



Next Generation of Battery Management Systems to increase Interoperability, bridge the Gap between 1st and SL-BESS, Extend Adaptability and emPower battery value chains

D3.2 - Development of data-driven SoX and RUL algorithms for increase BMS interoperability

1st period report

Lead Contractor: IKERLAN

Project Coordinator: Imane Worighi

Authors and organisation(s): Josu Olmos (IKERLAN), Markel Azkue (IKERLAN), Carmen Leticia Castrejón Barrón (BRING), Yunus Ay (BRING), Bruno Lemoine (BFH), Priscilla Caliandro (BFH), Joel Wooden (BFH), Yohan Aymon (BFH), Akhtar Zeb (VTT), Pankaj Saha (VTT), Jiating Ye (FHG)

Date: 30/06/2025

Doc. Version: 1



Co-funded by
the European Union

Project funded by



Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Federal Department of Economic Affairs,
Education and Research EAER
State Secretariat for Education,
Research and Innovation SERI

Co-funded by the European Union under grant agreement 101137815. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or CINEA. Neither the European Union nor the granting authority can be held responsible for them.

PROJECT DETAILS			
Project name	Next Generation of Battery Management Systems to increase Interoperability, bridge the Gap between 1st and SL-BESS, Extend Adaptability and emPower battery value chains		
Start	01/01/2024	Duration	42M
Project acronym	BIG LEAP	GA number	101137815
Topic identifier	HORIZON-CL5-2023-D2-01-04	Call identifier	HORIZON-CL5-2023-D2-01
Type of Action	Horizon IA	Coordinator	BRING
Project Coordinator	Imane Worighi		Imane.worighi@bringvzw.be
Project Manager	Carmen Leticia Castrejón Barrón		carmen.barron@bringvzw.be
Website	https://bigleaproject.eu/		

DELIVERABLE DETAILS			
Number	3.2		
Title	Development of data-driven SoX and RUL algorithms for increase BMS interoperability (1 st period report)		
Short description	Report on the specifications, development, and validation (in local environment) of the SoX and RUL Algorithms stated in the task. The 1st period report will focus on the first functional version of the algorithms, prior to their integration in the multi-operational BMS.		
Work Package	WP3	Task	T3.2
Dissemination level	SEN - Sensitive		
Due date (M)	M18	Submission date (M)	30/06/2025
Deliverable responsible	Josu Olmos (IKERLAN)	Contact	jolmos@ikerlan.es

DELIVERABLE CONTRIBUTORS			
	Name	Organisation	E-mail
Deliverable Author	Josu Olmos	IKERLAN	jolmos@ikerlan.es
Contributing Author(s)	Markel Azkue	IKERLAN	mazkue@ikerlan.es
	Yunus Ay	BRING	yunus.ay@bringvzw.be
	Carmen Leticia Castrejon Barron	BRING	carmen.barron@bringvzw.be
	Akhtar Zeb	VTT	akhtar.zeb@vtt.fi
	Pankaj Saha	VTT	pankaj.saha@vtt.fi
	Bruno Lemoine	BFH	Bruno.lemoine@bfh.ch
	Priscilla Caliandro	BFH	Priscilla.caliandro@bfh.ch
	Yohan Aymon	BFH	Yohan.aymon@bfh.ch
	Joel Wooden	BFH	Joel.wooden@bfh.ch
	Jiating Ye	FhG	jiating.ye@iisb.fraunhofer.de
Internal Reviewer(s)	Pankaj Saha	VTT	pankaj.saha@vtt.fi
	Tobias Huf	FhG	tobias.huf@iisb.fraunhofer.de
External Reviewer(s)	Emeric BRUN	EDF	emeric.brun@edf.fr
	Kristina Meškerevičienė	Solitek	kristina.meskereviciene@solitek.eu
Final review and quality approval	Carmen Leticia Castrejon Barron	BRING	carmen.barron@bringvzw.be

DOCUMENT HISTORY

Date	Version	Name	Changes
28/10/2024	0.0.1	20241028_BIGLEAP_D3.2_v0.0.1	Frist draft version of the document, only battery models section added.
12/05/2025	0.1	20250320_BIGLEAP_D3.2_v0.1	First complete draft version of the document.
02/06/2025	0.2	20250602_BIGLEAP_D3.2_v0.2	Version reviewed after internal review process
30/06/2025	1	20250629_BIGLEAP_D3.2_v1	Version for submission after external review



TABLE OF CONTENT

Executive Summary	15
Acronyms and abbreviations.....	16
Introduction.....	17
1. Battery State Estimators (SoX)	20
1.1. State of Charge (SoC) and State of Energy (SoE)	20
1.1.1. Introduction	20
1.1.2. Design.....	21
1.1.3. Results and Validation	23
1.1.4. Discussion on Algorithm Interoperability	26
1.1.5. Conclusions.....	32
1.2. State of Health. BFH version (SoH-BFH)	32
1.2.1. Open-source dataset.....	33
1.2.2. Model development	34
1.2.3. Results and Validation.....	40
1.2.4. BFH Statistical Dataframe	47
1.3. State of Health. FHG version (SoH-FGH).....	49
1.3.1. Introduction and Methodology	49
1.3.2. The Model Structure.....	50
1.3.3. Data and Data processing	51
1.3.4. Model Implementation, Hyperparameter Tuning and Model Training.....	55
1.3.5. Baseline Model.....	56
1.3.6. Transfer Learning (TL)	59
1.3.7. Summary and Outlook	64
1.4. State of Power (SoP)	65
1.4.1. Introduction.....	65



1.4.2. Design	65
1.4.3. Results.....	70
1.4.4. Discussion	74
1.5. State of Safety (SoS)	74
1.5.2. Concept.....	75
1.5.3. Methodology	77
1.5.4. Results.....	81
2. Remaining Useful Life (RUL) Estimators.....	86
2.1. 1 st Life RUL (RUIL).....	87
2.1.1. Introduction	87
2.1.2. Design Guidelines for RUIL.....	88
2.1.3. Design of RUIL.....	88
2.1.4. Selection of Databases for RUIL	92
2.1.5. Baseline RUIL: Results and Validation.....	98
2.1.6. Towards Interoperability: RUIL with Transfer Learning.....	103
2.1.7. RUIL with Transfer Learning: Results and Validation.....	106
2.2. 2 nd Life RUL (RU2L).....	111
2.2.1. Introduction	111
2.2.2. Data Preparation	112
2.2.3. Model Development.....	117
2.2.4. Results and Discussion	118
2.2.5. Conclusions	124
3. Battery Equivalent Circuit Models.....	126
3.1. Development of LFP Model	128
3.2. Development of LCO Model.....	133
3.3. Development of NMC Model	138
3.4. Development of NCA model.....	142
4. Conclusions.....	147



References.....148



LIST OF TABLES

Table 1. MAE and Max. errors obtained by the SoC/SoE estimation algorithm for the train and test datasets.	24
Table 2. MAE and Max. errors obtained by the SoC/SoE estimation algorithm for the different trained algorithms using TL for the NCA test dataset.	29
Table 3. MAE and Max. errors obtained by the SoC/SoE estimation algorithm for the different trained algorithms using TL for the LFP test dataset.	31
Table 4. Summary of datasets and cells characteristics.	33
Table 5. Train-Test data split	41
Table 6. SoH prediction performance across NN and RF models for the Severson and Stanford datasets.	45
Table 7. The selected hyperparameters for the baseline model	58
Table 8. Selected hyperparameters for the baseline model.....	59
Table 9. Sample of Safety Parameters for NMC.....	78
Table 10. Updated Sample of Safety Parameters for NMC	85
Table 11. Analysis of potential datasets identified in Deliverable 3.1.	93
Table 12. Matrix of tests of University of Maryland database (Baseline model).	95
Table 13. Matrix of tests of SANDIA (NMC) database (TL model within same chemistry).	96
Table 14. Matrix of tests of SANDIA (LFP) database (TL model between different chemistries).....	96
Table 15. Configured sweep of hyperparameters.....	99
Table 16. Main results of selected best trainings for Data Case A, B and C (Baseline Model).....	100
Table 17. Hyperparameters of best models selected in each data case	100



Table 18. Main metrics for Transfer Learning models.....	107
Table 19. Key variables extracted from the AMPERE and CALCE datasets for RU2L model development.	114
Table 20. Training and test sets from the AMPERE and CALCE datasets used for RU2L model development.....	116
Table 21. RU2L model prediction results on the test sets of the AMPERE dataset.	119
Table 22. RU2L model prediction results on the test sets of the CALCE dataset.	123
Table 23. Model characterization results.....	130
Table 24. Model characterization results.....	136
Table 25. NMC model characterization results.	140
Table 26. NCA model characterization results.	144



LIST OF FIGURES

Figure 1. GRU neural network architecture for joint estimation of SoC and SoE from multiple input signals.....	22
Figure 2. SoC and SoE estimation for a cell tested at 25°C, 0.5C CHA/DCH and 91% SoH.	25
Figure 3. SoC and SoE estimation for a cell tested at 25°C, 0.5C CHA, 3C DCH and 80% SoH	25
Figure 4. Complete model retraining	26
Figure 5. Partial freezing with retraining of the final layers.....	26
Figure 6. Retraining with GRU layer update.	27
Figure 7. Partial freezing followed by complete fine-tuning	27
Figure 8. Retraining with GRU followed by full fine-tuning	28
Figure 9. SoC and SoE estimation for a NCA cell tested at 15°C, 0.5C CHA, 1C DCH and 95% SoH.....	29
Figure 10. SoC and SoE estimation for an LFP cell tested at 25°C, 0.5C CHA, 1C DCH and 90% SoH.....	31
Figure 11. dQdV profiles as a function of SoH for NMC pouch cells, Left: during discharging; Right: during charging.	35
Figure 12. Features correlation matrices for Severson (on the left) and Stanford dataset (on the right).....	36
Figure 13. Feature evolution during discharge over cycle life – Severson.	38
Figure 14. Feature evolution during charge over cycle life – Stanford...39	
Figure 15. dQdV curve for one battery cell of the Severson dataset.	40
Figure 16. Real and predicted SoH for multiple cells using RF and NN models with and without charge throughput for the Severson dataset.	42
Figure 17. Real and predicted SoH for multiple cells using RF and NN models with and without charge throughput for the Stanford dataset.	43



Figure 18. Feature importance scores from RF models trained with and without charge throughput for the Severson dataset.....44

Figure 19. Feature importance scores from RF models trained with and without charge throughput for the Stanford dataset.44

Figure 20. Bar plots showing performance metrics (MSE, R², RMSE, and Max Error) for NN and RF models on the Severson dataset (top) and Stanford dataset (bottom).45

Figure 21. Real and predicted SoH for one test cell of the Stanford dataset using RF and NN models with and without charge throughput.....46

Figure 22. Bar plots showing performance metrics (MSE, R², RMSE, and Max Error) for NN & RF models on the test cell of the Stanford dataset. 47

Figure 23. SoH degradation trend for 3 batteries of the Severson dataset.48

Figure 24. Example of SDF visualization for 3 batteries of the Severson dataset.....49

Figure 25. The structure of the designed model..... 51

Figure 26. First 1000 data samples of cut and shuffled timestamps, min-max scaled features, and SoH labels (NASA data).....54

Figure 27. Distribution of SoH (%) in the training, validation, and test data (NASA data) 54

Figure 28. Distribution of SoH (%) in the training, validation, and test data (“UofM Pouch Cell Voltage and Expansion Cyclic Aging Dataset”) 55

Figure 29. Infrastructure for training and tuning ML model using HPC-cluster.....56

Figure 30. Parallel coordinate plot of the test run to compare 'TCN_ATT_LSTM', 'TCN_ATT' and 'TCN' (best result is marked in green color).....56

Figure 31. Scatter plot of the test run to compare 'TCN_ATT_LSTM', 'TCN_ATT' and 'TCN' 57

Figure 32. Histories of learning rate during hyperparameter tuning58



Figure 33. Histories of the loss (MAE) and the evaluation loss during hyperparameter tuning.....	59
Figure 34. Five TL configurations.....	60
Figure 35. Comparison between a reference run with a baseline model in combination with TL.....	61
Figure 36 Example of SOH prediction for randomly organized data frames.....	61
Figure 37. The evaluation loss (“MAE”) histories of the TL training with five configurations (experiment 1).....	62
Figure 38. The evaluation loss (“MAE”) histories of the TL training with five configurations (experiment 2).....	63
Figure 39. Comparison of TL Training Sessions Using Configuration 1 With and Without an Additional LSTM Layer.....	64
Figure 40. Second-Order Thevenin ECM.....	66
Figure 41. Functional diagram of SOP prediction loop.....	68
Figure 42. Interpolated SOP prediction up to 3600s starting from 20% (green), 50% (red) and 80% SOC (purple).....	71
Figure 43. SOP prediction (red) vs. measurement (blue) at 50% initial SOC.....	72
Figure 44. Relative estimation error of SOP predictions vs. measurements and measured temperature starting from 80% (Blue), 50% (Orange) and 20% SOC (green).....	73
Figure 45. Relative estimation error of SOP predictions vs. Measurements for $P \leq 100W$	73
Figure 46. Safety Operation Area.....	75
Figure 47. SoS regions.....	77
Figure 48. MLP Neural Network.....	79
Figure 49. MLP Model MSE Loss Function.....	80
Figure 50. MLP model validation.....	81
Figure 51. Simulation 1.....	82



Figure 52. Simulation 2.....	83
Figure 53. Simulation 3	84
Figure 54. Interfaces of FNN based RUIL algorithm.....	92
Figure 55. Example of generated input/output data, test #7 of University of Maryland Database.....	97
Figure 56. Predictions with non-observed data (testing data), for Data Case B model (Baseline RUIL).....	102
Figure 57. Predictions with observed data (training data), for Data Case B model (Baseline RUIL).....	103
Figure 58. Complete model retraining.....	104
Figure 59. Partial freezing with retraining of the final layers.....	105
Figure 60. Partial freezing with retraining of the initial and final layers.	105
Figure 61. Partial freezing (training of final layers) followed by complete fine-tuning.....	105
Figure 62. Partial freezing (training of initial and final layers) followed by complete fine-tuning.....	106
Figure 63. Predictions with unobserved data (testing data), for NMC TL and full trained models.....	108
Figure 64. Predictions with unobserved data (testing data), for LFP TL and full trained model.....	109
Figure 65. RU2L data-driven modelling workflow.	112
Figure 66. Battery capacity per cycle for each cell in the AMPERE dataset. Data points below the horizontal grey line (80% of rated nominal capacity) were used for RU2L model development.	115
Figure 67. Battery capacity per cycle for each cell in the CALCE dataset. Data points below the horizontal grey line (80% of rated nominal capacity) were used for RU2L model development.	116
Figure 68. Predicted versus actual capacity values on the test sets of the AMPERE dataset.....	120



Figure 69. Relative error distribution on the test sets of the AMPERE dataset.....	121
Figure 70. Predictions of battery capacity and estimated number of cycles until EOL.....	122
Figure 71. Predicted versus actual capacity values on the test sets of the CALCE dataset.....	124
Figure 72. Second-order Thevenin-based Equivalent Circuit Model.....	127
Figure 73. Characterization test data (Example of 25°C).....	129
Figure 74. Validation test data (Example of 25°C).....	129
Figure 75. Characterization results (Example of 25°C).....	131
Figure 76. Validation results (Example of 25°C).....	131
Figure 77. Obtained parameters (100% SOH).....	132
Figure 78. Increase of R0 while battery ageing (example at 25°C).....	133
Figure 79. HPPC test data (Example at 30°C and 100% SOH).....	134
Figure 80. Validation test data (Example at 30°C and 100% SOH).....	135
Figure 81. Characterization results (Example at 30°C and 100% SOH).....	137
Figure 82. Validation results (Example at 30°C and 100% SOH).....	137
Figure 83. Obtained parameters at different SOHs (Example at 30°C).....	138
Figure 84. NMC cell HPPC test data (Example at 25 °C and 100% SOH).....	139
Figure 85. NMC validation test at 25 °C.....	139
Figure 86. Characterization results NMC model. Example at 25 °C and 100% SOH.....	141
Figure 87. Validation results for NMC model. At 25°C and 100% SOH.....	141
Figure 88. NMC model parameter values at 100% SOH.....	142
Figure 89. NCA characterization test at 25°C and 100% SOH.....	143
Figure 90. NCA validation test at 25°C and 100% SOH.....	144



Figure 91. Characterization results NCA model. Example at 25 °C and 100% SOH..... 145

Figure 92. Validation results NCA model. Example at 25 °C and 100% SOH 145

Figure 93. NCA model parameter values at 100% SOH..... 146

Executive Summary

Deliverable D3.2 of BIG LEAP project presents the development of the State of X (SoX) and Remaining Useful Life (RUL) algorithms of BIG LEAP, which have been addressed in Task 3.2 of the project. Additionally, the battery models required for the Digital Twin platform of BIG LEAP are also developed within this deliverable.

On the one hand, SoX and RUL algorithms are regarded as the main outcome of Task 3.2. These algorithms are critical for a safe, reliable, and optimized battery operation, as they provide internal states and estimations that are not directly measurable in a battery. To do so, these algorithms are embedded into Battery Management Systems (BMS), the electronic components in charge of monitoring the operation of the battery.

SoX and RUL algorithms require of a tailored parametrization process, due to the varying physical, chemical, and electrical performances of different battery products. In other words, SoX and RUL algorithms parametrized for a specific battery might not obtain accurate results when implemented with different batteries. In order to advance into more transversal and interoperable BMSs (which is aligned with BIG LEAP project objectives 2 and 3), this deliverable presents novel methodologies to ensure easier adaptability of SoX and RUL algorithms between different battery products. To do so, first novel designs of the SoX and RUL algorithms are provided, and then they are adapted to different scenarios. The results obtained for each of the algorithms demonstrate that the proposed methods are efficient to advance into a transversal and interoperable BMS.

On the other hand, battery models allow simulating the performance of the device under different operational conditions, which eventually allows optimizing the design or performance of the battery. The battery models developed within BIG LEAP are based on an Equivalent Circuit Modelling (ECM) approach and are crucial for the Digital Twin platform of the project. Specifically, four different models for LFP, LCO, NMC, and NCA chemistries are presented.