



Optimization of satellite operations scheduling using an AI-based tool

Introduction:

Satellite platforms need to be constantly monitored by satellite operators and action needs to be taken in order to keep the satellites' performance nominal. Such activities can be scheduled in advance, because of the knowledge of the orbit of the satellites and the environment they cope with. However, the conditions they face are dynamic and constantly changing and as a result additional operational procedures need to be conducted out of schedule.

Methodology:

Firstly, the data were pre-processed and prepared to be used as input in the models, by being split in new datasets for training, validation and testing. Multiple architectures were tested for each telemetry dataset and additionally hyperparameter optimization was performed on the parameters that constitute each model, in order to get the best performing architecture. In the following table there are the results just for one telemetry dataset on different possible architectures, regarding the number of layers, input window and number of units on each layer. The best model was chosen based on metrics of performance, such as validation loss and RMSE.

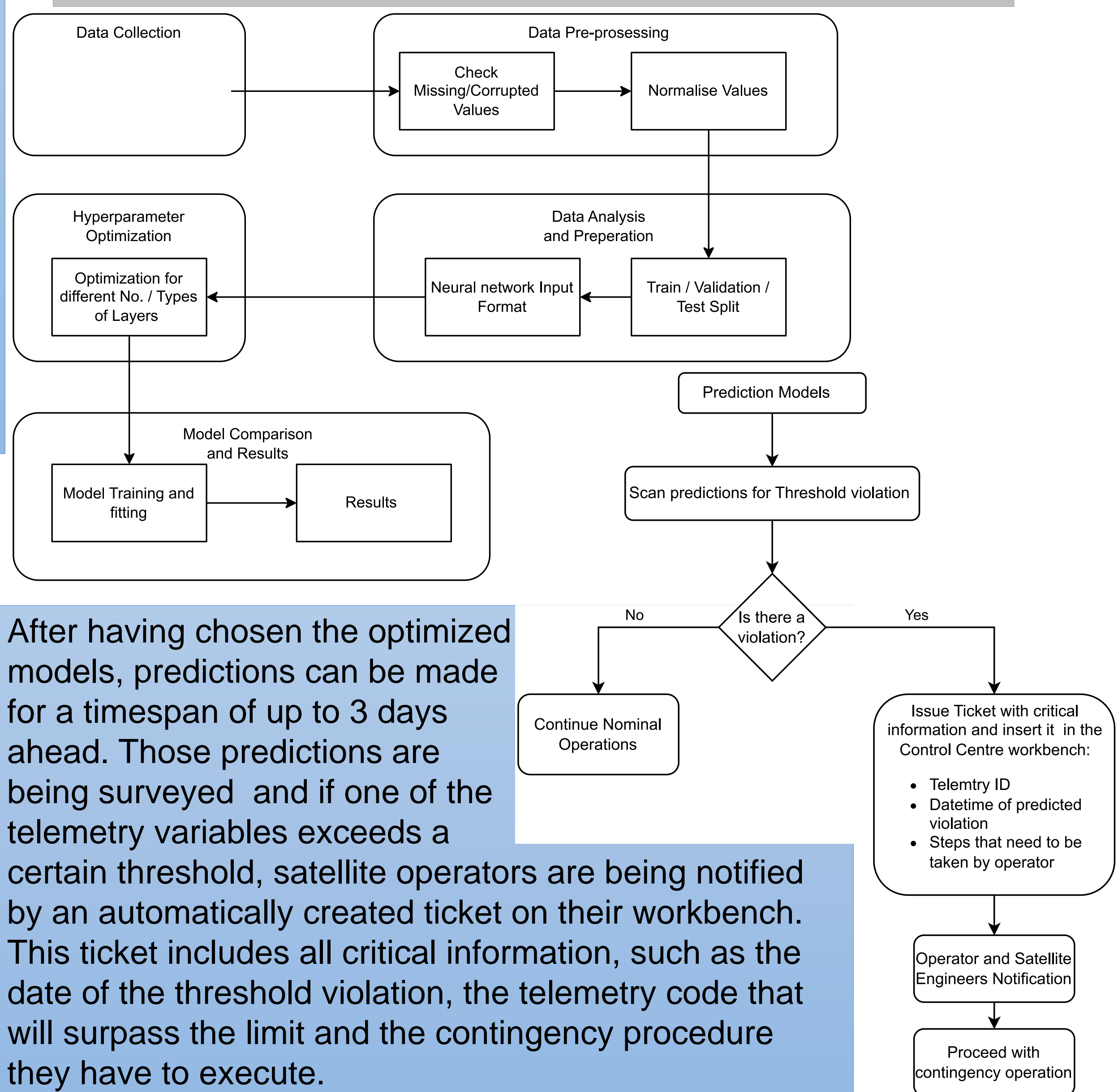
Network	Window Size	Layers	Output Shape	No. of Parameters	Total Parameters	Trainable Parameters
RNN	(24, 1)	LSTM	(None, 32)	7296	7329	7329
		Dense	(None, 1)	33		
RNN	(48, 1)	LSTM	(None, 256)	312320	312577	312577
		Dense	(None, 1)	257		
RNN	(48, 1)	LSTM	(None, 64)	28928	45825	45825
		Dense	(None, 256)	16640		
RNN	(24, 1)	LSTM	(None, 64)	16896	41857	41857
		Dense	(None, 128)	8320		
RNN	(48, 1)	LSTM	(None, 128)	16512	119937	119937
		Dense	(None, 1)	129		
RNN	(72, 1)	LSTM	(None, None, 128)	90624	273537	273537
		LSTM	(None, 32)	20608		
RNN	(72, 1)	LSTM	(None, 256)	8448	245121	245121
		Dense	(None, 1)	257		
RNN	(72, 1)	LSTM	(None, None, 192)	203520	267585	267585
		LSTM	(None, 64)	65792		
RNN	(72, 1)	LSTM	(None, 64)	4160	245121	245121
		Dense	(None, 1)	65		
RNN	(72, 1)	LSTM	(None, None, 64)	35072	267585	267585
		LSTM	(None, None, 32)	12416		
RNN	(72, 1)	LSTM	(None, 192)	172800	267585	267585
		Dense	(None, 128)	24704		
RNN	(72, 1)	LSTM	(None, 1)	129	267585	267585
		LSTM	(None, None, 64)	35072		
RNN	(72, 1)	LSTM	(None, None, 192)	197376	267585	267585
		LSTM	(None, 32)	28800		
RNN	(72, 1)	LSTM	(None, 64)	2112	267585	267585
		Dense	(None, 64)	4160		
RNN	(72, 1)	LSTM	(None, 1)	65	267585	267585
		Dense	(None, 1)	65		

Aim:

The aim of this IRP was to create a tool that will allow satellite operators to predict how specific values of the telemetry will evolve over time and warn them when they exceed a threshold, using timeseries forecasting with Recurrent Neural Network. Then the operators can take action by implementing contingency procedures to make sure that the spacecraft and its mission will not be put in danger.

Development:

The tool that was developed is based on Hellas Sat 3, a telecommunications geostationary satellite operated by Hellas Sat. They provided all the necessary data and information in order to be able to create the tool.



Results: The resulting product is an end-to-end pipeline tool that includes forecasting values for specific telemetry, surveying those predictions and creating a ticket on the operator's workbench to notify them in case of future detected threshold violation. Using this tool, operators can be notified about contingency cases and plan their actions accordingly with enough time margin, to assess and investigate the situation properly.

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