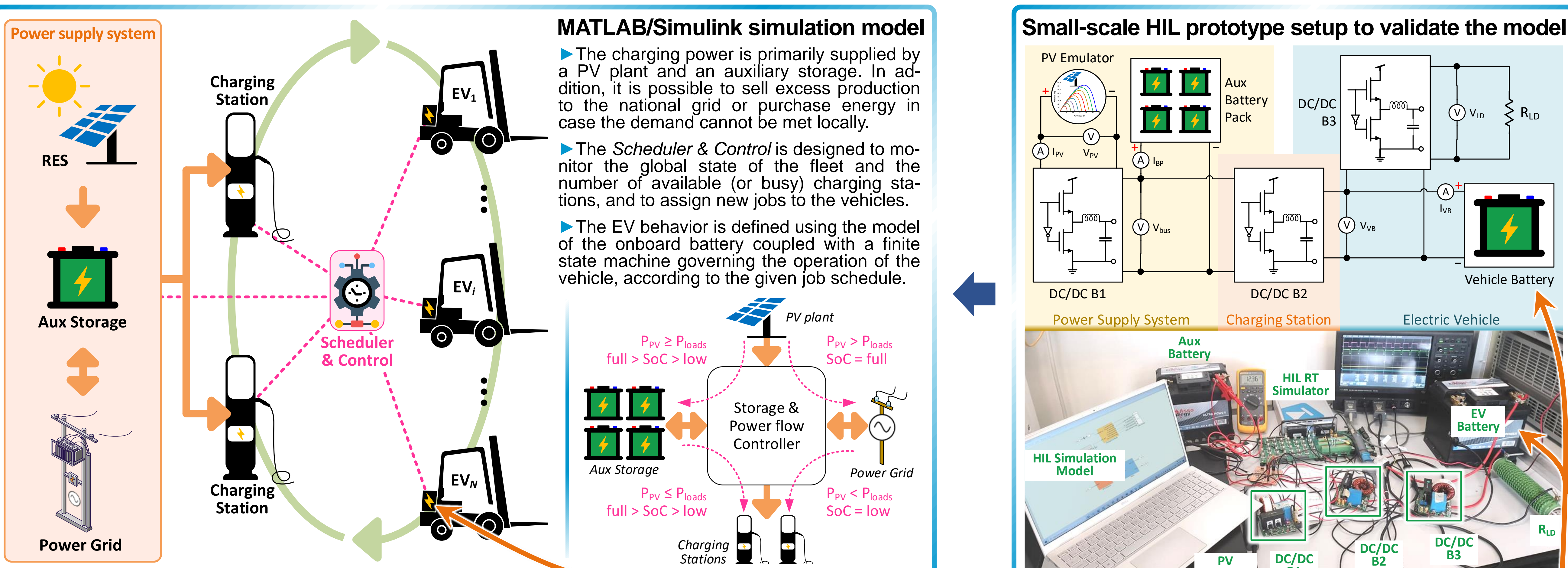


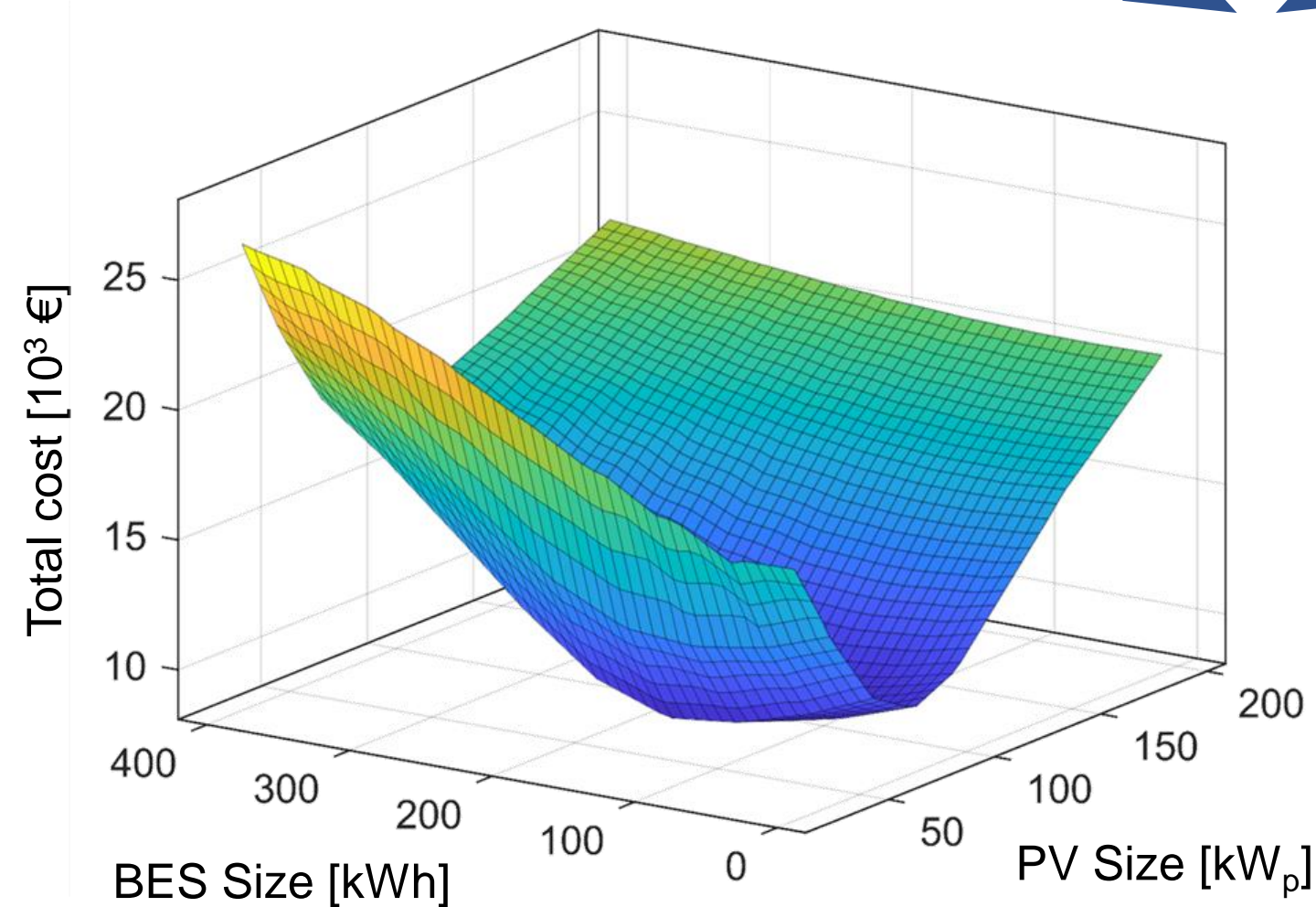
Electrical Vehicle Fleet Management for Industrial Environment with Battery SoH prediction through Neural Networks

Paolo Cova^a, Nicola Delmonte^a, Stefano Ferrari^b, Massimo Lazzaroni^b, Roberto Menozzi^a, Danilo Santoro^a, Marco Simonazzi^a
(^a) Università di Parma, Italy • (^b) Università degli Studi di Milano, Italy

Abstract – The design of the grid architecture for electric vehicle fleets in industrial environments (e.g., battery-powered forklifts) requires considering different parameters. The increased use of renewable energy sources and the need for efficient energy use, leads the designers to make considerations about the best size of the renewable energy system, energy storage system capacity, number of vehicles and their autonomy. Artificial intelligence algorithms could be used and make crucial changes to the design approach. In this work, we present a novel approach to define the most suitable grid architecture. Behavioral Matlab models, validated through tests carried out on a reduced-scale system, together with artificial intelligence algorithms for the battery state-of-health are used to determine the number of vehicles, initial investment cost, power grid consumption costs, CO₂ footprint, and vehicle working time specifications. The optimum sizing of the system has been defined considering economic, technological, or environmental aspects.



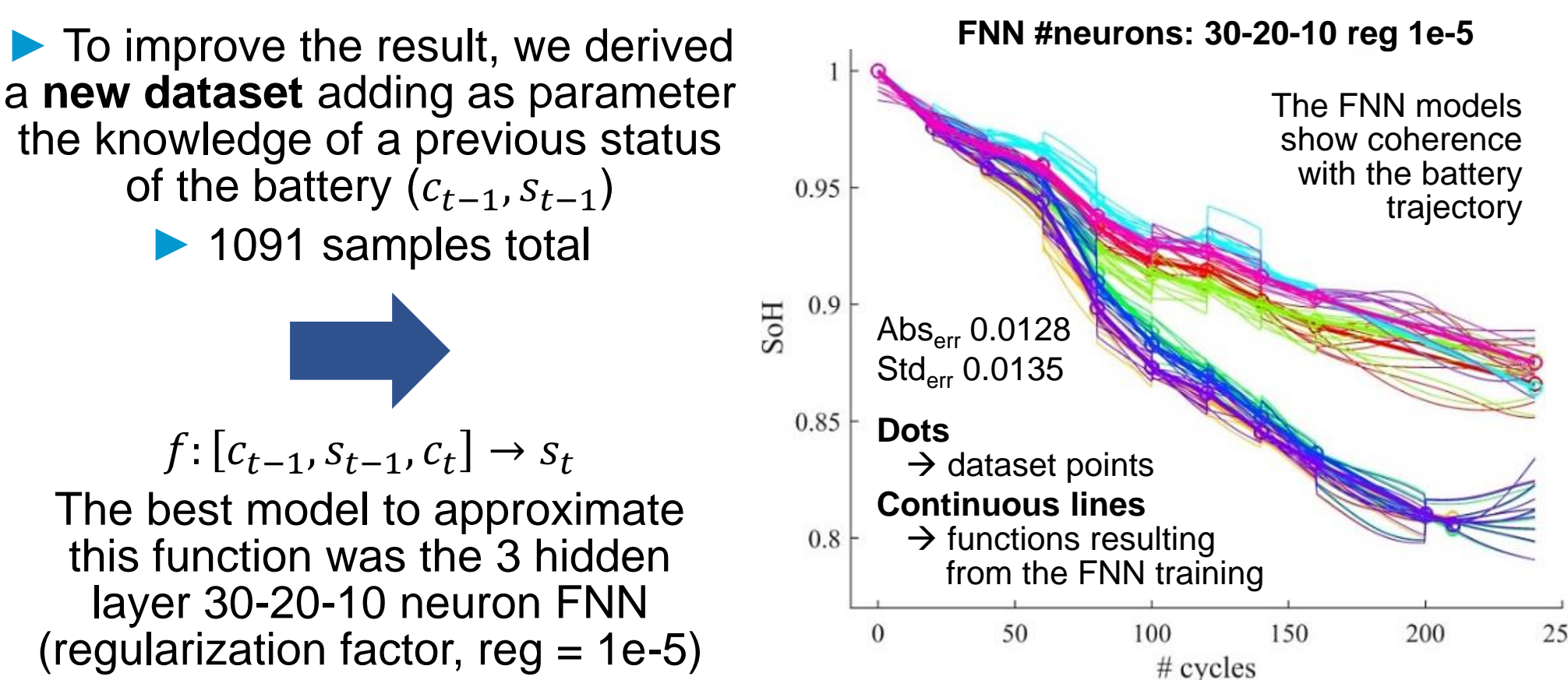
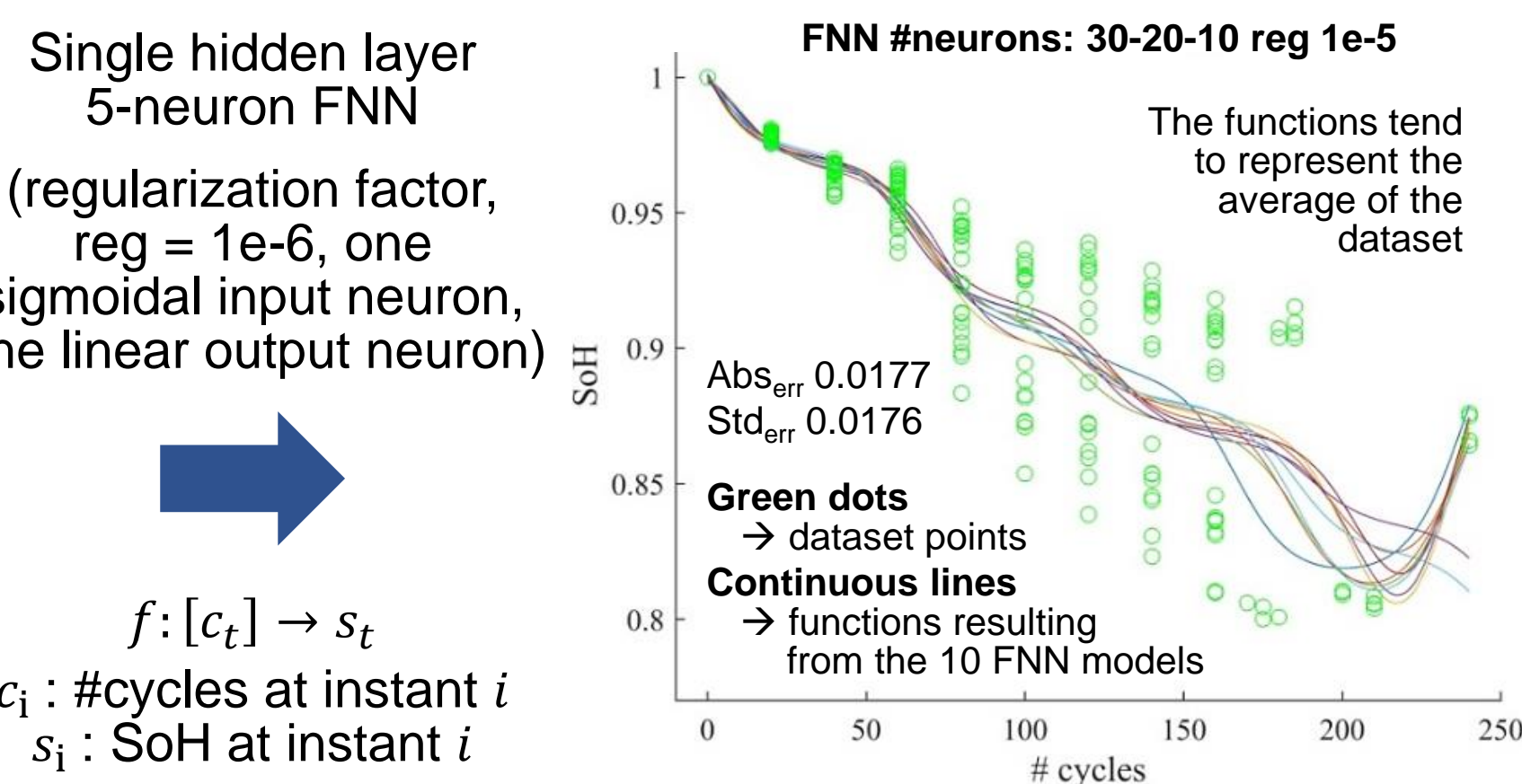
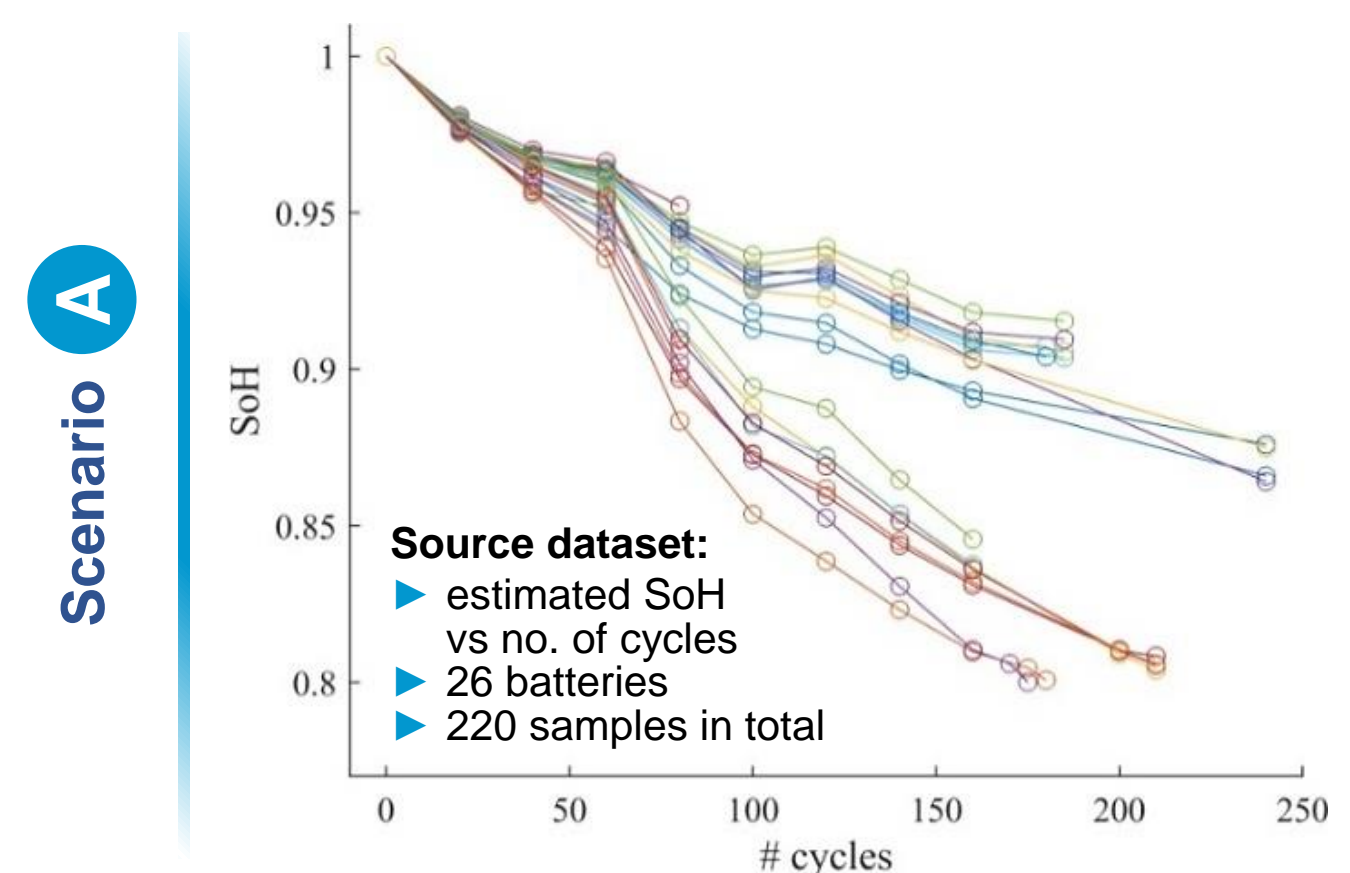
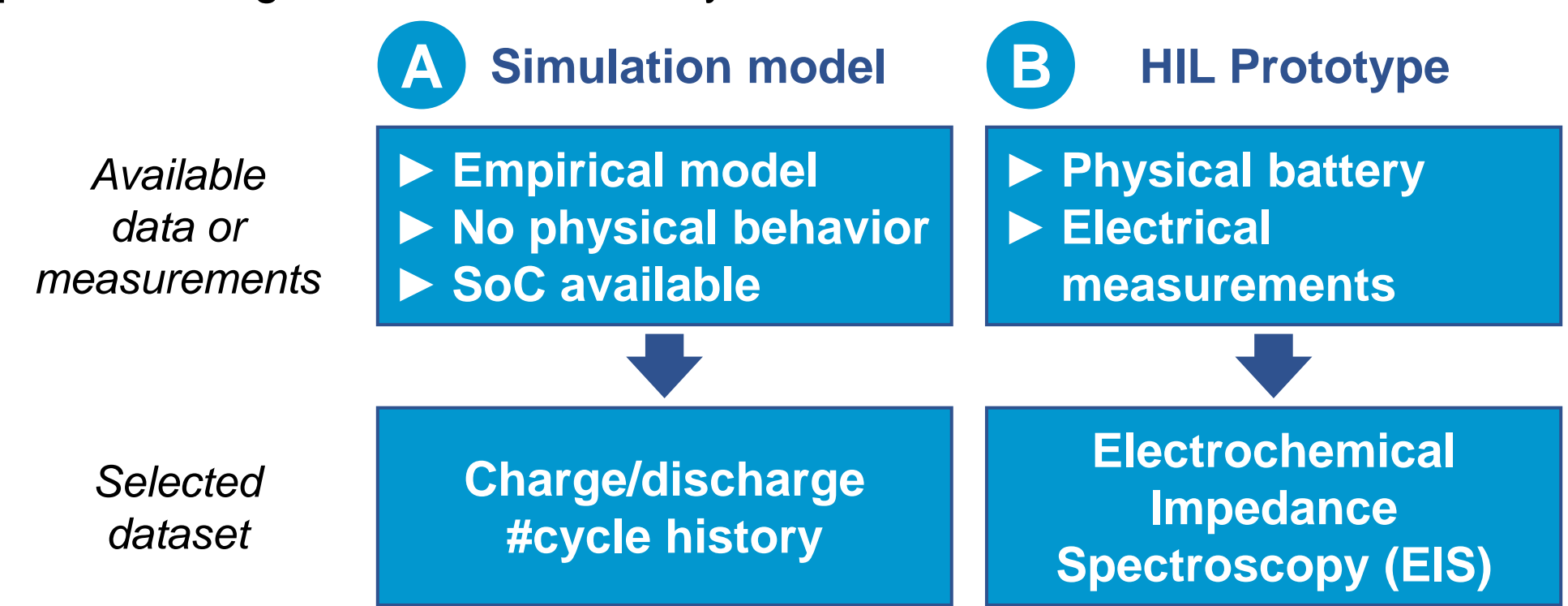
By performing multiple parametric simulations, we find the optimum size of PV and BESS



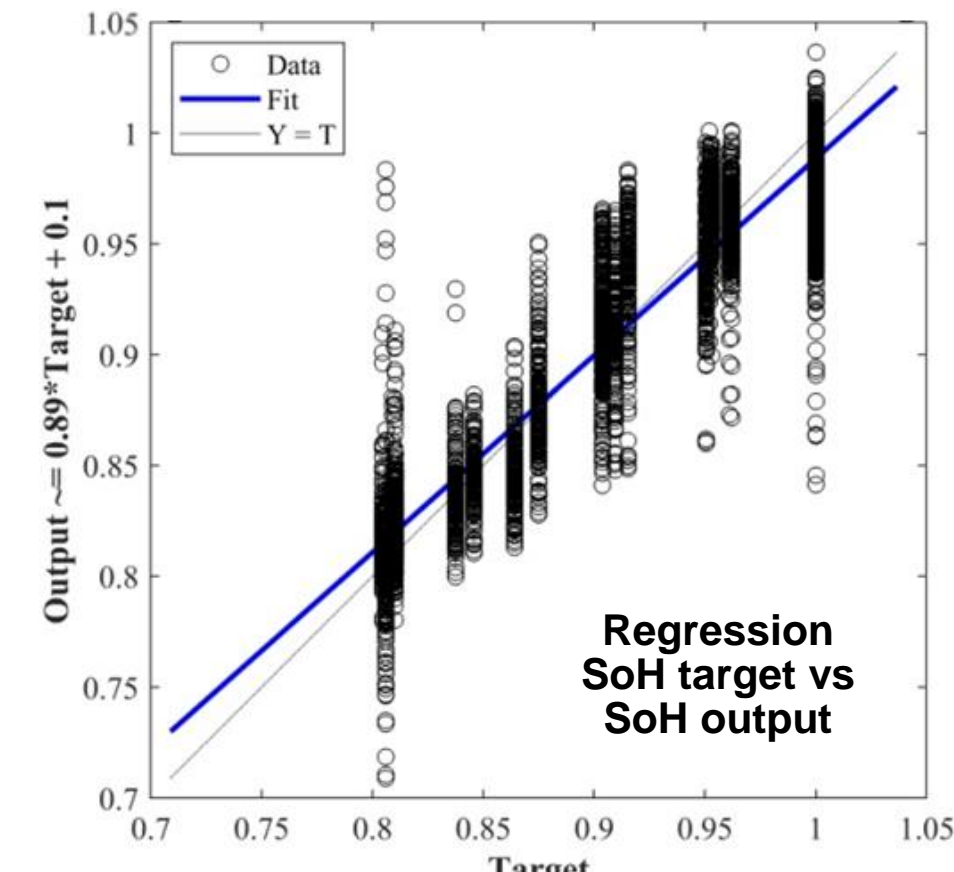
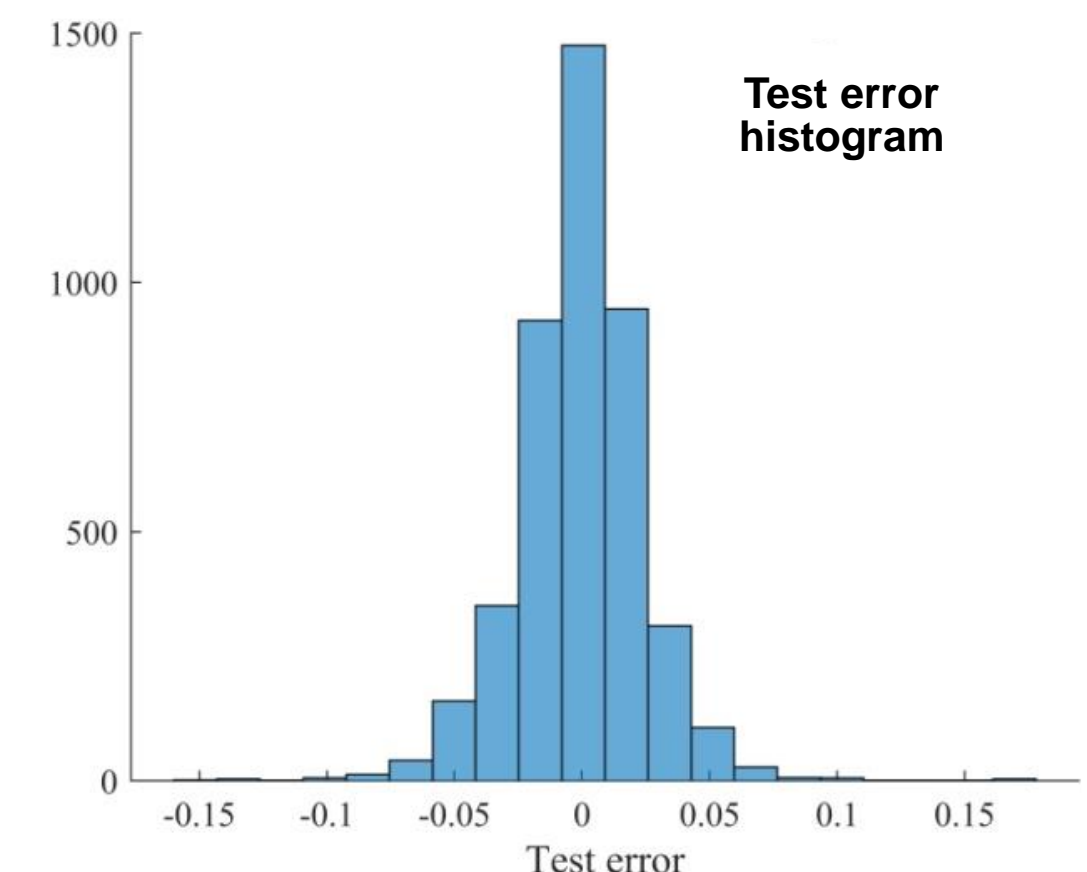
| PV size [kW _p] | BESS size [kWh] | PV inst. cost [10 ³ €] | BESS inst. cost [10 ³ €] | Energy cost [10 ³ €] | Tot. cost [10 ³ €] |
|----------------------------|-----------------|-----------------------------------|-------------------------------------|---------------------------------|-------------------------------|
| 60 | 0 | 1.5 | 0 | 10.07 | 11.57 |
| 60 | 50 | 1.5 | 1.7 | 7.18 | 10.38 |
| 60 | 100 | 1.5 | 3.4 | 4.64 | 9.54 |
| 60 | 150 | 1.5 | 5.1 | 2.62 | 9.22 |
| 60 | 200 | 1.5 | 6.8 | 1.92 | 10.22 |
| 60 | 250 | 1.5 | 8.5 | 2.34 | 12.34 |
| 60 | 300 | 1.5 | 10.2 | 3.17 | 14.87 |
| 60 | 350 | 1.5 | 11.9 | 3.92 | 17.32 |
| 60 | 400 | 1.5 | 13.6 | 4.32 | 19.42 |
| 80 | 0 | 2 | 0 | 8.49 | 10.49 |
| 80 | 50 | 2 | 1.7 | 5.84 | 9.54 |
| 80 | 100 | 2 | 3.4 | 3.62 | 9.02 |
| 80 | 150 | 2 | 5.1 | 1.90 | 9.00 |
| 80 | 200 | 2 | 6.8 | 1.03 | 9.83 |
| 80 | 250 | 2 | 8.5 | 0.98 | 11.48 |
| 80 | 300 | 2 | 10.2 | 1.38 | 13.58 |
| 80 | 350 | 2 | 11.9 | 1.86 | 15.76 |
| 80 | 400 | 2 | 13.6 | 2.16 | 17.76 |
| 100 | 0 | 2.5 | 0 | 8.81 | 11.31 |
| 100 | 50 | 2.5 | 1.7 | 6.45 | 10.65 |
| 100 | 100 | 2.5 | 3.4 | 4.49 | 10.39 |
| 100 | 150 | 2.5 | 5.1 | 3.00 | 10.60 |
| 100 | 200 | 2.5 | 6.8 | 2.04 | 11.34 |
| 100 | 250 | 2.5 | 8.5 | 1.58 | 12.58 |
| 100 | 300 | 2.5 | 10.2 | 1.45 | 14.15 |
| 100 | 350 | 2.5 | 11.9 | 1.45 | 15.85 |
| 100 | 400 | 2.5 | 13.6 | 1.40 | 17.50 |

Machine Learning models for battery SoH prediction

To enhance the capabilities of our framework and make more sophisticated estimations, it is important to consider additional optimization goals, like the estimation of the optimal number of charging stations and EVs in the fleet, by selecting SoC operating ranges that minimize battery degradation. From this perspective, we started investigating the possibility to include SoH prediction algorithms in our battery models.



Scenario B
 The best model approximating this scenario (EIS) dataset was the 3-hidden-layer 30-20-10-neuron FNN (regularization factor, reg = 1e-6) with AbsErr of 0.0175 and StdErr of 0.0164. Figures show the histogram and the regression of one of the trained models (the statistics of the other models are similar and have been omitted for clarity). Most of the approximations fall in a [-0.05, 0.05] error range.



Conclusions

In this work, we presented a novel approach to define the most suitable grid architecture for supplying power to fleets of electric vehicles in the industrial environment. The simulation model, coupled with a Hardware-in-the-Loop scaled prototype, allows to find the best trade-off combination of renewable energy generation systems and storage systems size. In addition, preliminary experiments are presented to model the State-of-Health behavior of batteries using Machine Learning techniques. The results obtained on a sample dataset are encouraging. Machine Learning models can be introduced in the system level simulation framework to obtain more accurate optimizations.