A project report on

ELECTRICITY DEMAND FORECASTING AND ANALYSIS USING TIME-SERIES ALGORITHMS

Submitted in partial fulfilment for the award of the degree of

B.Tech. (Information Technology)

by

SOUBHIK SINHA (19BIT0303)

VIT

Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)

SCHOOL OF INFORMATION TECHNOLOGY & ENGINEERING

January , 2023

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DECLARATION

I hereby declare that the project report entitled "ELECTRICTY DEMAND FORECASTING AND ANALYSIS USING TIME-SERIES ALGORITHMS" submitted by me, for the award of the degree of B.Tech. (Information Technology) is a record of bonafide work carried out by me under the supervision of Dr. Bimal Kumar Ray

I further declare that the word reported in this report has not been submitted and will not be submitted, either in part or full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore

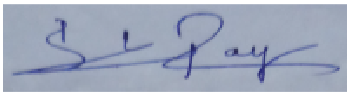
Date : 20/01/2023

Signature of the Candidate

CERTIFICATE

This is to certify that the project report entitled “ELECTRICTY DEMAND FORECASTING AND ANALYSIS USING TIME-SERIES ALGORITHMS” submitted by SOUBHIK SINHA (19BIT0303), School of Information Technology & Engineering, Vellore Institute of Technology, Vellore for the award of the degree B.Tech. (Information Technology) is a record bonafide work carried out by him under my supervision.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The project report fulfils the requirements and regulations of VELLORE INSTITUTE OF TECHNOLOGY, VELLORE and in my opinion meets the necessary standards for submission.



Signature of the Guide **Signature of the HoD**

Internal Examiner **External Examiner**

ABSTRACT

The ability to estimate demand is crucial for the power supply sector. In order to fulfil future demand, power production plants must be scheduled far in advance because electricity cannot be stored. Time series techniques on the historical demand series have been employed for demand prediction up till now in cases when online information about the external circumstances is not accessible. This paper introduces a project, which proposes the approach of using the appropriate Time-Series algorithm among LSTM (Long Short-Term Memory), ARIMA (Auto-Regressive Integrated Moving Average) and STM (Short Term Memory - RNN) Neural Networks on the basis of error rate (RMSE – Root Mean Squared Error) and R^2-score, as the evaluation metrics, on the dataset acquired from websites regulated by the Ministry of Power, Govt. of India. Later I show the prediction values of power production for 10 blocks of 15 minutes interval each for the next day. Afterwards I compare the prediction results to declare the winner among the 3 algorithms chosen.

ACKNOWLEDGMENT

It is my pleasure to express with deep sense of gratitude to Dr. Bimal Kumar Ray, Professor (Higher Academic Grade), School of Information Technology & Engineering (SITE), Vellore Institute of Technology, Vellore, for his constant guidance, continual encouragement, understanding; more than all, he taught me patience in my endeavour. My association with him is not confined to academics only, but it is a great opportunity on my part of work with an intellectual and expert in the field of Database Management Systems and Java Programming.

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It is indeed a pleasure to thank my friends who persuaded and encouraged me to take up and complete this task. At last, but not least, I express my gratitude and appreciation to all those who have helped me directly or indirectly toward the successful completion of this project.

Place : Vellore

Date : 20/01/2023 **SOUBHIK SINHA**

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LIST OF ACRONYMS

MW	Mega-Watt
PSO	Particle Swarm Optimization
SVR	Support Vector Regression
ARIMA	Auto-Regressive Integrated Moving Average
ANN	Artificial Neural Network
AFD	Adaptive Fourier Decomposition
FFT	Fast Fourier Transform
HW	Holt-Winters
FOASVR	Fruit-fly Optimization Algorithm, optimized Support Vector Regression
GASVR	Genetic Algorithm, optimized SVR
MTP	Multiple Temporal Aggregation
MAPA	Multiple Aggregation Prediction Algorithm
GPU	Graphical Processing Unit
RAM	Random Access Memory
BP	Back-Propagation
DBN	Deep Belief Network
SVM	Support Vector Machine
ML	Machine Learning
MAPE	Mean Absolute Percentage Error
K-NN	K-Nearest Neighbour
NNDR	Neural Network Dynamic Regression
DRSARIMA	Dynamic Regression in Seasonal ARIMA
GUI	Graphical User Interface
DG	Distributed Generation
LSTM	Long Short-Term Memory (Neural Network)
STM	Short Term Memory
RNN	Recurrent Neural Network

Chapter 1

Problem Definition

Because of the nation's exponential industrial expansion and the resulting constant demand for power, several power plants have been built all around the country. Today's electricity demand, however, is driven by factors more than just expanding industry. Power demands are rising more quickly than anticipated. India is currently one of the world's top consumers of electricity; the country can thank its industrialisation and rising economy for this. But hold on! We simply specified how much energy the power plants will need to generate overall to meet our daily consumption. But in reality, it won't take place. Each power plant has a limit capacity for producing energy that it cannot exceed. Additionally, building a power plant in such a short amount of time is virtually unfeasible. If we break down our daily energy requirements, we may see a variety of patterns and swings, ranging from minor to large. It is challenging for power plants to meet the requests of the purchasers (state governments) because of the wide variety of electricity demands and consumption. As was already indicated, the electricity produced fluctuates. The maximum output of a power plant, let's say one with a capacity of 2540 MW, can be changed depending on the situation. But on what condition? The government must get reports from the power plants every 15 minutes on a daily basis detailing how much electricity they are producing. As a result, the state government plans to ask for the power demand for the next day. In this manner, data may be produced, but there is no analysis or forecast for the amount of electricity that will be produced in the future. Let us assume that powerplant officials put ‘gut-instinct’ which is derived from their experience. But at times, sudden fluctuation of demand (i.e., a sudden need of electricity in a particular area OR a complete shutdown of power) can eventually cause the equipments to breakdown and decreasing efficiency.

Chapter 2

Literature Survey

2.1 SUMMARY OF THE EXISTING WORKS

S.no.	Title	Merits	Demerits
[1]	A hybrid data mining driven algorithm for long term electric peak load and energy demand forecasting	1. A major advantage of the proposed hybrid method is the combination of analytic time series method and the data mining approach which can handle the nonlinearity and seasonal trends in input samples (i.e., input observations). 2. The proposed hybrid approach prioritizes each algorithm based on its error over the input observations. The proposed hybrid method gives robust and accurate forecasting results. 3. It was shown that the proposed PSO-SVR and hybrid methods give more accurate results rather than ARIMA and ANN methods. 4. The PSO-SVR method is capable to forecast the load and energy demand with small errors without any sensitivity to seasonal trends in the original time series.	1. The ARIMA methods may results in undesired overestimation or underestimation in load and energy demand forecasting results. 2. For non-stationary time series (e.g., load and energy time series) identification of ARIMA orders and parameters is not an easy task. 3. Long term yearly peak load and energy demand forecasting in carried out in this paper.

		The reliable forecasts are obtained provided that the SVR parameters are set optimally using an optimization method such as the PSO algorithm.	
[2]	A novel hybrid forecasting scheme for electricity demand time series	1. AFD method can produce its basis adaptively based on processed signals to realize fast energy convergence. 2. The metaheuristics algorithm was applied to tune the parameters. And the hybrid method generally presents superior forecast performance. 3. The metaheuristic optimization algorithm is considered for combination to improve the instability.	1. The major disadvantage of the AFD is the inherent compromise that exists between frequency and time resolution. The length of AFD used can be critical in ensuring that subtle changes in frequency over time. 2. Metaheuristics Algorithms can be very effective on a given instance of a problem and, at the same time, show long running times on another without finding a satisfactory solution. 3. FFT cannot extract enough frequencies without enough samples
[3]	Holt–Winters smoothing enhanced by fruit fly optimization algorithm to forecast monthly electricity consumption	1. The proposed model can substantially improve the prediction accuracy of monthly electricity consumption even when few training samples are available. 2. The computation time of the proposed model is the shortest among the evaluated hybrid benchmark	1. The first disadvantage is that HW can take more time to generate forecasts. This is because the smoother curve requires more time to calculate and predict future values. The second disadvantage is that the HW method is

		algorithms. 3. The proposed hybrid model represents approximately twice the accuracy of the GASVR and FOASVR models.	less reliable than other forecasting methods. 2. FOA has weak ability to solve complex, high-dimensional and nonlinear optimization problems.
[4]	Cross-temporal aggregation: Improving the forecast accuracy of hierarchical electricity consumption	1. MTA has been shown to mitigate the model selection problem for low-frequency time series. 2. Propose a modification of the Multiple Aggregation Prediction Algorithm, a special implementation of MTA, for high-frequency time series to better handle the undesirable effect of seasonality shrinkage that MTA implies and combine it with conventional cross-sectional hierarchical forecasting. 3. The proposed MTA approach, combined with the optimal reconciliation method, demonstrates superior accuracy, aggregation consistency, and reliable automatic forecasting. 4. MTA significantly improves forecasting performance in terms of accuracy and bias. 5. Cross-sectional aggregation further enhances forecasting performance	1. Disadvantages of Cross-Sectional Study : - Cannot be used to analyse behaviour over a period to time - Does not help determine cause and effect - The timing of the snapshot is not guaranteed to be representative - Findings can be flawed or skewed if there is a conflict of interest with the funding source - May face some challenges putting together the sampling pool based on the variables of the population being studied. 2. MTA & MAPA : the exact demand from a specific region can't be ascertained, because it is aggregated.

		by combining appropriately, the base forecasts produced. 6. Applying MTA to seasonally adjusted data leads to better forecasts than applying MTA to the original series.	
[5]	Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings	1. Boosted-tree, random forest, and ANN provided the best outcomes for prediction at hourly granularity when metrics such as computational time and error accuracy are compared. 2. Clustering decreases the amount of collected data, but the result for the grid side which is the predicted load will still be the same. 3. Considering computational power and time as well as error accuracy, boosted-tree, random forest, and ANN models were chosen for electricity demand pre- diction.	1. Two years of data were used in training the model and the prediction was performed using another year of untrained data. 2. Decision trees cannot be used well with continuous numerical variables. A small change in the data tends to cause a big difference in the tree structure, which causes instability. Calculations involved can also become complex compared to other algorithms, and it takes a longer time to train the model. 3. A forest is less interpretable than a single decision tree. Single trees may be visualized as a sequence of decisions. A trained forest may require significant memory for storage, due to the need for retaining the information from several hundred individual trees.

			4. ANNs usually require the use of expensive graphics processing units (GPUs) that allow parallel processing. They also need a lot of RAM. Once you have trained an ANN, sharing it is difficult. ANNs are prone to overfitting on the training data. ANNs do not guarantee convergence on a prediction or solution.
[6]	A building energy consumption prediction model based on rough set theory and deep learning algorithms	1. The integrated rough set and deep neural network was the most accurate. 2. The implementation of rough set theory was able to eliminate redundant influencing factors of building energy consumption. The DBN with reduced number of inputs had improved accuracy in building energy simulation. 3. The DBN had more accurate prediction of either short-term or long-term building energy consumption than the shallow neural networks such as BP, Elman and fuzzy neural networks.	1. Rough set don't handle data belong to quantitative 2. Following are the drawbacks of DBN : - DBN has hardware requirements. - DBN requires huge data to perform better techniques. - DBN is expensive to train because it has complex data models. - Hundreds of machines are required. - DBN is difficult to be used by less skilled people. - DBN requires classifiers to grasp the output.
[7]	Energy Consumption Prediction by using Machine Learning for Smart Building: Case Study in Malaysia	1. SVM result shows a lower mean absolute error. SVM predicted demand also had better accuracy when average consumption was	1. The SVM model took 13-18 hours to train. 2. Azure ML particularly does not

		calculated from the demand, in which it achieved a lower MAPE than the rest of the methods for all tenants. 2. K-NN proves to be much faster in getting trained – by only taking 40 seconds.	have many algorithms needed for desired purpose. 3. SVM does not execute very well when the data set has more sound i.e., target classes are overlapping. In cases where the number of properties for each data point outstrips the number of training data specimens, the support vector machine will underperform. 4. Following are the demerits of K-NN : - Accuracy depends on the quality of the data. - With large data, the prediction stage might be slow. - Sensitive to the scale of the data and irrelevant features. - Require high memory – need to store all of the training data. - Given that it stores all of the training, it can be computationally expensive
[8]	Superiority of the Neural Network Dynamic Regression Models for Ontario Electricity Demand Forecasting	1. The proposed NNDR model is superior over the commonly used DRSARIMA errors model and the Prophet model. 2. Long-term point forecasts and	1. Regression models cannot work properly if the input data has errors (that is poor quality data). If the data pre-processing is not performed well to remove missing values or redundant

		innovations are used to obtain two classes of prediction intervals (PIs) using data-driven probabilistic innovation distribution and bootstrapping for NNDR, DRSARIMA and Prophet models.	data or outliers or imbalanced data distribution, the validity of the regression model suffers. 2. Regression models work with datasets containing numeric values and not with categorical variables. There are ways to deal with categorical variables though by creating multiple new variables with a yes/no value. 3. Disadvantages of Prophet: - Works primarily on one time series - Requires data to be specified in a specific format - Performance varies by data set - All limitations that come with additive models
[9]	Pandemic-Aware Day-Ahead Demand Forecasting Using Ensemble Learning	1. Boosting and bagging-boosting models, are capable of accurate country-level demand forecast. 2. Utilizing the pandemic policy data as features increases the forecasting accuracy during the pandemic situation significantly. 3. The probabilistic quantile regression demonstrated high accuracy for the aforementioned case study.	1. Ensembling is less interpretable, the output of the ensembled model is hard to predict and explain. Hence the idea with ensemble is hard to sell and get useful business insights. 2. When using quantile classification gaps can occur between the attribute values. These gaps can sometimes lead to an

			over-weighting of the outlier in that class division.
[10]	Electrical Energy Demand Forecasting Using Artificial Neural Network	1. ANN was able to predict accurately the year of highest inflation - that too in a 15-year span. 2. ANN can make proper inferences, if given proper dataset.	- ANN can be a bit hefty to arrange and organize. - ANN can often create incomplete results or outputs. - ANNs are highly dependent on the data made available to them. This infers that the efficiency of any neural network is directly proportional to the amount of data it receives to process. - Minimal control, the trainers have over the actual performance and overall functioning of the ANNs.

2.2 CHALLENGES PRESENT IN EXISTING SYSTEM

In **[1]**, the project is carried out by considering normal environmental conditions – unlike during climate change or global warming, because they could not acquire data for the given ‘unlike’ condition. Using of hybrid univariate method by enhancing the same by a multi-variate method is still a topic of debate as there seems no dataset collected which stores data with respect other factors that can affect power production/consumption. Moreover, the analysis was done on non-renewable source of energy – rather than on the sustainable ones. The computational complexity of the proposed hybrid method in **[2]** get becoming incremental as the improvement process is more complex. There is no such investigation or analysis which claims that the forecasting performance can be improved if other predictive strategies and variables are integrated. Also, whether the model can balance the forecasting accuracy and the computational complexity such that the hybrid method performs well in performance under acceptable cost – is still doubted. Even though the proposed study of **[3]** claims that the monthly electric consumption can be accurately predicted – industries today are more inclined towards daily predictions, because nothing can be rigid for a long time period (here, a months’ time). The performance might have been evaluated by considering only one dataset, but what if we include other datasets, having chances of being quite imprecise. For **[4]**, they haven’t combined the forecasting methods across multiple temporal aggregation levels. Also, whether the outcome will be fruitful if combining temporal hierarchical levels to cross-sectional ones. A predictive probability distribution over future quantities or events of interest is a probabilistic forecast. Thus, expanding cross-temporal aggregation for probabilistic forecasting could have been tested. The inconsistency in the collected data and poor performance of ANN in **[5]** is a commonplace in most projects. The authors still have to figure out deciding the levels at which the data should be used, the required computational speed and the required architecture for this conversion and which actors should be involved to make use of these data sets in an economical manner. Apart from the aforementioned, real-time analysis could have been employed which can eventually turn up industries to utilize on-site energy produced. In **[6]**, streaming data could not be analysed with the proposed model – though it may lack accuracy, but energy producers might be more interested whether the error rate of the model is high or low. In **[7]**, the study inculcated the use of Azure Machine Learning. But Azure ML has a major drawback - it offers fewer algorithms and other transformations built-in. Thus, one can of course reference

Python and R to do this, but that is much tougher than using the GUI. If one can figure out how to call Python/R from within Azure ML, he/she likely can do it on their own. This study's flaw is the length of time it took to run the SVM algorithm should thus be executed on a higher capable machine or platform. Second, given the limitations on the data collection in this study, more variables and data should be gathered as input. The focus of this work was more on the platform than the approach, hence a hybrid classifier was not presented. To distinguish the findings received, a comparison with another smart building might be added. It is challenging, as mentioned in **[10]**, to determine inflation accurately due to unpredictable reasons. By developing a high-accuracy prediction model, it will be possible to make reinforcements for the existing power system infrastructure more accurately and at the right time. In addition, as the management and control of the DG facilities to be established at the consumption points will be done more healthily, the power system management will be easier.

Chapter 3

Objectives

The aim of this project is to predict the values of power production for the initial 10 blocks (15 mins. Interval each) for the next day. First, prediction will be made on the values of last few blocks of the current day, giving out error rates and fitting values, w.r.t. test data. Later the models of LSTM, STM(RNN) and ARIMA will be taken as input parameter in a function to predict the electricity production values for the next day. Afterwards, comparison shall be made to conclude the best appropriate model for the issue – that can be efficacious for the power industry.

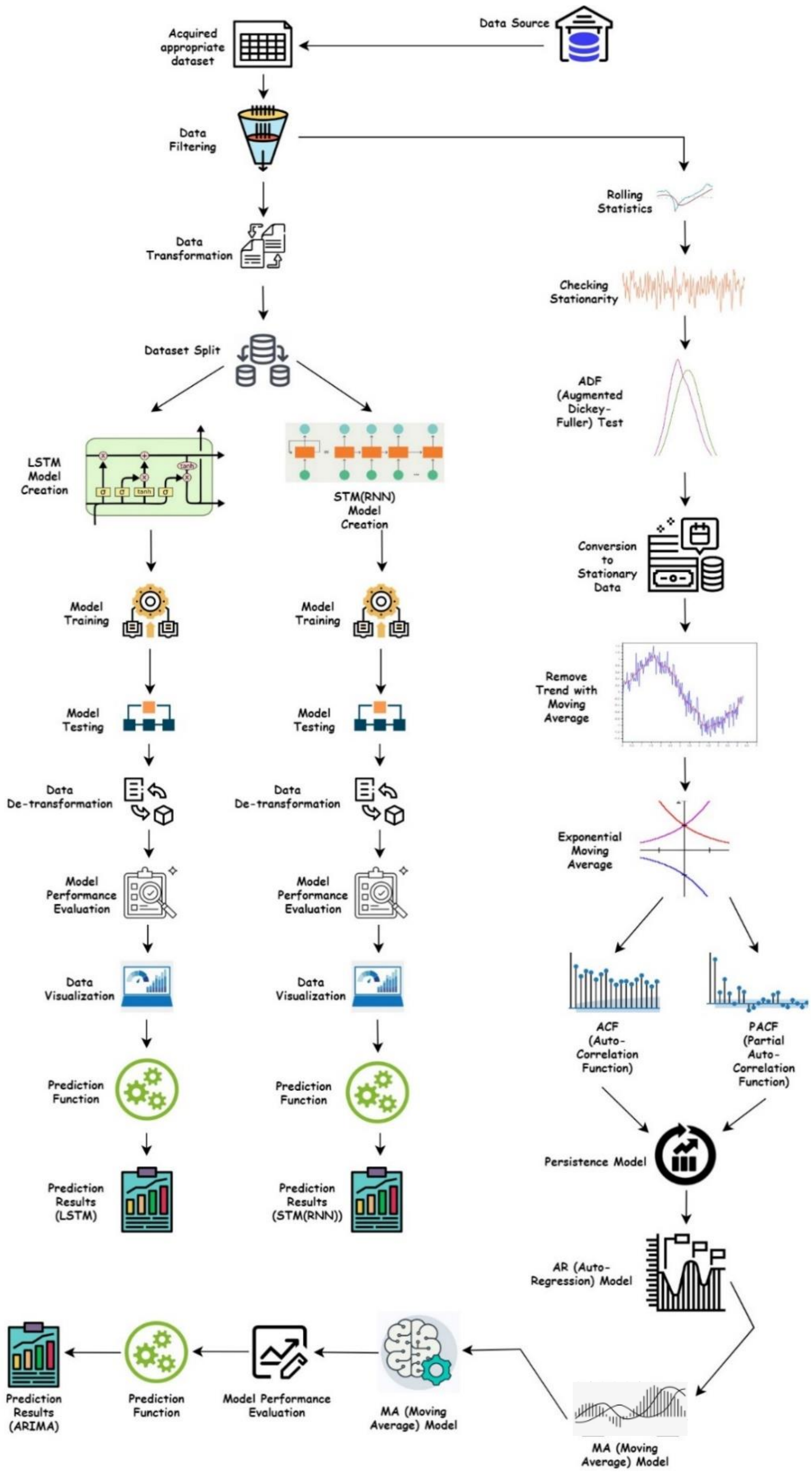
Chapter 4

Scope of the Project

The commencement of the project shall be done by keeping in mind that the end result should be industrially useful. For the very same reason, I am using a dataset, which is acquired from a government regulated website, which holds information about energy production and consumption – on daily basis. Then appropriate data shall be filtered out with necessary attributes. Data transformation and splitting can be carried out for creating training and testing data. Afterwards, model creation can take place and start the training procedure. As the prediction results have to be de-transformed, we should take care by keeping in mind the making of inverse transform function. Meanwhile, we can check for the error rate and positive or negative fitting of the predictions on the test data. Finally, the trained models will be exported and taken as an input parameter for a function which will provide the output as the final answer to our project. But the aforementioned was all about LSTM and STM. For ARIMA, the procedure deviates after data acquisition. We shall check for stationarity and seasonality and remove any trend that persists. Later, we make create persistence model, AR, MA and the ARIMA model. The model performance can be evaluated on the basis of error rates and fitting level. At last, comparison will be made to figure the best algorithm – suitable for low-frequency dataset. This study will enhance the efficiency of the power plants in terms of cost as well as power production - which will later lead to lowering the equipment failure frequency and demand for coal (as coal prices are growing exponentially - nowadays they are being imported !).

Chapter 5

Proposed Architecture



Firstly, dataset will be acquired from the government website. As the dataset shall have many attributes - denoting the values of power production of a particular powerplant and power consumption rate of various states the plant cater, data filtering procedure will come handy. As the models won't efficiently accept large values, data will be transformed. Afterwards, data splitting will be done for training and testing purpose. Model creation will take place after importing appropriate libraries. The training data will be fed to the model by setting numerous epochs - for greater accuracy and lower loss value. The trained model will be tested on the remaining data. Eventually, evaluation of the model performance will be done through evaluation metrics. The models will then be exported and fed to a function as the input parameter - to predict the unknown future values. The aforementioned procedure is relevant for LSTM and STM algorithms. For ARIMA, the data has to be stationary and that too without trend. Hence, the data after getting filtered out will be test for any stationarity and thus, be de-trended. Also, correlation will also be found with respect to the current data and lagged data. Then, models will be created for training and testing purpose, which eventually lead to exporting the model to be fed as function input parameters. At last, the prediction results will be compared to figure out the best algorithms - effective for industrial usage.

Chapter <N/A>

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