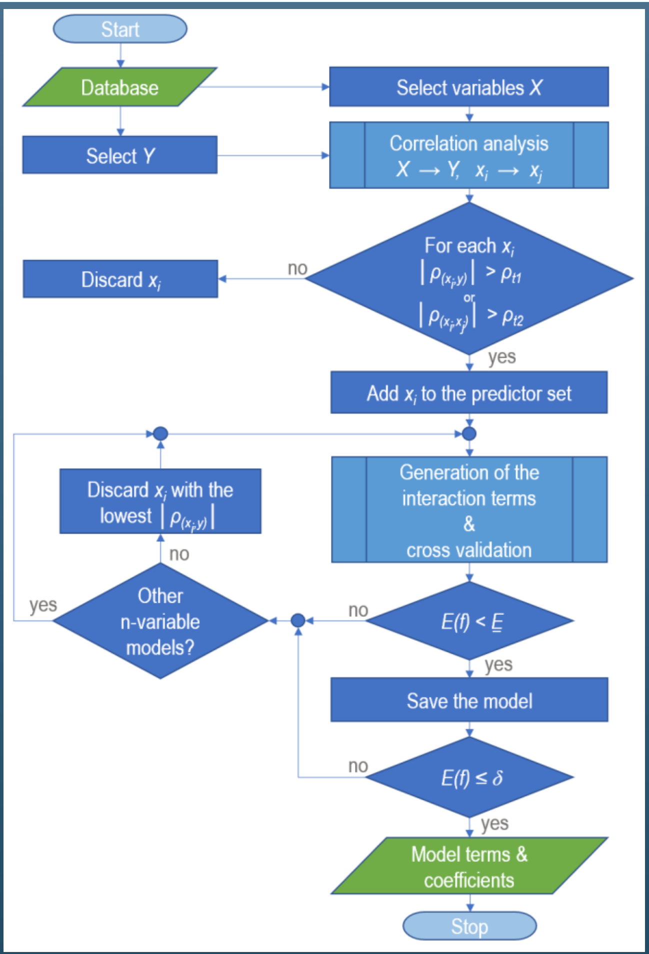

Methodology: flow chart

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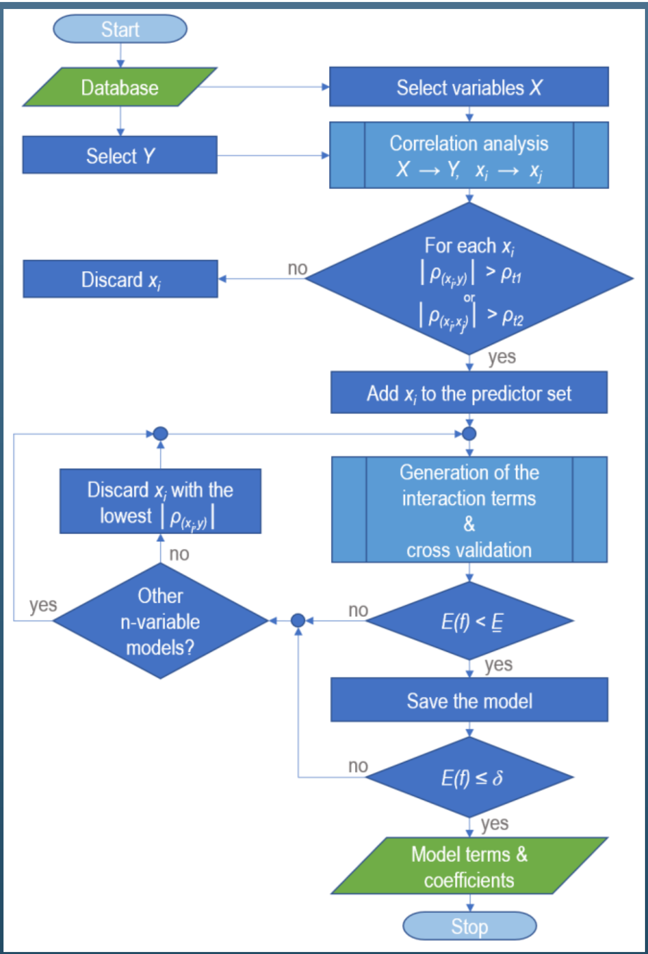
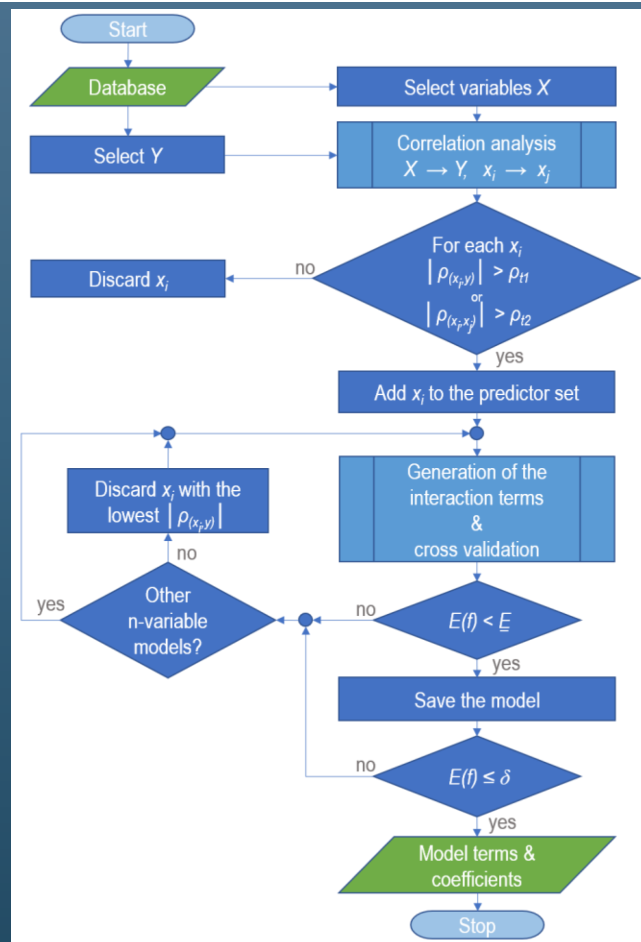
- Select variables as predictors
  - Generation of the interaction terms
  - Cross validation for each model



Methodology: flow chart

- Correlation analysis
  - x_i vs. y
  - x_i vs. x_j
- Select variables as predictors
  - Generation of the interaction terms
  - Cross validation for each model
- Stepwise backward selection
  - If the accuracy of any model is lower than the one expected:
    - discard the variable with the lowest ρ
    - start the loop again
  - Otherwise, save the best model.



Methodology: flow chart

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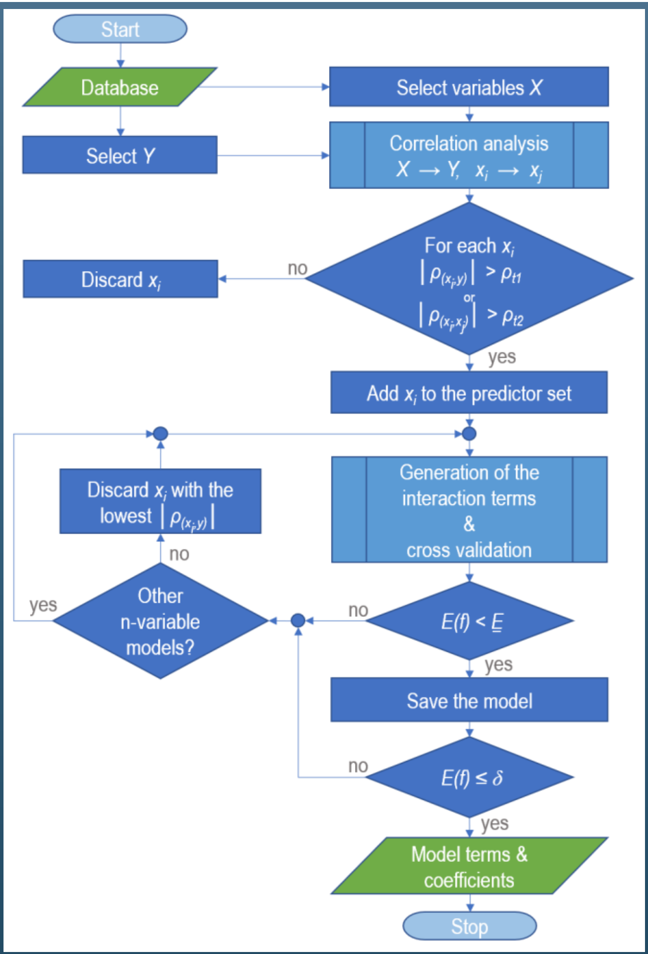

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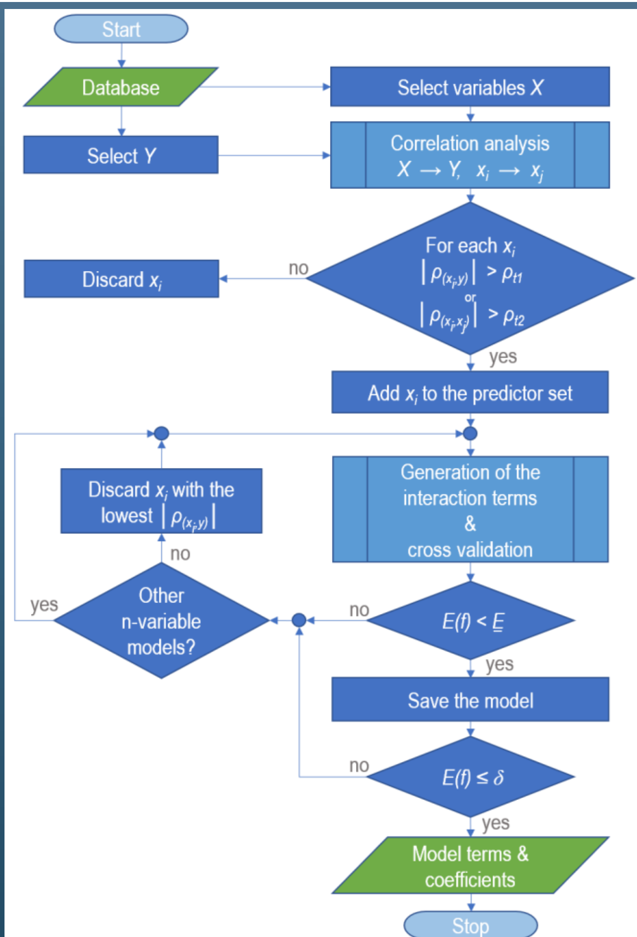
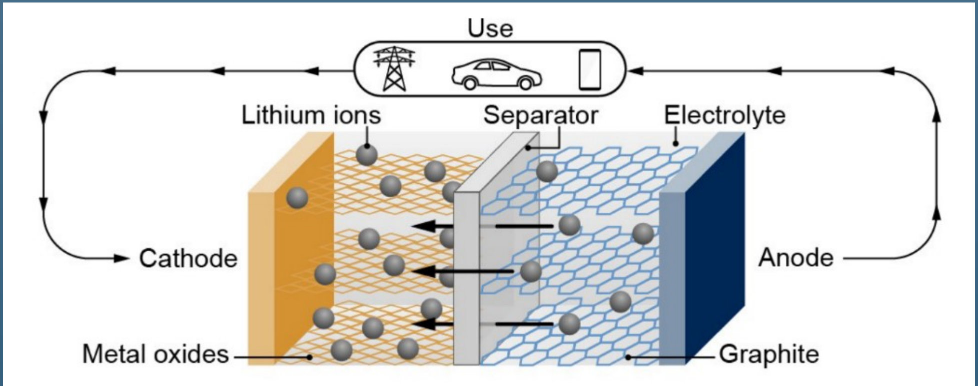


Battery performance analysis



Source: U.S. Government Accountability Office (GAO): GAO-23-106332

- A. Bocca, Y. Chen, W. Wang, A. Macii, E. Macii, and M. Poncino, "A quantitive analysis of the recovery effect in batteries from datasheets," *2021 International Conference on Synthesis, Modeling, Analysis and Simulation Methods, and Applications to Circuit Design (SMACD)*, July 2021, online event, pp. 96-99.
- A. Bocca, Y. Chen, A. Macii, E. Macii, and M. Poncino, "Adapting the Peukert equation to batteries discharged at pulse currents," *2022 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM),* 22-24 June 2022, Sorrento, Italy, pp. 64-69.
- A. Bocca, Y. Chen, A. Macii, E. Macii, and M. Poncino, "A cost-benefit analysis of batteries for Internet-of-Things applications," *2022 AEIT International Annual Conference*, 3-5 October 2022, Rome, Italy, pp. 1-6.

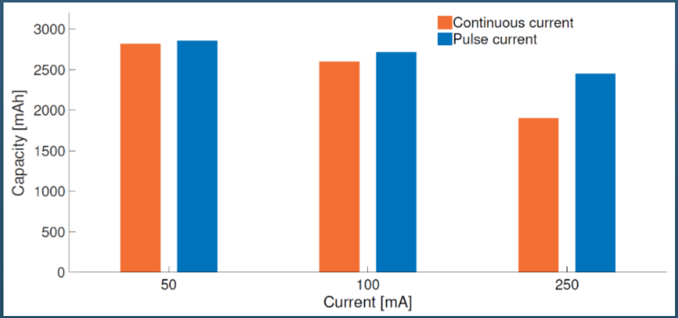
The adapted Peukert equation

- Peukert's law:

$$C_P = I^k \cdot t$$

  - C_p is the Peukert capacity [Ah] at the discharge current I of 1 A
  - k is called the Peukert coefficient (close to 1): it depends on the chemistry
    - battery runtime may vary depending on the discharge mode
    - for pulse currents: by analyzing the “recovery effect” during rest times
- Adapting the model (while focusing on service time):

$$t_{s_x} = \frac{C_{ref_x}}{{I_x}^{k_x}}$$



Energizer, E91 alkaline (Zn/MnO2) battery

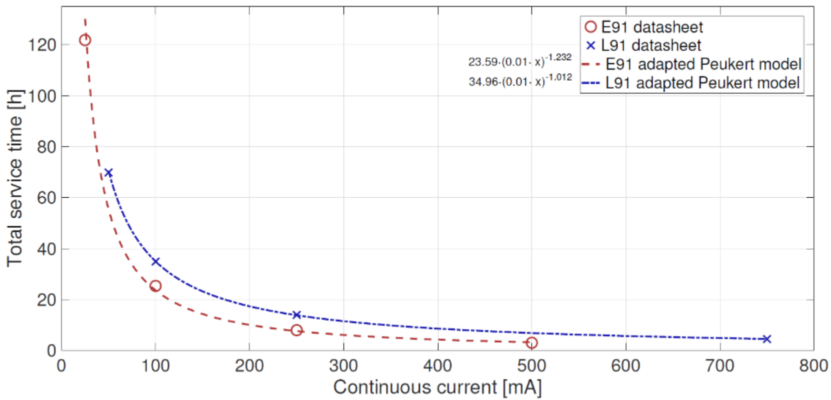
Adapted Peukert equation: parameters

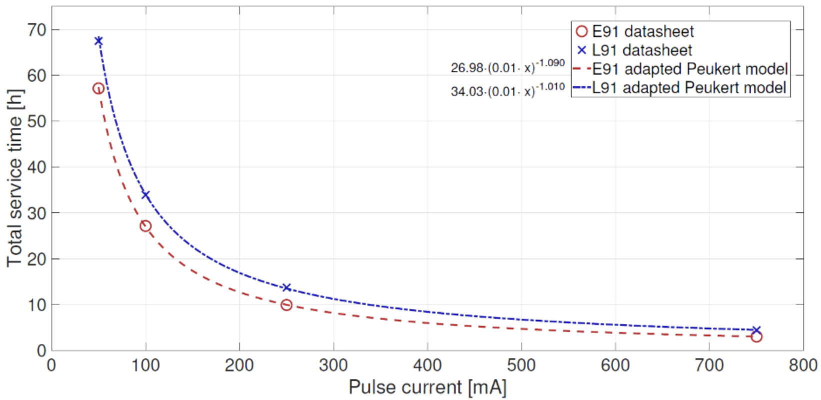
- The model is applied to two cylindrical primary batteries:
  - Energizer E91 (Zn/MnO_2)
  - Energizer L91 (Li/FeS_2)
- At low and medium currents (from 50 to 750 mA):

Battery	C_{nom} [mAh] @ 100 mA	Continuous currents		Pulse currents	
		C_{ref_c}	k_c	C_{ref_p}	k_p
E91	2500	2359	1.232	2698	1.090
L91	3500	3496	1.012	3403	1.010

- The maximum absolute error of the models:
  - less than 2.0%, except for the E91 model at continuous current: 6.9%.

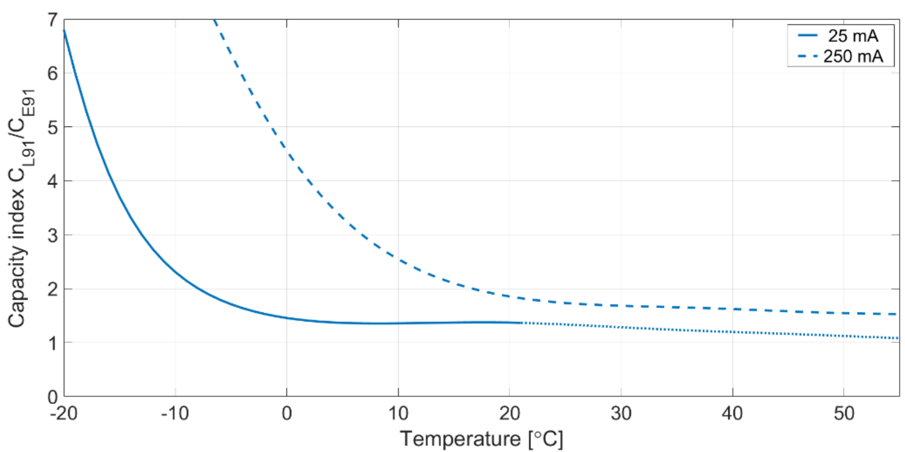
E91 vs. L91


E91 datasheet
L91 datasheet
E91 adapted Peukert model
L91 adapted Peukert model
23.59·(0.01· x)^-1.232
34.96·(0.01· x)^-1.012
Total service time [h]
Continuous current [mA]
0
20
40
60
80
100
120
0
100
200
300
400
500
600
700
800


E91 datasheet
L91 datasheet
E91 adapted Peukert model
L91 adapted Peukert model
26.98·(0.01· x)^-1.090
34.03·(0.01· x)^-1.010
Total service time [h]
Pulse current [mA]
0
10
20
30
40
50
60
70
0
100
200
300
400
500
600
700
800

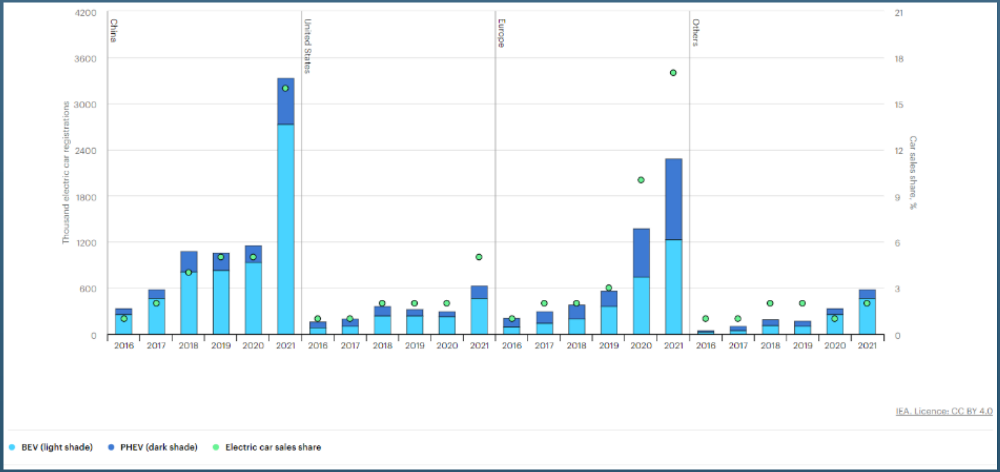
Capacity vs. temperature

- IoT applications include indoor and outdoor sensors.
- At low temperatures, the difference in performance between L91 and E91 is relevant.
- At T >= 21°C the gap is reduced.
- At low currents and high temperatures, the difference could be almost negligible.



Energy optimization for EVs

- Worldwide EV sales (source: https://www.ev-volumes.com):
  - 6.6 million in 2021
  - 10.5 million in 2022 (+55 %)
- A general exponential increase:



IEA, *Electric car registrations and sales share in China, United States, Europe and other regions, 2016-2021*, IEA, Paris https://www.iea.org/data-and-statistics/charts/electric-car-registrations-and-sales-share-in-china-united-states-europe-and-other-regions-2016-2021, IEA. License: CC BY 4.0

- D. Baek, A. Bocca and A. Macii, “A cost of ownership analysis of batteries in all-electric and plug-in hybrid vehicles,” *Energy, Ecology and Environment*, Springer Nature, vol. 7, n. 6, pp. 604-613, 2022.
- A. Bocca, A. Macii, and E. Macii, “Forecasting the grid power demand of charging stations from EV drivers' attitude,” *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, July 2021, online event, pp. 1867-1872.

BEVs and PHEVs

- A cost index for the analysis of the optimal battery use

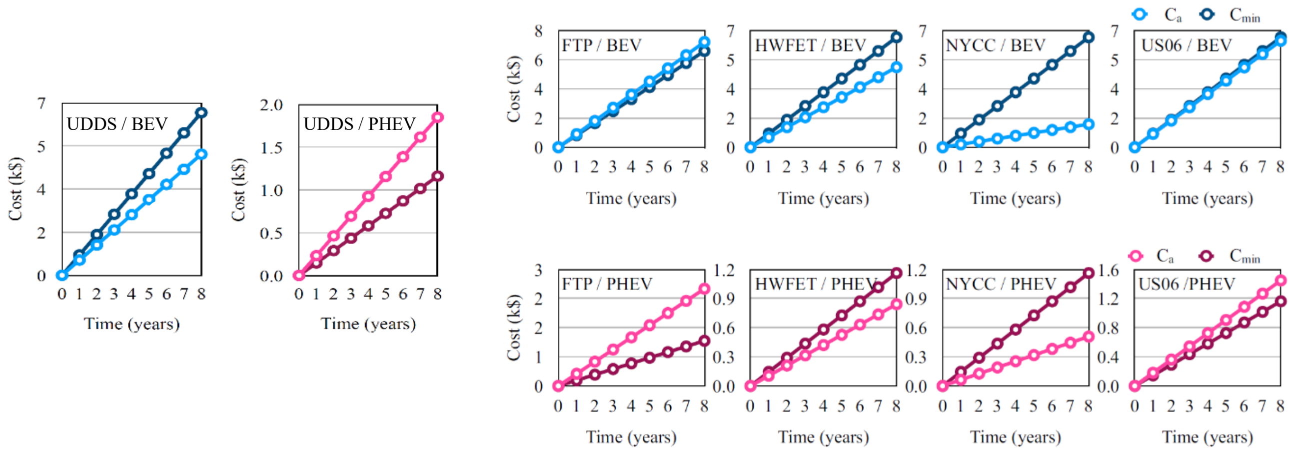
$$\alpha = \frac{c_{\mathrm{a}}}{c_{\min}} \begin{cases} < 1 & : \text{battery is underused} \\ = 1 & : \text{battery is used optimally} \\ > 1 & : \text{battery is overused} \end{cases}$$

$$c_a = c_{tot} \cdot \frac{C_f}{C_{f_{max}}} \qquad c_{\min} = c_{\mathrm{d}_{\min}} \cdot N_{\mathrm{d}}$$

- c_{a} : actual cost
- $c_{\min}$: minimum (i.e., optimal) cost
- c_{tot} : total cost of the battery pack
- C_f : actual capacity fade
- $C_{f_{max}}$: maximum capacity fade
- $c_{\mathrm{d}_{\min}}$: minimum daily cost of battery usage
- N_{d} : number of days of service

BEVs and PHEVs

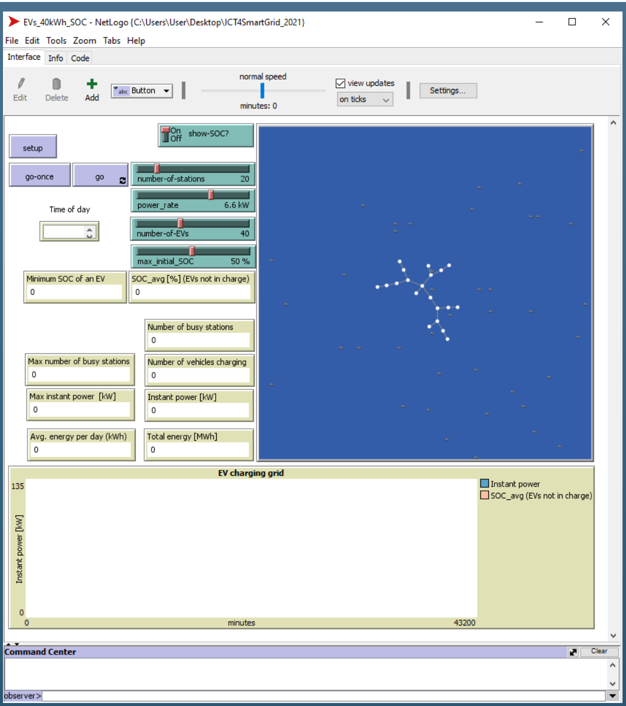
- Application of the cost model to two different EVs:
  - BEV: Tesla Model 3
  - PHEV: Toyota Prius Prime
- Simulation (ADVISOR) using different driving tests
  - UDDS, HWFET, etc., by the United States Environmental Protection Agency
  - BEV: the battery aging depends mainly on daily driving distance
  - PHEV: the use of the ICE in city traffic affects battery degradation



An Agent-Based Model for EV grid

- The model was implemented using NetLogo

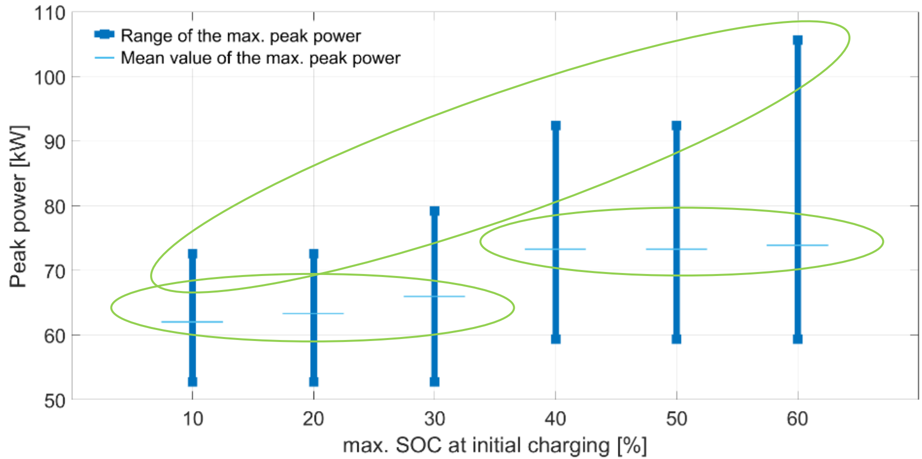
Electric vehicles: 40
Battery pack: 40 kWh
Charging stations: 20
Charge power 6.6 kW
SOC threshold: from 10% to 60% (step 10%)



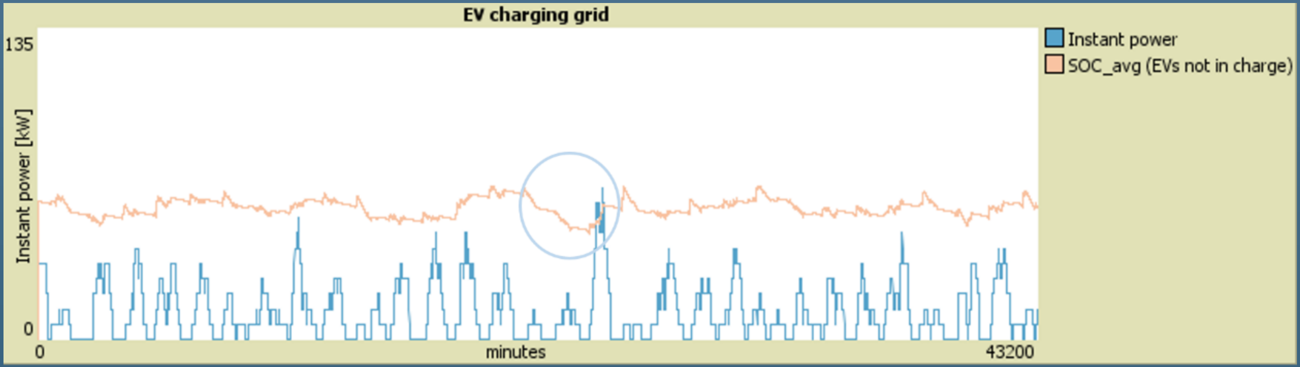
- Daytime: from 7 a.m. to 7 p.m.
- It includes overstay conditions
- 6 scenarios: one for each value of SOC_{th}
- For each scenario: 10 simulations of 30 days each

Peak power

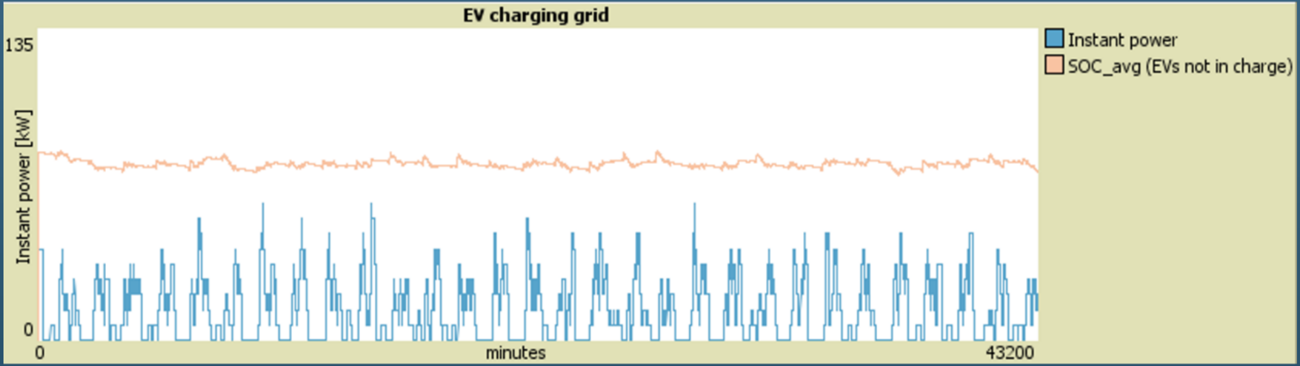
- The maximum peak power and the range of its values (vertical lines) increase as SOC_{th} becomes greater.
- The mean values (horizontal line markers) are mostly grouped into two different levels of values:
  - for $SOC_{th} \leq 30\%$ and $SOC_{th} \geq 40\%$, respectively.



Peak power vs. mean SOC value



(a)



(b)

High power peaks generally follow the prolonged declining phase of the avg. SOC value of the fleet.

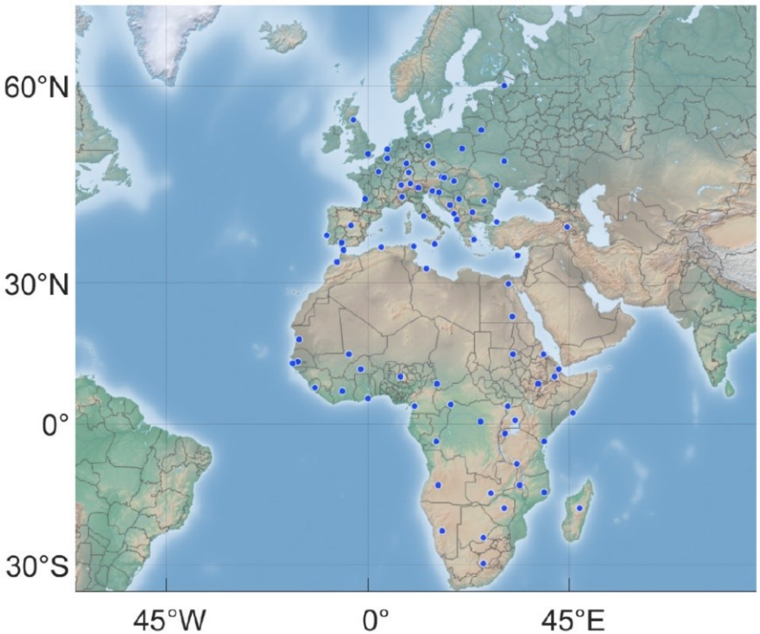
Solar energy analysis

- Models are required for preliminary analysis (e.g., investments) and forecasting:
  - Energy production (e.g., renewables)
  - Energy consumption (e.g., smart grids)

- Modeling solar energy:
  - Sunshine-based models
  - Temperature-based models
  - Cloud-based models
  - Hybrid-parameter-based models

- A. Bocca, A. Macii, and E. Macii, “A nonlinear two-parameter model for the spatial analysis of solar irradiation,” *2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC)*, 27 June - 1 July 2022, online event, pp. 1362-1367.

Solar irradiation [kWh/m²]



$$H_y = a_1 + \frac{a_2}{T_m} + a_3 \cdot \mid \phi \mid \cdot T_m^2 + a_4 \cdot \phi^2$$

MAPE [%]	RMSE [kWh/m²]
4.1	102.75

- 80 locations in Europe and Africa were selected.
- Total area:
  - about 90° of latitude
  - > 60° of longitude.
- The model considers:
  - Latitude (ϕ)
  - Mean temperature (T_m)
- Reference geodata from the PVGIS tool.
- Two different data sets, one for each continent:
  - 2-fold cross validation

Conventional regression models

- Application of conventional regression models to the same data sets.
- Same cross-validation method.
- Two tests:
  - with 2 predictors
  - with 3 predictors, after including the *altitude* as an additional parameter.

$$H_y = a_1 + \frac{a_2}{T_m} + a_3 \cdot \mid \phi \mid \cdot T_m^2 + a_4 \cdot \phi^2$$

MAPE [%]	RMSE [kWh/m²]
4.1	102.75

Regression model	RMSE	
	2p	3p
Linear	194.52	167.51
Interactions Linear	136.45	136.47
Robust linear	192.94	167.90
Stepwise Linear	136.45	132.30
Linear SVM	191.38	166.83
Quadratic SVM	146.29	159.33
Cubic SVM	138.13	182.45
Fine Gaussian SVM	212.07	200.77
Medium Gaussian SVM	132.60	123.95
Coarse Gaussian SVM	183.06	187.55
Optimizable SVM	123.45	406.67
Squared Exponential GPR	127.46	127.65
Matern 5/2 GPR	122.48	120.38
Exponential GPR	129.65	111.10
Rational Quadratic GPR	127.44	118.64
Optimizable GPR	120.97	113.51

Conclusions and future work

- A study has been launched to define a methodology for building compact models for complex systems.
- Although it cannot be assumed that the methodology can be generalized to all cases, the results are encouraging.
- Both the adaptation of existing models and the development of new models were considered.
- Agent-based models are useful for analyzing the *emergent* behavior of systems in order to model them more compactly.

Future work should further outline and automate the methodology, even for other application areas.

Thank you!

Time for questions