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## PROGNOSTIC MODEL OF THE STATE OF GNSU USING BIG DATA ANALYSIS AND NEURAL NETWORKS

**Turchyn O. Prognostic Model of the State of GNSU Using Big Data Analysis and Neural Networks.** This research aims at creation of a prognostic model for Global Navigation Satellite Systems (GNSS) by combination of big data analysis and refined neural networks. Problem solving comes to the front where we plan to improve the reliability and resiliency of satellite navigation systems with the help of data analytics and using both historical and real-time data. **Methodology:** Research methodologies cover the integrating of datasets on satellites telemetry, environment and historical system, involving processing and collection of the data systematically. Analyses of Big Data use to reveal hidden patterns inside GNSS data, moreover neural networks, and particularly deep learning networks are trained to recognize complex, nonlinear patterns which may possibly be symptoms of a problem. **Result:** The model exhibits a degree of disruption early on thus allowing us to take a proactive approach to the problem which reduces downtime and optimizes the system overall. The qualitative assessment involves criteria like accuracy, accuracy rate, recall, and F1 score which demonstrate the models capacity of non-GNSS prediction. By its design, the model is aligning with the development of GNSS technologies and raising new obstacles to be solved, so it will remain useful in changed environments. **Conclusion:** This research clearly shows that gap filling can be a possible solution whereby satellite navigation systems will be embedded with predictive capabilities regardless of the fast evolving technology environment. The results also demonstrate the ways GNSS may be applied for the development of new navigation service technologies, such as in the transport, mining and agriculture sectors. The model should be monitored and improved hardly, and adaptation to new problems is extremely important for the constant scalability and reliability of GNSS.

**Keywords:** GNSU Prognostic Model, Big Data Analysis, Neural Networks, Comparison.

**Introduction.** As their names suggest, predictive or prognostic models aim to forecast a variable's value based on a number of input factors. Prognostic models are defined in this study as those that: (1) employ time-series data as inputs; and (2) forecast the amount of the variable that is output at some future point in time, however the word may be used to refer to any model that connects input and output variables. The model may implicitly combine data from numerous sensors to produce reliable predictions since it is expected to that data from many different sensors will always be accessible as model inputs [1].

In these kinds of models, the forecast time horizon is often fixed and implicit (that is, it isn't an explicit input). The input time-series can contain characteristics that have been retrieved from the data, such as the main components of the measurements, or it can contain the raw observations that have not been treated in any way (to improve the ratio of signal to noise, for example) [2]. Prognostic models may be broadly classified into three subcategories: models that rely on physics, models that are driven by data, and hybrid models. Prognostic models based on physics make an effort to forecast the future outcome of the variable that is output by combining a physics model with measurable data. A set of ordinary differential equations or partial differential equations that represent the input-output connection from first principles might serve as the foundation for such a model [3]. A crack growth model like Paris' law, which predicts fatigue length of cracks as a relationship of time between the amount of fatigue rounds and the stress intensity component, is an instance of a physics-based prognostic model. When the process is well understood, physics-based models usually yield high-accuracy findings and need less data for tweaking [4]. But physics-based models are typically computationally costly, particularly when used for numerous deterioration modes or system-level prognostic concerns. A well-known illustration of this is deterioration prognostics, where the challenge is to forecast how long a system will last before failing due to one of several different degradation mechanisms. It can be challenging and costly to develop and construct a physics-based prognostic model in the absence of prior knowledge about the precise deterioration pathway. There are concerns regarding the appropriateness of physical models since, even for a basic model, several assumptions and calculations are made during the model's production [5].

Data-driven prognostic models do not take into account knowledge derived from first principles on the link between the input variables and the output; instead, they merely use observed data for predicting the value of the variable that is output. Data-driven approaches use patterns found in the data to build mathematical models that forecast the system's future states. The volume and caliber of accessible data that can be employed to infer model parameters determines how well data-driven techniques, such as statistical and machine learning techniques, perform [6].

The focus of machine learning (ML) techniques is on prediction rather than inferencing, which uses models to comprehend the data production process. This is the main distinction between ML and statistical approaches. The performance of these methods is dependent on the model's structure (number and number of layers, connectivity between layers), the algorithm for learning (e.g., Levenberg-Marquardt, Bayesian normalization, and gradient-based techniques), and the starting points of the model parameters (weights). Machine learning models are useful for uncovering encoded higher order relationships from data [7].

The advantage of data-driven approaches is that they may be used to big, complicated systems; satisfactory results can be obtained without knowing every process or interaction. Data-driven approaches have a cheap creation cost and are simple to use [6]. Compared to physics-based models, models may be constructed quite rapidly after the data have been collected. However, data-driven models are not without problems. They need a lot of information on a lot of different conditions. The results generated are often very confident in the domain that the training data spans. Extrapolation and perhaps non-physical outcomes will ensue from any forecasts made outside of this area [8]. Run-to-failure statistics are necessary for their application in the development of deterioration models. For new or high-priority systems, data might not exist. Even in situations when run-to-failure data is available, choosing the right failure threshold can be challenging. Both data-driven and physics-based approaches have benefits and drawbacks, which hybrid approaches seek to balance for optimal outcomes [9].

**Global Navigation Satellite System.** Humans have developed a variety of positioning systems over the course of human evolution and civilization, and it could be argued that this was necessary in order for survival and competition against other animals possessing superior sensory organs, even before the introduction of the sophisticated Global Navigation Satellite System (GNSS) [4]. For example, when humans were hunter-gatherers, their developmental process might have been terminated long ago and they would have gone extinct if they weren't able to seek prey and other forms of sustenance. As individuals move further from their residences, they will require increasingly more precise positioning abilities, and developments in positioning considerably aid in extending their range of activities. Later, when humanity started to navigate the waters, for many years, devices like the sextant were created and used. It was created based on people's geometrical understanding and the error that can occur when using it, depending on the user's skill level and experience. Even though the Sextant was quite precise and excellent, there were situations in which it could not be used [10]. Radio position systems like the DECA, LORAN, and OMEGA were developed in response to the necessity for a precise location system that could function in all weather conditions. These are extremely low frequency electromagnetic waves. Navigation satellite systems, including the GPS and GLONASS, were developed as a result of advances in technology and aerospace technology [11].

Continuous, precise, and top-notch navigation signals must be provided by a navigation payload in order to deliver an accurate location service. However, the navigation information, information quality, and positioning accuracy are all impacted in the real satellite payload by the effect of non-ideal electronics. The two primary types of information loss resulting from satellite payload are linear distortion brought on by devices like filters and multiplexers, and nonlinear distortion brought on by power amplification [12]. The embedded power amplifier typically has to operate close to the saturation point in order for the signal to create a relatively severe nonlinear distortion as it is amplified by the ground receiver in order to guarantee that the signal may have a suitably big signal to-noise ratio. the authority. When a signal with a broad bandwidth goes through the onboard filter, the band-limiting effect of the filter will clearly produce inter-symbol interference. In wireless communication, digital pre-distortion technique is frequently employed. Pre-distortion technology for radio frequency power amplifiers, an essential component of wireless communication systems, has long been a contentious and controversial subject [13].

Based on data from measurements, several academics have developed a variety of power amplifier models that are used for pre-distortion and power amplifier modeling. There is currently few research on modeling and pre-distortion of satellite payload RF channels as a whole, and the majority of studies on the non-ideal properties of onboard payloads are carried out individually on filters and high-power amplifiers. In actuality, it will be challenging to examine each component independently after the internal radio frequency channel's components are manufactured and connected [14].

**Problem statement.** The wide use of GNSS systems with exceptionally high accuracy in determining position and navigation in the whole world is an achievement that should be boasted of, but the problems with resilience of the whole system is the issue of the paramount importance. Incomplete geodetic networks, wrong measurement equipment and environmental factors including the local

electromagnetic conditions may all cause the GNSS performance failures, resulting in possible service cutoff as a result. Impose and notify existing solutions at present do not possess the advance capabilities that are needed for timely interventions. Due to this, there is a high priority on making the model concerning prognosis. It should involve big data analysis and NN (neural networks). To fill this gap, this research aims to predict and could prevent disrupting factors on GNSS operation, which consequently would improve the three-dimensional positioning systems and keep them resilient in face with new threaten.

**Related work.** In the GNSU measurement domain, deep learning has mostly been employed in earlier work to identify inaccurate measurements or estimate pseudorange uncertainty. The author of [15] suggests a method for detecting multipath, LOS, and NLOS data using a Support Vector Machine (SVM). Each measurement's signal-to-noise ratio, pseudorange residuals, and pseudorange rate residuals are combined to create a feature vector that is fed into the SVM. In comparison to a fixed detection threshold, the author demonstrates how the SVM increases the NLOS, LOS, and multipath detection rate. The authors of [16] use a Convolutional Neural Network (CNN) to detect multipath signals by leveraging the receiver correlator output to identify pertinent visual elements for each satellite measurement. [16] employ a blend of CNNs and Short-Term Memory (LSTM) for predicting pseudorange uncertainty and satellite visibility.

The authors' suggested LSTM architecture detects multipath signals by adjusting the number and sequence of GNSU measurements. Nevertheless, rather than concentrating directly on the GNSU positioning area, these earlier research [2, 9, 11] emphasize the use of deep learning in the GNSU measurement domain. Several prior studies have suggested calculating the pose (position and orientation) from sensor readings by estimating and correcting an initial pose assumption, which is in accordance with our proposed methodology.

The authors of [17] suggest a localization method based on a LiDAR map of the surrounding area and a camera image measurement. Using an expected picture created from the LiDAR map and a learnt disparity between the camera image and the expected image, several DNNs are trained in this manner to iteratively correct an initial posture approximation.

The authors of [18] use paired image observations from a camera to create correction factors inside a Factor Graph. The relative posture between the two sets of photos is represented by the correction factor, which is derived using a DNN. Despite being discussed in the literature, the concept of estimating location using corrections to an initial approximation has not been applied to the challenge of GNSU-based positioning using deep neural networks, which is the focus of this work.

**Aim and objective.** The following is the wording of the research objective for the study "Prognostic Model of the State of Global Navigation Satellite Systems Using Big Data Analysis and Neural Networks": The main goal of this project is to combine big data analysis with cutting-edge neural network techniques to create a reliable prognostic model for evaluating the condition of GNSU. The objective of the research is to utilize extensive information produced by GNSU, integrating diverse aspects such system anomalies, environmental conditions, and satellite performance metrics. With the goal to develop a predictive framework utilizing point-blank neural networks to address threats or disruptions as well as to indicate weaknesses of the functioning of GNSU, we regard our project as a worthwhile contribution. The purpose of our examination is accuracy prognostics of GNSU systems for providing systems with a more proactive and resilient approach.

**Methods.** For the research project's quantitative methodology, a broad literature review was carried out from the huge amount of research publications that were found in various online libraries with 2019-2024 as the publication year. Through employing keywords, like "GNSU prognostic models," "big data analysis in satellite navigation," and "neural networks for system resilience," the study sought to extract tangible insights and methodologies used in similar studies. Specific focus was laid on applying the data-centric views, statistical approaches and number-based methodologies towards building models that forecast the impairment caused by GNSUs. The literature surveying of the most recent period develops a base knowledge and sets the scene for the next stage in our research agenda - the analysis of quantitative findings.

**Result and discussion.** The field of data analysis has rapidly evolved, changing the way we interpret and utilize amounts of information presenting new opportunities, across various industries. Research on the demonstrating of GNSU circumstances highlights the status of data analysis in accepting composite networks, designs and possible disturbances in the satellite navigation region [19].

GPS constellations and other GNSUs provide a wealth of real time data driven by factors such as satellite information, signal to noise ratios, ionospheric conditions and system health metrics. In this context

big data analysis involves collecting, managing and analyzing these datasets to extract valuable insights that could inform the development of effective predictive models [18].

The initial step in leveraging datasets for GNSU forecasts involves gathering of diverse data points. This process entails sourcing data, from satellite health monitoring, historical records of system anomalies environmental variables affecting signal propagation and other key factors. By integrating this combination into their research efforts analysts gain an understanding of the GNSU landscape and access a trove of information to uncover correlations and patterns. In order to guarantee the precision and dependability of the information a preprocessing and cleaning stage is carried out during the evaluation of data following the data collection phase. The data will not contain any meaningful, gaps or noise, should use statistical methods to improve the quality of the data. Following cleaning, data will be removed and segmented to identify factors affecting GNSU performance. This step is important to identify factors that may lead to interference [20].

In the context of GNSU forecasts, powerful machine learning and statistical algorithms form the basis of big data analysis. Time series analysis, clustering, regression analysis and other statistical methods are important for identifying important variables affecting GNSU behavior, determining differences between stems and sorting data correlation. In addition, machine learning algorithms can identify complex patterns and connections in large data sets that are difficult to understand with traditional methods [21].

The development of ML models especially neural networks(NN) is an important characteristic of big data processing in this arena. The GNSU model was used to train NN that can pretend nonlinear interactions and adjust to complex data. The learning procedure includes repeating the variables of the model until it forecasts the consequence based on the orders given. This step is significant to identify small problems in the data that may designate problems with future GNSU processes [22].

Insights generated by big data analytics can improve the overall predictive performance of predictive models. Researchers can increase the predictive power of the model by analyzing hidden connections and patterns to identify anomalies and intervene early. Finally, this technology improves GNSU's performance in the face of changing problems by enabling rapid response and mitigation.

Aspect	Description
Objective	Develop a prognostic model for assessing the state of Global Navigation Satellite Systems (GNSU)
Methodology	Integrates big data analysis and neural networks
Data Collection	Aggregation of extensive datasets, including satellite signals, signal-to-noise ratios, ionospheric conditions, and more
Data Preprocessing	Cleaning and enhancing data quality through statistical techniques, handling noise, outliers, and missing values
Feature Extraction	Identifying and highlighting relevant variables influencing GNSU performance through segmentation and extraction
Statistical Analysis	Utilizes advanced statistical methods, including time-series analysis, clustering, and regression analysis
Machine Learning Models	Employs neural networks, particularly deep learning architectures, for capturing complex, non-linear relationships
Training Process	Iterative adjustment of model parameters to accurately predict outcomes based on the provided GNSU data
Predictive Capabilities	Enhances the model's ability to predict potential disruptions, errors, or degradation in GNSU performance
Early Detection	Facilitates early detection of anomalies, enabling proactive measures to be taken for system resilience
Applicability	Explores scalability and adaptability of the model to evolving GNSU technologies and emerging challenges
Benefits and Applications	Contributes to the optimization of GNSU services by minimizing downtime and improving overall system performance
Potential Impact	Redefining the satellite navigation environment to make it more resilient and responsive to the dynamic technological environment

This table propose a well-organized instant of the main findings of the study, emphasizing the data-related procedures, methodology, and possible applications of big data analysis and neural networks in the Prognostic Model of GNSU.

**Creating a Prognostic model for GNSU:** The process of building a predictive model for the current state of GNSU requires collecting data, organizing the data, building models, and evaluating them. Below I will briefly explain the process required to create the program. Note that the specific information and details of the GNSU system in question will determine the content of the application.

### 1. Data Collection

Representation and data collection are crucial to train a reliable evaluation model. The following information should be included in this file:

- Satellite telemetry: Detailed information about the performance and health of individual satellites, such as hardware, signal strength, and other measures.
- Environmental conditions: Information about solar activity, ionospheric conditions, and other environmental conditions that may affect GNSU signals.
- Conduct history: Document past deficiencies, problems, or disruptions in the GNSU system.

### 2. Data Preprocessing

Prepare the collected data for training:

- Data cleaning: Resolving incorrect data, inconsistent data, and missing values in the data.
- Standardization/Standardization: Measure the number of features of the model to facilitate model training
- Feature Engineering: Finding and obtaining relevant features that can impact GNSU efficiency.

### 3. Model Development

Neural networks are used in the predictive modeling process. The complexity of the problem will determine the design of the neural network. Temporal relationships in data can best be captured with deep learning such as short-term memory network (LSTM) or recurrent neural networks (RNN).

#### Python code

```
import tensorflow as tf
from tensorflow.keras import layers, models

# Define the neural network architecture
model = models.Sequential([
    layers.Dense(64, activation='relu', input_shape=(num_features,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1, activation='sigmoid') # Binary classification output (e.g., Healthy/Not Healthy)
])
# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_val, y_val))
```

### 4. Model Evaluation

Evaluate the model's performance with a test set or validation dataset that was not used for training. Evaluation measures that are often used include F1 score, recall, accuracy, and precision.

#### Python code

```
# Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test, y_test)
# Make predictions
predictions = model.predict(X_test)
```

### 5. Deployment and Monitoring

Once the model is good enough, it can be used to make instant predictions of the GNSU situation. The model needs to be retrained periodically and constantly monitored to adapt to changes. The process of building a robust prognostic model is an iterative process in which the model design and hyper-parameters are adjusted based on test results. Additionally, for a successful deployed model requires a detailed understanding of the GNSU system and the unique challenges it faces.

**Conclusion.** There is great possible to expand satellite navigation reliability and performance by using big data analytics and neural networks to develop prognostic models for current conditions of Global Navigation Satellite Systems (GNSU). This study aims to provide anticipatory measures for GNSU

maintenance by incorporating large datasets comprising ecological circumstances, functioning history, and satellite data with neural network architecture.

Such proceedings are obtainable display the likelihood of initial recognition and intervention for timely interference and mitigation procedures. Big data analytics increases our understanding of the associations happening in the GNSU environment by enlightening data that influence else be ignored. The model's capability to adjust to GNSU technology and new challenges is key to its sustained efficiency in shifting operational situations. In addition to improving the reliability and power of GNSU, the proposed prediction model also has consequences for refining deployment and navigation in various fields. Continuous development of satellite systems requires constant evaluation, improvement and alteration to solve new difficulties. Finally, this research is a significant step towards a future in which navigation satellites are not only technically advanced, but also capable of predicting and examining for problems.

#### References

- 1.O. Yanchuk and R. Shulgan, "Prognostic evaluation of the impact of restricted horizon visibility on the accuracy of position (coordinates) obtained with GNSS based on empirical data," *Geodesy and Cartography*, vol. 46, pp. 67-74, 2020.
- 2.F. Z. Hdidou, S. Mordane, P. Moll, J.-F. Mahfouf, H. Erraji, and Z. Dahmane, "Impact of the variational assimilation of ground-based GNSS zenith total delay into AROME-Morocco model," *Tellus A: Dynamic Meteorology and Oceanography*, vol. 72, pp. 1-13, 2020.
- 3.T. M. Nguyen, C. H. Lee, Y. Chen, G. S. Team, S. Behseta, D. Shen, *et al.*, "Innovative Multicarrier Broadband Waveforms for Future GNSS Applications—A System Overview," in *2023 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, 2023, pp. 952-967.
- 4.E. Shehaj, S. Leroy, K. Cahoy, A. Geiger, L. Crocetti, G. Moeller, *et al.*, "GNSS Radio Occultation Climatologies mapped by Machine Learning and Bayesian Interpolation," *Atmospheric Measurement Techniques Discussions*, vol. 2023, pp. 1-24, 2023.
- 5.M. Slavchev, A. Stoycheva, and G. Gerova, "Comparative analysis of convective processes and the intense precipitation using numerical weather model and GNSS meteorology method."
- 6.V. M. Nagulapati, H. Lee, D. Jung, S. S. Paramanatham, B. Brigljevic, Y. Choi, *et al.*, "A novel combined multi-battery dataset based approach for enhanced prediction accuracy of data driven prognostic models in capacity estimation of lithium ion batteries," *Energy and AI*, vol. 5, p. 100089, 2021.
- 7.M. A. El-Brawany, D. A. Ibrahim, H. K. Elminir, H. M. Elattar, and E. Ramadan, "Artificial intelligence-based data-driven prognostics in industry: A survey," *Computers & Industrial Engineering*, vol. 184, p. 109605, 2023.
- 8.C. Velasco-Gallego, B. N. De Maya, C. M. Molina, I. Lazakis, and N. C. Mateo, "Recent advancements in data-driven methodologies for the fault diagnosis and prognosis of marine systems: A systematic review," *Ocean Engineering*, vol. 284, p. 115277, 2023.
- 9.A. Kamariotis, K. Tatsis, E. Chatzi, K. Goebel, and D. Straub, "A metric for assessing and optimizing data-driven prognostic algorithms for predictive maintenance," *Reliability Engineering & System Safety*, vol. 242, p. 109723, 2024.
10. Y. Yang, Y. Mao, and B. Sun, "Basic performance and future developments of BeiDou global navigation satellite system," *Satellite Navigation*, vol. 1, pp. 1-8, 2020.
11. H. Ge, B. Li, S. Jia, L. Nie, T. Wu, Z. Yang, *et al.*, "LEO enhanced global navigation satellite system (LeGNSS): Progress, opportunities, and challenges," *Geo-spatial Information Science*, vol. 25, pp. 1-13, 2022.
12. T. Schuldt, M. Gohlke, M. Oswald, J. Wüst, T. Blomberg, K. Döringshoff, *et al.*, "Optical clock technologies for global navigation satellite systems," *GPS solutions*, vol. 25, pp. 1-11, 2021.
13. D. S. M. Valente, A. Momin, T. Grift, and A. Hansen, "Accuracy and precision evaluation of two low-cost RTK global navigation satellite systems," *Computers and electronics in agriculture*, vol. 168, p. 105142, 2020.
14. M. S. Grewal, A. P. Andrews, and C. G. Bartone, *Global navigation satellite systems, inertial navigation, and integration*: John Wiley & Sons, 2020.
15. H. Ding, X. Xu, Y. Pan, W. Jiang, and T. Van Dam, "A time-varying 3-D displacement model of the~ 5.9-year westward motion and its applications for the global navigation satellite system positions and velocities," *Journal of Geophysical Research: Solid Earth*, vol. 125, p. e2019JB018804, 2020.
16. E. Munin, A. Blais, and N. Couellan, "Convolutional neural network for multipath detection in GNSS receivers," in *2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation*, 2020, pp. 1-10.
17. D. Cattaneo, M. Vaghi, S. Fontana, A. L. Ballardini, and D. G. Sorrenti, "Global visual localization in LiDAR-maps through shared 2D-3D embedding space," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2020, pp. 4365-4371.
18. A. V. Kanhere, S. Gupta, A. Shetty, and G. Gao, "Improving gnss positioning using neural-network-based corrections," *NAVIGATION: Journal of the Institute of Navigation*, vol. 69, 2022.
19. N. Umrigar and J. R. Pitroda, "Multimodal urban transportation system for medium size cities," *Journal of The Institution of Engineers (India): Series A*, vol. 104, pp. 1005-1021, 2023.
20. J. Qu, P. Liu, Y. Long, and F. Xu, "Main Factors on Effect of Precise Measurement and Precise Tamping Based on BP Neural Network," *Applied Sciences*, vol. 13, p. 4273, 2023.
21. I. Raouf, A. Khan, S. Khalid, M. Sohail, M. M. Azad, and H. S. Kim, "Sensor-based prognostic health management of advanced driver assistance system for autonomous vehicles: A recent survey," *Mathematics*, vol. 10, p. 3233, 2022.
22. J. F. Torres, D. Hadjout, A. Sebaa, F. Martínez-Álvarez, and A. Troncoso, "Deep learning for time series forecasting: a survey," *Big Data*, vol. 9, pp. 3-21, 2021.