

Functional oxide layers for electrical isolation and chemical passivation of steel substrates

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Abstract

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Preface

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Acronyms

1F one-fold concentrated solution. 6

2F two-fold concentrated solution. 6, 7

3F three-fold concentrated solution. 6

4F four-fold concentrated solution. 6

5F five-fold concentrated solution. 6

AcOH acetic acid. 6, 7

BuOH 1-buthanol. 6, 7, 12

DB doctor blading. 7

FTO fluorine doped tin oxide. 5

H₂O deionized water. 5, 6

H₂SO₄ sulfuric acid. 6

Hacac acetylacetone. 6, 7, 12

HCl hydrochloric acid. 6

IPO 2-Propanol. 5–7

ITO indium doped tin oxide. 5

N₂ nitrogen. 5

NaOH sodium hydroxide. 6

SDS sodium dodecyl sulfate. 6

Zr(PrO)₄ zirconium(IV)propoxide. 6, 7, 12

1 Introduction

describe everything what is mentioned in 4 Photovoltaik is cool and a big hope when trying to become carbon neutral as it uses the energy provided by sun directly. One sort of PV is CIGS (copper indium gallium sulfide. <https://doi.org/10.1016/j.tsf.2009.09.033> In order to make a module, multiple cells are stacked in series. Glas is a good non-conducting substrate, but very rigid and brittle. An alternative is steel, which is ductile, inexpensive and highly available, but unfortunately conducting. An insulating layer must therefore be applied. to the steel substrate before any cigs cells can be stacked. A non-toxic material is ZrO₂. A economic and scalable method is doctor blading via a sol-gel process. SG processes often produce porous layers. In this work a dense, insulating and homogeneous layer is angestrebt. ML can help to uncover complex non-linear relations, such as the influence of the verarbeitungs factors on the thickness and resistivity of the resulting layer.

2 Aims and Objectives

was hab ich gemacht, warum?

3 Theoretical Background aka How does it work?

3.1 Sputtering

3.2 SEM

3.3 Infrared absorbance

3.4 Particle Swarm Optimization

3.5 Machine Learning

4 Experimental

In this section the used chemicals and substrates, experimental procedures and any used equipment are described.

4.1 Substrate Preparation

Five different substrates were used throughout this work: microscope glass slides (2.5 cm × 7.5 cm) from Sigma Aldrich, thinner, squared glass plates (2.5 cm × 2.5 cm) from Sigma Aldrich, indium doped tin oxide (ITO) glass plates (2.5 cm × 2.5 cm) from Sigma Aldrich, fluorine doped tin oxide (FTO) glass plates (5 cm × 5 cm) from Sigma Aldrich and steel foil (10 cm x 10 cm) provided by Sunplugged GmbH (<http://sunplugged.at/>). The glass slides and FTO were scratched with a scratching tool and broken with a glass breaker into pieces with dimensions 2.5 cm × 2.5 cm. The steel foil was cut with a foil cutter, a cutter knife (repeatedly), a paper cutter or a scissors (ordered by increasing curvature of resulting plates). All substrates were cleaned in three steps before usage:

1. 15 min in 50 mL deionized water (H₂O) and 1 mL of Hellmanex III in a sonic bath
2. 15 min in H₂O in a sonic bath
3. 15 min in 2-Propanol (IPO) in a sonic bath

After the last cleaning step, the samples were dry blown with dry nitrogen (N₂) gas.

4.2 Solution

Two main recipes were used and their compositions were varied. The first recipe - adopted from Anwar et. al. [1] - was based on zirconium(IV)propoxide ($\text{Zr}(\text{PrO})_4$) in acetylacetone (Hacac) and H_2O . The second recipe - adopted from Hu et. al. [2] - was based on $\text{Zr}(\text{PrO})_4$ in 1-buthanol (BuOH).

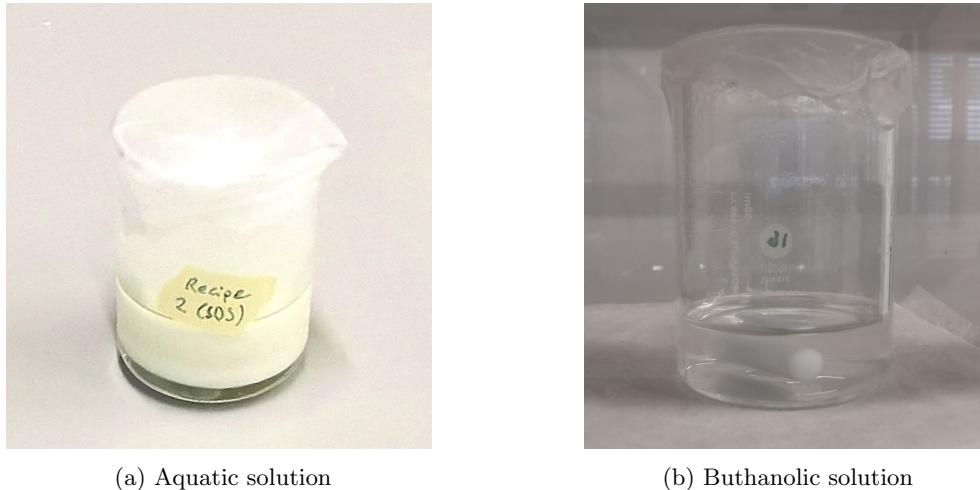


Figure 1: Aquatic and buthanolic solution in beaker glass sealed with Parafilm

4.2.1 Aquatic solution

The procedure for the aquatic solution is as follows: $\text{Zr}(\text{PrO})_4$ was added to Hacac while stirring and in a separate vessel H_2O (including any additives such as sodium dodecyl sulfate (SDS), hydrochloric acid (HCl), sulfuric acid (H_2SO_4) or sodium hydroxide (NaOH)) was added to IPO and both were stirred for one hour. The H_2O -IPO mixture was added to the other solution and stirred over night. The exact volumes can be taken from table 1.

Table 1

recipe	1	2	3	4	5	6	7
$\text{Zr}(\text{PrO})_4$ [mL]	8	8	8	8	8	8	8
Hacac [mL]	8	8	8	8	8	8	8
IPO [mL]	2	2	2	2	2	2	2
H_2O [mL]	2.6	2.6	2.5	2	2	2	2
SDS [mg]	-	5.9	-	-	-	-	-
HCl [mL]	-	-	-	-	0.5	-	-
H_2SO_4 [mL]	-	-	-	-	-	0.5	-
NaOH [mL]	-	-	-	-	-	-	0.5

4.2.2 Buthanolic solution

Five different concentration were prepared. The one-fold concentrated solution (1F) was closest to the recipe proposed by Hu et. al. [2]. The other four solutions (two-fold concentrated solution (2F), three-fold concentrated solution (3F), four-fold concentrated solution (4F), five-fold concentrated solution (5F)) were similar with higher concentrations of $\text{Zr}(\text{PrO})_4$ (see table 2). The solvent (BuOH) is put into a beaker glass (or similar, preferably with an air-tight cap) with a stirrer and $\text{Zr}(\text{PrO})_4$ is added while stirring. After stirring 15 min one mole equivalent chelating agent (Hacac) is added and stirred for another 15 min. Finally, the stabilisation solvent[2] (IPO or acetic acid (AcOH)) is added to the mixture and stirred for additional 30 min. Following stirring times

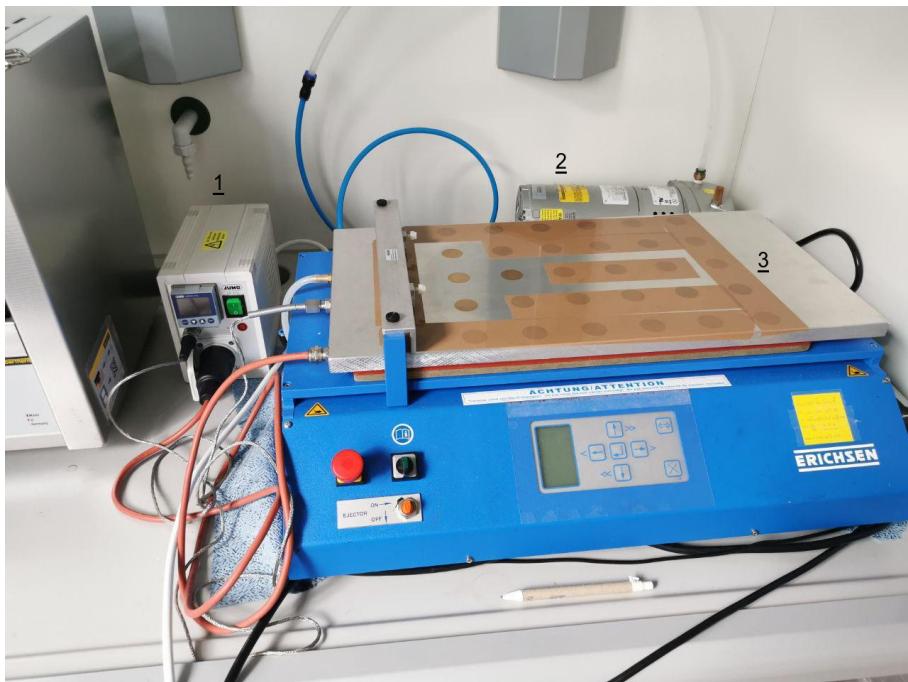


Figure 2: Erichsen Coatmaster 510 with vacuum pump in the background and temperature regulator on the left.

(in minutes) were tested and didn't have an influence on stability of the solution: 10-10-20, 10-10-45, 30-30-180. In order to make a 2F solution, the volume of Zr(PrO)₄ and Hacac is doubled and BuOH is decreased by the volume of Zr(PrO)₄.

Table 2

	1F	2F	3F	4F	5F
BuOH [mL]	4.95	4.9	4.85	4.8	4.75
Zr(PrO) ₄ [mL]	0.05	0.1	0.15	0.2	0.25
Hacac [mL]	0.0125	0.025	0.0375	0.05	0.0625
IPO/AcOH [mL]	2	2	2	2	2

4.3 Doctor blading

After setting the heating plate temperature, the vacuum plate temperature (see figure 2) and the doctor blading (DB) velocity, the DB blade is put into position and the sample placed on the vacuum plate. The vacuum is switched on and the blade is sent over the sample without liquid to see if it is held in position. 100 µL of solution is applied with an 10-1000 µL pipette and the doctor blading is started immediately. After evaporation of the solution, the vacuum is turned off, the 'blade pusher' put into initial position, the blade removed and excess solution removed with a wipe. The small metal plate is transferred to the hot heating plate and rests on there for 3-5 min. The process is repeated as wished.

4.4 Calcination

A LabTech EH45 C heating plate and a Naberterm **L B410** furnace were used to calcinate the doctor bladed samples. The heating plate can hold temperature for a certain amount of time, but doesn't have configurable heating rates. In order to achieve a lower overall heating rate several temperature ramps and plateaus were **used** (see table 3). This procedure will be called HP1 from

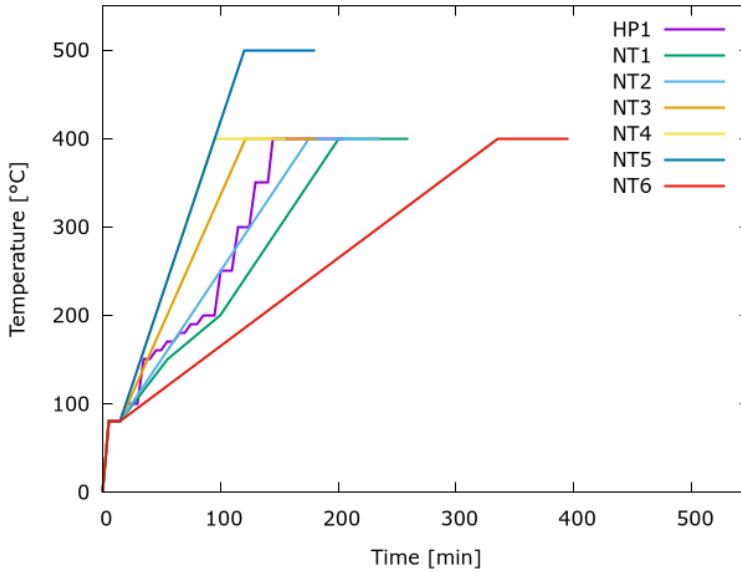


Figure 3: Heatings rates

now on, which stands for heating plate procedure. The HP1 procedure was optimized for the available hardware by a colleague working on the the project prior to me.

HP1												
T [°C]	80	100	150	160	170	180	190	200	250	300	350	400
t [min]	10	10	5	5	5	5	5	10	10	10	10	60

Table 3: Time the temperature was held constant at certain temperatures on the heating plate

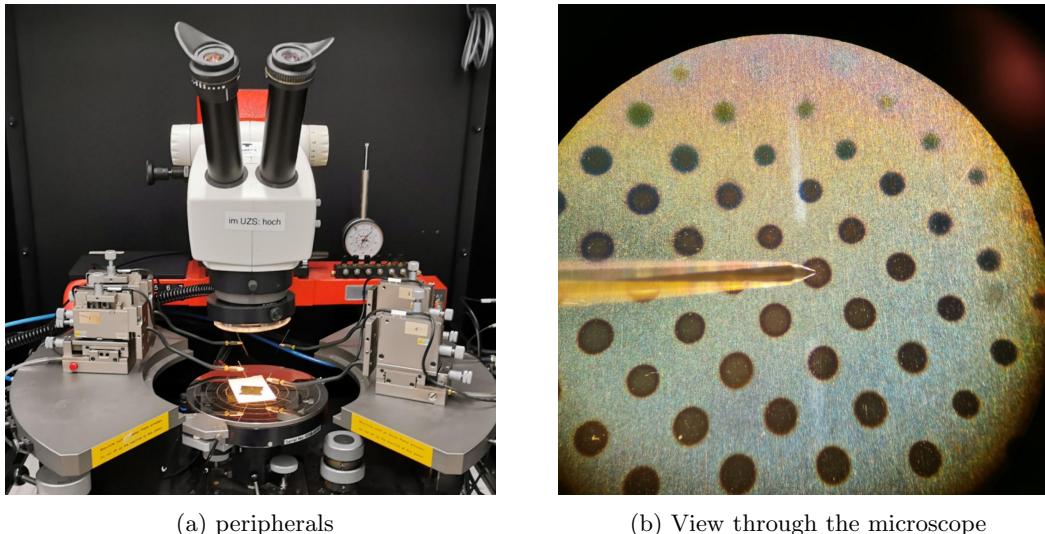
The NT1 heating program was used to mimic the HP1 heating procedure. NT2 is an simplification of NT2 and further programs are the same with increased heating rate and partly increased calcination temperature (NT5). In figure 3 the different heating ramps are depicted. All heating programmes are held at the calcination temperature (T_{Cal}) for one hour.

Name	80-150 [°C/min]	150-200 [°C/min]	200- T_{Cal} [°C/min]	T_{Cal} [min]	T_{Cal} [°C]
NT1	2	1	2	60	400
NT2	2	2	2	60	400
NT3	3	3	3	60	400
NT4	4	4	4	60	400
NT5	4	4	4	60	500
NT6	1	1	1	60	400

Table 4: Heating rates and constant temperature times. **Macht dieser tisch ueberhaupt sinn?**

4.5 Characterisation

<https://link.springer.com/content/pdf/10.1186/2228-5326-3-8.pdf> All scanning electron microscopy images were taken with a Zeiss Supra 40. Infrared spectra were recorded with a Bruker Vertex 70 spectrometer. Diffraction spectra were obtained with a Thermo Scientific ARL Equinox 100 X-Ray Diffractometer. The sample was placed in a way such that it absorbed half of the beam. All spectra were taken at 5° incident angle. And compared to an internal database.



(a) peripherals

(b) View through the microscope

Figure 4: I-V curve abnehm aperature and sicht durch das micro scope.

4.5.1 SEM

Zeiss Supra 40

4.5.2 Infrared

Bruker Vertex 70

4.5.3 X-Ray Diffraction

Thermo Scientific ARL Equinox 100 X-Ray Diffractometer

<https://doi.org/10.1016/B978-0-12-816806-6.00017-0>

[https://chem.libretexts.org/Courses/Franklin_and_Marshall_College/Introduction_to_Materials_Characterization__CHM_412_Collaborative_Text/Diffraction_Techniques/X-ray_diffraction_\(XRD\)_basics_and_application](https://chem.libretexts.org/Courses/Franklin_and_Marshall_College/Introduction_to_Materials_Characterization__CHM_412_Collaborative_Text/Diffraction_Techniques/X-ray_diffraction_(XRD)_basics_and_application)

4.5.4 Current-Voltage Curve

Agilent 4156C Precision Semiconductor Parameter Analyzer

4.6 Finding base process

After a fitting recipe was found, the process to produce an acceptable layer was untersucht. There were many variables which had to be taken into account. The damals current procedure produced clear and continuous films, but was plagued from unhomogenities due to drying stains. Using a heat gun the drying stain can be surcumvented (umgangen), but the results were unreproduceable. The glass unterlage was therefore exchanged with a metal plate which allowed both to hold the sample via underpressure and heat it to a certain temperature. The bounds fore the process were then explored. Especially the doctor blading velocity.

5 Evaluation and Computational Details

5.1 Evaluation of Samples

For every I-V curve (aluminium dot) the gradient g at $V = 0$ is calculated by taking 5 points after the origin and 5 points before the origin, averaging their V and I values and calculating i

$$g = \frac{I_{n+1} - I_n}{V_{n+1} - V_n}. \quad (1)$$

As a measure of conductance a distance D from an ideal non-conducting case. The average of the negative base 10 logarithm subtracted from an ideal non-conducting gradient of 10^{-13}

$$D = \sum_i^N \frac{-\log_{10}(g_i) - 13}{N} \quad (2)$$

Another measure is the density of shorted species ρ_s is calculated in following way:

$$s_i = \begin{cases} 1 & \text{if } -\log(g_i) < 5 \\ 0 & \text{if } -\log(g_i) \geq 5 \end{cases} \quad (3)$$

$$\rho_s = \sum_i^N \frac{s_i}{N} \quad (4)$$

Other estimates of the conductance are the averages:

$$G_1 = \log \left(\sum_i^N \frac{g_i}{N} \right) \quad (5)$$

$$G_2 = \sum_i^N \frac{\log(g_i)}{N} \quad (6)$$

5.2 Sample Selection

An evolutionary approach was chosen, namely a multi-objective Particle Swarm Optimization (PSO) with a multi-response Multivariate Adaptive Regression Splines (MARS) model[3, 4, 5, 6]. "PSO is a population based heuristic inspired by the flocking behavior of birds. To simulate the behavior of a swarm, each bird (or particle) is allowed to fly towards the optimum solution." [3] Initially the input parameters (independent variables), their boundaries and number of equidistant levels for each parameter are declared (see table 5). Next, the output variables (dependant variables), their weights in the objective function (the function which should be optimized) are specified and if they should be minimized or maximized is noted.

Zr(PrO) ₄ conc. [21 g/L]	layers	T_{DB} [°C]	v_{DB} [mm/s]	T_{cal} [°C]	v_{cal} [°C/h]
2	4	40	10	300	120
3	6	50	12	400	360
4	8	60	14	500	600
5	10	70	16		840
	12	80	18		1080
			20		

Table 5: Discrete levels of each input parameter **are concentrations correct?**

The first step is to select an initial population (ensemble of experiments), which is chosen randomly from the population space. The samples are made, measured and evaluated according to section 4 and the distance D (see eq. 2), ρ_s (see eq. 4), n_{layers} (numbers of layers) and v_{cal}

(heating rate of calcination process in °C/min) are supplied to the program. The program uses this data to estimate a response for each output variable (and to choose a fraction of the initial population which is allowed to propagate). The response variables for the entire population space is calculated. The current population - each of the particles independently - moves towards the optimum solution. The population for the next time step is outputted and the experiments are again executed, measured and evaluated.

5.3 EMMA Propagation

5.4 Fitting via Machine Learning

scarce data may lead to overfitting[7]

Python and sci-kit learn [cite](#) was used to implement a linear fit model, and SVR with the kernels polynomial, rbf and sigmoid. The space of hyper parameters C, the degree (in case of polynomial), epsilon and gamma was scanned.

conc	layers	vDOC	TDOC	vCal	Tcal	
1	10	5	20	120	400	
1	4	0.1	20	120	500	
5	10	0.1	20	120	500	
5	4	5	20	480	400	
1	5	5	80	120	500	
1	10	1	80	480	400	
5	5	1	80	120	400	
5	10	5	80	480	500	
2	8	0.5	40	360	470	
2	6	2	40	360	430	
1	4	12	70	120	500	
1	9	18	80	240	400	
4	6	14	60	240	500	
4	6	14	60	240	500	
4	6	14	60	240	500	
2	10	20	40	120	500	6113
3	8	18	70	1080	300	2850
3	6	10	50	1080	400	5526
3	10	16	80	120	500	6554
4	6	16	80	1080	300	2947
3	12	12	80	840	500	8318
3	10	14	50	600	500	7374
5	6	10	60	1080	400	5648
5	10	20	60	360	300	3956
5	12	14	60	1080	300	2700
2	4	10	80	1080	300	6101
2	4	10	40	600	300	7201
3	4	12	60	600	300	1462
4	4	10	80	1080	300	2883
5	12	20	70	600	300	1680
2	4	10	40	120	300	1
2	4	10	40	120	500	6001
3	4	10	40	120	500	6102
5	4	10	80	1080	300	2884
5	12	20	60	120	300	360
3	4	10	40	600	400	4202
2	6	20	40	120	500	6105
5	12	14	60	600	300	1500
3	6	14	60	600	300	1486
4	4	14	80	1080	300	2923
4	8	18	80	1080	300	2971
3	8	10	50	1080	300	2530
2	12	16	40	120	400	3077
2	10	18	60	1080	300	2733
4	10	10	50	1080	300	2535

Table 6

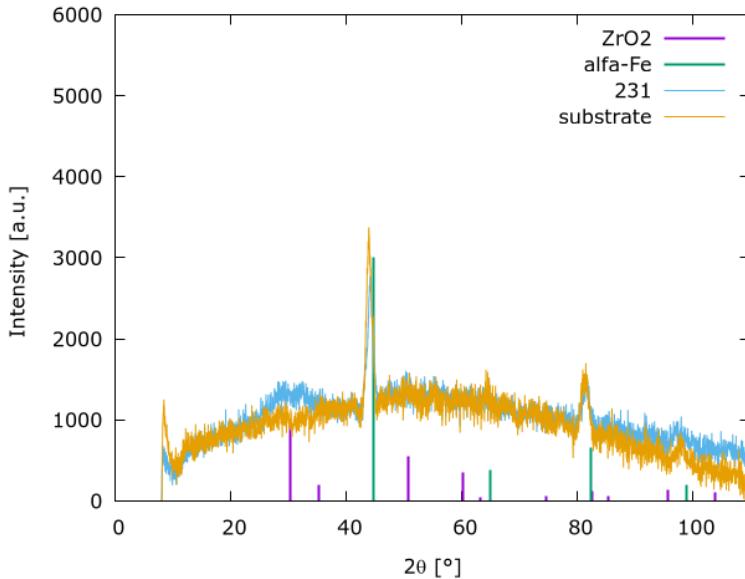


Figure 5: XRD spectra

6 Results and Discussion

The space seems to be too big for the small sample size. Look at relation of space size and sample size here and in Hu2016.

Would be easier to fit with single factor at a time variation or latin hyper cuber? Would it also be easier for PSO or ML to find fitting function? Every output var is independent of each other, so v_{cal} can act as test

plot predictions from EMMA and ML.

6.1 XRD

7 Outlook

Making of the solution for the sol-gel process: For a single concentrated solution 0.05 mL of $\text{Zr}(\text{PrO})_4$ are added while stirring to 4.95 mL of BuOH and stirred for 15 min. 0.013 mL (or one molar equivalent of Zr) of Hacac is added to the stirring solution. After another 15 min 1 mL of acetic acid is added and stirred for 30 min to stabilize the solution up to 24 h.

The concentration can be increased up to 5 times being stable for a minimum of 4 h. The sol-gel process produces am homogeneous transparent crystalline zirconia oxide layer. homogeneity can be mainly controlled via blade velocity and temperature and layers can be stacked.

It should have been alos verglichen with grid search with comparable size but most time was used to find a vernuenfig base recipe and process

It is still very human Der process is - as it the case with all ML and most fitting processes - is very abhaengig von hyper parameters, In the current work population size, number of generations, and most importantly boundaries (grenzen).

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