Data-driven predictive maintenance and time-series applications

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Appendix A

Appendix

A.1 Introduction

This Appendix serves as supplemental material to Chapter 6[1]. It holds in detail all the results from the experiments performed together with plots and explanations. We should note that the *engineering validity* of the symbolic expression model 6.9 in Chapter 6 was confirmed, while the work presented in this Appendix was meant to be presented as an example of the process and the possible factors associated with the prediction of the EGT. Future work can address the validity of some of these additional expressions, especially if interesting correlations between some engine parameters and EGT are identified.

The rest of this Appendix is organized as follows. In Sections A.2, A.3, A.4 we describe in detail the performed experiments described in Chapter 6, we present the experimental results, the generated formulas, and we show figures comparing the predicted to the ground truth EGT values of the test set.

A.2 Experiment 1 Results

For this experiment, a correlation analysis is performed upon the input variables, so that those which are highly correlated are discarded. The threshold used is 0.90. Those above this threshold have been dropped, only keeping the first representative from a set of highly correlated variables. After these variables are deleted, 114 remain to be used as final input variables in addition to the EGT. The training, validation, and test[2] error metrics results are

[1]Contents of this Appendix are based on the Appendix of [113]; Marios Kefalas, Juan de Santiago Rojo, Asteris Apostolidis, Dirk van den Herik, Bas van Stein, and Thomas Bäck. Explainable Artificial Intelligence for Exhaust Gas Temperature of Turbofan Engines. Journal of Aerospace Information Systems, pages 1–8, 2022. Publisher: American Institute of Aeronautics and Astronautics eprint: https://doi.org/10.2514/1.I011058; reprinted with permission of the American Institute of Aeronautics and Astronautics, Inc.

[2]Please note that the terminology here is different from the original publication [113]. In this Appendix and its corresponding main chapter, we note as validation set (test set) what we noted as test set (validation set)

displayed in Tables A.1, A.2, and A.3, respectively, for all ten models resulting from the ten independent runs. The Equations A.1 - A.10, below, show the generated symbolic regression models for all ten models resulting from the ten independent runs. In Figures A.1 - A.5 we show the per model predictions (ten models resulting from the ten independent runs) against the actual values of the EGT on the test set.

Table A.1: Experiment 1 training error metrics.

R^2	RMSE	MAE	MSE
0.998102	1.239205	0.763866	1.535629
0.997968	1.281986	0.786991	1.643489
0.997507	1.420041	0.828125	2.016517
0.997964	1.283411	0.786591	1.647145
0.998020	1.265571	0.765595	1.601671
0.998023	1.264679	0.738129	1.599412
0.997745	1.350609	0.754343	1.824146
0.998036	1.260616	0.746105	1.589153
0.998123	1.232339	0.740111	1.518661
0.997676	1.371248	0.791502	1.880321

Table A.2: Experiment 1 validation error metrics.

R^2	RMSE	MAE	MSE
0.99822	1.20770	0.75207	1.45853
0.99803	1.27203	0.77908	1.61805
0.99767	1.38459	0.82148	1.91708
0.99808	1.25604	0.77368	1.57764
0.99810	1.24747	0.75516	1.55618
0.99813	1.24030	0.72427	1.53834
0.99788	1.32030	0.74576	1.74320
0.99817	1.22514	0.73863	1.50097
0.99814	1.23560	0.73759	1.52672
0.99783	1.33519	0.78411	1.78273

in the original publication. This has been done for consistency of the terminology between the chapters of this dissertation.

Table A.3: Experiment 1 test error metrics.

R^2	RMSE	MAE	MSE
0.981343	3.240743	1.357668	10.502417
0.947178	5.452943	2.940967	29.734585
0.808921	10.371179	3.410746	107.561345
0.984409	2.962510	1.224247	8.776463
0.754388	11.758352	3.642960	138.258840
0.805126	10.473665	3.333293	109.697659
0.812055	10.285767	3.238445	105.797008
0.809934	10.343668	3.325208	106.991471
0.855140	9.030162	4.563011	81.543823
0.805914	10.452461	3.109154	109.253937

$$\begin{aligned} Y_1^1 &= 0.141 \cdot x_4 + 0.123 \cdot x_5 + 0.8 \cdot x_6 + 0.0214 \cdot x_{12} - 0.123 \cdot x_{18} \\ &+ 0.751 \cdot x_{21} + 0.0261 \cdot x_{60} + 0.0405 \cdot x_{74} - 0.0371 \cdot |\log(x_{39})| \\ &+ 1.32 \cdot 10^{-4} \cdot e^{(2 \cdot x_{21})} - 0.0428 \cdot |x_4| - 0.0261 \cdot e^{(x_{21})} + 0.00762 \cdot x_{74}^2 + 0.133 \end{aligned} \tag{A.1}$$

$$\begin{aligned} Y_1^2 &= 0.13 \cdot x_4 + 0.668 \cdot x_6 + 0.0264 \cdot x_{12} - 0.0796 \cdot x_{14} + 0.759 \cdot x_{21} \\ &+ 0.0484 \cdot x_{43} - 0.00864 \cdot x_{57} + 0.0219 \cdot x_{110} - 0.0219 \cdot x_{113} - 0.0264 \cdot |x_4| \\ &+ 0.0219 \cdot |x_6| - 0.00702 \cdot |x_{43} - 2.0 \cdot x_{46} + 0.2 \cdot {x_{21}}^3| - 0.00579 \cdot {x_{21}}^3 \\ &- 6.3 \cdot 10^{-4} \cdot |x_{14} - 1.0 \cdot x_{21}| \cdot |x_{21}|^3 \cdot |x_{43}| + 0.0119 \end{aligned} \tag{A.2}$$

$$\begin{aligned} Y_1^3 &= 0.169 \cdot x_4 - 0.0168 \cdot x_1 + 0.125 \cdot x_5 + 0.712 \cdot x_6 - 0.0336 \cdot x_{18} + 0.704 \cdot x_{21} \\ &+ 0.0376 \cdot x_{43} + 0.0156 \cdot x_{110} - 0.00778 \cdot e^{-x_{12}} - 0.0808 \cdot |x_4| - 0.0513 \cdot |x_8| \\ &- 0.0156 \cdot |x_{21}| + 0.0432 \cdot |x_4|^{1/2} - 0.00102 \cdot |x_{21} + |(x_{21})||^3 \\ &+ 0.0368(|x_{74}|^3)^{1/2} + 0.0736 \end{aligned} \tag{A.3}$$

$$\begin{aligned} Y_1^4 &= 0.0758 \cdot x_4 + 0.885 \cdot x_6 - 0.2 \cdot x_{13} - 0.156 \cdot x_{14} + 0.43 \cdot x_{21} - 0.0244 \cdot x_{23} \\ &- 0.495 \cdot e^{(-e^{(e^{(x_{43})})})} + 0.2 \cdot e^{(-e^{(-x_4)})} + 0.156 \cdot e^{(-e^{(-x_{14})})} + 0.00361 \cdot e^{(x_{110})} \\ &- 0.787 \cdot e^{(-e^{(x_{21})})} + 0.00719 \cdot {x_{14}}^2 + 0.214 \end{aligned} \tag{A.4}$$

$$\begin{aligned} Y_1^5 &= 0.0887 \cdot x_4 + 0.111 \cdot x_5 + 0.69 \cdot x_6 + 0.0296 \cdot x_{11} + 0.523 \cdot x_{21} \\ &- 0.0442 \cdot x_{39} - 0.121 \cdot e^{(-x_{39})} - 0.499 \cdot e^{(-e^{(x_{21})})} + 0.0559 \cdot x_4 \left(e^{(x_5)}\right)^{1/2} \\ &- 0.00493 \cdot x_{74} \cdot x_{113} + 0.353 \end{aligned} \tag{A.5}$$

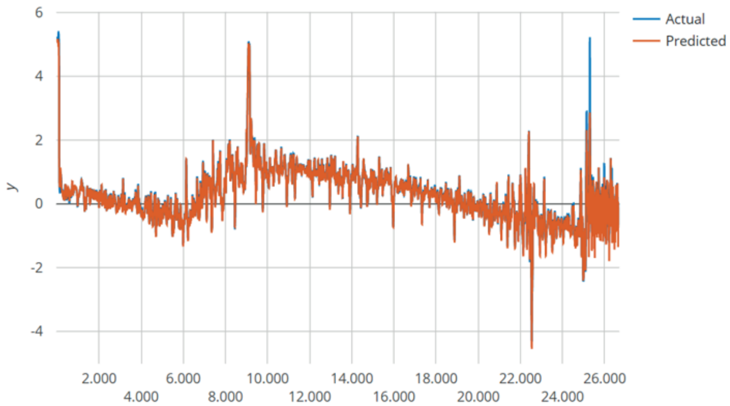
$$\begin{aligned} Y_1^6 &= 0.204 \cdot x_4 + 0.592 \cdot x_6 + 0.0242 \cdot x_{11} + 0.485 \cdot x_{21} + 0.0698 \cdot x_{43} \\ &+ 0.122 \cdot x_{59} - 0.642 \cdot e^{(-e^{(x_{21})})} - (0.00133 \cdot |x_{43}|)/|x_{94}|^2 - 0.0205 \cdot {x_4}^2 \\ &+ 0.00106 \cdot {x_4}^3 + 0.365 \end{aligned} \tag{A.6}$$

$$\begin{aligned}
Y_1^7 = {} & 0.111 \cdot x_4 + 0.601 \cdot x_6 + 0.0264 \cdot x_{11} + 0.448 \cdot x_{21} - 0.0361 \cdot x_{25} \\
& + 0.0459 \cdot x_{43} + 0.111 \cdot x_{59} - 0.0346 \cdot x_{113} - 0.0553 \cdot e^{(-x_4)} \\
& + 0.02 \cdot e^{(x_{113})} - 0.774 \cdot e^{(-e^{(x_{21})})} + 0.326
\end{aligned} \tag{A.7}$$

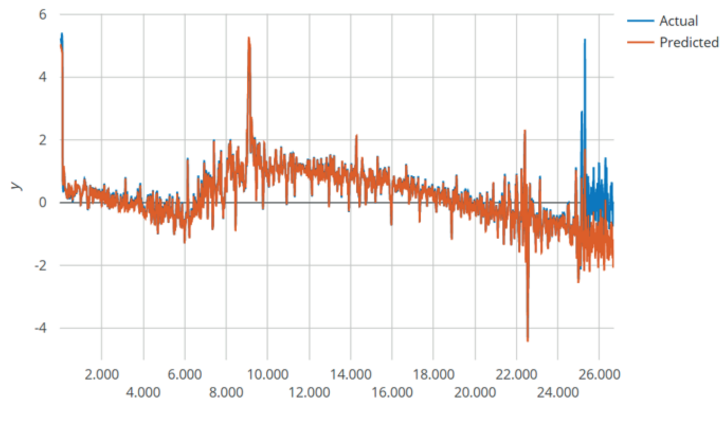
$$\begin{aligned}
Y_1^8 = {} & 0.133 \cdot x_4 + 0.649 \cdot x_6 + 0.00805 \cdot x_{12} - 0.101 \cdot x_{14} + 0.749 \cdot x_{21} \\
& - 0.0178 \cdot x_{23} + 0.0268 \cdot x_{24} + 0.0463 \cdot x_{43} + 0.00805 \cdot x_{52} + 0.0155 \cdot x_{74} \\
& + 0.0268 \cdot x_{110} - 0.0115 \cdot x_{111} - 0.0178 \cdot x_{113} - 0.0178 \cdot |x_4| \\
& - 0.0178 \cdot |x_{74}| + 0.00455 \cdot x_4 \cdot x_6 - 0.0176 \cdot x_{21} \cdot x_{74} + 0.0176 \cdot x_{23} \cdot x_{74} \\
& - 0.0176 \cdot x_{52} \cdot x_{74} + 0.0176 \cdot x_{74}|x_{21}| - 0.00228 \cdot {x_4}^2 \\
& - 0.00228 \cdot {x_6}^2 - 0.0311 \cdot {x_{21}}^2 + 0.0271
\end{aligned} \tag{A.8}$$

$$\begin{aligned}
Y_1^9 = {} & 0.136 \cdot x_4 + 0.592 \cdot x_6 + 0.701 \cdot x_{21} + 0.0567 \cdot x_{43} \\
& + 0.127 \cdot x_{59} + 0.0291 \cdot x_{96} - 0.0263 \cdot x_{113} - 0.00304|(x_8 - 5.11)| \cdot |x_{21}|^2 \\
& + 0.00248 \cdot x_4 x_{59} - 0.0307 \cdot x_{21} \cdot |x_{21}| - 4.08 \cdot 10^{-4} \cdot {x_{113}}^3 + 0.0092
\end{aligned} \tag{A.9}$$

$$\begin{aligned}
Y_1^{10} = {} & 0.17 \cdot x_4 - 0.00532 \cdot x_3 + 0.121 \cdot x_5 + 0.685 \cdot x_6 + 0.0105 \cdot x_{12} \\
& + 0.65 \cdot x_{21} + 0.0375 \cdot x_{24} - 0.00532 \cdot x_{39} + 0.075 \cdot x_{74} - 0.0079 \cdot x_{112} \\
& - 0.00532 \cdot x_{43}/x_{94} - 0.0108 \cdot {x_4}^2 + 4.7 \cdot 10^{-4} \cdot {x_4}^3 - 0.0202 \cdot {x_{21}}^2 \\
& - 0.00258 \cdot {x_{21}}^3 - 0.00258 \cdot {x_{39}}^2 + 0.0246
\end{aligned} \tag{A.10}$$

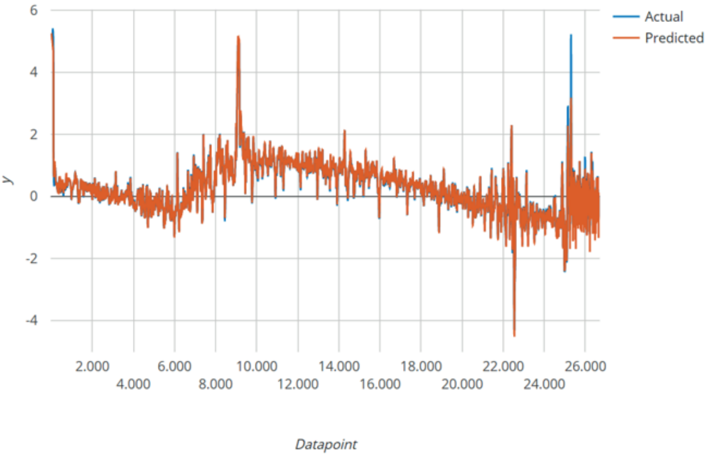


(a) Model 1

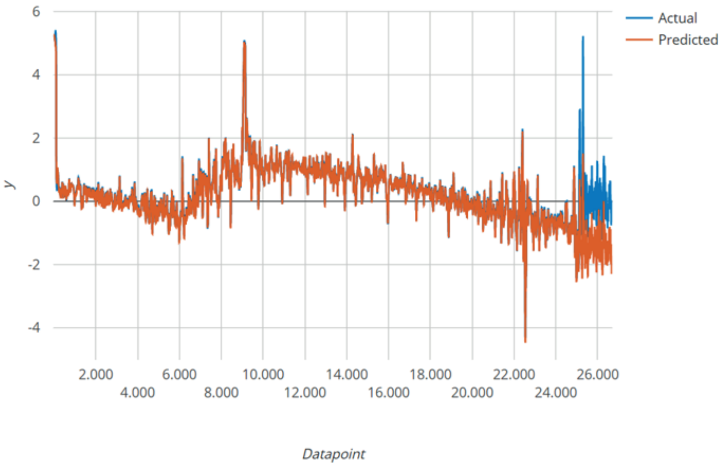


(b) Model 2

Figure A.1: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 1 and 2 Experiment 1). x-axis shows the data sample index in consecutive order according to their sampling over time.

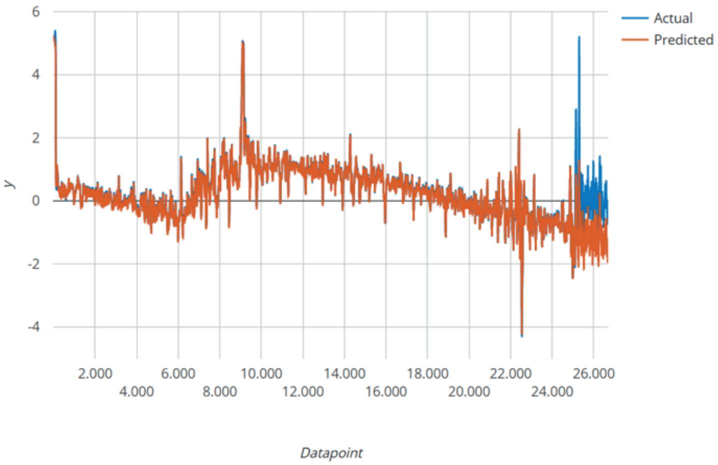


(a) Model 3

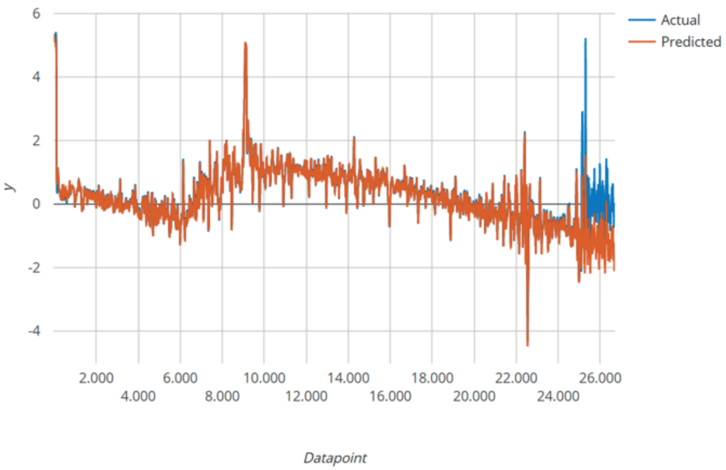


(b) Model 4

Figure A.2: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 3 and 4 Experiment 1). x-axis shows the data sample index in consecutive order according to their sampling over time.

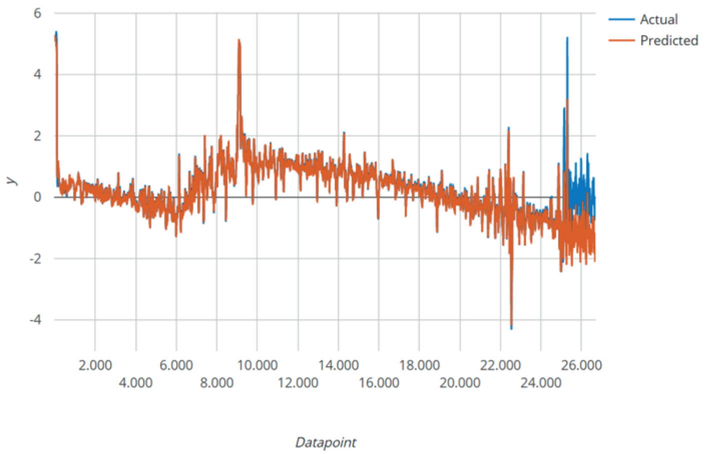


(a) Model 5

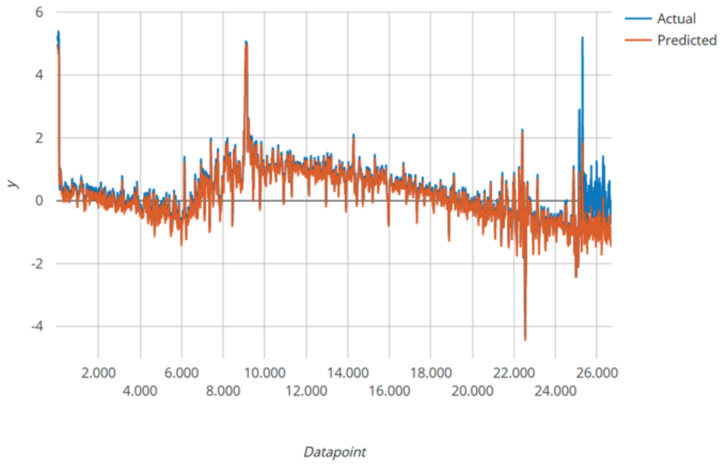


(b) Model 6

Figure A.3: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 5 and 6 Experiment 1). x-axis shows the data sample index in consecutive order according to their sampling over time.

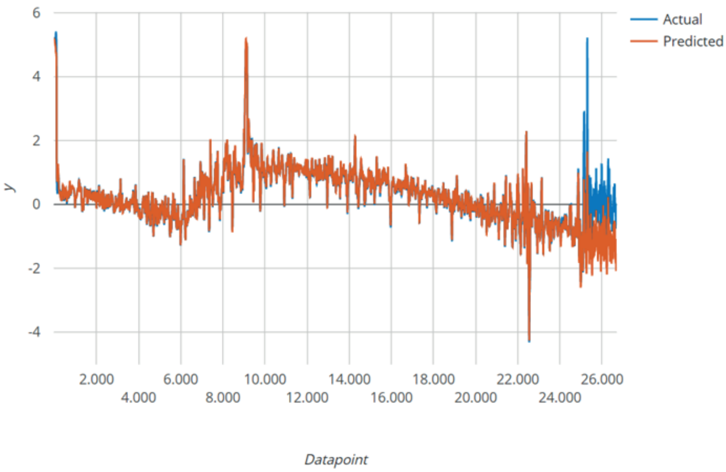


(a) Model 7

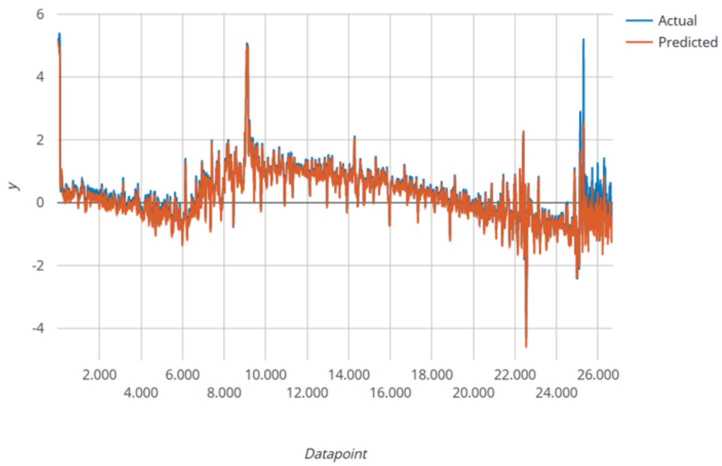


(b) Model 8

Figure A.4: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 7 and 8 Experiment 1). x-axis shows the data sample index in consecutive order according to their sampling over time.



(a) Model 9



(b) Model 10

Figure A.5: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 9 and 10 Experiment 1). x-axis shows the data sample index in consecutive order according to their sampling over time.

A.3 Experiment 2 Results

Once experiment 1 was completed and results were analyzed, the need for developing a control model is satisfied by experiment 2. Here, one highly correlated variable, which is not above the proposed threshold, was dropped from the input variables. This variables is the *Average Temperature at Station 25 (DEG_C)*. Therefore, 113 input variables were used in GPTIPS in order to model the EGT. The training, validation, and test error metrics results are displayed in tables A.4, A.5, and A.6, respectively, for all ten models resulting from the ten independent runs. The Equations A.11 - A.20, below, show the generated symbolic regression models for all ten models resulting from the ten independent runs. In Figures A.6 - A.10 we show the per model predictions (ten models resulting from the ten independent runs) against the actual values of the EGT on the test set.

Table A.4: Experiment 2 training error metrics.

R^2	**RMSE**	**MAE**	**MSE**
0.99768	1.36893	0.85751	1.87396
0.99756	1.40389	0.88441	1.97090
0.99751	1.41842	0.87606	2.01192
0.99696	1.56913	0.95831	2.46217
0.99743	1.44187	0.87915	2.07899
0.99765	1.37774	0.85544	1.89818
0.99741	1.44669	0.86240	2.09291
0.99756	1.40450	0.87028	1.97263
0.99746	1.43365	0.86886	2.05535
0.99762	1.38674	0.85581	1.92304

Table A.5: Experiment 2 validation error metrics.

R^2	**RMSE**	**MAE**	**MSE**
0.99781	1.34160	0.84267	1.79988
0.99766	1.38506	0.87861	1.91840
0.99766	1.38600	0.86851	1.92098
0.99701	1.56784	0.95604	2.45812
0.99751	1.42995	0.87120	2.04477
0.99784	1.33301	0.84164	1.77691
0.99748	1.43730	0.85617	2.06582
0.99767	1.38220	0.86608	1.91047
0.99755	1.41698	0.86252	2.00783
0.99777	1.35305	0.84415	1.83074

Table A.6: Experiment 2 test error metrics.

Rˆ2	**RMSE**	**MAE**	**MSE**
0.760114	11.62049	3.508928	135.0357
0.796653	10.69894	3.228156	114.4673
0.781762	11.08375	3.578363	122.8495
0.879283	8.243387	3.037525	67.95342
0.805173	10.4724	3.198549	109.6712
0.794995	10.74246	3.204305	115.4005
0.78722	10.94429	3.307758	119.7775
0.809058	10.36747	3.247515	107.4844
0.79427	10.76145	3.539824	115.8089
0.891921	7.799965	2.70033	60.83946

$$\begin{aligned} Y_2^1 &= 0.0789 \cdot x_4 + 0.143 \cdot x_5 + 0.0207 \cdot x_{10} + 0.799 \cdot x_{17} - 0.524 \cdot x_{19} \\ &+ 0.575 \cdot x_{20} - 0.0789 \cdot e^{(-e^{(-x_{20})})} - 0.441 \cdot e^{(-e^{(-e^{(-x_4)})})} - e^{(-e^{(-e^{(-x_{20})})})} \\ &- ((0.0186 \cdot |x_{38}|)/|x_{98}|) + ((0.0092 \cdot x_{38})/x_{51}) + 1.13 \end{aligned} \tag{A.11}$$

$$\begin{aligned} Y_2^2 &= 0.13 \cdot x_4 + 0.0229 \cdot x_{11} + 0.694 \cdot x_{17} - 0.394 \cdot x_{19} + 0.723 \cdot x_{20} \\ &+ 0.0604 \cdot x_{42} + 0.107 \cdot x_{58} - 0.0261 \cdot |x_{19}| \cdot |x_{20}| + 0.0168 \cdot x_{42} \cdot x_{112} \\ &- 0.033 \cdot x_{20} \cdot |x_{20}| - 0.0162 \cdot x_{42} \cdot |x_{20}| - 0.013 \cdot x_{112} \cdot |x_{19}| + 0.0126 \end{aligned} \tag{A.12}$$

$$\begin{aligned} Y_2^3 &= 0.123 \cdot x_4 + 0.0305 \cdot x_{10} + 0.713 \cdot x_{17} - 0.327 \cdot x_{19} + 0.628 \cdot x_{20} \\ &+ 0.0582 \cdot x_{42} + 0.0949 \cdot x_{58} + 0.0263 \cdot x_{73} - 0.0303 \cdot x_{112} \\ &- 0.0119 \cdot {x_{20}}^2 \cdot x_{42} + 0.00167 \end{aligned} \tag{A.13}$$

$$\begin{aligned} Y_2^4 &= 0.1 \cdot x_4 + 0.671 \cdot x_{17} - 0.389 \cdot x_{19} + 0.506 \cdot x_{20} - 0.0408 \cdot x_{38} \\ &+ 0.138 \cdot x_{58} - 0.108 \cdot e^{(-x_{38})} + 0.929 \cdot e^{(-e^{(-e^{(-e^{(-x_4)})})})} - 0.0472 \cdot |x_7| \\ &- 0.633 \cdot e^{(-e^{(x_{20})})} - 0.0392 \end{aligned} \tag{A.14}$$

$$\begin{aligned} Y_2^5 &= 0.11 \cdot x_4 + 0.662 \cdot x_{17} - 0.39 \cdot x_{19} + 0.526 \cdot x_{20} + 0.0537 \cdot x_{42} + 0.141 \cdot x_{58} \\ &+ 0.0269 \cdot x_{95} - 0.0609 \cdot e^{(-x_4)} - 0.00223 \cdot e^{(x_{20})} - 0.587 \cdot e^{(-1.1e^{(x_{20})})} \\ &- 0.00143 \cdot x_{23} \cdot {x_{112}}^2 - 0.00143 \cdot {x_{23}}^2 \cdot x_{112} - 4.76 \cdot 10^4 \cdot {x_{23}}^3 \\ &- 4.76 \cdot 10^4 \cdot {x_{112}}^3 + 0.276 \end{aligned} \tag{A.15}$$

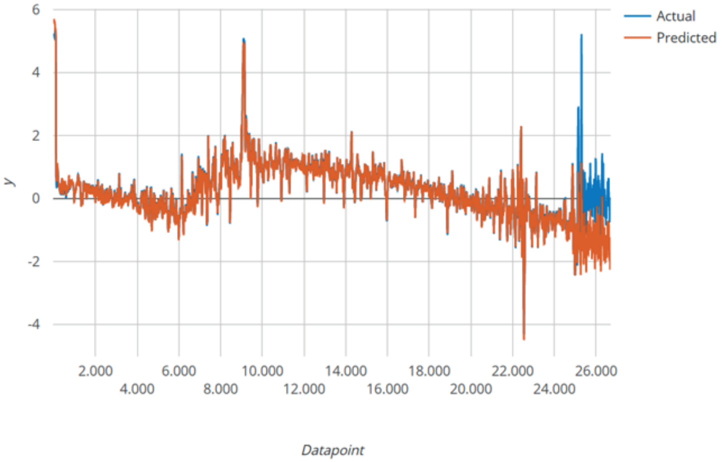
$$\begin{aligned} Y_2^6 &= 0.647 \cdot x_{17} - 0.412 \cdot x_{19} + 0.549 \cdot x_{20} + 0.0505 \cdot x_{42} + 0.157 \cdot x_{58} \\ &+ 0.0243 \cdot x_{95} - 0.826 \cdot e^{(-e^{(-e^{(-x_{20})})})} - 1.59 \cdot e^{(-e^{(-e^{(-x_4)^{1/2}})})} \\ &+ 0.00578 \cdot {x_4}^2 - 7.58 \cdot 10^5 \cdot {x_{51}}^4 + 1.69 \end{aligned} \tag{A.16}$$

$$\begin{aligned}
Y_2^7 &= 0.0925 \cdot x_4 + 0.113 \cdot x_5 + 0.0195 \cdot x_{11} + 0.797 \cdot x_{17} - 0.427 \cdot x_{19} \\
&+ 0.518 \cdot x_{20} - 0.0181 \cdot x_{112} - 0.452 \cdot e^{(-x_{38})} - 1.13 \cdot e^{(-e^{(-x_{38})})} \\
&- 0.45 \cdot e^{(-e^{(-e^{(-x_4)})})} - 0.847 \cdot e^{(-e^{(-e^{(-x_{20})})})} + 1.89
\end{aligned} \tag{A.17}$$

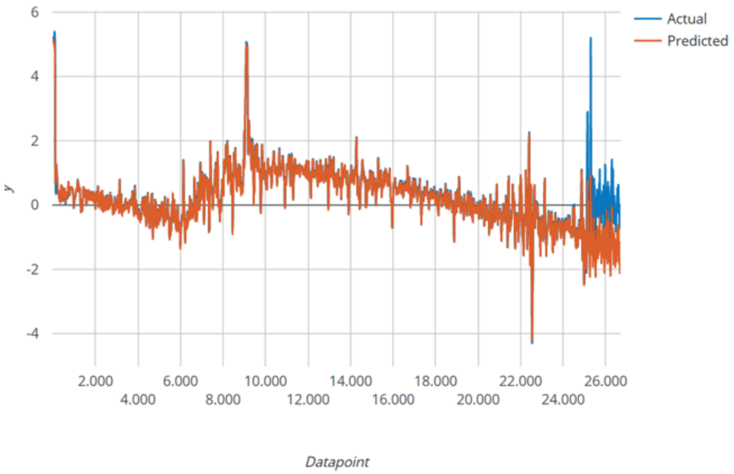
$$\begin{aligned}
Y_2^8 &= 0.158 \cdot x_4 + 0.131 \cdot x_5 + 0.8 \cdot x_{17} - 0.46 \cdot x_{19} + 0.53 \cdot x_{20} - 0.0231 \cdot x_{22} \\
&- 0.0231 \cdot e^{(-x_4)} - 0.0826 \cdot e^{(-x_{38})} - 0.0826 \cdot e^{(-2 \cdot e^{(-x_{20})})} \\
&- 0.928 \cdot e^{(-e^{(-e^{(-x_{20})})})} - 0.00491 \cdot {x_4}^2 - 0.00827 \cdot {x_{38}}^2 + 0.811
\end{aligned} \tag{A.18}$$

$$\begin{aligned}
Y_2^9 &= 0.172 \cdot x_4 + 0.0239 \cdot x_{10} + 0.667 \cdot x_{17} - 0.403 \cdot x_{19} + 0.593 \cdot x_{20} \\
&+ 0.0475 \cdot x_{42} + 0.133 \cdot x_{58} + 0.0481 \cdot x_{73} - 0.0481 \cdot e^{(0.567 \cdot x_{20})} \\
&- 0.623 \cdot e^{(-e^{0.73 \cdot x_{20}})} - 0.0647 \cdot |x_4| + 0.316
\end{aligned} \tag{A.19}$$

$$\begin{aligned}
Y_2^{10} &= 0.129 \cdot x_4 + 0.69 \cdot x_{17} - 0.373 \cdot x_{19} + 0.455 \cdot x_{20} - 0.0382 \cdot x_{24} \\
&+ 0.121 \cdot x_{58} - 0.0303 \cdot x_{112} + 0.509 \cdot e^{(-e^{(-e^{(-e^{(-x_{42})})})})} + 0.0771 \cdot e^{(-2 \cdot {x_7}^2)} \\
&- 0.707 \cdot e^{(-e^{x_{20}})} - 0.0137
\end{aligned} \tag{A.20}$$

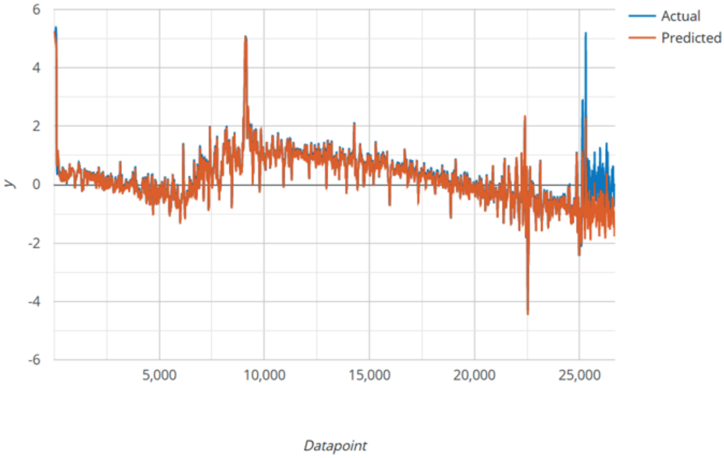


(a) Model 1

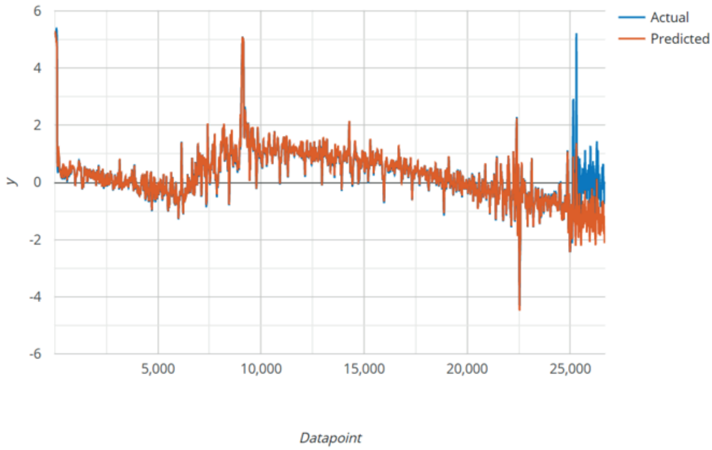


(b) Model 2

Figure A.6: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 1 and 2 Experiment 2). x-axis shows the data sample index in consecutive order according to their sampling over time.

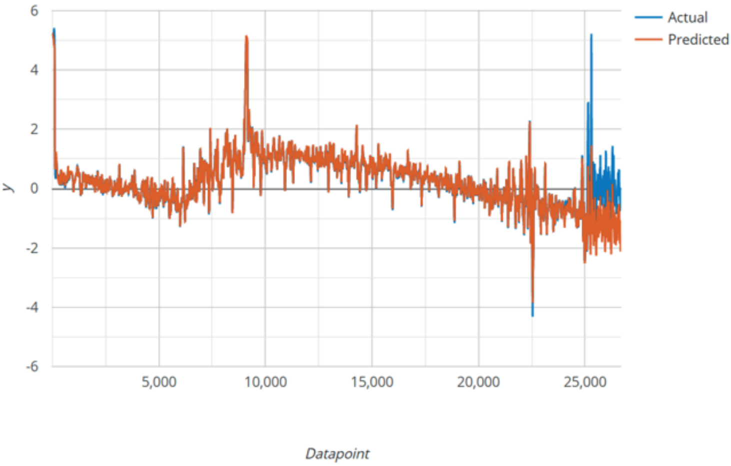


(a) Model 3

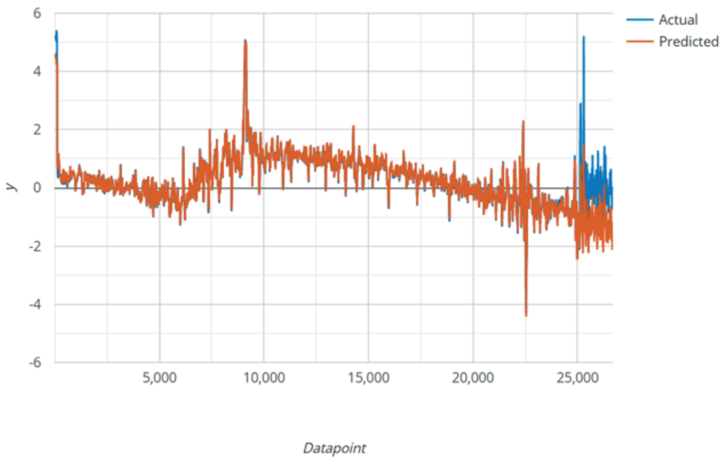


(b) Model 4

Figure A.7: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 3 and 4 Experiment 2). x-axis shows the data sample index in consecutive order according to their sampling over time.

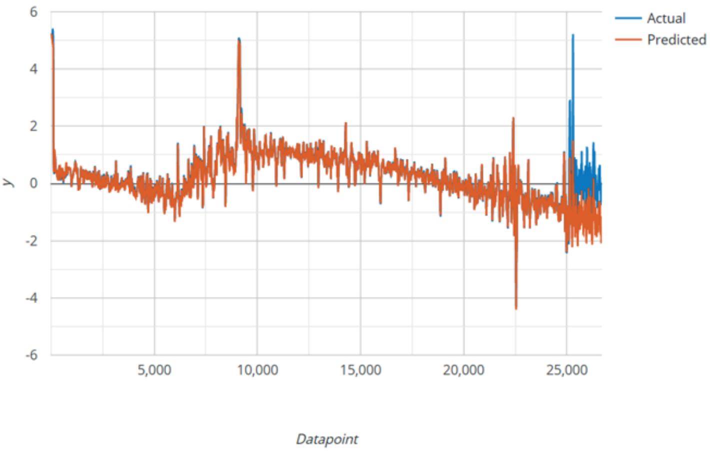


(a) Model 5

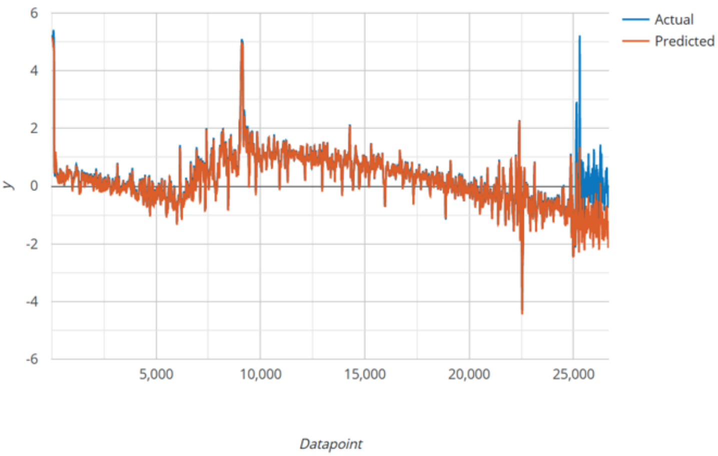


(b) Model 6

Figure A.8: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 5 and 6 Experiment 2). x-axis shows the data sample index in consecutive order according to their sampling over time.

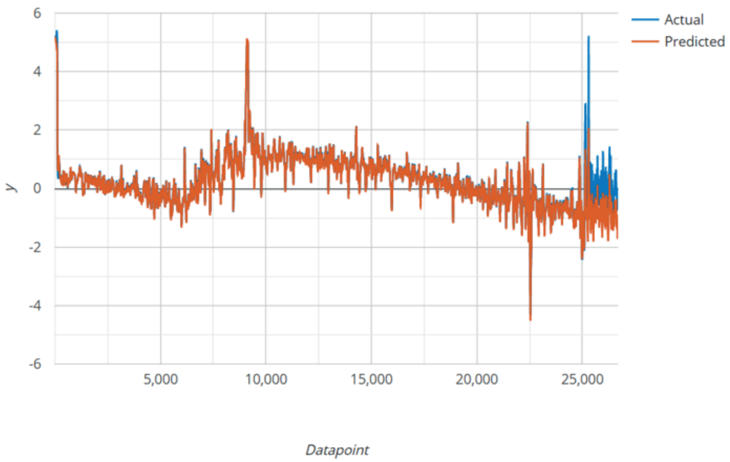


(a) Model 7

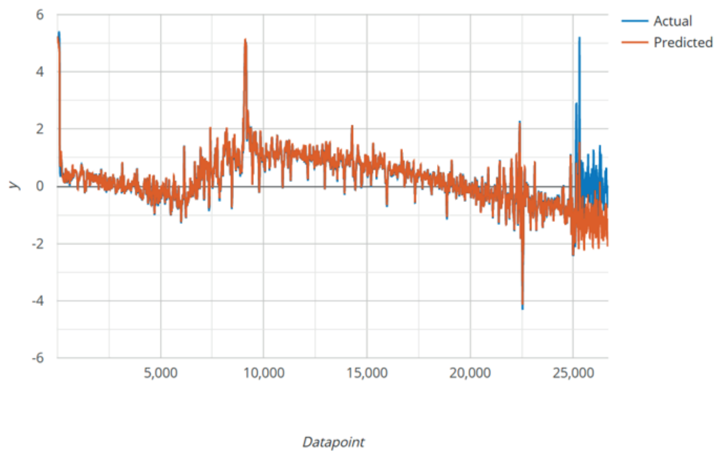


(b) Model 8

Figure A.9: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 7 and 8 Experiment 2). x-axis shows the data sample index in consecutive order according to their sampling over time.



(a) Model 9



(b) Model 10

Figure A.10: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 9 and 10 Experiment 2). x-axis shows the data sample index in consecutive order according to their sampling over time.

A.4 Experiment 3 Results

A correlation analysis between the input variables and the output variable, EGT, is performed, dropping those variables whose correlation with EGT is higher than 0.90. After doing so, 186 input variables remained. Once this was done, and following experiment's 1 logic, a correlation analysis upon the remaining input variables is done. Again, those above the proposed threshold are deleted, only keeping the first representative from a set of highly correlated variables. Once this step was done, 112 input variables remained, plus the output variable, EGT. The training, validation, and test error metrics results are displayed in tables A.7, A.8, and A.9, respectively, for all ten models resulting from the ten independent runs. In Figures A.11 - A.15 we show the per model predictions (ten models resulting from the ten independent runs) against the actual values of the EGT on the test set.

Table A.7: Experiment 3 training error metrics.

R^2	**RMSE**	**MAE**	**MSE**
0.99800	1.27580	0.74480	1.62768
0.99812	1.23542	0.75659	1.52627
0.99807	1.25291	0.76230	1.56978
0.99822	1.20218	0.75237	1.44524
0.99809	1.24816	0.73935	1.55789
0.99832	1.16893	0.75271	1.36640
0.99801	1.27283	0.78877	1.62009
0.99818	1.21660	0.73428	1.48011
0.99820	1.21099	0.72872	1.46649
0.99835	1.16035	0.71518	1.34641

Table A.8: Experiment 3 validation error metrics.

R^2	**RMSE**	**MAE**	**MSE**
0.99792	1.29194	0.74879	1.66910
0.99799	1.26866	0.76180	1.60950
0.99801	1.26294	0.75916	1.59503
0.99810	1.23463	0.75536	1.52432
0.99802	1.26004	0.74229	1.58769
0.99823	1.19080	0.75385	1.41801
0.99793	1.28963	0.78988	1.66315
0.99812	1.22731	0.73710	1.50629
0.99813	1.22366	0.73682	1.49735
0.998197	1.202644	0.720882	1.446352

Table A.9: Experiment 3 test error metrics.

R^2	RMSE	MAE	MSE
0.788536	10.91038	3.23724	119.03647
0.834811	9.64300	2.97148	92.98735
0.985225	2.88393	1.18922	8.31704
0.985034	2.90254	1.31293	8.42474
0.800509	10.59703	3.35942	112.29699
0.819613	10.07684	3.18990	101.54277
0.802258	10.55046	3.35021	111.31211
0.933994	6.09554	2.08652	37.15565
0.794766	10.74848	4.10824	115.52974
0.822608	9.99285	3.21731	99.85703

$$\begin{aligned} Y_3^1 &= 0.114 \cdot x_5 + 0.771 \cdot x_6 + 0.0249 \cdot x_{11} - 0.0763 \cdot x13 + 0.395 \cdot x_{19} \\ &+ 1.62 \cdot log(x_4 + e^{(-x_{23})} + 8.9) + 0.233 \cdot e^{(-x_{23})} - 0.0534 \cdot e^{(-x_{41})} \\ &- 1.36 \cdot 10^{-5} e^{(-x_{103})} - 1.14 \cdot e^{(-e^{(-e^{(-x_{19})})})} - 3.11 \end{aligned} \tag{A.21}$$

$$\begin{aligned} Y_3^2 &= 0.0789 \cdot x_4 + 0.123 \cdot x_5 + 0.696 \cdot x_6 + 0.0219 \cdot x_{11} + 0.68 \cdot x_{19} \\ &+ 0.156 \cdot x_{72} + 0.357 \cdot e^{(-e^{(-x_4)})} + 0.29 \cdot e^{(-e^{(-x_{37})})} + 0.54 \cdot e^{(-{x_{19}}^4 \cdot {x_{72}}^2)} \\ &+ 0.393 \cdot e^{(-{x_{37}}^2)} - 0.996 \end{aligned} \tag{A.22}$$

$$\begin{aligned} Y_3^3 &= 0.0765 \cdot x_4 + 0.683 \cdot x_6 - 0.114 \cdot x_{14} + 0.683 \cdot x_{19} - 0.0189 \cdot x_{21} \\ &- 0.0228 \cdot x_{40} + 0.0371 \cdot x_{41} + 0.159 \cdot x_{72} - 0.585 \cdot e^{(-e^{(-e^{(-x_4)})})} \\ &+ 0.0371 \cdot e^{(-e^{(-e^{(-x_{26})})})} - 0.136 \cdot |x_{19} - 1.23| + 0.114 \cdot e^{(-Re(e^{(-x_{26})}))} \\ &- 0.699 \cdot e^{(-real(e^{(-x_{72})}))} + 0.766 \end{aligned} \tag{A.23}$$

$$\begin{aligned} Y_3^4 &= 0.139 \cdot x_4 + 0.107 \cdot x_5 + 0.698 \cdot x_6 + 0.438 \cdot x_{19} - 0.039 \cdot x_{23} \\ &+ 0.0508 \cdot x_{41} - 0.0265 \cdot x_{111} - 0.145 \cdot e^{(-e^{(-e^{(-x_{11})})})} - 0.825 \cdot e^{(-e^{(x_{19})})} \\ &- 2.66 \cdot 10{-}4 \cdot {x_4}^3 + 0.411 \end{aligned} \tag{A.24}$$

$$\begin{aligned}
Y_3^5 &= 0.0906 \cdot x_4 + 0.642 \cdot x_6 + 0.028 \cdot x_{11} + 0.562 \cdot x_{19} + 0.0752 \cdot x_{37} \\
&+ 0.0171 \cdot x_{67} + 0.0338 \cdot x_{74} - 0.791 \cdot e^{(-Re(e^{(-e^{(-x_{19})})}))} - 0.115 \cdot |x_{37}| \\
&+ (0.208 \cdot 0.657^{x_{14}} \cdot 0.657^{x_{74}})/0.657^{x_{108}} + 0.417
\end{aligned} \tag{A.25}$$

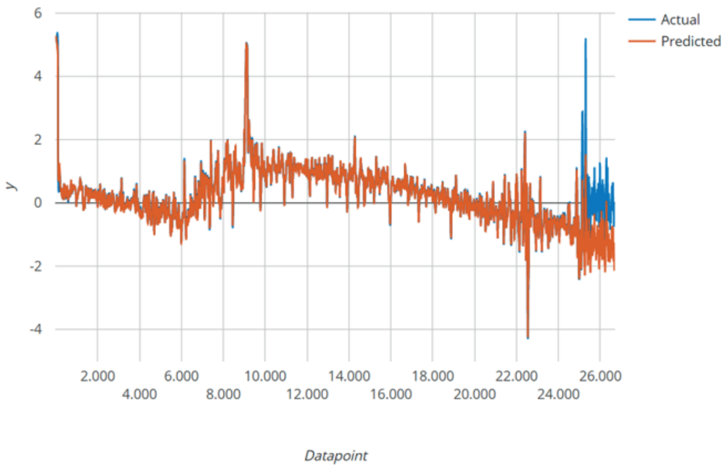
$$\begin{aligned}
Y_3^6 &= 0.101 \cdot x_4 + 0.136 \cdot x_5 + 0.654 \cdot x_6 + 0.448 \cdot x_{19} - 0.0226 \cdot x_{21} \\
&+ 0.0426 \cdot x_{26} + 0.0484 \cdot x_{41} - 0.0602 \cdot x_{74} + 0.082 \cdot x_{108} \\
&- 0.605 \cdot e^{(-e^{(x_{19})})} + 0.224
\end{aligned} \tag{A.26}$$

$$\begin{aligned}
Y_3^7 &= 0.0831 \cdot x_4 + 0.117 \cdot x_5 + 0.695 \cdot x_6 + 0.0233 \cdot x_{11} + 0.461 \cdot x_{19} \\
&- 0.0436 \cdot x_{23} + 0.0436 \cdot x_{41} + 0.0544 \cdot x_{72} - 0.729 \cdot e^{(e^{(-e^{(x_{19})})})} \\
&+ 0.81 \cdot e^{(-e^{(e^{(x_{19})})})} + 0.368 \cdot e^{(-e^{(-x_4)})} + 0.883
\end{aligned} \tag{A.27}$$

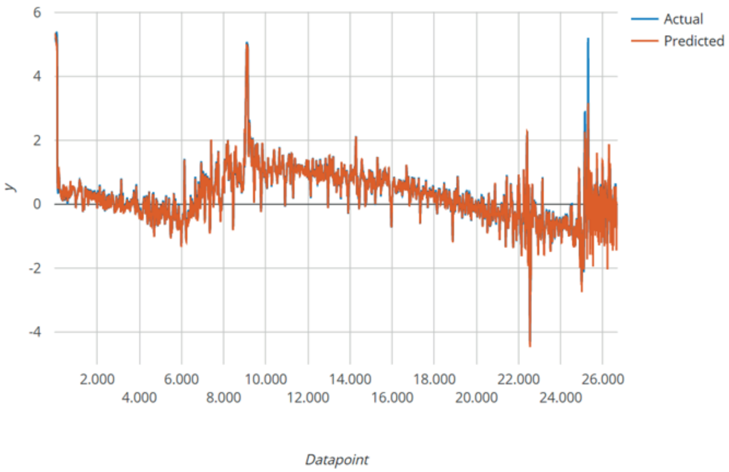
$$\begin{aligned}
Y_3^8 &= 0.0596 \cdot x_4 + 0.118 \cdot x_5 + 0.671 \cdot x_6 + 0.474 \cdot x_{19} + 0.0446 \cdot x_{41} \\
&+ 0.0298 \cdot x_{108} - 0.014 \cdot x_{111} - 0.735 \cdot e^{-e^{(x_{19})}} + 0.753 \cdot e^{(-e^{(-x_4)^{1/2}})^{1/2}} \\
&- 3.52 \cdot 10^{-6} \cdot {x_{111}}^3 \cdot x_4 + x_5 + {x_{21}}^3 - 0.175 \cdot e^{(-e^{(-x_{21})})^{1/2}} - 0.0498
\end{aligned} \tag{A.28}$$

$$\begin{aligned}
Y_3^9 &= 0.106 \cdot x_4 + 0.125 \cdot x_5 + 0.689 \cdot x_6 + 0.0261 \cdot x_{11} + 0.45 \cdot x_{19} \\
&+ 0.0515 \cdot x_{41} + 0.00826 \cdot x_{58} - 0.744 \cdot e^{(-e^{(x_{19})})} \\
&+ 2.08 \cdot 10^{-7} e^{(2 \cdot x_{97})} \cdot |x_{111}|^2 + 0.00826 \cdot x_5 \cdot x_6 - 0.00826 \cdot x_5 \cdot x_{28} \\
&- 0.00511 \cdot x_4 \cdot x_{74} + 0.00826 \cdot x_{38} \cdot x_{74} + 0.00511 \cdot {x_4}^2 e^{(-x_4)} \\
&- 0.176 \cdot e^{(-x_4)^{1/2}} + 0.467
\end{aligned} \tag{A.29}$$

$$\begin{aligned}
Y_3^{10} &= 0.0825 \cdot x_4 + 0.134 \cdot x_5 + 0.688 \cdot x_6 + 0.0174 \cdot x_{12} + 0.47 \cdot x_{19} \\
&+ 0.0304 \cdot x_{26} + 0.0409 \cdot x_{41} - 0.523 \cdot e^{(-e^{(-e^{(-x_4)})})} - 0.703 \cdot e^{(-e^{(x_{19})})} \\
&+ 2.93 \cdot 10^{-4} \cdot {x_{72}}^3 e^{(-x_1)} + 0.635
\end{aligned} \tag{A.30}$$

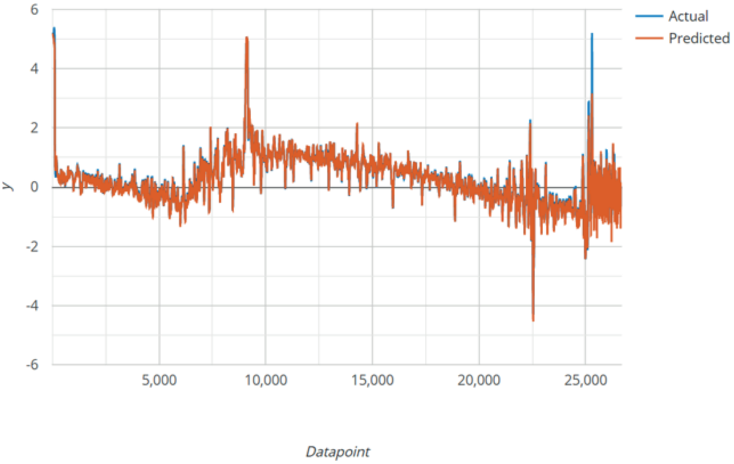


(a) Model 1

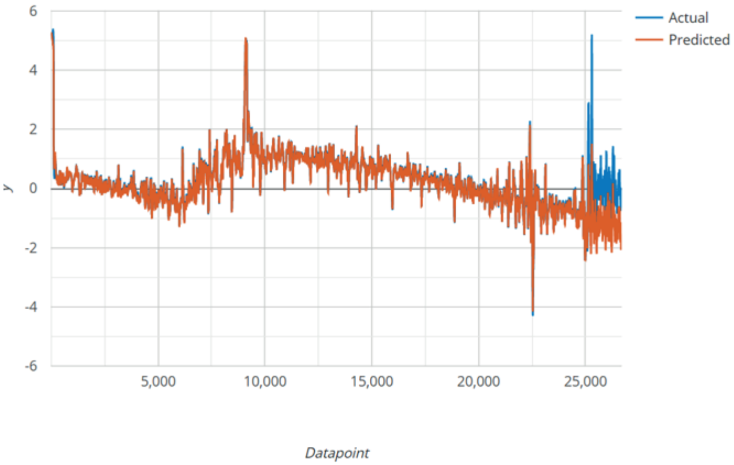


(b) Model 2

Figure A.11: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 1 and 2 Experiment 3). x-axis shows the data sample index in consecutive order according to their sampling over time.

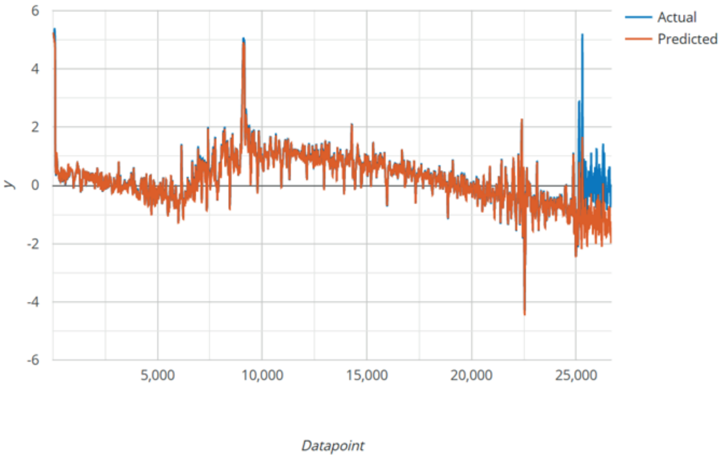


(a) Model 3

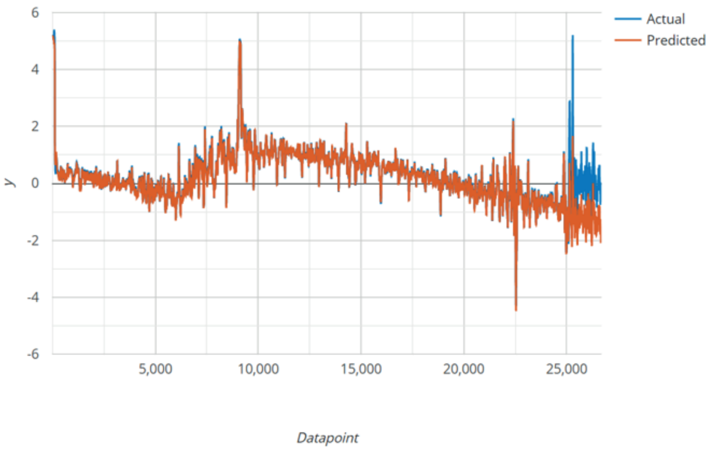


(b) Model 4

Figure A.12: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 3 and 4 Experiment 3). x-axis shows the data sample index in consecutive order according to their sampling over time.

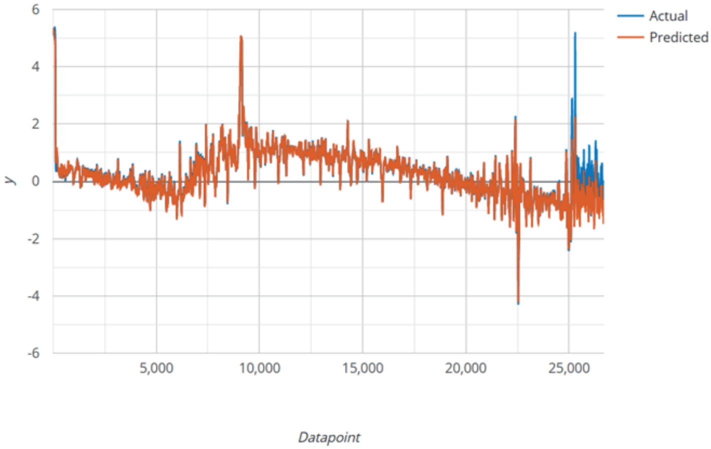


(a) Model 5

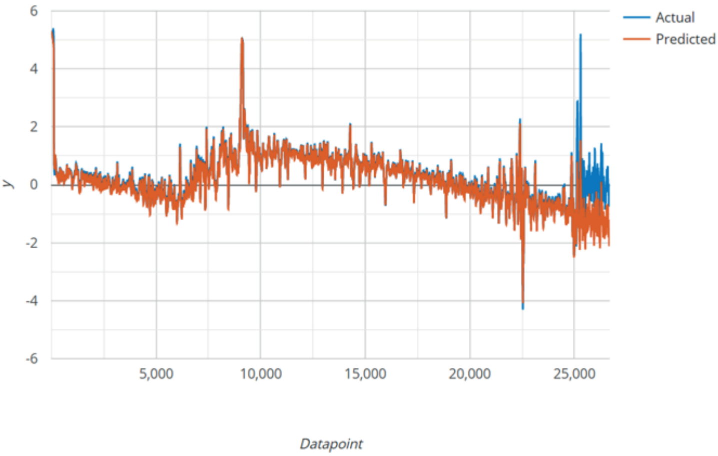


(b) Model 6

Figure A.13: Scaled EGT pre dictions (red) (y-axis) on the test set vs. observed (blue) values (Models 5 and 6 Experiment 3). x-axis shows the data sample index in consecutive order according to their sampling over time.

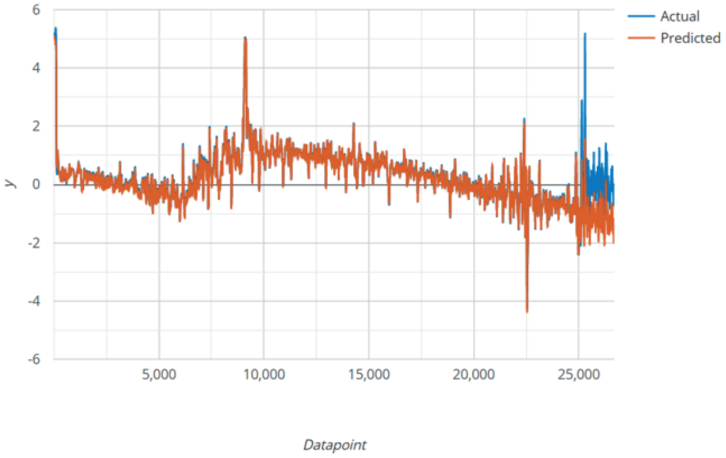


(a) Model 7

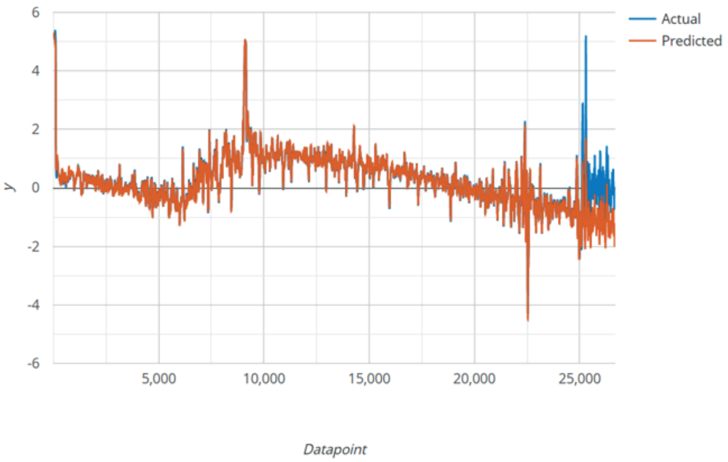


(b) Model 8

Figure A.14: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 7 and 8 Experiment 3). x-axis shows the data sample index in consecutive order according to their sampling over time.



(a) Model 9



(b) Model 10

Figure A.15: Scaled EGT predictions (red) (y-axis) on the test set vs. observed (blue) values (Models 9 and 10 Experiment 3). x-axis shows the data sample index in consecutive order according to their sampling over time.

Bibliography

[1] The prophet of gases. *Science*, October 2006.

[2] Left engine failure and subsequent depressurization, Southwest Airlines flight 1380, boeing 737-7H4, N772SW. *National Transportation Safety Board (NTSB)*, November 2019.

[3] A. Saxena and K. Goebel. Turbofan engine degradation simulation data set, 2008.

[4] M. Abdar, F. Pourpanah, S. Hussain, D. Rezazadegan, L. Liu, M. Ghavamzadeh, P. Fieguth, X. Cao, A. Khosravi, U. R. Acharya, V. Makarenkov, and S. Nahavandi. A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Information Fusion*, 76:243–297, December 2021. arXiv: 2011.06225.

[5] A. Abraham. Adaptation of fuzzy inference system using neural learning. In Janusz Kacprzyk, Nadia Nedjah, and Luiza de Macedo Mourelle, editors, *Fuzzy Systems Engineering*, volume 181, pages 53–83. Springer Berlin Heidelberg, Berlin, Heidelberg, July 2005.

[6] H. G. Abreha, M. Hayajneh, and M. A. Serhani. Federated learning in edge computing: A systematic survey. *Sensors*, 22(2), 2022.

[7] D. Acemoglu, U. Akcigit, and W. R. Kerr. Innovation network. *Proceedings of the National Academy of Sciences of the United States of America*, 113(41):11483–11488, October 2016.

[8] F. Ahmadzadeh and J. Lundberg. Remaining useful life estimation: review. *International Journal of System Assurance Engineering and Management*, 5(4):461–474, December 2014.

[9] H. Ali, R. Haque, and F. Rahman. Chronological evolution of flexible job shop scheduling: A review. In *Proceedings of the 4th International Conference on Mechanical Engineering and Renewable Energy 2017 (ICMERE2017)*, page 7, CUET, Chittagong, Bangladesh, 2017.

[10] J. Ben. Alia, B. Chebel-Morello, L. Saidi, S. Malinowski, and F. Fnaiech. Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network. *Mechanical Systems and Signal Processing*, pages 150–172, 2015.

[11] G. M. Arellano, R. Cant, and L. Nolle. Prediction of jet engine parameters for control design using genetic programming. In *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*, pages 45–50, Cambridge, United Kingdom, March 2014. IEEE.

[12] V. Arkov, C. Evans, P. J. Fleming, and D. C. Hill. System identification strategies applied to aircraft gas turbine engines. *Annual Reviews in Control*, 24:67–81, 2000.

[13] N. T. Artug, I. Goker, B. Bolat, G. Tulum, O. Osman, and M. B. Baslo. Feature extraction and classification of neuromuscular diseases using scanning EMG. In *2014 IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA) Proceedings*, pages 262–265, Alberobello, Italy, June 2014. IEEE.

[14] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing*, 50(2):15, 2002.

[15] K. D. Ashley. *Artificial intelligence and legal analytics: New tools for law practice in the digital age*. Cambridge University Press, Cambridge, 2017.

[16] V. Atamuradov, K. Medjaher, P. Dersin, B. Lamoureux, and N. Zerhouni. Prognostics and health management for maintenance practitioners - Review, implementation and tools evaluation. *International Journal of Prognostics and Health Management. Special Issue on Railway Systems & Mass Transportation*, 8(3):32, 2017.

[17] U. A. Badrising, M. Maat-Schieman, S. G. van Duinen, F. Breedveld, P. van Doorn, B. van Engelen, F. van den Hoogen, J. Hoogendijk, C. Höweler, A. de Jager, F. Jennekens, P. Koehler, H. van der Leeuw, M. de Visser, J. J. Verschuuren, and A. R. Wintzen. Epidemiology of inclusion body myositis in the Netherlands: A nationwide study. *Neurology*, 55(9):1385–1387, November 2000.

[18] H. Bal, D. Epema, C. de Laat, R. van Nieuwpoort, J. Romein, F. Seinstra, C. Snoek, and H. Wijshoff. A medium-scale distributed system for computer science research: Infrastructure for the long term. *Computer*, 49(5):54–63, May 2016.

[19] E. Balas. Machine sequencing via disjunctive graphs: An implicit enumeration algorithm. *Operations Research*, 17(6):941–957, December 1969.

[20] M. Banghart, L. Bian, L. Strawderman, and K. Babski-Reeves. Risk assessment on the EA-6b aircraft utilizing Bayesian networks. *Quality Engineering*, 29(3):499–511, July 2017.

[21] M. Baptista, E. M. P. Henriques, I. P. de Medeiros, J. P. Malere, C. L. Nascimento, and H. Prendinger. Remaining useful life estimation in aeronautics: Combining data-driven and Kalman filtering. *Reliability Engineering & System Safety*, 184:228–239, 2019.

[22] M. Baptista, S. Sankararaman, I. P. de Medeiros, C. Nascimento, H. Prendinger, and E. M. P. Henriques. Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. *Computers & Industrial Engineering*, 115:41–53, January 2018.

[23] P. Baraldi, M. Compare, S. Sauco, and E. Zio. Ensemble neural network-based particle filtering for prognostics. *Mechanical Systems and Signal Processing*, 41(1):288 – 300, 2013.

[24] E. Bechhoefer, A. Bernhard, D. He, and P. Banerjee. Use of hidden semi-Markov models in the prognostics of shaft failure. In *American Helicopter Society 62nd Annual Forum*, pages 1–7, Phoenix, AZ, USA, May 2006. American Helicopter Society International, Inc.

[25] M. Benker, L. Furtner, T. Semm, and M. F. Zaeh. Utilizing uncertainty information in remaining useful life estimation via Bayesian neural networks and Hamiltonian Monte Carlo. *Journal of Manufacturing Systems*, 61:799–807, October 2021.

[26] L. Biggio, A. Wieland, M. A. Chao, I. Kastanis, and O. Fink. Uncertainty-aware remaining useful life predictor. *arXiv:2104.03613 [cs, stat]*, April 2021.

[27] D. M. Blei, A. Kucukelbir, and J. D. McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112(518):859–877, April 2017.

[28] C. Blundell, J. Cornebise, K. Kavukcuoglu, and D. Wierstra. Weight uncertainty in neural networks. *arXiv:1505.05424 [cs, stat]*, May 2015. arXiv: 1505.05424.

[29] J. Z. De Boer and J. R. Hale. The geological origins of the oracle at Delphi, Greece. *Geological Society, London, Special Publications*, 171(1):399–412, January 2000. Publisher: Geological Society of London.

[30] J. Bongard and H. Lipson. Automated reverse engineering of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences*, 104(24):9943–9948, 2007.

[31] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung. *Time series analysis: Forecasting and control*. John Wiley & Sons, 2015.

[32] P. Brandimarte. Routing and scheduling in a flexible job shop by tabu search. *Annals of Operations Research*, 41(3):157–183, September 1993.

[33] D. Brunt. Meteorology and Weather Lore. *Folklore*, 57(2):66–74, June 1946. Publisher: Routledge _eprint: https://doi.org/10.1080/0015587X.1946.9717813.

[34] T. Bäck. *Evolutionary algorithms in theory and practice: Evolution strategies, evolutionary programming, genetic algorithms*. Oxford University Press, Inc., USA, 1996.

[35] J. Caceres, D. Gonzalez, T. Zhou, and E. L. Droguett. A probabilistic Bayesian recurrent neural network for remaining useful life prognostics considering epistemic and aleatory uncertainties. *Structural Control and Health Monitoring*, 28(10), October 2021.

[36] G. Chandrashekar and F. Sahin. A survey on feature selection methods. *Computers & Electrical Engineering*, 40(1):16–28, 2014. 40th-year commemorative issue.

[37] H.-C. Chang, Y.-P. Chen, T.-K. Liu, and J.-H. Chou. Solving the flexible job shop scheduling problem with makespan optimization by using a hybrid Taguchi-genetic algorithm. *IEEE Access*, 3:1740–1754, 2015.

[38] I. A. Chaudhry and A. A. Khan. A research survey: Review of flexible job shop scheduling techniques. *International Transactions in Operational Research*, 23(3):551–591, May 2016.

[39] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16:321–357, June 2002.

[40] C. Chen, G. Vachtsevanos, and M. E. Orchard. Machine remaining useful life prediction: An integrated adaptive neuro-fuzzy and high-order particle filtering approach. *Mechanical Systems and Signal Processing*, 28:597–607, April 2012.

[41] X. Chen, J. Yu, D. Tang, and Y. Wang. Remaining useful life prognostic estimation for aircraft subsystems or components: A review. In *IEEE 2011 10th International Conference on Electronic Measurement & Instruments*, pages 94–98, Chengdu, China, August 2011. IEEE.

[42] T.-C. Chiang and H.-J. Lin. Flexible job shop scheduling using a multiobjective memetic algorithm. In De-Shuang Huang, Yong Gan, Phalguni Gupta, and M. Michael Gromiha, editors, *Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence*, volume 6839, pages 49–56. Springer Berlin Heidelberg, Berlin, Heidelberg, 2012.

[43] M. Christ, N. Braun, J. Neuffer, and A. W. Kempa-Liehr. Time Series FeatuRe Extraction on basis of Scalable Hypothesis tests (tsfresh – A Python package). *Neurocomputing*, 307:72–77, September 2018.

[44] M. Claesen and B. De Moor. Hyperparameter search in machine learning. *arXiv:1502.02127 [cs, stat]*, April 2015.

[45] F. M. Cox, M. J. Titulaer, J. K. Sont, A. R. Wintzen, J. J. G. M. Verschuuren, and U. A. Badrising. A 12-year follow-up in sporadic inclusion body myositis: An end stage with major disabilities. *Brain: A Journal of Neurology*, 134(Pt 11):3167–3175, November 2011.

[46] J. D. Cryer and K.-s. Chan. *Time series analysis: With applications in R*. Springer texts in statistics. Springer, New York, 2nd ed edition, 2008. OCLC: ocn191760003.

[47] M. Zwarts D. Dumitru and, A. A. Amato and. *Electrodiagnostic Medicine*. Hanley & Belfus, Philadelphia, 2 edition, September 2001.

[48] R. Dabby, D. J. Lange, W. Trojaborg, A. P. Hays, R. E. Lovelace, T. H. Brannagan, and L. P. Rowland. Inclusion body myositis mimicking motor neuron disease. *Archives of Neurology*, 58(8):1253–1256, August 2001.

[49] N. Daroogheh, A. Baniamerian, N. Meskin, and K. Khorasani. A hybrid prognosis and health monitoring strategy by integrating particle filters and neural networks for gas turbine engines. In *2015 IEEE Conference on Prognostics and Health Management (PHM)*, pages 1–8, Austin, TX, USA, June 2015. IEEE.

[50] N. Daroogheh, N. Meskin, and K. Khorasani. Particle filtering for state and parameter estimation in gas turbine engine fault diagnostics. In *2013 American Control Conference*, pages 4343–4349, Washington, DC, June 2013. IEEE.

[51] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, April 2002.

[52] D. den Hertog, J. P. C. Kleijnen, and A. Y. D. Siem. The correct Kriging variance estimated by bootstrapping. *Journal of the Operational Research Society*, 57(4):400–409, April 2006. Publisher: Taylor & Francis _eprint: https://doi.org/10.1057/palgrave.jors.2601997.

[53] A. P. Dobrowolski, M. Wierzbowski, and K. Tomczykiewicz. Multiresolution MUAPs decomposition and SVM-based analysis in the classification of neuromuscular disorders. *Computer Methods and Programs in Biomedicine*, 107(3):393–403, September 2012.

[54] M. Dong, D. He, P. Banerjee, and J. Keller. Equipment health diagnosis and prognosis using hidden semi-Markov models. *The International Journal of Advanced Manufacturing Technology*, 30(7-8):738–749, October 2006.

[55] O. E. Dragomir, R. Gouriveau, F. Dragomir, E. Minca, and N. Zerhouni. Review of prognostic problem in condition-based maintenance. In *2009 European Control Conference (ECC)*, pages 1587–1592, Budapest, August 2009. IEEE.

[56] Capt. J. Drappier. A380: Challenges for the Future, 2008.

[57] S. Ekwaro-Osire, F. M. Alemayehu, and A. Carlos Gonçalves. *Probabilistic prognostics and health management of energy systems*. Springer International Publishing, 2017.

[58] I. Elamvazuthi, N.H.X. Duy, Z. Ali, S.W. Su, M.K.A. A. Khan, and S. Parasuraman. Electromyography (EMG) based classification of neuromuscular disorders using multilayer perceptron. *Procedia Computer Science*, 76:223–228, 2015. 2015 IEEE International Symposium on Robotics and Intelligent Sensors (IEEE IRIS2015).

[59] H. M. Elattar, H. K. Elminir, and A. M. Riad. Prognostics: A literature review. *Complex & Intelligent Systems*, 2(2):125–154, June 2016.

[60] T. Elsken and F. Metzen, J. H.and Hutter. Neural architecture search: A survey. *arXiv:1808.05377 [cs, stat]*, April 2019.

[61] M. Emmerich, N. Beume, and B. Naujoks. An EMO algorithm using the hypervolume measure as selection criterion. In D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, M. Friedemann, John C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, S. Bernhard, Madhu Sudan, D. Terzopoulos, Dough Tygar, Moshe Y. Vardi, Gerhard Weikum, C. A. Coello Coello, A. Hernández Aguirre, and E. Zitzler, editors, *Evolutionary Multi-Criterion Optimization*, volume 3410, pages 62–76. Springer Berlin Heidelberg, Berlin, Heidelberg, 2005.

[62] M. T. M. Emmerich and A. H. Deutz. A tutorial on multiobjective optimization: Fundamentals and evolutionary methods. *Natural Computing*, 17(3):585–609, September 2018.

[63] J. Enriquez-Zárate, L. Trujillo, S. De Lara, M. Castelli, E. Z-Flores, L. Muñoz, and A. Popovič. Automatic modeling of a gas turbine using genetic programming: An experimental study. *Applied Soft Computing*, 50:212–222, January 2017.

[64] C. Evans, P. J. Fleming, D. C. Hill, J. P. Norton, I. Pratt, D. Rees, and K. Rodr. Application of system identification techniques to aircraft gas turbine engines. *Control Engineering Practice*, 9(2):14, February 2001.

[65] H. Faris, B. Al-Shboul, and N. Ghatasheh. A genetic programming based framework for churn prediction in telecommunication industry. In *International Conference on Computational Collective Intelligence*, pages 353–362, Seoul, Korea, 2014. Springer.

[66] H. Faris, A. Sheta, and E. Öznergiz. Modelling hot rolling manufacturing process using soft computing techniques. *International Journal of Computer Integrated Manufacturing*, 26(8):762–771, 2013.

[67] S. Ferreiro and A. Arnaiz. Prognostics applied to aircraft line maintenance: Brake wear prediction based on Bayesian networks. *IFAC Proceedings Volumes*, 43(3):146–151, 2010.

[68] M. Feurer and F. Hutter. Hyperparameter optimization. In F. Hutter, L. Kotthoff, and J. Vanschoren, editors, *Automated Machine Learning: Methods, Systems, Challenges*, The Springer Series on Challenges in Machine Learning, pages 3–33. Springer International Publishing, Cham, 2019.

[69] F. Forest, J. Lacaille, M. Lebbah, and H. Azzag. A generic and scalable pipeline for large-scale analytics of continuous aircraft engine data. In *2018 IEEE International Conference on Big Data (Big Data)*, pages 1918–1924, Seattle, WA, USA, 2018. IEEE.

[70] S. Forrest. Genetic algorithms: principles of natural selection applied to computation. *Science*, 261(5123):872–878, 1993.

[71] F.-A. Fortin, F.-M. De Rainville, M.-A. G. Gardner, M. Parizeau, and C. Gagné. Deap: Evolutionary algorithms made easy. *Journal of Machine Learning Research*, 13(1):2171–2175, 2012.

[72] J. Foster and D. Lehoux. The delphic oracle and the ethylene-intoxication hypothesis. *Clinical Toxicology (Philadelphia, Pa.)*, 45(1):85–89, 2007.

[73] P. A. Gagniuc. *Markov Chains: From Theory to Implementation and Experimentation*. John Wiley & Sons, USA, NJ, July 2017.

[74] Y. Gal and Z. Ghahramani. Dropout as a Bayesian approximation: Representing model uncertainty in deep learning. *arXiv:1506.02142 [cs, stat]*, 2015.

[75] A. Gambhire and B. N. Shaikh Mohammad. Use of artificial intelligence in agriculture. SSRN Scholarly Paper ID 3571733, Social Science Research Network, Rochester, NY, April 2020.

[76] A. H. Gandomi and A. H. Alavi. A new multi-gene genetic programming approach to nonlinear system modeling. Part I: Materials and structural engineering problems. *Neural Computing and Applications*, 21(1):171–187, February 2012.

[77] M. R. Garey, D. S. Johnson, and R. Sethi. The complexity of flowshop and jobshop scheduling. *Mathematics of Operations Research*, 1(2):117–129, May 1976.

[78] A. Geron. *Hands-on machine learning with scikit-learn & tensorflow*. O'Reilly Media, Inc., Sebastopol, CA, USA, 1 edition, 2017.

[79] Z. Ghahramani. An introduction to hidden Markov models and Bayesian networks. *International Journal of Pattern Recognition and Artificial Intelligence*, 15(1):9–42, 2001.

[80] J. M. Gilchrist, S. D. Nandedkar, C. S. Stewart, J. M. Massey, D. B. Sanders, and P. E. Barkhaus. Automatic analysis of the electromyographic interference pattern using the turns: Amplitude ratio. *Electroencephalography and Clinical Neurophysiology*, 70(6):534–540, December 1988.

[81] F. Glover. Future paths for integer programming and links to artificial intelligence. *Computers & Operations Research*, 13(5):533–549, January 1986.

[82] K. Goebel, B. Saha, and A. Saxena. A comparison of three data-driven techniques for prognostics. In *62nd meeting of the society for machinery failure prevention technology (mfpt)*, pages 119–131, 2008.

[83] N. Gorjian, L. Ma, M. Mittinty, P. Yarlagadda, and Y. Sun. A review on degradation models in reliability analysis. In D. Kiritsis, C. Emmanouilidis, A. Koronios, and J. Mathew, editors, *Engineering Asset Lifecycle Management*, pages 369–384. Springer London, London, 2010.

[84] F. Govaers. *Introduction and implementations of the Kalman filter*. IntechOpen, Rijeka, 2019.

[85] T. Hastie, R. Tibshirani, and J. Friedman. *The elements of statistical learning: Data mining, inference, and prediction*. Springer Series in Statistics. Springer New York, NY, 2 edition, 2009.

[86] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *arXiv:1512.03385 [cs]*, December 2015.

[87] W. He, N. Williard, C. Chen, and M. Pecht. State of charge estimation for li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation. *International Journal of Electrical Power and Energy Systems*, 62:783 – 791, 2014.

[88] F. O. Heimes. Recurrent neural networks for remaining useful life estimation. In *2008 International Conference on Prognostics and Health Management*, pages 1–6, Denver, CO, USA, October 2008. IEEE.

[89] A. Hertz, E. Taillard, and D. De Werra. A tutorial on tabu search. In *Proceedings of Giornate di Lavoro AIRO*, pages 13–24, 1995.

[90] M. Hofmann and A. Chisholm. *Text mining and visualization: Case studies using open-source tools*. Taylor & Francis Group, USA, 2016.

[91] J. H. Holland. *Adaptation in natural and artificial systems : An introductory analysis with applications to biology, control, and artificial intelligence*. Cambridge, Massachusetts.: MIT Press, 1992.

[92] W. Holzer. A380 Advanced Cabin Line Maintenance, 2011.

[93] S. Hradecky. Accident: France A388 over Greenland on September 30th 2017, uncontained engine failure, fan and engine inlet separated. *The Aviation Herald (www.avherald.com)*, 2017.

[94] C.-S. Hsu and J.-R. Jiang. Remaining useful life estimation using long short-term memory deep learning. In *2018 IEEE International Conference on Applied System Invention (ICASI)*, pages 58–61, Chiba, April 2018. IEEE.

[95] B. Hudgins, P. Parker, and R.N. Scott. A new strategy for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering*, 40(1):82–94, January 1993.

[96] E. Hüllermeier and W. Waegeman. Aleatoric and epistemic uncertainty in machine learning: An introduction to concepts and methods. *Machine Learning*, 110(3):457–506, March 2021.

[97] F. Hutter, L. Kotthoff, and J. Vanschoren, editors. *Automated machine learning: Methods, systems, challenges*. The Springer Series on Challenges in Machine Learning. Springer International Publishing, Cham, 2019.

[98] I. Goodfellow, Y. Bengio, and A. Courville. *Deep Learning*. MIT Press, Cambridge, MA, USA, 2016. `http://www.deeplearningbook.org`.

[99] IATA. Fact sheet fuel, June 2018.

[100] H. Ishibuchi, T. Yoshida, and T. Murata. Balance between genetic search and local search in memetic algorithms for multiobjective permutation flowshop scheduling. *IEEE Transactions on Evolutionary Computation*, 7(2):204–223, April 2003.

[101] R. Istenič, P. A. Kaplanis, C. S. Pattichis, and D. Zazula. Multiscale entropy-based approach to automated surface EMG classification of neuromuscular disorders. *Medical & Biological Engineering & Computing*, 48(8):773–781, August 2010.

[102] J.-B. Itier. A380 integrated modular avionics: ARTIST2 – IMA & ADCN, 2007.

[103] A. K.S. Jardine, D. Lin, and D. Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7):1483–1510, October 2006.

[104] K. Javed, R. Gouriveau, and N. Zerhouni. Novel failure prognostics approach with dynamic thresholds for machine degradation. In *IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society*, pages 4404–4409, Vienna, Austria, November 2013. IEEE.

[105] Y. Jin, W. Fu, J. Kang, J. Guo, and J. Guo. Bayesian symbolic regression. *arXiv:1910.08892 [stat]*, January 2020.

[106] J. L. Joy, S. J. Oh, and A. I. Baysal. Electrophysiological spectrum of inclusion body myositis. *Muscle & Nerve*, 13(10):949–951, October 1990.

[107] P. Juesas, E. Ramasso, S. Drujont, and V. Placet. On partially supervised learning and inference in dynamic Bayesian networks for prognostics with uncertain factual evidence: Illustration with Markov switching models. In *Proceedings of the European Conference of the PHM Society 2016*, volume 3, page 10, 2016.

[108] I. Kacem, S. Hammadi, and P. Borne. Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, 32(1):1–13, February 2002.

[109] P. W. Kalgren, C. S. Byington, M. J. Roemer, and M. J. Watson. Defining phm, a lexical evolution of maintenance and logistics. In *2006 IEEE Autotestcon*, pages 353–358, 2006.

[110] R. E. Kalman. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*, 82(1):35–45, March 1960.

[111] M. S. Kan, A. C.C. Tan, and J. Mathew. A review on prognostic techniques for non-stationary and non-linear rotating systems. *Mechanical Systems and Signal Processing*, 62-63:1–20, October 2015.

[112] M. Kefalas, M. Baratchi, A. Apostolidis, D. van den Herik, and T. Bäck. Automated machine learning for remaining useful life estimation of aircraft engines. In *2021 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 1–9, Detroit (Romulus), MI, USA, June 2021. IEEE.

[113] M. Kefalas, J. de Santiago Rojo, A. Apostolidis, D. van den Herik, B. van Stein, and T. Bäck. Explainable artificial intelligence for exhaust gas temperature of turbofan engines. *Journal of Aerospace Information Systems (JAIS)*, 19(6):447–454, 2022.

[114] M. Kefalas, M. Koch, V. Geraedts, H. Wang, M. Tannemaat, and T. Bäck. Automated machine learning for the classification of normal and abnormal electromyography data. In *2020 IEEE International Conference on Big Data (Big Data)*, pages 1176–1185. IEEE, December 2020.

[115] M. Kefalas, S. Limmer, A. Apostolidis, M. Olhofer, M. Emmerich, and T. Bäck. A tabu search-based memetic algorithm for the multi-objective flexible job shop scheduling problem. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, GECCO '19, page 1254–1262, New York, NY, USA, 2019. Association for Computing Machinery.

[116] M. Kefalas, B. van Stein, M. Baratchi, A. Apostolidis, and T. Bäck. An end-to-end pipeline for uncertainty quantification and remaining useful life estimation: An application on aircraft engines. In *2022 7th European Conference of the Prognostics and Health Management Society (PHME22)*, pages 1–16, Turin, Italy, July 2022. Forthcoming.

[117] D. S. Kermany, M. Goldbaum, W. Cai, C. C. S. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, J. Dong, M. K. Prasadha, J. Pei, M. Y. L. Ting, J. Zhu, C. Li, S. Hewett, J. Dong, I. Ziyar, A. Shi, R. Zhang, L. Zheng, R. Hou, W. Shi, X. Fu, Y. Duan, V. A. N. Huu, C. Wen, E. D. Zhang, C. L. Zhang, O. Li, X. Wang, M. A. Singer, X. Sun, J. Xu, A. Tafreshi, M. A. Lewis, H. Xia, and K. Zhang. Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, 172(5):1122–1131.e9, February 2018.

[118] M. Kim and K. Liu. A Bayesian deep learning framework for interval estimation of remaining useful life in complex systems by incorporating general degradation characteristics. *IISE Transactions*, 53(3):326–340, March 2021.

[119] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *arXiv:1412.6980 [cs]*, January 2017.

[120] A. D. Kiureghian and O. Ditlevsen. Aleatory or epistemic? Does it matter? *Structural Safety*, 31(2):105–112, March 2009.

[121] M. Koch and T. Bäck. Machine learning for predicting the impact point of a low speed vehicle crash. In *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pages 1432–1437, Dec 2018.

[122] M. Koch, V. Geraedts, H. Wang, M. Tannemaat, and T. Bäck. Automated machine learning for EEG-based classification of Parkinson's disease patients. In *2019 IEEE International Conference on Big Data (Big Data)*, pages 4845–4852, Los Angeles, CA, USA, December 2019. IEEE.

[123] M. Koch, H. Wang, and T. Bäck. Machine learning for predicting the damaged parts of a low speed vehicle crash. In *13th International Conference on Digital Information Management*, pages 179–184, 2018.

[124] M. F. Korns. Accuracy in symbolic regression. In Rick Riolo, Ekaterina Vladislavleva, and Jason H. Moore, editors, *Genetic Programming Theory and Practice IX*, Genetic and Evolutionary Computation, pages 129–151. Springer, New York, NY, 2011.

[125] J. R. Koza. *Genetic programming: On the programming of computers by means of natural selection*. MIT press, Cambridge, MA, USA, 1992.

[126] J. R. Koza. Genetic programming as a means for programming computers by natural selection. *Statistics and Computing*, 4(2):87–112, 1994.

[127] M. Kraus and S. Feuerriegel. Forecasting remaining useful life: Interpretable deep learning approach via variational Bayesian inferences. *Decision Support Systems*, 125:113100, October 2019. arXiv: 1907.05146.

[128] M. S. Krishna and K. T. Baghaei. Recent approaches in prognostics: State of the art. In *International Conference on Artificial Intelligence (ICAI'19)*, 2019.

[129] M. Kursa and W. Rudnicki. Feature selection with the boruta package. *Journal of Statistical Software, Articles*, 36(11):1–13, 2010.

[130] G. Lapizco-Encinas, C. Kingsford, and J. Reggia. A cooperative combinatorial particle swarm optimization algorithm for side-chain packing. In *2009 IEEE Swarm Intelligence Symposium*, pages 22–29, Nashville, March 2009. IEEE.

[131] E. L. Lawler, J. K. Lenstra, A. H.G. Rinnooy Kan, and D. B. Shmoys. Sequencing and scheduling: Algorithms and complexity. In *Handbooks in Operations Research and Management Science*, volume 4, pages 445–522. Elsevier, 1993.

[132] Y. LeCun, Y. Bengio, and G. Hinton. Deep learning. *Nature*, 521(7553):436–444, May 2015.

[133] J. Lee, M. Ghaffari, and S. Elmeligy. Self-maintenance and engineering immune systems: Towards smarter machines and manufacturing systems. *Annual Reviews in Control*, 35(1):111–122, April 2011.

[134] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel. Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42(1-2):314–334, January 2014.

[135] S. Lee, I. Moon, H. Bae, and J. Kim. Flexible job-shop scheduling problems with 'AND'/'OR' precedence constraints. *International Journal of Production Research*, 50(7):1979–2001, April 2012.

[136] S. Legg and M. Hutter. A Collection of definitions of intelligence. *arXiv:0706.3639 [cs]*, June 2007.

[137] D. Lehoux. The predictive sciences: Measuring and forecasting weather conditions. *Oxford Handbooks Online*, October 2015. ISBN: 9780199935390.

[138] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin. Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, 104:799–834, May 2018.

[139] G. Li, L. Yang, C.-G. Lee, X. Wang, and M. Rong. A Bayesian deep learning RUL framework integrating epistemic and aleatoric uncertainties. *IEEE Transactions on Industrial Electronics*, 68(9):8829–8841, September 2021.

[140] R. Li, W. J. C. Verhagen, and R. Curran. A functional architecture of prognostics and health management using a systems engineering approach. In *Proceedings of the European Conference of the PHM Society 2018*, volume 4, page 10, 2018.

[141] S. Li, G. Zhang, and J. Wang. Civil aircraft health management research based on big data and deep learning technologies. In *2017 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 154–159, Dallas, TX, USA, June 2017. IEEE.

[142] W. Li, F. Milletarì, D. Xu, N. Rieke, J. Hancox, W. Zhu, M. Baust, Y. Cheng, S. Ourselin, M. J. Cardoso, and A. Feng. Privacy-preserving federated brain tumour segmentation. In H.-I. Suk, M. Liu, P. Yan, and C. Lian, editors, *Machine Learning in Medical Imaging*, pages 133–141, Cham, 2019. Springer International Publishing.

[143] X. Li, Q. Ding, and J.-Q. Sun. Remaining useful life estimation in prognostics using deep convolution neural networks. *Reliability Engineering & System Safety*, 172:1–11, April 2018.

[144] Y.-h. Li and X.-k. Wei. Linear-in-parameter models based on parsimonious genetic programming algorithm and its application to aero-engine start modeling. *Chinese Journal of Aeronautics*, 19(4):295–303, November 2006.

[145] Z. C. Lipton. A critical review of recurrent neural networks for sequence learning. *arxiv:1506.00019 [cs]*, 2015.

[146] A. Listou Ellefsen, E. Bjørlykhaug, V. Æsøy, S. Ushakov, and H. Zhang. Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture. *Reliability Engineering & System Safety*, 183:240–251, March 2019.

[147] H. Liu and H. Motoda. *Feature extraction, construction and selection: A data mining perspective*. Kluwer Academic Publishers, USA, 1998.

[148] N. Liundi, A. W. Darma, R. Gunarso, and H. L. H. S. Warnars. Improving rice productivity in Indonesia with artificial intelligence. In *2019 7th International Conference on Cyber and IT Service Management (CITSM)*, volume 7, pages 1–5, November 2019.

[149] A. Lovelace. Notes up on L. F. Menabrea's "Sketch of the Analytical Engine invented by Charles Babbage", 1842.

[150] D. D. Luxton. Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice*, 45(5):332–339, 2014. Place: US Publisher: American Psychological Association.

[151] R. Lwears. Rethinking healthcare as a safety–critical industry. *Work*, 41 Suppl 1:4560–4563, 2012.

[152] J. Ma, C. Lu, N. Zerhouni, and Y. Cheng. Aircraft Engine Health State Classification Using Stacked Denoising Autoencoder. In *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)*, page 6, Seattle, WA, USA, 2018.

[153] P. Malhotra, V. TV, A. Ramakrishnan, G. Anand, L. Vig, P. Agarwal, and G. Shroff. Multi-sensor prognostics using an unsupervised health index based on LSTM encoder-decoder. *arXiv:1608.06154 [cs]*, August 2016.

[154] E. Martinsson. Wtte-rnn: Weibull time to event recurrent neural network. Master's thesis, University of Gothenburg, Sweden, 2016.

[155] K. Medjaher and N. Zerhouni. Residual-based failure prognostic in dynamic systems. *IFAC Proceedings Volumes*, 42(8):716–721, 2009. 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes.

[156] K. Medjaher and N. Zerhouni. Hybrid prognostic method applied to mechatronic systems. *The International Journal of Advanced Manufacturing Technology*, 69(1-4):823–834, October 2013.

[157] R. J. Meinhold and N. D. Singpurwalla. Understanding the Kalman filter. *The American Statistician*, 37(2):123–127, 1983.

[158] W. Minnebo and S. Stijven. Empowering knowledge computing with variable selection - On variable importance and variable selection in regression random forests and symbolic regression. Master's thesis, University of Antwerp, Antwerp, Belgium, 2011.

[159] T. M. Mitchell. *Machine Learning*. McGraw-Hill series in computer science. McGraw-Hill, New York, 1997.

[160] R. K. Mobley. *An introduction to predictive maintenance*. Butterworth-Heinemann, Amsterdam ; New York, 2nd ed edition, 2002.

[161] M. Mohri, A. Rostamizadeh, and A. Talwalkar. *Foundations of machine learning*. Adaptive computation and machine learning series. MIT Press, Cambridge, MA, 2012.

[162] P. Moscato and C. Cotta. A gentle introduction to memetic algorithms. In Fred Glover and Gary A. Kochenberger, editors, *Handbook of Metaheuristics*, volume 57, pages 105–144. Kluwer Academic Publishers, Boston, 2003.

[163] P. Moscato et al. On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. *Caltech concurrent computation program, C3P Report*, 826:1989, 1989.

[164] G. Moslehi and M. Mahnam. A Pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search. *International Journal of Production Economics*, 129(1):14–22, January 2011.

[165] G. R. Naik, S. E. Selvan, and H. T. Nguyen. Single-channel EMG classification with ensemble-empirical-mode-decomposition-based ICA for diagnosing neuromuscular disorders. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(7):734–743, July 2016.

[166] B. Naujoks, N. Beume, and M. Emmerich. Multi-objective optimisation using S-metric selection: application to three-dimensional solution spaces. In *2005 IEEE Congress on Evolutionary Computation*, volume 2, pages 1282–1289 Vol. 2, Sep. 2005.

[167] H. Nayyeri and K. Khorasani. Modeling aircraft jet engine and system identification by using genetic programming. In *2012 25th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, pages 1–4, Montreal, QC, April 2012. IEEE.

[168] E. Nowicki and C. Smutnicki. A fast taboo search algorithm for the job shop problem. *Management Science*, 42(6):797–813, 1996.

[169] R. S. Olson, N. Bartley, R. J. Urbanowicz, and J. H. Moore. Evaluation of a tree-based pipeline optimization tool for automating data science. In *Proceedings of the Genetic and Evolutionary Computation Conference 2016*, GECCO '16, pages 485–492, New York, NY, 2016. ACM.

[170] C. Ordóñez, F. Sánchez Lasheras, J. Roca-Pardiñas, and F. J. de C. Juez. A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines. *Journal of Computational and Applied Mathematics*, 346:184–191, January 2019.

[171] I. Osband, J. Aslanides, and A. Cassirer. Randomized prior functions for deep reinforcement learning. *arXiv:1806.03335 [cs, stat]*, November 2018.

[172] M. Ossendrijver. Weather prediction in Babylonia. *Journal of Ancient Near Eastern History*, 8(1-2):223–258, 2021.

[173] E. Oyetunji. Some common performance measures in scheduling problems: Review article. *Research Journal of Applied Sciences, Engineering and Technology*, 1(2):5, January 2009.

[174] C.S. Pattichis and M.S. Pattichis. Time-scale analysis of motor unit action potentials. *IEEE Transactions on Biomedical Engineering*, 46(11):1320–1329, November 1999.

[175] S. Paul, K. Kapoor, D. Jasani, R. Dudhwewala, V. B. Gowda, and T. R. G. Nair. Application of artificial neural networks in aircraft maintenance, repair and overhaul solutions. *arXiv:1001.3741 [cs]*, 2010.

[176] M. Pecht and R. Jaai. A prognostics and health management roadmap for information and electronics-rich systems. *Microelectronics Reliability*, 50(3):317–323, March 2010.

[177] W. Peng, Z.-S. Ye, and N. Chen. Bayesian deep-learning-based health prognostics toward prognostics uncertainty. *IEEE Transactions on Industrial Electronics*, 67(3):2283–2293, March 2020.

[178] F. Pezzella, G. Morganti, and G. Ciaschetti. A genetic algorithm for the flexible job-shop scheduling problem. *Computers & Operations Research*, 35(10):3202–3212, October 2008.

[179] A. Poritz. Linear predictive hidden Markov models and the speech signal. In *ICASSP '82. IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 7, pages 1291–1294, Paris, France, 1982. Institute of Electrical and Electronics Engineers.

[180] S. Qi and W. Zhang. Prognostic and health management system based on flight data. In *Proceedings of the 32nd Chinese Control Conference*, pages 7142–7144, 2013.

[181] L.R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286, 1989.

[182] S. H. A. Rahmati, M. Zandieh, and M. Yazdani. Developing two multi-objective evolutionary algorithms for the multi-objective flexible job shop scheduling problem. *The International Journal of Advanced Manufacturing Technology*, 64(5-8):915–932, February 2013.

[183] E. Ramasso and A. Saxena. Performance benchmarking and analysis of prognostic methods for CMAPSS datasets. *International Journal of Prognostics and Health Management*, 5(2):15, 2014.

[184] Y. Ran, X. Zhou, P. Lin, Y. Wen, and R. Deng. A survey of predictive maintenance: Systems, purposes and approaches. *arXiv:1912.07383 [cs, eess]*, December 2019.

[185] C. E. Rasmussen and C. K. I. Williams. *Gaussian processes for machine learning*. Adaptive computation and machine learning. MIT Press, Cambridge, Mass, 2006.

[186] T. R. Reed, N. E. Reed, and P. Fritzson. Heart sound analysis for symptom detection and computer-aided diagnosis. *Simulation Modelling Practice and Theory*, 12(2):129–146, May 2004.

[187] E. K. Richfield, B. A. Cohen, and J. W. Albers. Review of quantitative and automated needle electromyographic analyses. *IEEE Transactions on Biomedical Engineering*, BME-28(7):506–514, July 1981. Conference Name: IEEE Transactions on Biomedical Engineering.

[188] N. Riquelme, C. Von Lücken, and B. Baran. Performance metrics in multi-objective optimization. In *2015 Latin American Computing Conference (CLEI)*, pages 1–11, 2015.

[189] T. J. Ross. *Fuzzy logic with engineering applications.* John Wiley, Chichester, U.K, 3rd ed edition, 2010.

[190] A.E. Ruano, P.J. Fleming, C. Teixeira, K. Rodriguez-Vazquez, and C.M. Fonseca. Nonlinear identification of aircraft gas-turbine dynamics. *Neurocomputing*, 55(3-4):551–579, October 2003.

[191] C. Rudin. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *arXiv:1811.10154 [cs, stat]*, September 2019.

[192] S. J. Russell and P. Norvig. *Artificial intelligence: A modern approach.* Prentice Hall series in artificial intelligence. Prentice Hall, Upper Saddle River, 3rd edition, 2010.

[193] S. Saha, J. R. Celaya, V. Vashchenko, S. Mahiuddin, and K. F. Goebel. Accelerated aging with electrical overstress and prognostics for power MOSFETs. In *IEEE 2011 EnergyTech*, pages 1–6, May 2011.

[194] A. L. Samuel. Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development*, 3(3):210–229, 1959.

[195] G. Sateesh Babu, P. Zhao, and X.-L. Li. Deep convolutional neural network based regression approach for estimation of remaining useful life. In S. B. Navathe, W. Wu, S. Shekhar, X. Du, X. S. Wang, and H. Xiong, editors, *Database Systems for Advanced Applications*, volume 9642, pages 214–228. Springer International Publishing, Cham, 2016.

[196] A. Saxena, J. Celaya, B. Saha, S. Saha, and K. Goebel. Evaluating algorithm performance metrics tailored for prognostics. In *2009 IEEE Aerospace conference*, pages 1–13, Big Sky, MT, USA, March 2009. IEEE.

[197] A. Saxena, J. Celaya, B. Saha, S. Saha, and K. Goebel. Evaluating prognostics performance for algorithms incorporating uncertainty estimates. In *2010 IEEE Aerospace Conference*, pages 1–11, Big Sky, MT, March 2010. IEEE.

[198] A. Saxena, K. Goebel, D. Simon, and N. Eklund. Damage propagation modeling for aircraft engine run-to-failure simulation. In *2008 International Conference on Prognostics and Health Management*, pages 1–9, Denver, CO, USA, October 2008. IEEE.

[199] M. Schmelzer, R. Dwight, and P. Cinnella. Data-driven deterministic symbolic regression of nonlinear stress-strain relation for rans turbulence modelling. In *2018 Fluid Dynamics Conference*, AIAA AVIATION Forum, page 13. American Institute of Aeronautics and Astronautics, June 2018.

[200] M. Schmidt and H. Lipson. Distilling free-form natural laws from experimental data. *Science*, 324(5923):81–85, 2009.

[201] D. P. Searson. GPTIPS 2: An open-source software platform for symbolic data mining. In A. H. Gandomi, A. H. Alavi, and C. Ryan, editors, *Handbook of Genetic Programming Applications*, pages 551–573. Springer International Publishing, Cham, 2015.

[202] D. P. Searson, D. E. Leahy, and M. J. Willis. GPTIPS: An open-source genetic programming toolbox for multigene symbolic regression. In *Proceedings of the International multiconference of engineers and computer scientists*, volume 1, pages 77–80, Hong Kong, 2010. Newswood Ltd.

[203] S. Sette and L. Boullart. Genetic programming: principles and applications. *Engineering Applications of Artificial Intelligence*, 14(6):727–736, 2001.

[204] S. Sharma and D. Mahto. Condition monitoring of wind turbine gear box. *International Journal of Research Studies in Science, Engineering and Technology*, 1(5):19, August 2014.

[205] M. V. Shcherbakov, A. Brebels, N. L. Shcherbakova, A. P. Tyukov, T. A. Janovsky, and V. A. Kamaev. A survey of forecast error measures. *World Applied Sciences Journal*, 24(24):171–176, 2013.

[206] T. I.-P. Shih and V. Yang, editors. *Turbine aerodynamics, heat transfer, materials, and mechanics.* Number 243 in Progress in astronautics and aeronautics. American Institute of Aeronautics and Astronautics, Inc, Reston, Va, 2014.

[207] R. H. Shumway and D. S. Stoffer. *Time series analysis and its applications: With R examples.* Springer Texts in Statistics. Springer International Publishing, Cham, 2017.

[208] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou. Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research*, 213(1):1–14, August 2011.

[209] J.Z. Sikorska, M. Hodkiewicz, and L. Ma. Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, 25(5):1803–1836, July 2011.

[210] D. Simon. A comparison of filtering approaches for aircraft engine health estimation. *Aerospace Science and Technology*, 12(4):276–284, June 2008.

[211] C. R. Stewart, S. D. Nandedkar, J. M. Massey, J. M. Gilchrist, P. E. Barkhaus, and D. B. Sanders. Evaluation of an automatic method of measuring features of motor unit action potentials. *Muscle & Nerve*, 12(2):141–148, February 1989.

[212] S. Su, W. Zhang, and S. Zhao. Fault prediction for nonlinear system using sliding ARMA combined with online LS-SVR. *Mathematical Problems in Engineering*, 2014:1–9, 2014.

[213] A. Subasi. Medical decision support system for diagnosis of neuromuscular disorders using DWT and fuzzy support vector machines. *Computers in Biology and Medicine*, 42(8):806–815, August 2012.

[214] A. Subasi, E. Yaman, Y. Somaily, H. A. Alynabawi, F. Alobaidi, and S. Altheibani. Automated EMG signal classification for diagnosis of neuromuscular disorders using DWT and bagging. *Procedia Computer Science*, 140:230–237, 2018.

[215] Y. Sun and V. Latora. The evolution of knowledge within and across fields in modern physics. *Scientific Reports*, 10(1):12097, July 2020. Number: 1 Publisher: Nature Publishing Group.

[216] T. Sutharssan, S. Stoyanov, C. Bailey, and C. Yin. Prognostic and health management for engineering systems: a review of the data-driven approach and algorithms. *The Journal of Engineering*, 2015(7):215–222, July 2015.

[217] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus. Intriguing properties of neural networks. *arXiv:1312.6199 [cs]*, February 2014.

[218] Y. Tabourier. Problème d'ordonnancement à contraintes purement disjonctives. *Revue française d'informatique et de recherche opérationnelle. Série verte*, 3(V3):51–65, 1969.

[219] M. Tahan, E. Tsoutsanis, M. Muhammad, and Z.A. Abdul Karim. Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review. *Applied Energy*, 198:122–144, July 2017.

[220] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, 4:58–73, January 2020.

[221] C. Thornton, F. Hutter, H. H. Hoos, and K. Leyton-Brown. Auto-WEKA: Combined selection and hyperparameter optimization of classification algorithms. *arXiv:1208.3719 [cs]*, March 2013.

[222] M. Tipping. The relevance vector machine. *Advances in Neural Information Processing Systems*, 12, 1999.

[223] N. Togun and S. Baysec. Genetic programming approach to predict torque and brake specific fuel consumption of a gasoline engine. *Applied Energy*, 87(11):3401–3408, November 2010.

[224] K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang. Prognostics and health management: A review on data driven approaches. *Mathematical Problems in Engineering*, 2015:1–17, 2015.

[225] S.-M. Udrescu and M. Tegmark. AI Feynman: A physics-inspired method for symbolic regression. *Science Advances*, 6(16):16, April 2020.

[226] H. Uesugi, M. Sonoo, E. Stålberg, K. Matsumoto, M. Higashihara, H. Murashima, Y. Ugawa, Y. Nagashima, T. Shimizu, H. Saito, and I. Kanazawa. "Clustering Index method": A new technique for differentiation between neurogenic and myopathic changes using surface EMG. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, 122(5):1032–1041, May 2011.

[227] G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, and B. Wu. *Intelligent fault diagnosis and prognosis for engineering systems.* John Wiley & Sons, Inc., Hoboken, NJ, USA, September 2006.

[228] H. Vaddireddy, A. Rasheed, A. E. Staples, and O. San. Feature engineering and symbolic regression methods for detecting hidden physics from sparse sensors. *Physics of Fluids*, 32(1):015113, January 2020.

[229] L. van der Maaten, E. Postma, and J. van den Herik. Dimensionality reduction: A comparative review. *Journal of Machine Learning Research*, 10:66–71, 2009.

[230] D. van Nguyen, M. Kefalas, K. Yang, A. Apostolidis, M. Olhofer, S. Limmer, and T. Bäck. A review: Prognostics and health management in automotive and aerospace. *International Journal of Prognostics and Health Management*, 10(2):35, 2019.

[231] B. van Stein, H. Wang, and T. Bäck. Automatic configuration of deep neural networks with parallel efficient global optimization. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7, Budapest, Hungary, July 2019. IEEE.

[232] V. N. Vapnik. *The nature of statistical learning theory.* Springer New York, New York, NY, 1995.

[233] A. Vatani, K. Khorasani, and N. Meskin. Health monitoring and degradation prognostics in gas turbine engines using dynamic neural networks. In *Volume 6: Ceramics; Controls, Diagnostics and Instrumentation; Education; Manufacturing Materials and Metallurgy; Honors and Awards*, page 13, Montreal, Quebec, Canada, June 2015. ASME.

[234] W. O. L. Vianna, L. R. Rodrigues, and T. Yoneyama. Aircraft line maintenance planning based on PHM data and resources availability using large neighborhood search. In *Proceedings of the Annual Conference of the PHM Society 2015*, volume 7, page 7, 2015.

[235] G. W. Vogl, B. A. Weiss, and M. A. Donmez. Standards for prognostics and health management (PHM) techniques within manufacturing operations. In *Annual Conference of the Prognostics and Health Management Society 2014*, page 13, Fort Worth, TX, 2014.

[236] A. Von Moll, A. R. Behbahani, G. C. Fralick, J. D. Wrbanek, and G. W. Hunter. A review of exhaust gas temperature sensing techniques for modern turbine engine controls. In *50th AIAA/ASME/SAE/ASEE Joint Propulsion Conference*, pages 2014–3977, Cleveland, OH, USA, 2014.

[237] B. Wang, Y. Lei, T. Yan, N. Li, and L. Guo. Recurrent convolutional neural network: A new framework for remaining useful life prediction of machinery. *Neurocomputing*, 379:117–129, 2020.

[238] C. Wang, T. Bäck, H. H. Hoos, M. Baratchi, S. Limmer, and M. Olhofer. Automated machine learning for short-term electric load forecasting. In *2019 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 314–321, Xiamen, China, December 2019. IEEE.

[239] H. Wang, B. van Stein, M. Emmerich, and T. Bäck. A new acquisition function for Bayesian optimization based on the moment-generating function. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 507–512, Banff, AB, October 2017. IEEE.

[240] W.-C. Wang, K.-W. Chau, C.-T. Cheng, and L. Qiu. A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of Hydrology*, 374(3-4):294–306, 2009.

[241] X. Wang, L. Gao, C. Zhang, and X. Shao. A multi-objective genetic algorithm based on immune and entropy principle for flexible job-shop scheduling problem. *The International Journal of Advanced Manufacturing Technology*, 51(5-8):757–767, November 2010.

[242] L. Wen, Y. Dong, and L. Gao. A new ensemble residual convolutional neural network for remaining useful life estimation. *Mathematical Biosciences and Engineering*, 16(2):862–880, 2019.

[243] Z. Williams. Benefits of IVHM: An analytical approach. In *2006 IEEE Aerospace Conference*, pages 1–9, 2006.

[244] J. Wu. Introduction to convolutional neural networks. *National Key Lab for Novel Software Technology. Nanjing University. China*, 5(23):495, 2017.

[245] Y. Wu, M. Yuan, S. Dong, L. Lin, and Y. Liu. Remaining useful life estimation of engineered systems using vanilla LSTM neural networks. *Neurocomputing*, 275:167–179, January 2018.

[246] J. Xiong, X. Tan, K.-w. Yang, L.-n. Xing, and Y.-w. Chen. A hybrid multiobjective evolutionary approach for flexible job-shop scheduling problems. *Mathematical Problems in Engineering*, 2012:1–27, 2012.

[247] F. Yang, H. Ren, and Z. Hu. Maximum likelihood estimation for three-parameter Weibull distribution using evolutionary strategy. *Mathematical Problems in Engineering*, 2019:1–8, May 2019.

[248] L. Yang, J. Wang, and G. Zhang. Aviation PHM system research framework based on PHM big data center. In *2016 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 1–5, Ottawa, ON, Canada, June 2016. IEEE.

[249] T. Yeung. What's the difference: Edge computing vs cloud computing. *The Official NVIDIA Blog*, January 2022.

[250] W. Yi, X. Li, and B. Pan. Solving flexible job shop scheduling using an effective memetic algorithm. *International Journal of Computer Applications in Technology*, 53(2):157–163, jan 2016.

[251] Y. Yuan and H. Xu. Multiobjective flexible job shop scheduling using memetic algorithms. *IEEE Transactions on Automation Science and Engineering*, 12(1):336–353, January 2015.

[252] C. Zhang, P. Li, Y. Rao, and S. Li. A new hybrid GA/SA algorithm for the job shop scheduling problem. In Günther R. Raidl and Jens Gottlieb, editors, *Evolutionary Computation in Combinatorial Optimization*, pages 246–259, Berlin, Heidelberg, 2005. Springer Berlin Heidelberg.

[253] C. Zhang, P. Lim, A. K. Qin, and K. C. Tan. Multiobjective deep belief networks ensemble for remaining useful life estimation in prognostics. *IEEE Transactions on Neural Networks and Learning Systems*, 28(10):2306–2318, October 2017.

[254] C. Zhang, Y. Rao, P. Li, and X. Shao. Bilevel genetic algorithm for the flexible job-shop scheduling problem. *Chinese Journal of Mechanical Engineering*, 43(4):120–124, January 2007.

[255] M. Zhang and W. Smart. Multiclass object classification using genetic programming. In *Workshops on Applications of Evolutionary Computation*, pages 369–378, Coimbra, Portugal, 2004. Springer.

[256] X. Zhang, P. Xiao, Y. Yang, Y. Cheng, B. Chen, D. Gao, W. Liu, and Z. Huang. Remaining useful life estimation using CNN-XGB with extended time window. *IEEE Access*, 7:154386–154397, 2019.

[257] Y. Zhang, J. Liu, H. Hanachi, X. Yu, and Y. Yang. Physics-based model and neural network model for monitoring starter degradation of APU. In *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 1–7, Seattle, WA, USA, 2018. IEEE.

[258] Z. Zhao, B. Liang, X. Wang, and W. Lu. Remaining useful life prediction of aircraft engine based on degradation pattern learning. *Reliability Engineering and System Safety*, 164:74 – 83, 2017.

[259] Z. Zhao, J. Wu, D. Wong, C. Sun, and R. Yan. Probabilistic remaining useful life prediction based on deep convolutional neural network. *SSRN Electronic Journal*, 2020.

[260] S. Zheng, K. Ristovski, A. Farahat, and C. Gupta. Long short-term memory network for remaining useful life estimation. In *2017 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 88–95, Dallas, TX, USA, jun 2017. IEEE.

[261] Shisheng Zhong, Mr Zhen Li, Mr Lin Lin, and Dr Yongjian Zhang. Aero-engine exhaust gas temperature prognostic model based on gated recurrent unit network. In *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pages 1–5, Seattle, WA, USA, 2018.

[262] T. Zhou, E. L. Droguett, A. Mosleh, and F. T. S. Chan. An uncertainty-informed framework for trustworthy fault diagnosis in safety-critical applications. *arXiv: 2111.00874 [cs]*, pages 1–49.

[263] E. Zitzler, K. Deb, and L. Thiele. Comparison of multiobjective evolutionary algorithms: Empirical results. *Evolutionary Computation*, 8(2):173–195, June 2000.

[264] K.-X. Zou, H.-D. Ma, H.-Z. Fang, and D.-W. Yi. Study of prognostics for spacecraft based-on particle swarm optimized neural network. In *2011 Prognostics and System Health Management Conference*, pages 1–5, Shenzhen, China, May 2011. IEEE.