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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

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

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

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

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

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

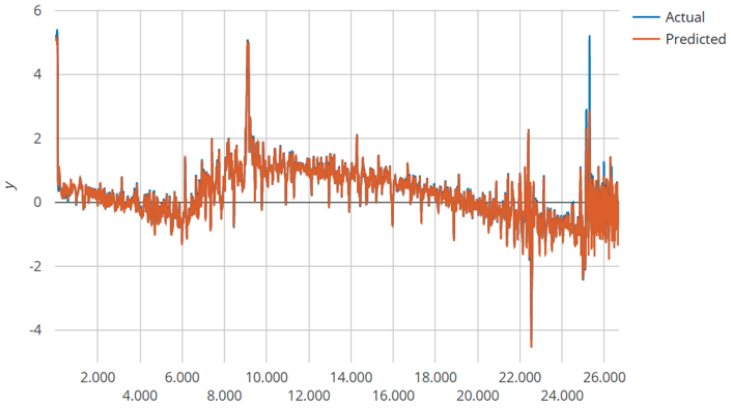
$$\begin{aligned} Y_1^6 &= 0.204 \cdot x_4 + 0.592 \cdot x_6 + 0.0242 \cdot x_{11} + 0.485 \cdot x_{21} + 0.0698 \cdot x_{43} \\ &+ 0.122 \cdot x_{59} - 0.642 \cdot e^{(-e^{(x_{21})})} - (0.00133 \cdot |x_{43}|)/|x_{94}|^2 - 0.0205 \cdot {x_4}^2 \\ &+ 0.00106 \cdot {x_4}^3 + 0.365 \end{aligned} \tag{A.6}$$

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

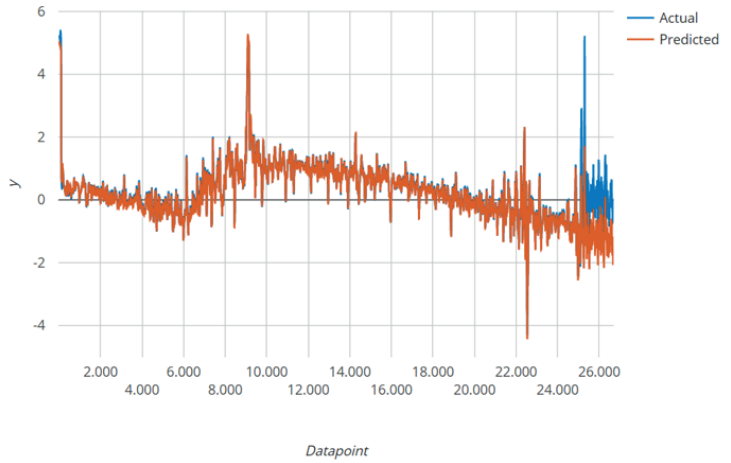
$$
\begin{aligned}
Y_1^8 &= 0.133 \cdot x_4 + 0.649 \cdot x_6 + 0.00805 \cdot x_{12} - 0.101 \cdot x_{14} + 0.749 \cdot x_{21} \\
&- 0.0178 \cdot x_{23} + 0.0268 \cdot x_{24} + 0.0463 \cdot x_{43} + 0.00805 \cdot x_{52} + 0.0155 \cdot x_{74} \\
&+ 0.0268 \cdot x_{110} - 0.0115 \cdot x_{111} - 0.0178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

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

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

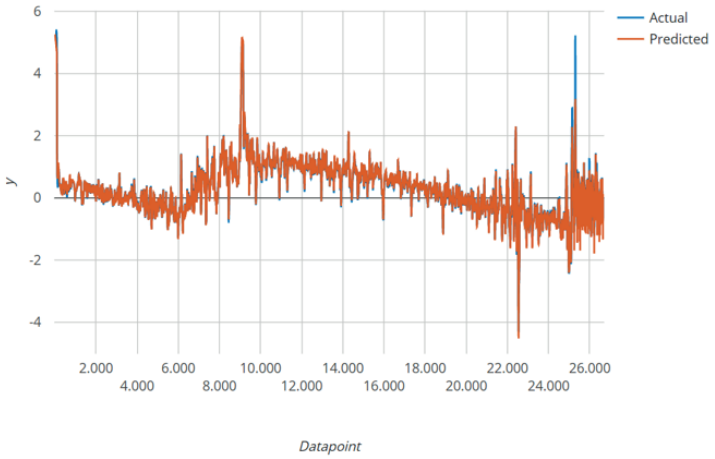


(a) Model 1

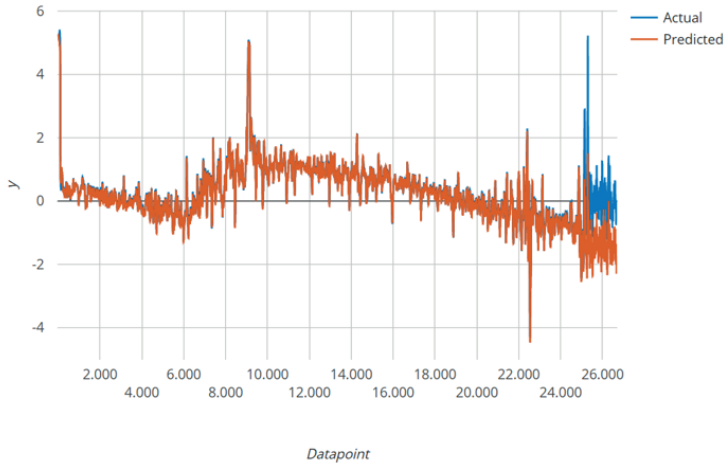


(b) Model 2

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.

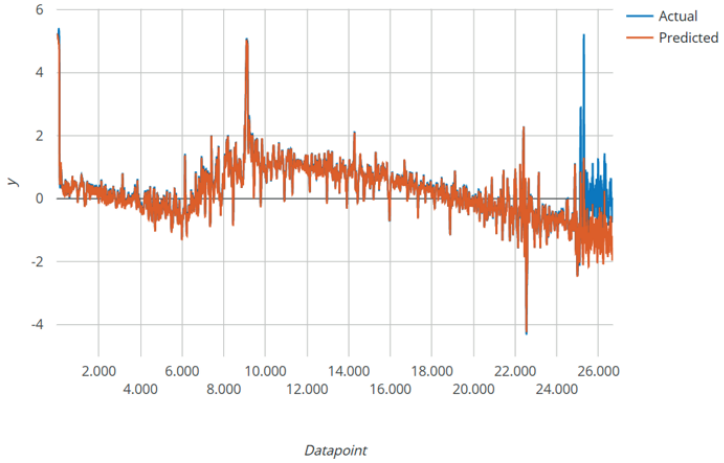


(a) Model 3

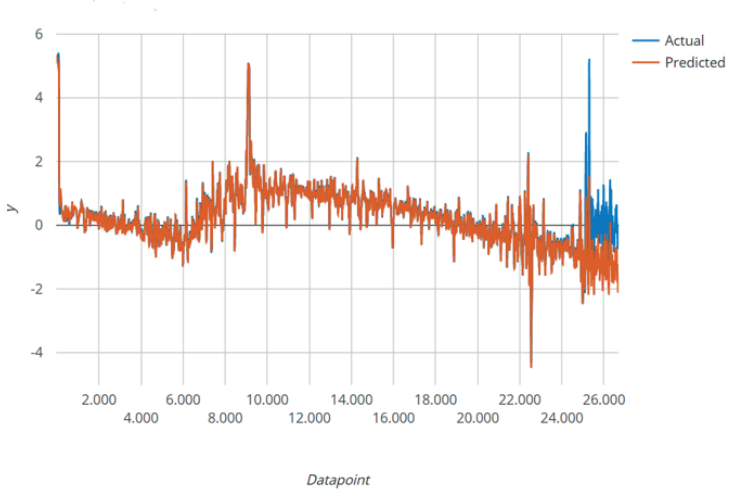


(b) Model 4

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.

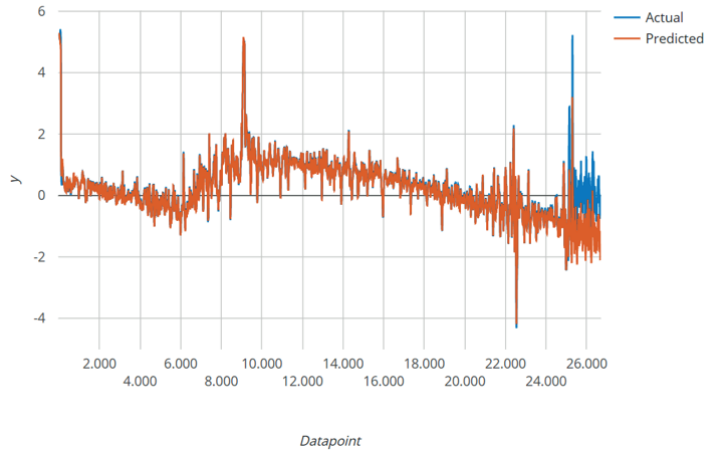


(a) Model 5

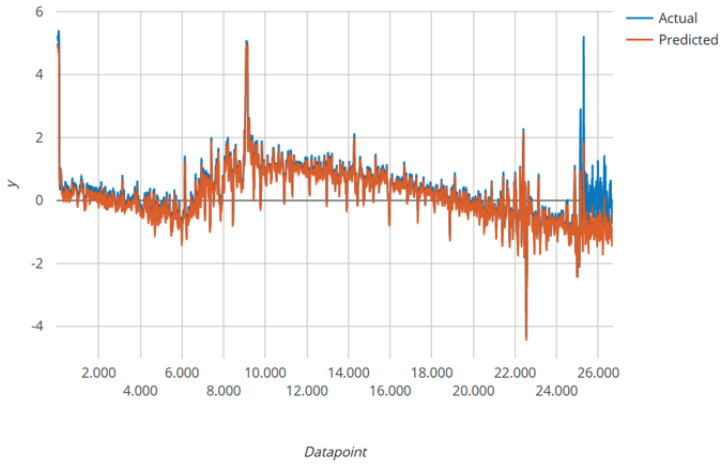


(b) Model 6

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.

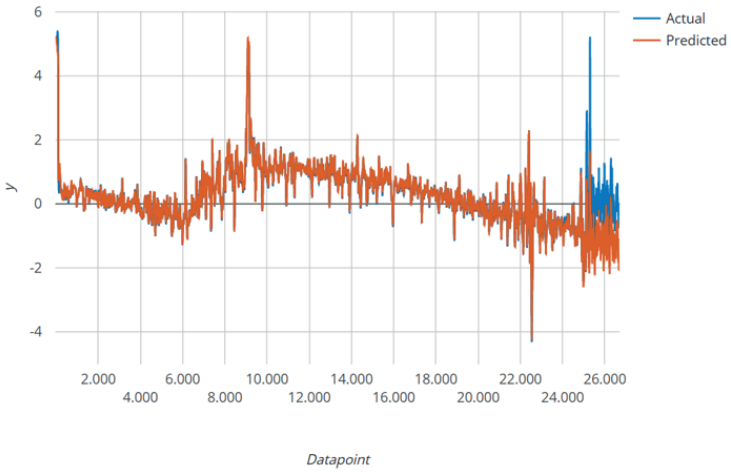


(a) Model 7

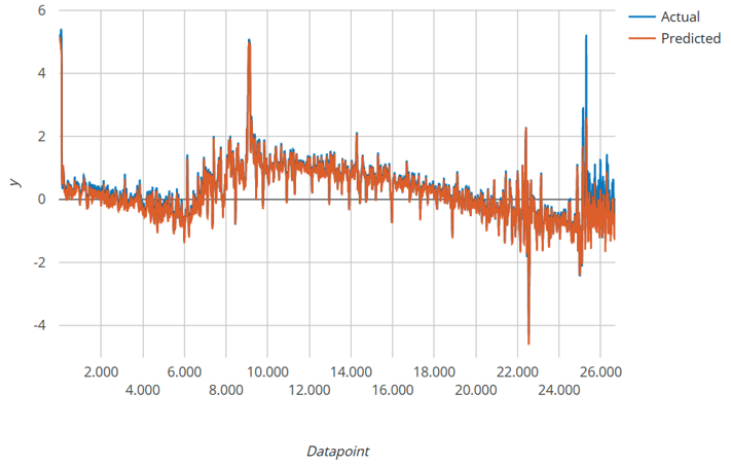


(b) Model 8

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.

R^2	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

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

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

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

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

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

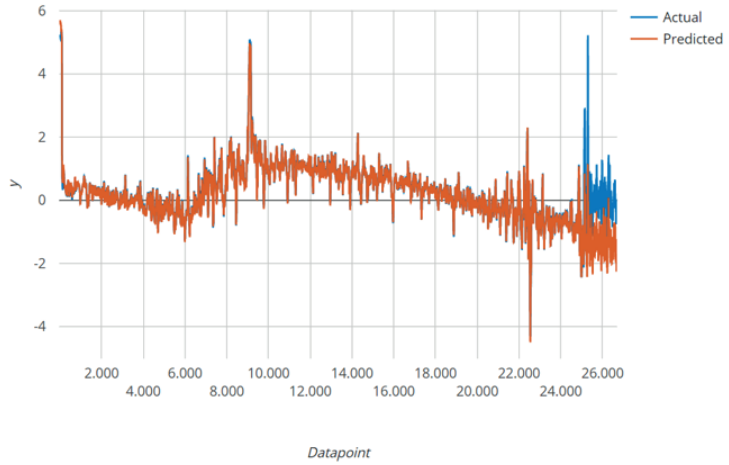
$$
\begin{aligned}
Y_2^6 &= 0.647 \cdot x_{17} - 0.412 \cdot x_{19} + 0.549 \cdot x_{20} + 0.0505 \cdot x_{42} + 0.157 \cdot x_{58} \\
&+ 0.0243 \cdot x_{95} - 0.826 \cdot e^{(-e^{(-e^{(-x_{20})})})} - 1.59 \cdot e^{(-e^{(-e^{(-x_4)^{1/2}})})} \\
&+ 0.00578 \cdot {x_4}^2 - 7.58 \cdot 10^5 \cdot {x_{51}}^4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

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

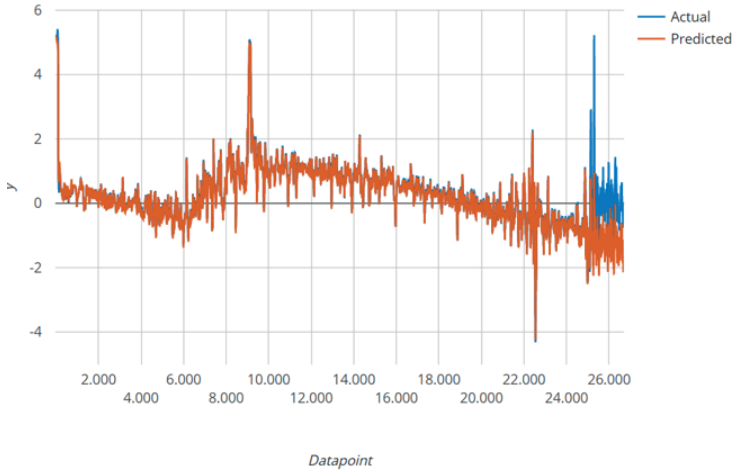
$$
\begin{aligned}
Y_2^8 = {} & 0.158 \cdot x_4 + 0.131 \cdot x_5 + 0.8 \cdot x_{17} - 0.46 \cdot x_{19} + 0.53 \cdot x_{20} - 0.0231 \cdot x_{22} \\
& - 0.0231 \cdot e^{(-x_4)} - 0.0826 \cdot e^{(-x_{38})} - 0.0826 \cdot e^{(-2 \cdot e^{(-x_{20})})} \\
& - 0.928 \cdot e^{(-e^{(-e^{(-x_{20})})})} - 0.00491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

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

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

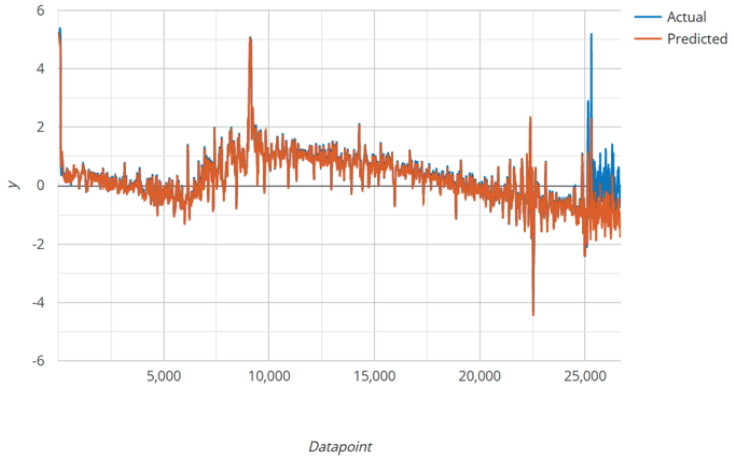


(a) Model 1

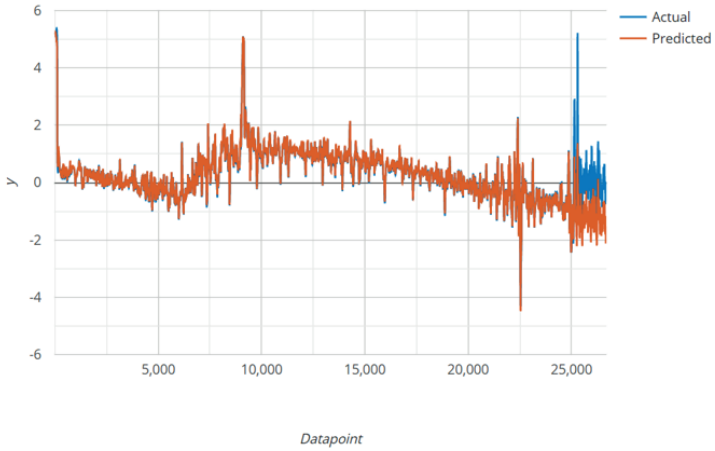


(b) Model 2

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.

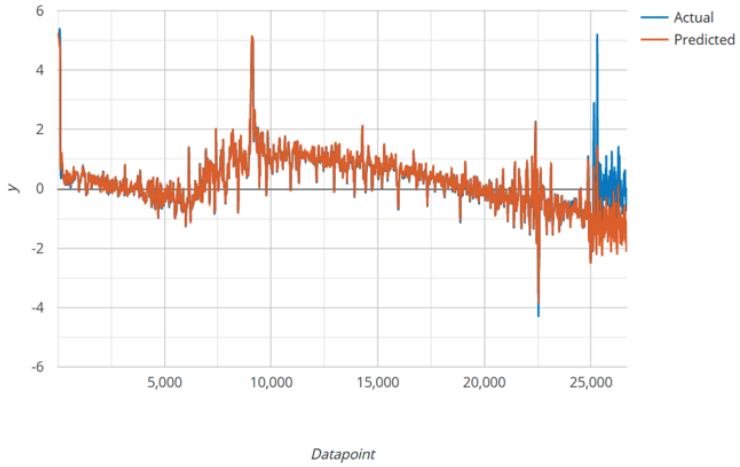


(a) Model 3

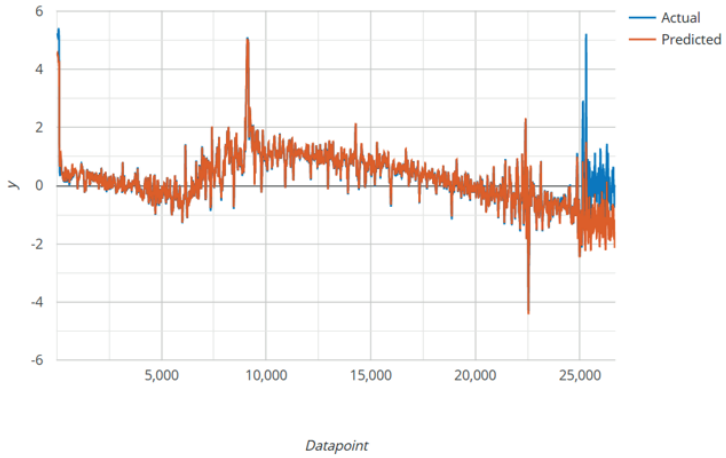


(b) Model 4

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.

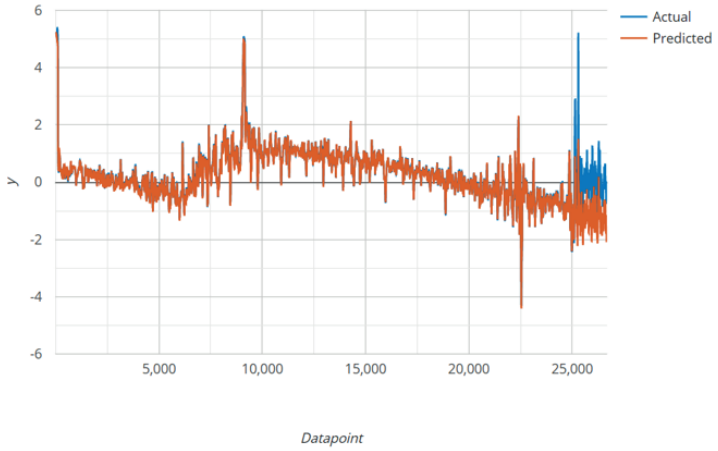


(a) Model 5

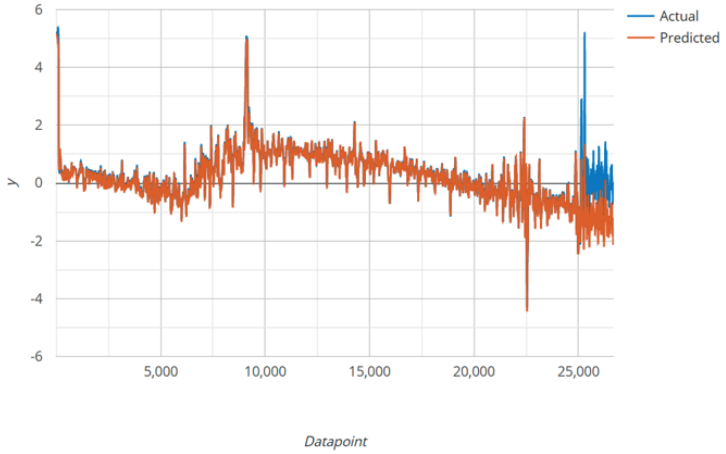


(b) Model 6

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.

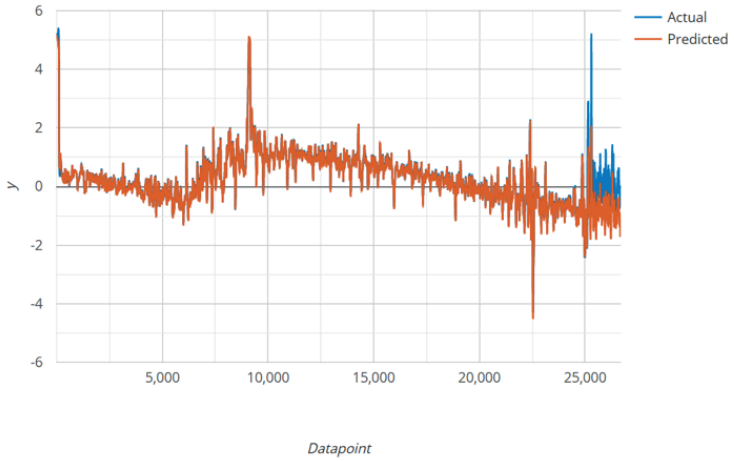


(a) Model 7

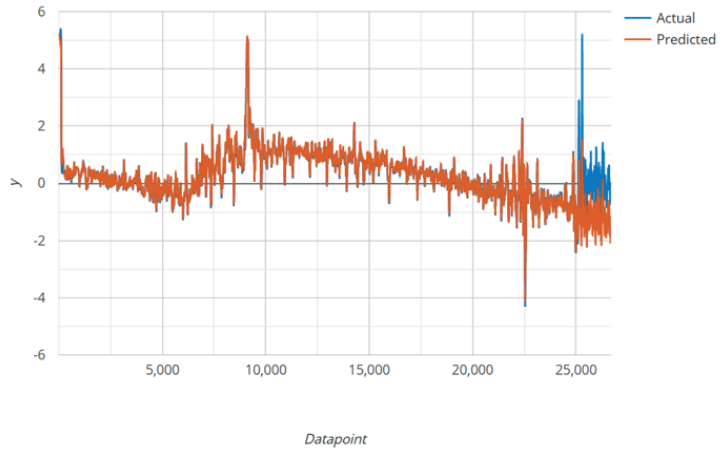


(b) Model 8

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

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

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

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

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

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

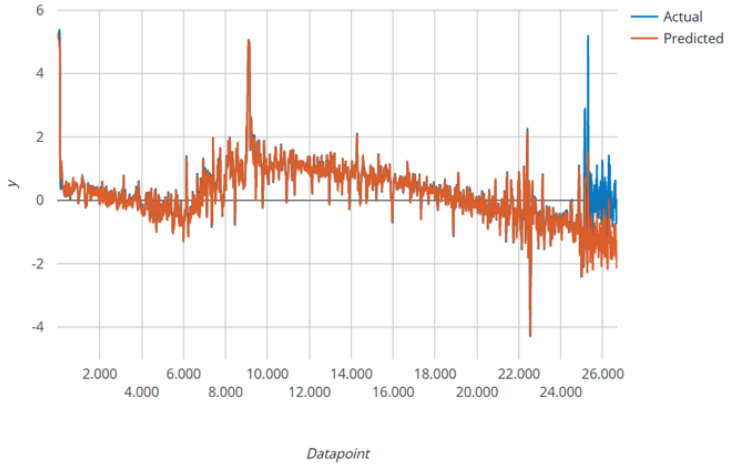
$$
\begin{aligned}
Y_3^6 &= 0.101 \cdot x_4 + 0.136 \cdot x_5 + 0.654 \cdot x_6 + 0.448 \cdot x_{19} - 0.0226 \cdot x_{21} \\
&+ 0.0426 \cdot x_{26} + 0.0484 \cdot x_{41} - 0.0602 \cdot x_{74} + 0.082 \cdot x_{108} \\
&- 0.605 \cdot e^{(-e^{(x_{19})})} + 0.224
\end{aligned} \tag{A.26}
$$

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

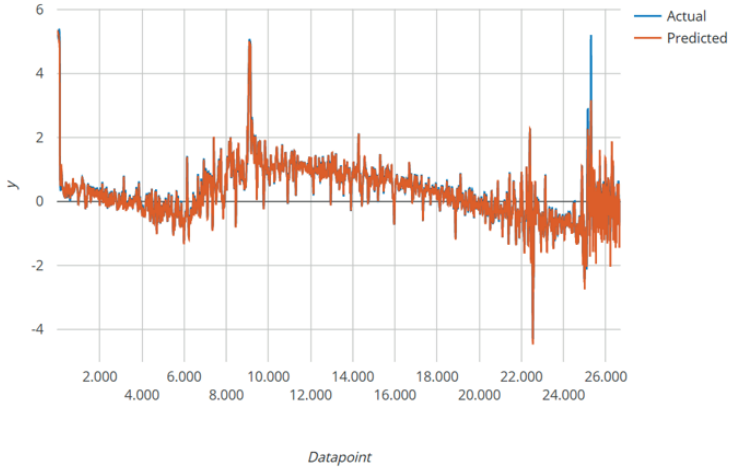
$$
\begin{aligned}
Y_3^8 &= 0.0596 \cdot x_4 + 0.118 \cdot x_5 + 0.671 \cdot x_6 + 0.474 \cdot x_{19} + 0.0446 \cdot x_{41} \\
&+ 0.0298 \cdot x_{108} - 0.014 \cdot x_{111} - 0.735 \cdot e^{-e^{(x_{19})}} + 0.753 \cdot e^{(-e^{(-x_4)^{1/2}})^{1/2}} \\
&- 3.52 \cdot 10^{-6} \cdot {x_{111}}^3 \cdot x_4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

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

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

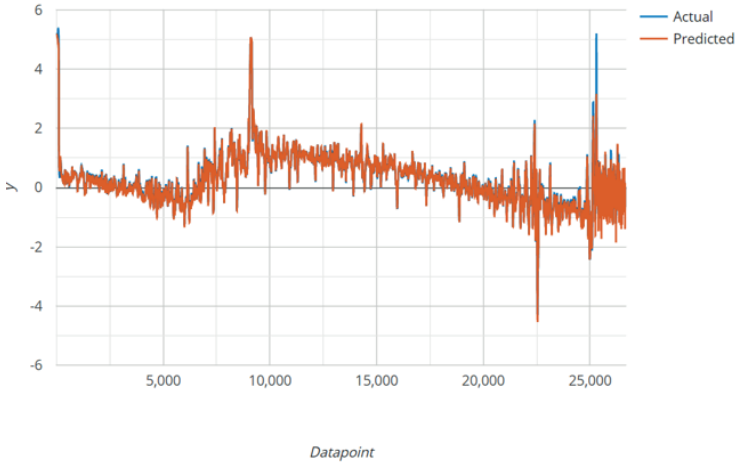


(a) Model 1

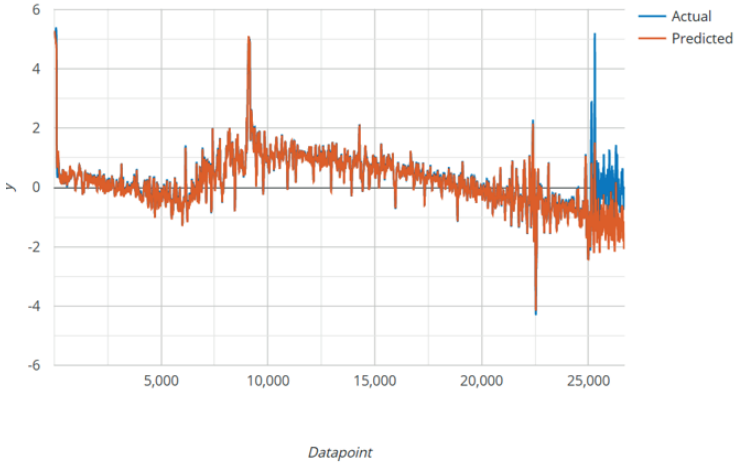


(b) Model 2

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.

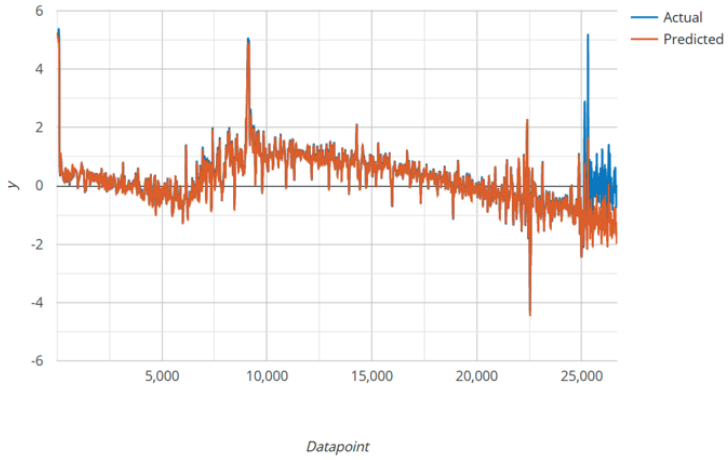


(a) Model 3

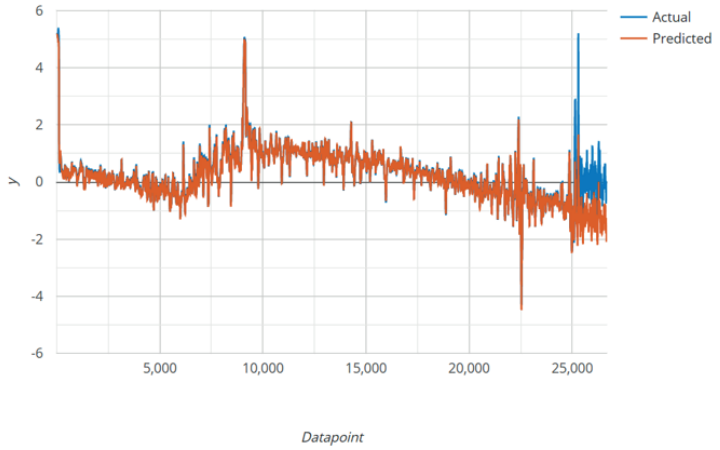


(b) Model 4

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.

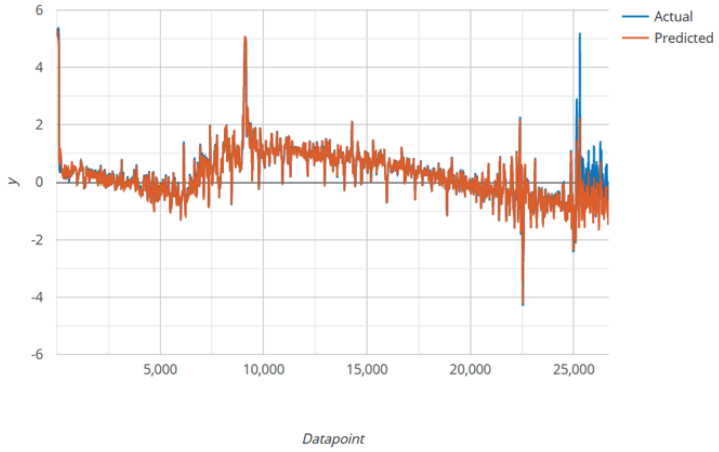


(a) Model 5

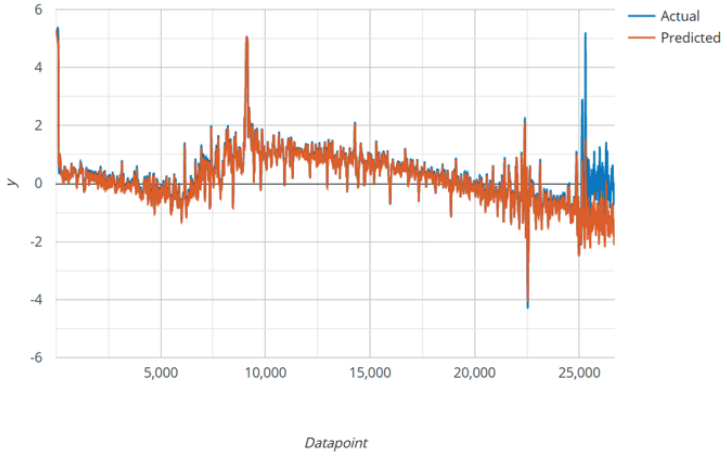


(b) Model 6

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.

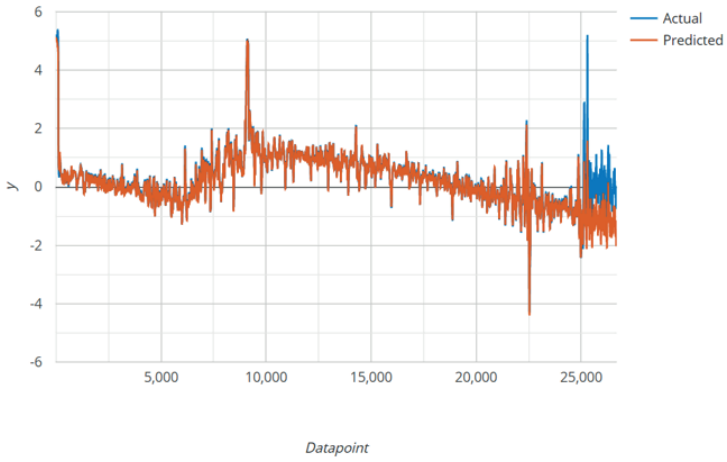


(a) Model 7

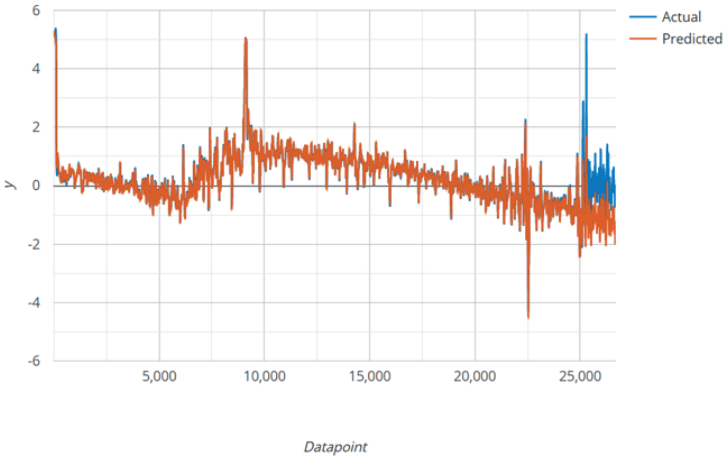


(b) Model 8

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.

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