Adaptive Driver Model for Velocity Profile Prediction

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Abstract: Modern driver assistant systems are responsible for maintaining safe and reliable operation and reducing the energy consumption in electric vehicles since these systems have to possess the capability to predict the expected load. Drive cycles can not fully coincide with real driving behaviour and a one-time test does not reflect the overall traffic and road conditions. The Interval-Type-2 (IT2) Fuzzy System is proved to be a higly efficient tool for modeling uncertainties. In contrast to conventional Type-1 fuzzy modeling an IT2 Fuzzy System has the ability to deal with flexible the various types of uncertainties and modeling errors simultaneously and approximates better real-life systems. This paper presents an Adaptive IT2 Fuzzy System for velocity profile forecasting from the measured velocity and acceleration data. The adaptive driver model is based on Interval Type-2 fuzzy sets. Histograms of input features are used for generating membership functions which parameters are adaptiveley tuned according to the driver's behaviour. Simulation results validate the efficiency and demonstrate that the proposed method is a viable alternative of conventional time series prediction.

Key–Words: Interval Type-2 Fuzzy System (IT2FS), adaptive fuzzy model, driver model, driving cycle, velocity profile, driver assistant system, time series prediction, intermittent operation, electric vehicles, intelligent systems

1 Introduction

Modern electric drive systems require more sophisticated monitoring and diagnosis methods for determining the expected life-time and reliability. Recently, continuous assessment of the electrical condition of electrical machines and future energy demand prediction have become increasingly important. The energy demand is influenced by the operation mode, typically driving cycles give recommendations for the system design however they do not provide precise information on the expected intermittent operation and can not be applied directly in an intelligent energy management and driving assistance system. The base theory of predicting future values of a time series covers a range of disciplines. The main goal of time series analysis is to forecast future values of the series, formally to determine the time series $v(t+1)$ from its past data $v(t, t-1, t-2, ..., t-(n-1))$. Various forecasting methods are exist [1], however the choice of the type of the model to develop involves trade-offs between time, computation costs and desired forecast precision. Data-driven approaches are based on data collected by on-line measures gathered with sensors in order to approximate and track features for revealing and forecasingt the global behavior of a system that leads to its deeper understanding. Data-based techniques can be separated into two categories. The statistical methods, such as multivariate statistical methods, linear and quadratic discriminators require quantitative measurements and the result is a stochastic estimation of the future state [2]. Artificial intelligence (AI) and Soft Computing techniques (fuzzy and neural network-based models, etc.) are found to be highly efficient due to their flexibility, robustness and easy interpretability. Especially in cases where the problem to be solved is highly nonlinear or when only partial, uncertain and/or inaccurate data is available. Soft Comupting methods are particularly fruitful also in situations which require data fusion technology to combine and propagate information received from various objects. Recent research activities in forecasting with soft computing techniques suggest various approaches, for example [3] presents a hybrid methodology that combines succesfully artificial neural networks with autoregressive moving average model.

Fuzzy logic is an efficient Soft Computing tool that allows a system to reason with uncertainty [4]. In real world situations the numerical data may be noisy, inconsistent and incomplete and the linguistic information is imprecise. A fuzzy inference system is based on a set of if-then rules defined over fuzzy sets, which generalize the traditional set theory by introducing a membership degree to be any value between 0 and 1. Fuzzy reasoning systems are widely applied in practice in the fields of multiple criteria decision making, computer vision, control engineering, diagnostics, etc, (see, for e.g. [5]). The knowledge that is used to build these fuzzy rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions Type-1 fuzzy systems. Type-2 fuzzy sets were introduced by Zadeh as an extension of the classical Type-1 fuzzy sets [6]. A Type-2 fuzzy set is characterized by a fuzzy membership function (MF). In contrast to Type-1 fuzzy sets, where the membership grade is a crisp number, a membership grade of a Type-2 set is a fuzzy set. The main advantages of these sets that they allow directly managing uncertainty about the membership grades themselves [7]. Type-1 fuzzy sets used in conventional fuzzy systems cannot fully handle the uncertainties may present in complex, dynamically changing or latest real-world intelligent systems. For instance, when linguistic information does not provide any information about the shapes of membership functions any available information about the linguistic or numerical uncertainty can be incorporated in the Interval Type-2 Fuzzy Systems (IT2FS) [8][9]. Therefore fuzzy sets are capable of capturing the uncertainty/imprecision in time-series prediction in comparision to other forecasting methods. However, in spite of all the benefits that IT2FSs could provide only few paper can be found and their use is not widespread yet [10][11][12][13].

Recent developments concerning driver modeling and personalized drive cycle prediction apply a variety of mathematical tools. For instance, paper [14] focuses on the development of a prediction system consisting of a combined driver and vehicle control loop in a a hybrid hydraulic truck. In paper [15] an iterative learning control is presented for vehicle speed following in driving cycle simulations. A neural network based solution is shown by the authors of study [16] which is used for identifyng the type of driving cycle. A Hidden Markov Model of driving cycle is proposed in [17], with the purpose of realizing the driving pattern in hybrid vehicles with fix routes. There is a considerable amount of literature on driving cycle analysis and recognition, however most of them rely on driving cycle standards [18][19][20][21][22].

This paper is organized as follows: Sectionc2 gives a brief summary on the driving cycles and IT2FS and outlines the new methodology for velocity profile prediction reflecting individual driving style. The described forecasting method may serve as a basis of intelligent energy and condition management system in EVs [23] [24]. The advantage of the proposed method is that the IT2 fuzzy modeling allows dealing with the uncertainties of the driver behaviour and uncertainties due to measurements noises, traffic situations, etc., simultaneously. The IT2FS employs a Mamdani-type IT2 fuzzy reasoning system in which the fuzzy membership functions are obtained directly from real driving data [25]. The adaptive data-driven tuning allows precise forecasting and catching the individual driving style. Simulation results provided in Section 4 support the applicability and efficiency of the IT2FS based prediction model. Finally, the main findings are concluded in Section 4.

2 Prediction of Velocity Profile based on IT2FS

2.1 Driving Cycles

In practice the driving profile is complicated, complex and consists of a series of frequent accelerations and regenerative breaking events. The typical values collected by sensors and GPS differ from values measured in laboratory test benches and requires the appropriate preprocessing. Two main approaches of standard driving cycles are distinguished. The New European Driving Cycle (NEDC) and Emission Test Cycles (ECE) composed of constant acceleration and decelerations values that are alternating. Such cycles are referred to as modal or polygonal [26]. For instance, the NEDC gives references for the European urban driving environment which has the average speed of 18 $[km/h]$. Its disadvantage is that it does not take into account the driving on highway which is a significant part of the vehicle's life cycle. Since from year 2000 the NEDC has been extended with the higway driving cycles (EUDC - Extra Urban Driving Cycle). The NEDC consists of four urban and one highway cycles, the total distance is 11 $[km]$, total time is 1200 $[s]$ and the average speed is $32,5$ $[km/h]$, maximum speed is 120 $[km/h]$. The other type is closer to the real speed profile, more dynamic than polygon models and composed from sudden accelerations and slowdowns since it reflects better the velocities according to the road conditions. The North American drive cycles belonging to the latter have different standards, such as the FTP-72 (Federal Test Procedure) driving cycle which simulates urban transport on 7.5 miles with frequent braking effects (see, Figure 1). Its average speed is $91,2$ $[km/h]$. The FTP-72 driving cycle consists of a 505 $[s]$ and a 864 $[s]$ long periods. During the second period the measurement is interrupted by a 10 $[s]$ no load operation.

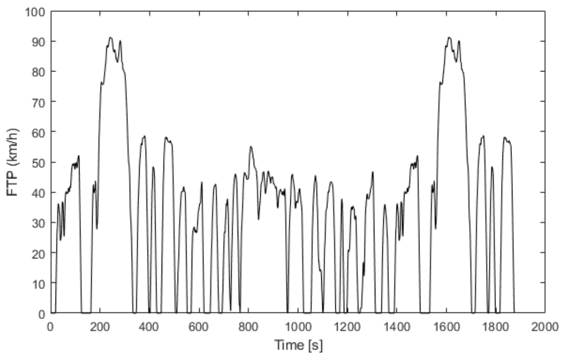

Figure 1: FTP Drive Cycle

The FTP-75 is the extension of the FTP-72 driving cycle by added a 505 $[s]$ duration with hot start. Though the driving cycles are originally created as a reference point for fossil fuelled vehicles, the recent recommendations are also used to estimate the travelled range by electrical vehicles and are capable for calculating and predicting energy demand, operational indicators, etc.

2.2 Interval Type-2 Fuzzy Systems

In this section we provide a brief summary on Interval Type-2 Fuzzy Systems. The main distinction between Type-1 and Type-2 fuzzy systems is associated with the character of the applied fuzzy set while the inherent principle is the same. The IT2 fuzzy membership function for discrete universe of discourse x and u is formulated as follows [11]:

$$\tilde{A} = \sum_{x \in X} \sum_{u \in J} \mu_{\tilde{A}}(x,u)/(x,u), \qquad (1)$$

in which $J_x \subseteq [0,1]$ denotes the first membership function of x. In case of $\mu_{\tilde{A}}(x,u) = 1, \forall u \in J_x \subseteq [0,1]$ it is an interval type membership function. Accordingly the membership grade of each element of an IT2 fuzzy set is an interval. Uncertainty is represented by the interval (commonly referred to as the footprint of uncertainty (FOU)) which is bounded by the upper membership function (UMF) and the lower membership function (LMF). Both of them are Type-1 functions. The LMF, i.e. the secondary function defines the possibilities of the first function.
The structure of the IT2FS system is displayed in Fig. 2. It can be observed, that it is equivalent with the conventional fuzzy system. Only the defuzzification process differs which contains a type reducer block that reduces the IT2 output set to a Type-1 set before performing a defuzzification method. Detailed description can be found, for instance in [12][13].

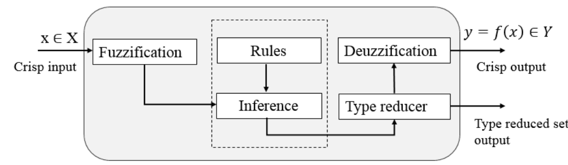

Figure 2: IT2 Fuzzy System

2.2.1 Membership Function Generation from Training Data

The determination of the suitable shape of membership function from data is still a challenging task and is the key issue in the application of fuzzy set theory. There is still considerable lack regarding the appropriate function generation technique even though the applied membership function has a significant impact on the result. Additionally its determination may limited by the available training/measurement data and the kind of application. In the literature various efforts are made to develop methods to estimate membership functions [27].
Most of the decision-making problems involve fuzzy sets that are based on imprecise, context-sensitive categories rather than concrete quantifiable values associated with the formulated problem. Assigning values to the imprecise categories requires the employment of techniques of the theory of measurement and scaling. Determination of membership functions based on perception include different methods, such as the likelihood approac and relative preference method and the parametric operators are considered suitable also [28][29]. The heuristic membership generating methods are usually applied in rule-based pattern recognition tasks because these heuristic functions can well approximate certain spatial relations or properties [30][31]. These are usually piecewise linear functions. In spite of their easy implementability the heuristic methods have several drawbacks; since these are tailored to a given problem, they work well only for problems for which they are intended; functions are not flexible enough to model different data, parameters should be maintained by experts. Other approaches are based on nearest neighbor techniques. The membership generation techniques using the rules of K-means or Fuzzy K-means methods are efficient when a priori probabilities and class conditional densities are unknown [32]. Furthermore various soft-computing techniques, such as neural networks can be applied.
A wide set of membership generating methods are

apply the histograms of the data as their input [33]. In this case the features provide information regarding the distribution of input feature values. By assigning n-dimensional attribute vectors for each class allows constructing a multidimensional histogram. After, the histogram can be approximated by the combination of various parametric fuzzy operators. Its implementation and tuning is easy once the proper training data is accessible. Since we have found this approach suitable for driver behaviour modeling.

2.3 IT2 System for Modeling Driver Behaviour

The behaviour of the driver may contain patterns related to the individual driving style, however may influenced by various external effects from the dynamically changing environment.

At first we predefine IT2 sets using averaged real driver data sets as training data obtained from [25] in urban driving environment. 80 percent of the data is used for training and the remaining is for validation. The initial data consisted of approximately 70000 samples. Alternatively drive cycle standards could be used for training also. The IT2 MFs represent the distribution of our data and the FOU catches the sensor noises, uncertainties of the driver's behaviour and traffic situations, etc. In case of high sampling rate the signal is resampled $s(x) = \frac{1}{100}$ in order to fit shorter universe. The velocity range is divided into seven inequally sized regions according to linguistic variables; $extremlyslow$, $veryslow$, $slow$, $medium$, $fast$, $very\ fast$, $extremely\ fast$ (Fig. 3). Each of them is represented by an IT2 set:

$$\rho_v^{(k)} = (\tilde{A}_1, ..., \tilde{A}_k),\ \text{k=1,...,7.} \tag{2}$$

The acceleration data is also separated into seven distinct regions which are approximated by IT2 functions built similarly. The sets are:

$$\rho_a^{(l)} = (\tilde{B}_1, ..., \tilde{B}_l),\ \text{l=1,...,7} \tag{3}$$

The ranges' histograms are approximated by Interval-Type 2 fuzzy membership functions (Fig. 4).

The upper memebership functions is a spline-based Π-shape function that is evaluated by the vector x. Its shape is controlled by four parameters; a and d is responsible for the *foot* while parameters b and c controls the shape of the function's shoulder. The

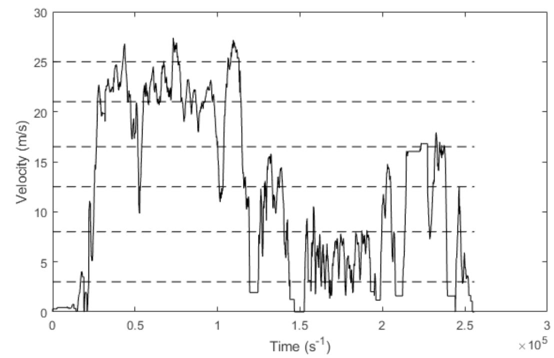

Figure 3: Regions of velocity

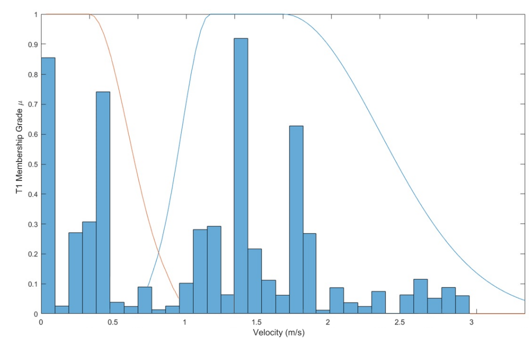

Figure 4: Extraction of UMFs from data

formula of the μ_{UMF} is defined as follows:

$$\Pi(x; a, b, c, d) = \begin{cases} 0 & x \leq a \\ 2(\frac{x-a}{b-a})^2 & a \leq x \leq \frac{a+b}{2} \\ 1 - 2(\frac{x-b}{b-a})^2 & \frac{a+b}{2} \leq x \leq b \\ 1 & b \leq x \leq c \\ 1 - 2(\frac{x-c}{d-c})^2 & c \leq x \leq \frac{c+d}{2} \\ 2(\frac{x-d}{d-a})^2 & \frac{c+d}{2} \leq x \leq d \\ 0 & x \geq d \end{cases} \tag{4}$$

The lower membership function is a Gaussian 2 membership function that approximates the histogram reduced by eliminating the salient components. This is a combination of two Gaussian membership functions. Each of them depend on two parameters. The functions are used with the appropriate standard deviation σ and mean m values as follows:

$$\mu_{LMF} = f(x; \sigma, m) = e^{\frac{-(x-m)^2}{2\sigma^2}}. \tag{5}$$

The left side of the function is defined by σ_1 and m_1 while the right curve is defined by σ_2 and m_2. The resulted IT2 membership function $\tilde{A}_1$ for region $\rho_v^{(1)}$ can bee seen in Fig.5.

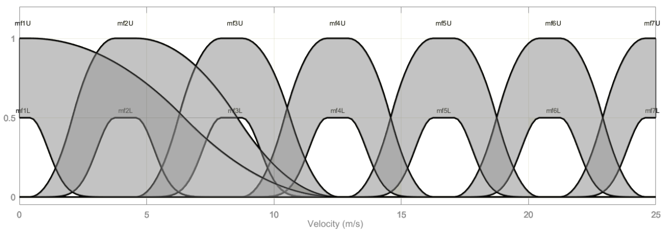

Figure 5: IT2 Membership Functions for velocity before tuning

2.3.1 Adaptive Tuning

The proposed method aims to allow real-time application by introducing adaptive tuning of the model. The dynamically changing behaviour requires continuous updates in the model in order to obtain precise prediction of the future velocity value. The membership functions are continuously tuned using the training data collected during the driving time. After the system has learned the drivers model starts the prediction. Since we perform in the time domain, this method provides efficient results independent of the type of contaminating noise. On the measured data an M long w sliding window is applied. The modeling starts with an experimentally predefined imprecise model using averaged driving cycle data of urban environment. The upper bound of the k^{th} velocity range is denoted by $r_k = r_{k-1} + d_k$, in which d_k is the covered velocity range. The algorithm at first counts the local maxima in the instantaneous sliding window and stores in vector l_{max}. If the number of local maxima in k^{th} range $l_{max}^{\rho_v^k} \leq \delta$ then range ρ_v^k is selected for alteration as follows:

$$\begin{aligned} &if\, \gamma \geq \frac{d_k}{2}\, then \\ &\tilde{r_k} = r_{k-1} + \frac{\gamma}{2} + d_k - \frac{\gamma}{2} \end{aligned} \tag{6}$$

in which $\gamma = mean(l_{max}^{\rho_v^k})$. Afterwards, the UMF and LMF parameters are modified according to the histogram evaluated from $\tilde{r_k}$.The predefined functions (Fig. 5) after tuning can be seen in Fig. 6

2.3.2 The Inference Engine

The important part that influence the quality of the result is the interference strategy which most depends on the proper rules and evaluationo. The antecedent incorporates the velocity and its adherent acceleration input. The inference engine is formulating the mapping from a given input to an output using IT2 system and provides the information on which decisions can be made. The fuzzy implication $x \rightarrow y$ is expressed

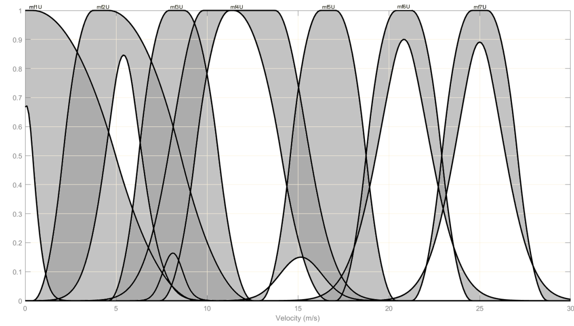

Figure 6: IT2 Membership Functions for velocity after tuning

as a fuzzy relation R, since the rules are given in the following form:

$$\begin{aligned} R_i = IF\, v(t_i)\, is\, \tilde{A}_k\, AND\, v(t_{i-1})\, is\, \tilde{A}_k \\ AND\, a(t)\, is\, \tilde{B}_l\, THEN\, v(t_{i+1})\, is\, \widetilde{A}, \\ i = 1, ..., q \end{aligned} \tag{7}$$

in which $\tilde{A}_k$ and $\tilde{B}_l$ are the antecedents and $\widetilde{A}$ is the consequent of the i^{th} rule. In this paper we consider a fifth order forecaster ($n = 5$). The rule base is built by assigning an IT2 set of acceleration for all the velocity input membership functions and for them an output velocity $\widetilde{A}$ is defined. The inference is evaluated by using product operator for both the UMF and LMF. Once a rule is fired the inference engine produces the output. For the inference the evaluated sets are aggregated by a product t-norm. Subsequently a simplified center of set type-reduction is performed [11]. After, the conventional CoG (Centre of Gravity) defuzzification method is applied for obtaining a crisp output value.

3 Simulation Results

The proposed method has been tested through simulation investigatoins in Matlab7. First we investigated the performance of the IT2FS subsequently we tested the performance of the adaptive version. The results of the velocity profile prediction performed on the validation set of the not adaptive one is displayed in Fig.7. The performance of the adaptive IT2FS can be seen in Figs.8-9

The performance has been evaluated by the metrics below. The mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) are computed as:

$$MAE = \sum_{t=1}^{s} |v_t - \hat{v}_t| / s, \tag{8}$$

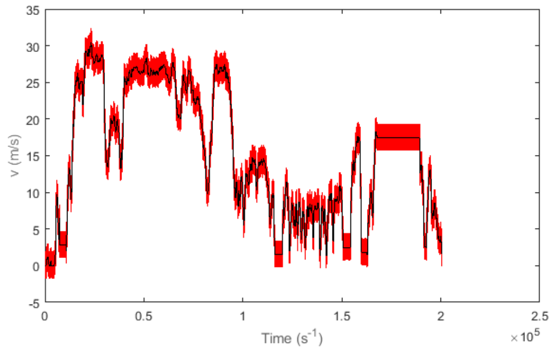

Figure 7: The measured $v(t)$ $(black)$ and predicted $\hat{v}(t)$ (red) velocity profile before the tuning

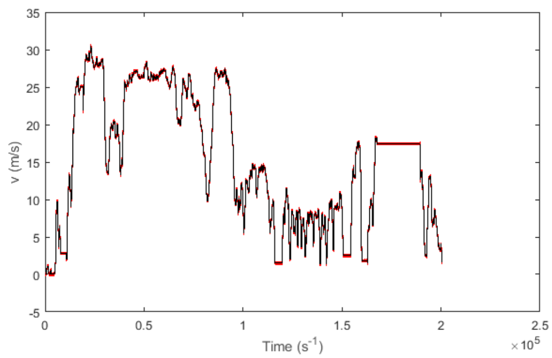

Figure 8: The measured $v(t)$ $(black)$ and predicted $\hat{v}(t)$ (red) velocity profile with the adaptive IT2FS

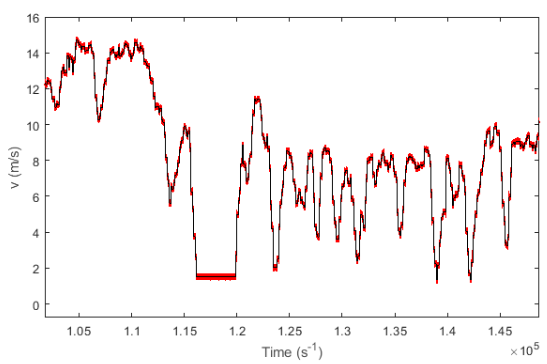

Figure 9: The measured $v(t)$ $(black)$ and predicted $\hat{v}(t)$ (red) velocity profile using the tuned model

$$MSE = \sum_{t=1}^{s} (v_t - \hat{v}_t)^2/s \tag{9}$$

$$RMSE = \sqrt{\sum_{t=1}^{s} (v_t - \hat{v}_t)^2/s}, \tag{10}$$

Table 1: Prediction errors.

	e^1	e^2
MAE	0.9034	0.0927
MSE	1.0908	0.0122
RMSE	1.0444	0.1107
Abs max error	3.997	2.0601

The results are collected in Table 1. in which $e^1 = v_t - \hat{v}_t$ stands for error of the non-adaptive case, $e^2 = v_t - \hat{v}_t$ represents the adaptiveIT2FS's error.

The computational results support the theoretically expected advantages of the method in connection with the modeling errors, sensor uncertainties and measurement noises. However, further improvement could be achieved by higher resolution of the velocity ranges and by applying a higher number of MFs. The results are encouraging and should be validated by a larger sample size.

4 Conclusions

This paper presents an Adaptive Interval-Type-2 Fuzzy System for predicting velocity profile in association with individual driver behaviour. The advantage of the proposed method is that the IT2 fuzzy modeling allows dealing with the uncertainties of the driver behaviour and uncertainties due to measurements noises, traffic situations, etc., simultaneously. The IT2FS employs a Mamdani-type IT2 fuzzy reasoning system in which the fuzzy membership functions are obtained directly from real driving data. The results provided in the previous sections show that the IT2FS is a suitable and efficient tool for driver model building and velocity profile predictions. Results have shown that by introducing adaptivity the prediction error can be significantly reduced. Its easy inmplementability allows its real time application and suitable for modern driving assistant systems providing considerable benefits e.g. for energy demand management. In conclusion our work represents a viable alternative of conventional time series prediction applicable .

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