

# Extraction of reliability indicators from large-scale, highly variable timing data of MEMS switches

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## Abstract

**In this paper we present a method for monitoring and processing large-scale highly variable and non-linear reliability data for MEMS RF Switches. The data is generated by measuring the switch actuation dynamics and a combination of statistical methods are applied to extract the switch closure/opening time. The signal processing is performed in a 2-step approach encompassing basic parametric and non-parametric statistical methods to correctly categorize the obtained datasets, supplemented with a mean-first derivative algorithm to extract the reliability indicators from the filtered data. The presented procedure proves to be highly accurate generating very low error in dataset classification. The acquired results give an insight into the evolution of switch health throughout its whole operation cycle and can lead to further understanding of failure mechanisms in micro-mechanical structures.**

## I. Introduction

Despite extensive research in the area of MEMS switches little is still known about the cause of their failure and how to prevent it. Some studies have highlighted the importance of mechanical effects like material creep[1,2], surface effects[3] or electrical influences[4]. But in most cases it is a combination of all of the above which decides if the device works or fails[5]. Therefore for MEMS there is currently no consistent method of predicting switch failure.

The first step in a device failure prediction is an established and reliable health monitoring system which can be generalized to many different designs and operational during a normal device usage. Unfortunately because of the MEMS sizes and their need to work in a strictly controlled environment the number of available health monitoring methods is very limited. The most popular ones are: pull-in voltage monitoring, resistance check after the device closes and optical methods such as SEM imaging or white light interferometry. Unfortunately the optical methods cannot be applied to final product - switches which are sealed in a hermetic package. For the remaining electrical methods their significant drawback is the fact they are a static-type measurement which can only be done when the device

operation is paused and therefore can miss the signs of a device approaching failure.

In the paper presented at the recent MME2012 conference[6] we proposed a dynamic approach (usable during the device operation) to the health monitoring of MEMS devices and proved that the switch opening and closure times evolve over the device life cycle and their change can be correlated with the degradation of device health. To verify the usability of this approach and understand the relation between the monitored response of the switch and its proximity to failure we have developed a large-scale reliability test which encompasses different types of MEMS switches.

Unfortunately, a major difficulty in this test is the amount of devices and data which have to be processed to generate useful results. Therefore, quantifying key parameters has to be automated. The challenges faced in this work are the large amount of data generated per switch test, high data variability and data non-linearity. In this paper, we present the algorithm used to process the data and provide a base for future development into a real-time monitoring and/or failure prediction system.

This paper is organized as follows: Section II introduces the reader to MEMS switches; Section III describes the tested samples; Section IV presents the testing setup and procedure, Section V presents the data processing methodology and identification of results; Section VI draws conclusions from the work outlined and presents future developments of this method.

## II. MEMS Switches

Microelectromechanical (MEMS) RF switches are a group of mechanical devices with their largest dimensions typically in the range of  $\mu\text{m}$ . They are produced in different types and shapes but their principle of operation can be differentiated into two main types: ohmic and capacitive[7]. In the first case the switching mechanism is based on breakage/formation of a direct electrical path whereas in the second case the switching is done by the increase/decrease of the existing capacitance in the circuit thus creating a "barrier" in high-frequency solutions. MEMS switches when compared to a more traditional p-i-n diode or FET switches have much better electrical parameters like: energy consumption in off-state, isolation or insertion loss but unfortunately as a mechanical device are susceptible to a higher amount of failure mechanisms[8] than a pure electronic device. Thus reliability issues are the major factors which slow down the MEMS switch market. To allow further development of this market it

is of crucial importance to establish a detailed understanding of the switch failure mechanism.

### III. Tested Samples

For the purpose of result comparison three types of MEMS ohmic RF switches have been tested.

The first two types represent a simple reference MEMS switch with a basic construction, differentiating only in the shape of the switch anchor (Figure 1):

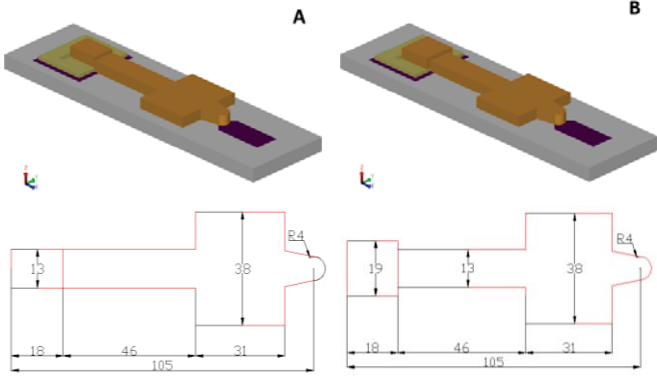


Figure 1: Basic reference MEMS switches type: Type1(A) and Type2(B), dimensions in  $\mu\text{m}$

In both Type1 and Type2 the material used for beam formation was  $h = 6 \mu\text{m}$  electroplated gold with a designed electrode gap  $g_d = 0.6 \mu\text{m}$  and a contact gap of  $g_c = 0.26 \mu\text{m}$ .

The third type of the tested samples was a high-reliability construction similar to that described in the work of Goggin et al.[9]. A SEM picture of the switch is presented in Figure 2

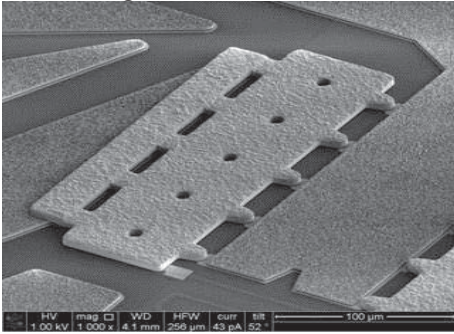


Figure 2: SEM image of Type3 tested sample

Similar to the Type1 and Type2 the switch material was  $6 \mu\text{m}$  electroplated gold. The dimensions of this design are: electrode gap  $g_d = 0.6 \mu\text{m}$ ; contact gap  $g_c = 0.26 \mu\text{m}$ ; rectangular region over the actuation electrode: length  $l_{oe} = 63 \mu\text{m}$ , width  $w_{oe} = 38 \mu\text{m}$ ; five tethers connecting the beam to the anchor have length  $l_t = 14 \mu\text{m}$  and width of  $w_t = 14 \mu\text{m}$ . Further in this article this switch will be referred to as Type3.

In total there were 20 of Type1 and 18 of Type2 tested. To supplement them 3 of Type3 switches were added to the test.

Before a reliability experiment each switch was tested for its actuation voltage (voltage at which the

switch closes). Results of those tests are presented in the Table 1.

Switch Type	Actuation Voltage Range
Type1	46.2 – 65.4 V
Type2	48.5 – 75.6 V
Type3	42.6 – 66 V

Table 1: Starting Actuation Voltage depending on the switch type

The visible spread of starting actuation voltage highlights one of the factors which makes reliability prediction and data analysis such a problem in micro-devices. Due to the specifics of the fabrication process there are no two identical devices. Even when created with the same method there will be minimal differences (asperities) in the surface of the contact pads as well as structural variances in the beam and anchor. Unfortunately, those differences can have a significant impact on the device performance due to changes in the resulting surface/restoring forces.

### IV. Testing Setup and procedure

The purpose of the reliability tests was to gather a detailed closure/opening characteristic of the switches in motion from an unused state to failure. Because of the fact that the tests had to be performed in an environment as close as possible to regular switch usage a removal of the protective cap over the MEMS switch was not an option, thus optical test methods were excluded. The chosen methodology was an electrical approach which in principle measures the existence of a current flow through a closed switch. This method was previously described by Do et al.[10] in his work on performance of MEMS switches.

The testing station consisted of a GPIB controlled waveform generator, x50 voltage amplifier, 500 mV voltage source and a GPIB controlled oscilloscope for data acquisition. The acquired data was transmitted via a GPIB connection to the PC with a Labview – based control and data saving program. A schematic of the experiment setup can be seen on the Figure 3

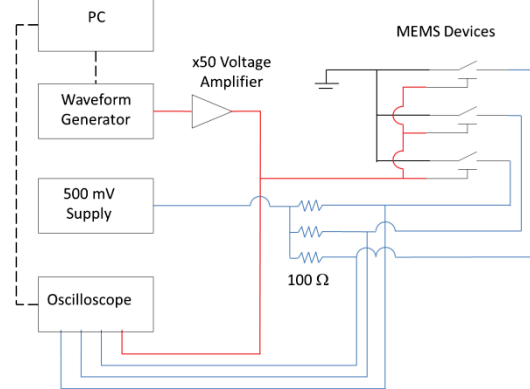


Figure 3: Testing Station Schematic

On this test setup two types of experiments were performed simultaneously:

a) The Cycling Test

The aim of this test type was to introduce the switches to a repeatable actuation to simulate their normal operation.

The tested samples were actuated with a 50% duty cycle square wave waveform from 0 to 70 V to introduce a repeatable closing motion in the switches. The frequency of the waveform was chosen to be 28 kHz as it allowed for a fairly fast switch failure event – for a typical  $10^{10}$  life cycles switch the estimated failure for a continuous 24h actuation would take ~4 days. The sampling resolution of the scope was set to 40 ns/point in a 500 sample length, further on exchanged into 20 ns/point in a 1000 sample length. This setting allowed to record the full response of the switch for the applied actuation voltage. To limit the amount of data the scope measurements were taken every 5 s.

b) The Pull-In Voltage test

The aim of this test type was to monitor the change of the closing voltage of the samples during the process of cycling actuation.

Additionally to the cycling test the pull-in voltage of the switches was checked every 110 measurement cycles (4 channels measurement + data saving = one measurement cycle). The procedure was to raise the actuation voltage of the switch from 0 till the point when a switch closure event was registered. This event was defined as a drop of the 500 mV signal to a level below 300 mV which would indicate a high resistance electrical connection between the switch tip and the contact pad.

## V. Data Processing and Analysis method

a) Scope of the problem

An initial evaluation of the combined static/dynamic characterization method was carried out by manual data analysis and yielded promising results[6]. Due to the large amount of data per each switch tested, scaling the experiment to a statistically significant sample size requires automatic parameter extraction from each dataset. For the dataset used in this work over 300 GB of data with a detailed record of switch movement and pull-in voltage characteristics changing with time have been recorded To the author’s knowledge this is the first report of an automated analysis algorithm for such a MEMS data set. Examples of the obtained datasets can be seen on figures below. Figure 4 illustrates a Type3 switch response and Figure 5 shows a Type1 switch response.

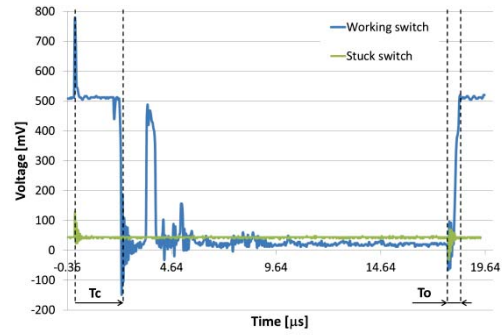


Figure 4: Example Type3 switch dataset

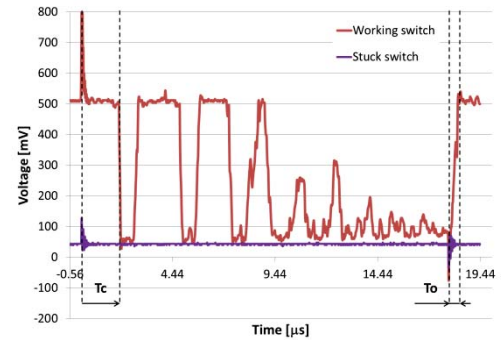
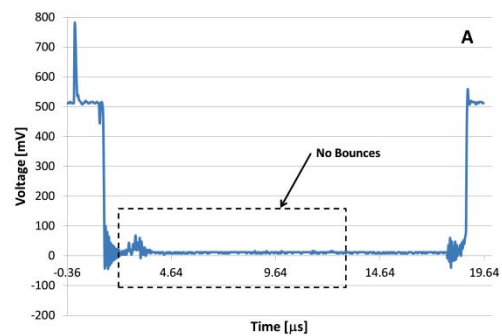


Figure 5: Example Type1 switch dataset

A failure of a switch was defined as a situation where the switch has become stuck–down to the contact surface thus producing a constant voltage drop across the circuit, an example comparison of working switch response vs. a stuck-down switch can be seen on the previously described Figure 4 and Figure 5.

The key parameters which are of interest in this experiment are marked  $T_c$  – Closure Time and  $T_o$  – Opening Time, during the course of the experiment it was proven that both of these parameters change with the degradation of switch health. Unfortunately each switch exhibited a high variability in its response an example of such a behavior has been show in Figure 6 below.



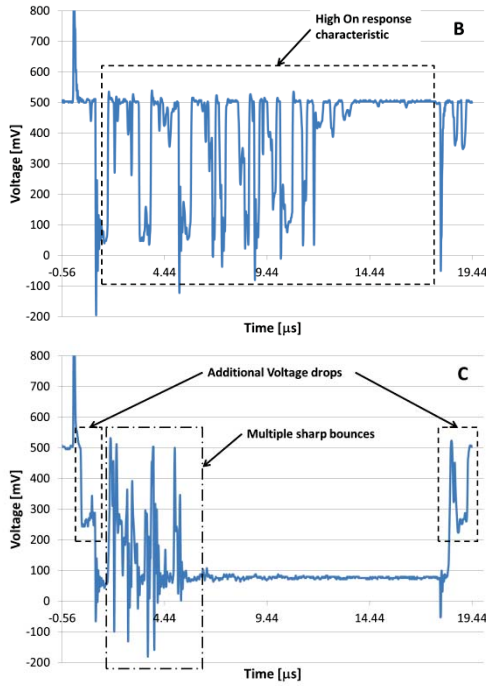


Figure 6: Examples of variability in acquired data: *A* - Bounces can disappear (also described by Fruehling et al. [11]), *B* – Switch response indicating no closure – high voltage value after supplying with actuation voltage, *C* – Additional voltage drops around the closure/opening events and/or sharp multiple bounces

Therefore the extraction method had to account for such variability in all of the acquired data on top of distinguishing between a working and a failed switch.

#### b) Signal Filtering

The first step to extraction of  $T_c/T_o$  was to separate the acquired data for usable and non-usable. After trying typical statistical methods (standard deviation, variance, median and others) and filtering techniques the method which was exhibiting the best results was using the kurtosis parameter to distinguish between a working and a failed device.

As described by Balanda et al.[12] the kurtosis parameter could be described as a measure of peakedness of the analyzed signal. Kurtosis of a distribution  $H$  is defined as:

$$\beta_2(H) = \frac{\mu_4(H)}{(\mu_2(H))^2} \quad (1)$$

Where:

- $\mu_4(H)$  – is the fourth moment about the mean of the distribution  $H$
- $\mu_2(H)$  – is the second moment about the mean of the distribution  $H$  or simply standard deviation of  $H$

With this definition a kurtosis value of a normal (Gaussian) distribution has a value of 3.

This analysis method was based on the fact that the general shape of a working device response was known and the typical obtained voltage values would follow a

Gaussian point distribution (majority of data points for a working switch would be in the “closed” region where the voltage values would not exceed 100 mV).

Through manual analysis of a limited set of samples it was determined that a normally working switch has a kurtosis value of its points in the range of 0 to 6 with some exceptions reaching values above 10. In case of the stuck-on data due to the fact that the spread of data was very limited the point distribution was more “sharp” in shape, the signal had more “peaks” when compared to its mean value and thus the kurtosis was reaching values over 30. After identifying the general kurtosis threshold for working switches as a value of 6, a “cut-off filter – type” process was designed:

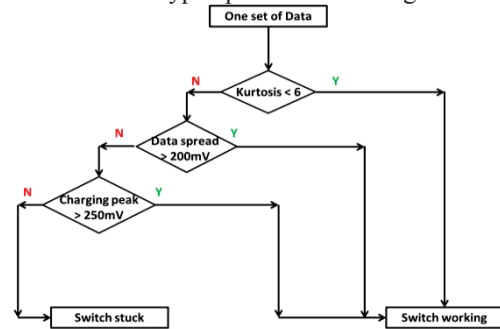


Figure 7: kurtosis Filter, 1 step: Stuck-On separation

This method proved to be highly successful in identifying and separating the unusable (either stuck-on or no distinct voltage drops) data from further analysis with no errors. This approach should be generally applicable to any MEMS switch with a similar operating behavior, although the kurtosis threshold value should be verified if using different designs also the voltage detection limits depend on the used testing setup and should be adjusted accordingly.

The second step of data preparation was to identify the variability of the data and validate its usefulness for  $T_c/T_o$  extraction. In some cases (see example in Figure 6B) the  $T_c$ ,  $T_o$  or both could be undetectable. Unfortunately using variance, mean and standard deviation proved to be not effective therefore an approach using boxplot parameters to describe the data spread was used. The parameters in question which were needed to describe the data were:  $Q_M$  – Median of the dataset,  $Q_U$  – Upper Quartile and  $Q_L$  – Lower Quartile. All of these parameters are defined as follows[13]:

- $Q_M$  – middle value of data after the dataset has been ordered from lowest to highest value.
- $Q_U$  – middle value among the data values above the median. Or 75% percentile of the dataset.
- $Q_L$  – middle value among the data values below the median. Or 25% percentile of the dataset.

For a working switch with a near-ideal spread of data (see Figure 4) the  $Q_M$  value should be close to the  $Q_L$  value due to the fact that the majority of data is situated in the closed position with values below the 100 mV level. At the same time the  $Q_U$  parameter should have a value much higher than the  $Q_L$  due to the

existence of the open regions when the switch has a value close to 500 mV level. Therefore the first criterion of the distinguishing algorithm is formed:

$$Q_U - Q_M > (Q_M - Q_L) * det\_const \quad (2)$$

The variable *det\_const* determines the sensitivity of this detection. Through manual testing on a limited number of datasets a value of *det\_const* = 1.3 was found to be optimal. In case of measurements with a large number of “sharp” bounces or a switch with no bounces at all the  $Q_U$  parameter can exhibit a lower value therefore it was a necessity to add a second criterion which would verify the  $Q_U$  level in respect to the kurtosis of the dataset. Therefore the finished second step of the filtering/distinguishing can be summarized as:

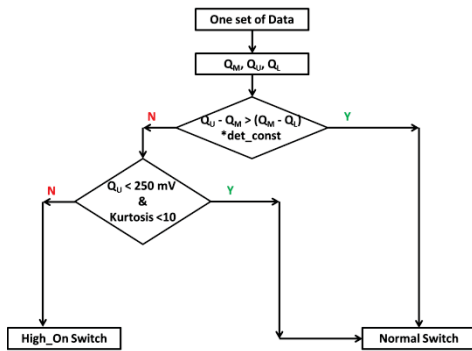


Figure 8: kurtosis Filter, II step: High\_On/High error signal type identification and separation

After application of the described method (both step I and step II) to the acquired data, three types of datasets have been produced for each tested device: UND – unusable data either after switch failure (visible as a continuous red area) or with no distinct voltage drops (single red lines); High\_On – highly variable data with large amount of voltage drops or no-closure events, impossible to generate a general  $T_c/T_o$  extraction method for all datasets in this category, Normal – data for analysis via a general  $T_c/T_o$  extraction method. Depending on the switch type the amount of datasets in each category was different. An example of a switch data distribution after applying the developed filtering method can be seen on Figure 9 below.

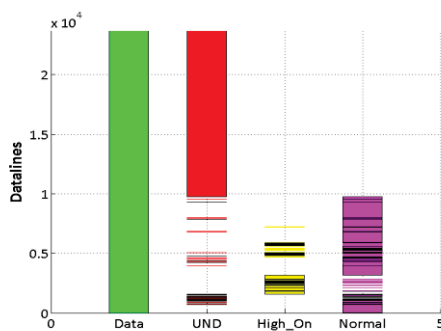


Figure 9: Type1 switch data separated into categories after filtering

### c) $T_c/T_o$ extraction method

The chosen method for  $T_c/T_o$  extraction was based on calculating the first derivative of the previously pre-processed input signal and using it to identify the existence of voltage peaks in the data. The locations of the peaks were afterwards processed using a  $T_c$  or  $T_o$  algorithm to correctly calculate the sought parameter. As the whole analysis was done using Matlab environment, Matlab in-built function *findpeaks.m* was selected as a method to detect peaks in switch data.

The first step to calculate either a  $T_c$  or  $T_o$  from the dataset was to identify the “charging peak” location in the dataset. The charging peak is a short voltage increase in the signal near the starting point. In the presented switch response graphs (Figure 4-6) it is located at point 0 on the x-axis. The charging peak is generated when the 70V actuation voltage is applied to the switch. Therefore, it indicates when the device has started to move downwards into the closed position. Because of the fact that this value is usually the largest voltage peak in the whole dataset and its position is known to high accuracy (location depends on the Scope triggering setup which does not change during the experiment) a simple Maximum value check with a detection threshold on a limited number of points is sufficient enough to identify its position in the dataset.

The  $T_c$  parameter extraction uses the extraction/verification algorithm outlined in Figure 10. To limit the processing time, the search is initially limited to the first half of the dataset. The first check starts from the charging peak to 10% of the length of the whole dataset. For the correct usage of Matlab *findpeaks.m* function the data is negated and shifted up by a constant 500 mV value. Next the *findpeaks.m* function is used to detect peaks in the data which would indicate that the switch voltage value has dropped (data is negated). A threshold detection limit is set to find only the voltage drops which are higher than half of the 500mV level. If no peaks have been found in the first data range, it is extended by 20 points. When a peak is found a recurring loop is created which checks the mean value of following 10 points after the detected peak. When these point values indicate that the switch has closed the search is completed and the  $T_c$  peak is defined. As the point resolution of the measurement is known the  $T_c$  value is equal to number of points between the charging peak and the  $T_c$  peak. A general view of the algorithm is attached below in Figure 10:

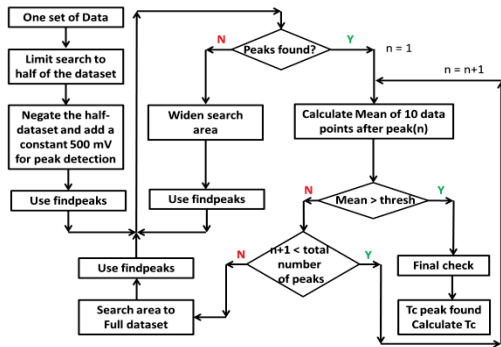


Figure 10:  $T_c$  extraction algorithm

The  $T_0$  parameter extraction uses a similar algorithm to that presented for  $T_c$  extraction. It is again based on the *findpeaks.m* function and mean calculation of following points after detected peaks. The difference lies in the fact that there is no need for data negation as the  $T_0$  is a rising edge in the data values. Additionally, the amount of following points had to be reduced due to the presence of post opening troughs in the measured profile. After manual tests the average of 4 points after peak detection was found to be optimal. The  $T_0$  value calculation was also slightly different as the  $T_0$  value should represent the switch time to open after turning off the actuation voltage, this was simply corrected by subtracting the known (from the test setup) actuation time of the switch.

Both of the sought parameters  $T_c$  and  $T_0$  were extracted from acquired measurement data and the detection error was in the range of 0 to 1 data points (0 – 40 ns). Figure 11 below presents an example of extracted  $T_c$  and  $T_0$  change during the course of the experiment on one switch.

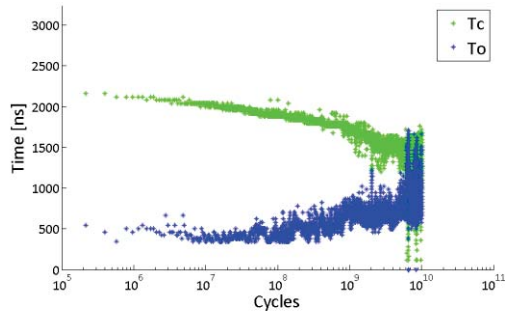


Figure 11: Example of extracted  $T_c$  and  $T_0$  change

## VI. Conclusions

The signal processing and analysis method presented here allows for reliable, automated extraction of MEMS switch closure and opening time from large measured datasets. Using simple statistical tools it was possible to develop a general processing algorithm for highly variable non-linear reliability data and to extract the novel dynamic parameters which initial results can indicate device health on various switch types. The extraction error generated by the algorithm is minimal thanks to a two-step filtering approach and allows for fast classification of the obtained reliability results. The

automated process will be further refined in future work but is now the basis for a large scale measurement of MEMS switch reliability where contact and opening times will be correlated with data from complimentary failure analysis methods. An investigation of the results obtained from this correlation will allow for an evaluation of the usability of this method for failure prediction of MEMS switches. In the long term improvements of this method could allow for the development of a real-time health monitoring system for MEMS switches.

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