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Research Paper

APPLIED MANAGEMENT & MATHEMATICS

An Adaptive Neuro-Fuzzy Inference System for the Prediction of Kansai International Airport Domestic Passenger Demand

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ABSTRACT

This paper proposes an adaptive neuro-fuzzy inference system for predicting an airport's domestic air passenger demand. Osaka's Kansai International Airport was selected as the case site for the study, which covered the period 1994 to 2018. The combination of an artificial neural network with a fuzzy inference system provides a hybrid neuro fuzzy inference system that can predict an airport's domestic air passenger demand with a high predictive capability. In this study, coefficient of determination (R^2-value), root mean square errors (RMSE), mean absolute errors (MAE) and the mean absolute percentage error (MAPE) were used to test the performance of the proposed ANFIS model. The mean absolute percentage error (MAPE) for the overall data set of the model was 5.15%. The highest R^2-value in the modelling was around 0.9742, which suggests that the ANFIS is an efficient model for predicting Kansai International Airport's domestic passenger demand.

Keywords: Adaptive neuro-fuzzy inference system, Airline passengers, Airport, ANFIS, Forecasting, Kansai International Airport, Subtractive clustering technique

Airports are one of the most important stakeholders in the global air transport industry value chains, acting as the critical interface point between the surface-based and air transport modes[1]. In 2018, the world's airports facilitated the movement of 4.32 billion passengers and 58 million tonnes of air freight[2]. Furthermore, the air transport industry passenger volumes could double to 8.2 billion passengers in 2037[3]. To handle the predicted air travel demand, airports all around the world will need to make capital intensive investments in airside and landside infrastructure. Considering this, highly accurate air transport forecasts will be of vital importance.

In recent times, air transport demand forecasting has been attracted growing attention, particularly due to the intrinsic difficulties and practical applications. When forecasting air transport demand, the total

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number of passengers are used as a proxy for air transport demand[4]. Forecasting air passenger demand is a vital element of formulating appropriate operation plans for airport operations[5]. Furthermore, the forecasting of future air transport demand is particularly critical in the development of airport master plans, including both to the airside (runways, taxiways, aprons, technological devices) and the landside (boarding/landing area, waiting rooms, and so forth)[6].

The objective of this study is to develop and empirically evaluate an adaptive neuro-fuzzy inference system model for estimating Osaka's Kansai International Airport domestic passenger demand. Kansai International Airport is a major air transport hub that handles both domestic and international passengers. The airport is Japan's third busiest airport. This is the first reported study where an ANFIS approach has been applied to predict an airport's domestic air travel demand.

The remainder of the paper is structured as follows: Section 2 presents the adaptive neuro-fuzzy inference system (ANFIS) modelling approach. The empirical results of the Kansai International Airport ANFIS domestic passenger modelling is presented in Section 3. The key findings of the study follow in Section 4.

MATERIALS AND METHODS

Study Data Set

The duration period of the study was from 1994 to 2018. The annual number of enplaned domestic passengers at Kansai International Airport was sourced from Kansai Airports. The world air fares data (a proxy for travel cost) was sourced from Boeing Commercial Airplanes. Japan's real gross domestic product (GDP) and the size of Japan's population were sourced from The Organisation for Economic Co-operation and Development (OECD). Japan's real interest and Japan's unemployment data came from the Bank of Japan. World jet fuel prices data was sourced from the United States Energy Information Administration. Japan's tourism attractiveness data was sourced from the Organisation for Economic Co-operation and Development (OECD).

Empirical Relationships for Estimating Kansai International Airport Domestic Passenger Demand

Air travel is a derived demand[7]. Accordingly, it significantly influenced by general economic conditions. GDP is a principal determinant of passenger air travel demand[9,10]. Real GDP and real GDP per capita were used in the modelling to measure the effect of Japan's income on Kansai International Airport domestic passenger demand. A decline in the real cost of air travel has a positive impact on passenger traffic growth[8,11]. Notwithstanding, the actual measurement of the price of air travel is generally complicated by the presence of different air fare classes that are offered by airlines[12]. Consequently, airline passenger yields are often used as a proxy for air fares[13,14].

The influence of changes in Japan's demography were considered through Japan's population and the size of the country's unemployed persons[15,16]. Population size has a direct influence on the size of an air travel market and may result in bias in the estimates if omitted from the modelling[14]. For example, a significant increase in air traffic may reflect a sudden increase in population rather than some other external factors[17]. A further factor that influences passenger air travel demand is a country's unemployment rates[7,18]. An increase in the levels of a country's employment tends to positively impact air travel demand, whilst, in contrast, rising levels of unemployment tends to depress air travel demand[19].

World jet fuel prices has been shown to influence air passenger demand[20]. During periods of jet fuel prices, airlines are often required to raise their air fares to offset the higher fuel costs. This often has a detrimental impact on air travel demand as the higher air fares make leisure travel more expensive[21]. A further factor that influences air passenger demand is a country's real interest rates[14,18]. This is because high interest rates will have a dampening influence on economic activity, and this leads to a diminishing effect on the levels of airline passenger traffic[18].

There is a symbiotic relationship between tourism and the demand for air transport services[22,23]. Considering this relationship, tourism expenditure was included in the modelling to account for the influence that tourism attractiveness has on domestic airline passenger demand[14,24].

There were three dummy variables included in the ANFIS modelling. The first dummy variable accounted for the downturn in passenger demand following the impact of the 9/11 terrorist attacks on air travel demand. The second dummy variable, the impact of SARS in Japan in 2003, which had an impact on Japanese travel patterns[25]. The third dummy variable modelled the impact of the 2008 global financial crisis (GFC) on Kansai International Airport domestic air travel demand as the 2008 GFC, as air travel demand was adversely impacted by the GFC[26].

Adaptive Neuro Fuzzy Inference System

The adaptive neuro-fuzzy inference system is comprised a fuzzy inference system (FIS) and an artificial neural network[27-29]. The membership functions are a key concept in fuzzy set theory. Zounemat-Kermani and Scholz[30] have observed "that these membership functions numerically represent the degree to which a given element belongs to a fuzzy set".

In this study, the neuro-fuzzy models were run for each combination of model parameter with varying numbers of epochs to avoid the possible over-fitting of the models[31].

This study used the Takagi-Sugeno fuzzy model. The Takagi-Sugeno Model was originally developed in 1985 and is comprised of four key elements of membership functions, internal functions, rules, and the subsequent outputs[30]. To present the study's ANFIS architecture, two fuzzy if-then rules based on a first order Takagi-Sugeno model are considered[32,33].

- Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$
- Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within a fuzzy rule, and p_i, q_i, and r_i are the design parameters which are determined during the ANFIS training process[33]. Fig. 1 shows the fuzzy reasoning mechanism.

Source: Adapted from[31].

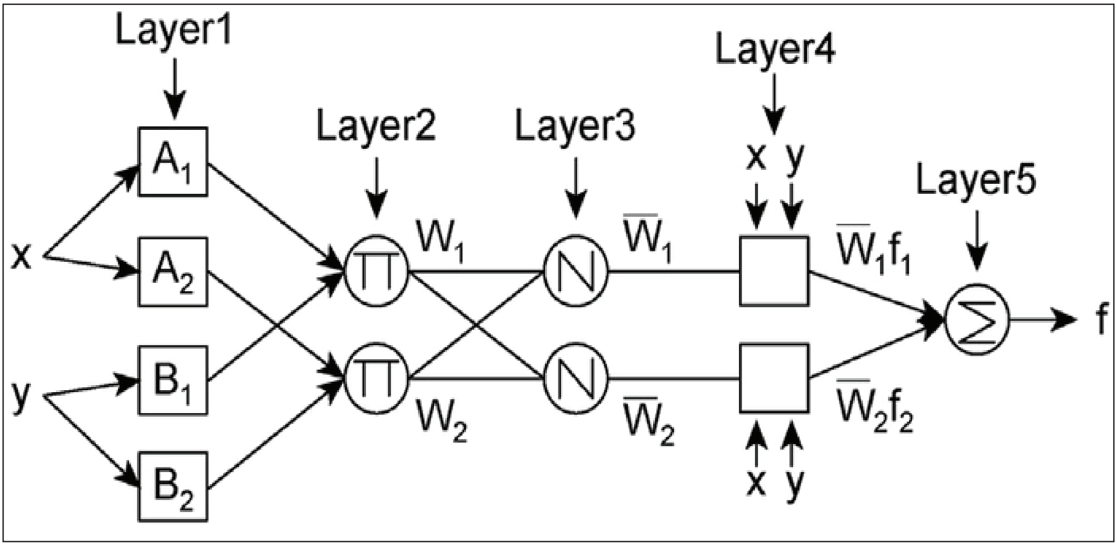

Fig. 1: Fuzzy reasoning mechanism

The study's ANFIS architecture is presented in Fig. 2. The fuzzy rules were configured based upon the Takagi-Sugeno fuzzy model and ANFIS with a back-propagation algorithm used for error correction[24,34,35].

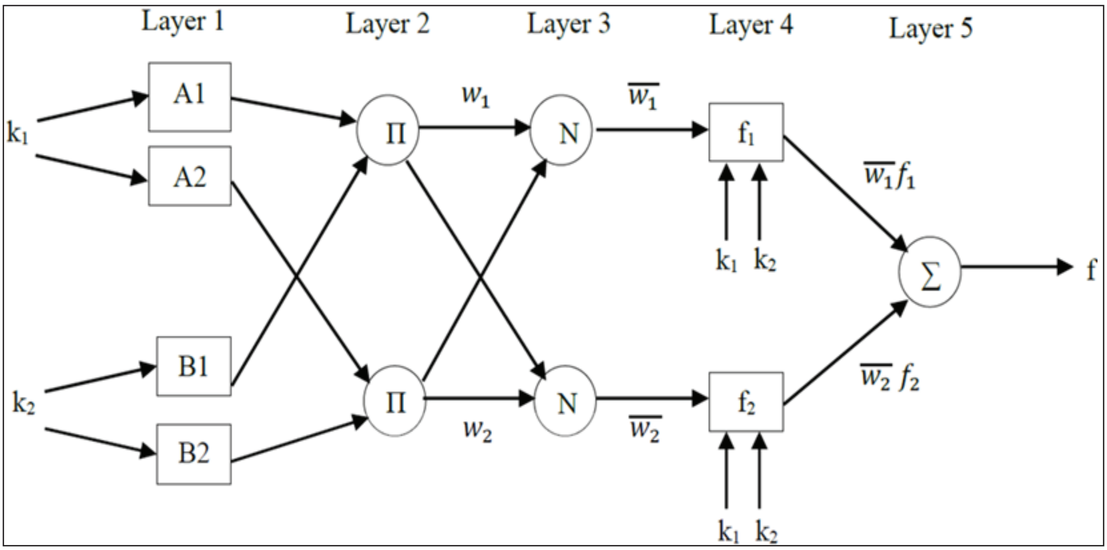

Fig. 2: The adaptive neuro-fuzzy inference system architecture

The structure of the ANFIS system is comprised of five different adaptive layers. Layer 1 is the fuzzification layer, where the names of the fuzzy sets are defined:

$$O_i^1 = \mu A_i(x), i = 1,2 \; or \; O_i^1 = \mu B_{i-2}(y), i = 3,4 \qquad \ldots(1)$$

where x and y are the input to the i^{th} node and A_i and B_{i-2} are linguistic labels associated with this node[31]. Layer 2 is a rule layer, and this layer represents the results from layer 1. Here the weight functions w_i for the following layer is defined[36].

$$O_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), i = 1,2 \quad \ldots(2)$$

Layer 3 is the normalization layer, whose nodes are labelled "*N*", indicating that they play a normalization role to the firing strengths from the previous layer[33,37].

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \quad \ldots(3)$$

where w_i is the firing strength of the i^{th} rule which is computed in Layer 2. Node i computes the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths[4]. Layer 4 is the defuzzification layer in which the nodes are adaptive nodes with a mode function[24,33].

$$O_i^4 = \bar{w}f_i = \bar{w}_i(p_1 x + q_1 y + r_1), i = 1,2 \quad \ldots(4)$$

The fifth ANFIS layer, whose node is labelled "∑", is the output layer, in which a single node calculates the overall output as a summation of all incoming signals[4,24].

$$O_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \ldots(5)$$

Prior to training the data in the ANFIS modelling process, it is critical to process the data into patterns. This normalization of the gathered data ensures that the ANFIS will be trained effectively whilst also preventing any variable skewing the results significantly[10,11]. Consequently, in this study, all the input parameters were of equal importance in training the ANN system within the ANFIS[17]. When normalizing data, the data are scaled so they come within a pre-specified range, for example, [0,1] [38,39]. In this study, all data were normalized prior to their use in the training phase using Eq. 6. Furthermore, data normalization was undertaken to transform the data into a symmetric distribution[40]. This practice enhances the ANFIS model performance, since the data appear to satisfy the assumptions of a statistical inference procedure more closely[24, 41]. The data collected for the study were normalized using the following equation:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad \ldots(6)$$

The most important steps in developing the ANFIS model are the training and testing steps as these steps define the model's characteristics [36, 41]. In this study, the total number of data used to produce the ANFIS model was 25. The data was split as follows: 80% of the overall data was used to successfully train the ANFIS model, and the remaining 5 data was used for verifying and testing the robustness of the ANFIS-based prediction models [14, 37, 41]. Hence, in this study, 20 training, 3 validating and 2 test data points were used in the ANFIS modelling.

In this study, the Gaussian membership and linear membership functions were selected. From the crisp input, the artificial neural network passes data utilizing the membership functions. The hybrid learning algorithm was applied during the training phase[14]. The training was conducted using 400 epochs. Following the guidance of Savkovic[36], "during the model training, new rules and forms of membership functions were constantly generated to produce the output with the smallest error". Once the ANFIS model's error rate was deemed acceptable, the model was subsequently tested. The final model was accepted once the relative errors of training and testing fell below 10%[36].

The ANFIS Modelling Goodness of Fit Measures

For evaluating the ANFIS models, the Root Mean Squared Error (RMSE), mean absolute error (MAE), the mean absolute percentage error (MAPE), mean square error (MSE), and coefficient of determination (R^2), were calculated using Eq. (7) –Eq. (11) [24, 42]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - td_i\right)^2} \quad \ldots(7)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left[\left|\left(\frac{t_i - td_i}{t_i}\right)\right|\right] \quad \ldots(8)$$

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\left(\frac{t_i - td_i}{t_i}\right)\right|\right]\right)\times 100 \quad \ldots(9)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(t_i - td_i\right)^2 \quad \ldots(10)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}\left(t_i - td_i\right)^2}{\sum_{i=1}^{n}\left(t_i - \left(\overline{t_i}\right)\right)^2}\right] \quad \ldots(11)$$

where t_i is the actual values td_i is the predicted values, N is the total number of data[43] (p. 104).

RESULTS AND DISCUSSION

The optimum adaptive neuro-fuzzy inference system (ANFIS) model architecture for forecasting of Kansai International Airport domestic enplaned passengers is shown in Fig. 3.

The ANFIS was trained using Matlab R2020a with the various possible combinations of the subtractive clustering parameters (range of influence (ROI) = 0.45-0.60, squash factor (SF) = 1.20-1.35, accept ratio (AR) = 0.40-0.55 and reject ratio (RR) = 0.10-0.20 for the range of epoch number from 1- 400 epochs. The constructed ANFIS model was run until the best settings were obtained based on the lowest RMSE value. The hybrid learning algorithm was applied in the training phase.

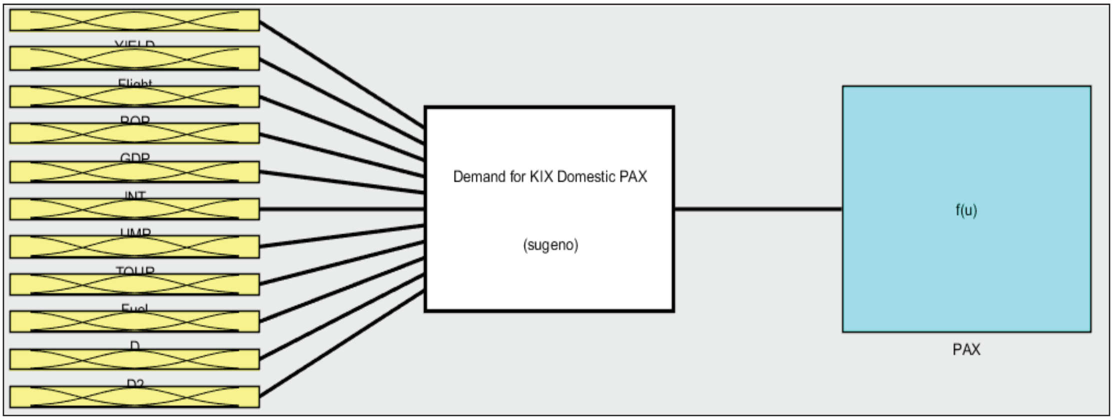

Fig. 3: The structure of Kansai International Airport domestic airline passenger ANFIS forecasting system

As previously noted, the data were normalized to the scale [0,1] in order to increase the training performance. The training process stopped whenever the maximum epoch number was reached, or the training error goal was achieved. The root mean square errors (RMSE) became steady after running 2 epochs for the training data. The final convergence value was 0.000000197.

Figures 4 presents the surface graphs obtained from the ANFIS. These graphs show the variation of output with respect to two various parameters (X and Y-axis) [44].

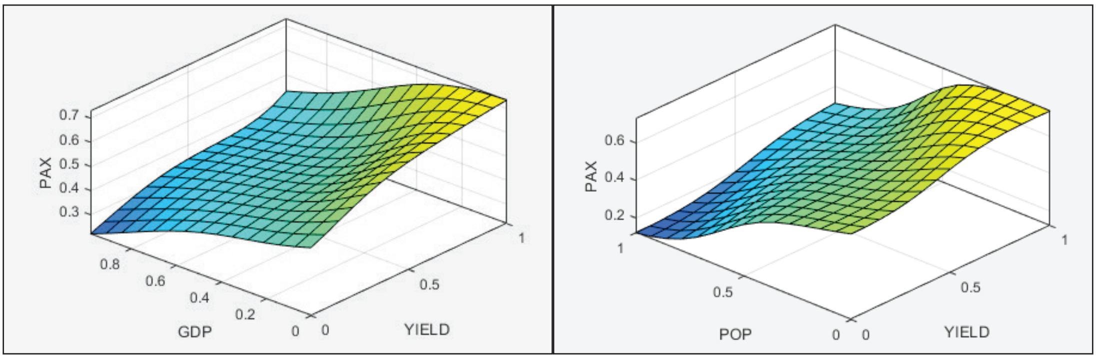

Fig. 4: Obtained surfaces in ANFIS model: Kansai Airport domestic passengers versus airline passenger yields, Japan GDP, and population

Following training, the ANFIS model for forecasting Kansai International Airport's domestic enplaned passengers was validated by selecting 5 data points, which are different from the other 20 points used for ANFIS training[45]. Each validation data point was fed into the system and then Kansai Airport predicted domestic airline enplaned passengers was computed and compared to the actual values. The performance index for the training, validating, testing, and overall data of the ANFIS model was calculated as shown in Table 1. Table 1 shows that the ANFIS model has a very satisfactory predictive accuracy. The model shows that MAE, MAPE, MSE, RMSE are very low for training, testing and overall data sets.

Table 1: Performance metrics for the different aspects of the ANFIS

Performance Index	Training Data	Validating Data	Testing Data	Overall Data
MAE	2.18×10^{-3}	1.22×10^{-1}	4.53×10^{-2}	2.01×10^{-2}
MAPE	0.92%	32.15%	6.97%	5.15%
MSE	7.45×10^{-6}	2.19×10^{-2}	2.08×10^{-3}	2.80×10^{-3}
RMSE	2.73×10^{-3}	1.48×10^{-1}	4.56×10^{-2}	5.29×10^{-2}

The actual and predicted values of Kansai International Airport domestic airline enplaned passengers are plotted in Fig. 5. The figures clearly show the fit of the ANFIS to the actual data, indicating the extremely high estimation accuracy of the study's ANFIS model.

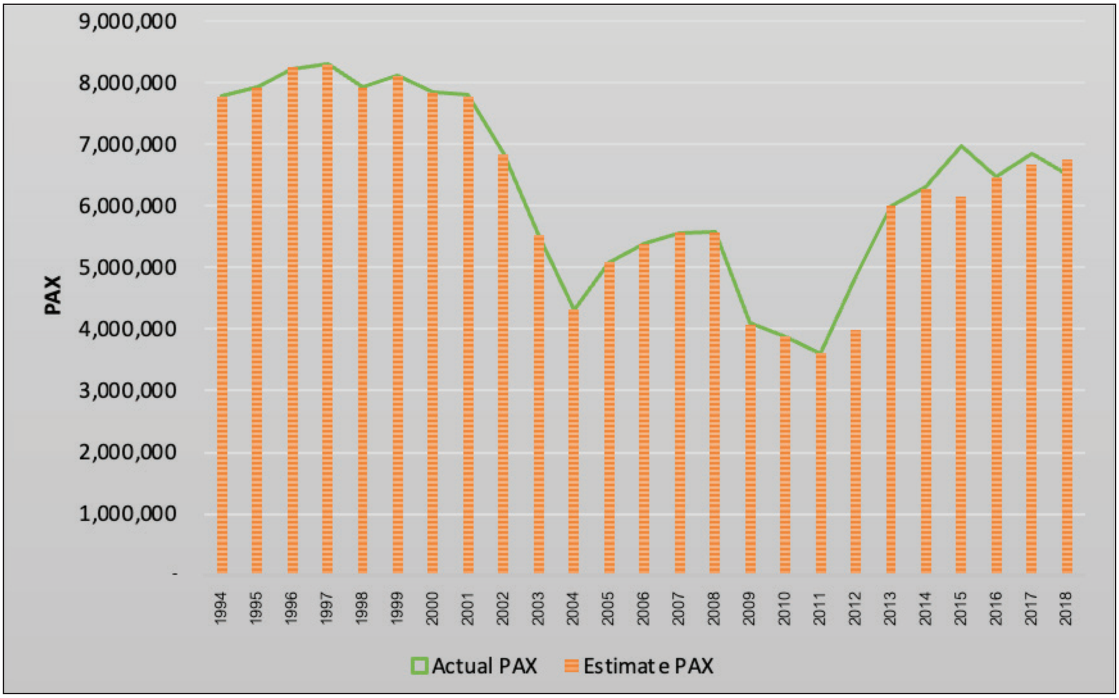

Fig. 5: A comparison of Kansai International Airport actual and estimated domestic airline enplaned passengers

CONCLUSION

This paper presents for the first time an adaptive neuro-fuzzy inference system that enables the prediction of an airport's domestic air travel demand. The study was based on Osaka's Kansai International Airport and covered the period 1994 to 2018. The ANFIS model demonstrates a high level of performance in predicting an airport's future domestic air passenger demand. This study can be usefully applied to other airport's that handle domestic passengers too, with the identical or similar input parameters.

Thus, in this study, a Takagi-Sugeno-based ANFIS model was successfully developed and applied for the prediction of an airport's domestic air passenger demand. The subtractive clustering algorithm was used to develop the optimum fuzzy model structure. The data used in the study were divided into three discrete data sets from which 80% of the data were used for training the ANFIS model, and the remainder were used for validating and testing the model. The results found that the mean absolute percentage error (MAPE) for the overall data set of Kansai International Airport domestic passenger demand model was 5.15%.

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