AUTOMATIC DETECTION OF PANEL SOILING AND CONTROL OF THE CLEANING PROCESS IN SOLAR PHOTOVOLTAIC POWER PLANTS

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Annotatsiya. *Maqolada quruq va changli iqlim sharoitida ishlovchi quyosh fotoelektr stansiyalarida (QFES) panellarning changlanishini avtomatik aniqlash va tozalash jarayonini boshqarish tizimi taklif etilgan. Chang konsentratsiyasi, havo namligi, shamol tezligi va yog‘ingarchilikni hisobga oluvchi changlanish dinamikasining matematik modeli, etalon modul usuli asosida changlanish koeffitsiyentini aniqlash algoritmi hamda energiya yo‘qotishi va tozalash xarajatini taqqoslovchi, ob-havo prognozini hisobga oluvchi adaptiv boshqarish algoritmi ishlab chiqilgan. 1 MW quvvatli QFES uchun 92 kunlik (iyun-avgust) modellashtirish natijalariga ko'ra, taklif etilgan algoritm tozalanmagan holatga nisbatan energiya ishlab chiqarishni 14,3% ga oshirdi, 14 kunlik qat'iy jadvalga nisbatan esa tozalash sikllari sonini 33% ga kamaytirib, sof daromadni 2,1% ga oshirdi.*

Kalit so'zlar: *quyosh fotoelektr stansiyasi, changlanish, changlanish koeffitsiyenti, avtomatik boshqarish, tozalash roboti, optimallash, adaptiv algoritm.*

Аннотация. *В статье предложена система автоматического определения загрязнения панелей солнечных фотоэлектрических станций и управления процессом их очистки в условиях сухого и пыльного климата. Разработаны математическая модель динамики загрязнения с учётом концентрации пыли, влажности, скорости ветра и осадков, алгоритм определения коэффициента загрязнения методом эталонного модуля и адаптивный алгоритм управления очисткой, учитывающий прогноз погоды. По результатам моделирования для СФЭС мощностью 1 МВт предложенный алгоритм увеличил выработку энергии на 14,3% по сравнению с работой без очистки и сократил число циклов очистки на 33% по сравнению с фиксированным 14-дневным графиком, увеличив чистый доход на 2,1%.*

Ключевые слова: *солнечная фотоэлектрическая станция, загрязнение, коэффициент загрязнения, автоматическое управление, робот очистки, оптимизация, адаптивный алгоритм.*

Abstract. *The paper proposes a system for automatic soiling detection and cleaning control for photovoltaic (PV) power plants operating in dry and dusty climates. A soiling dynamics model accounting for dust concentration, humidity, wind speed and rainfall, a reference-module algorithm for soiling ratio estimation, and a forecast-aware adaptive cleaning control algorithm are developed. Simulation of a 1 MW plant over 92 days (June-August) shows a 14.3% increase in energy yield compared with no cleaning, and a 33% reduction in cleaning cycles together with a 2.1% increase in net revenue compared with a fixed 14-day schedule.*

Keywords: *photovoltaic power plant, soiling, soiling ratio, automatic control, cleaning robot, optimization, adaptive algorithm.*

Introduction. In recent years, renewable energy, and solar energy in particular, has been developing rapidly in Uzbekistan. Solar photovoltaic power plants with capacities of hundreds of megawatts have been commissioned or are under construction in Navoi, Samarkand, Jizzakh, Bukhara, Kashkadarya and other regions. Up to 2800-3000 hours of sunshine per year are observed across the Republic [1], which creates very favorable conditions for photovoltaic technologies.

However, the same climatic conditions also give rise to a serious technical problem. Precipitation is very scarce in summer, the concentration of dust particles in the air is high, and dust storms occur frequently. Salty dust lifted from the Aral Sea region adheres to the panel surface and forms a hard layer. Dust accumulated on the panel surface prevents solar radiation from reaching the photovoltaic cells and reduces the generated electrical energy. In international studies, this phenomenon is called *soiling*, and it has been reported that in arid regions the monthly energy loss of uncleaned panels reaches 10-30% [2-4]. Studies conducted in our Republic have also found that a dust layer reduces panel efficiency by 15-25% [5], and it has been shown that quartz and hematite particles predominate in the composition of Aral region dust [6].

In practice, cleaning at PVPPs is mainly performed according to a fixed schedule (for example, every 2 or 4 weeks) or based on visual inspection by the operator. This approach has two main drawbacks. First, cleaning is carried out even during periods of low dust accumulation, and water, electricity, labor and

equipment resources are wasted. Second, after a dust storm the panels operate with large energy losses until the next scheduled date. In addition, weather factors (whether rain or a dust storm is expected in the coming days, air humidity) are not taken into account when choosing the cleaning time.

Thus, the development of a system that objectively determines the soiling level of PVPP panels in real time and automatically controls the cleaning process based on an energy-economic criterion and meteorological conditions is a relevant scientific and technical problem.

Mathematical model of soiling dynamics

The dust density on the panel surface m (g/m²) at a discrete time step (k is the day number) is described by the following balance equation [4, 7], which takes into account deposition, partial cleaning by wind and the effect of rain:

$$m_{k+1} = m_k + k_d C_k[1 + \gamma \cdot max(\varphi_k - \varphi_0, 0)] - \kappa \cdot max(v_k - v_0, 0)m_k \quad (1)$$

where C is the average daily concentration of PM10 particles in the air, μg/m³; φ is the relative humidity, %; v is the average wind speed, m/s; k_d is the deposition coefficient; γ is the coefficient of the effect of humidity on dust adhesion; κ is the wind cleaning coefficient; φ_0 and v_0 are the threshold values of humidity and wind speed, respectively.

When the amount of precipitation R exceeds the threshold value R_0, part of the dust layer is washed off, and after a cleaning operation residual dust remains:

$$m_{k+1} \leftarrow (1 - \eta_r)m_{k+1},\ R_k > R_0; \quad m \leftarrow (1 - \eta_c)m \quad (2)$$

where η_r is the rain cleaning efficiency, η_c is the efficiency of the cleaning system.

The soiling ratio SR is the ratio of the power of a soiled panel to the power of a clean panel. It is assumed to depend exponentially on the dust density (similar to the Bouguer-Lambert law) [2]:

$$SR_k = exp(-\beta m_k) \quad (3)$$

where β is the optical extinction coefficient of the dust layer, m²/g. SR = 1 corresponds to a clean panel, and SR = 0.8 corresponds to a 20% power loss. The daily energy generation of the plant is:

$$E_k = P_{nom} \cdot H_k \cdot PR \cdot SR_k \quad (4)$$

where P_{nom} is the nominal power of the plant, kW; H_k is the daily solar irradiation on the panel plane, kWh/m²; PR is the performance ratio accounting for losses other than soiling. The parameters adopted in the simulation are given in Table 1.

Table 1

Model parameters

Parameter	Symbol	Value	Unit
Deposition coefficient	k_d	$8.5 \cdot 10^{-4}$	$(g/m^2)/(\mu g/m^3 \cdot day)$
Humidity effect coefficient	γ	0.012	1/%
Humidity threshold	φ_0	40	%
Wind cleaning coefficient	κ	0.035	s/m
Wind speed threshold	v_0	6	m/s
Precipitation threshold	R_0	5	mm
Rain cleaning efficiency	η_r	0.75	-
Cleaning efficiency	η_c	0.97	-
Optical extinction coefficient	β	0.11	m^2/g
Nominal power	P_{nom}	1000	kW
Performance ratio	PR	0.80	-

The advantage of the model is that all its input quantities (PM10, humidity, wind, precipitation) are measured by an ordinary weather station and a dust sensor, while its parameters are identified by the least squares method from the SR values measured at the plant.

Hybrid soiling detection algorithm

To determine the soiling level, a hybrid algorithm is proposed that combines data from two sources: electrical parameters (the reference module method) and panel images.

Detection based on electrical parameters. Two reference modules of the same type are installed on the plant site. One of them is automatically cleaned every day (clean module, index c), while the other is left under the same conditions as the plant panels (soiled module, index s). This method is recommended in the IEC 61724-1 standard for soiling monitoring [8]. The short-circuit currents are corrected for temperature to standard conditions (25 °C):

$$I_{sc}^{*} = \frac{I_{sc}}{1+\alpha(T_m-25)} \quad (5)$$

where α is the temperature coefficient of the short-circuit current, 1/°C; T_m is the module temperature, °C. The instantaneous value of the soiling ratio is:

$$SR_{el} = K_{cal} \cdot \frac{I_{sc,s}^{*}}{I_{sc,c}^{*}} \quad (6)$$

where K_{cal} is the calibration coefficient determined on a day when both modules are clean at the same time. To reduce measurement error, only measurements with irradiance G > 500 W/m² taken within ±2 hours of solar noon are used, and their median is taken as the daily value. Using the ratio almost

completely eliminates the influence of changes in solar irradiance and temperature, while using the short-circuit current reduces the influence of module degradation and MPPT errors.

Image-based detection. Panel images obtained with a stationary camera or a drone are classified by a convolutional neural network (CNN) into four classes: clean, lightly soiled, moderately soiled and heavily soiled. The main purpose of image analysis is to detect uneven dust distribution across the plant and to indicate which rows should be cleaned first.

Data fusion rule. The final estimate is formed as follows:

$$SR = w \cdot SR_{el} + (1 - w) \cdot SR_{img}, \quad 0 \le w \le 1 \qquad (7)$$

where w is the confidence weight of the electrical method (w = 0.7-0.8 is recommended). In addition, a logical check is introduced: if SR_{el} drops sharply while the image shows the panel as clean, the system interprets this not as soiling but as shading or a module fault and sends a warning to the operator. This prevents unnecessary activation of the cleaning system.

In the simulation, when a relative random error of 1.2% was added to the reference module measurements, the root mean square error (RMSE) of SR estimation over 92 days was 0.0095 (approximately 0.95 percentage points). This accuracy is sufficient for making cleaning decisions.

Cleaning process control algorithm

Optimization criterion. The cleaning decision is based on comparing two types of costs: the revenue lost due to soiling and the cost of one cleaning cycle C_{cl} (water, electricity, labor, robot wear). The loss accumulated since the last cleaning is:

$$L_k = \sum_{j=k_0}^{k} p \cdot P_{nom} \cdot H_j \cdot PR \cdot \left(1 - SR_j\right) \qquad (8)$$

where p is the electricity tariff, UZS/kWh; k_0 is the day of the last cleaning. Cleaning is advisable when $L_k \ge C_{cl}$.

This criterion is consistent with the classical result presented in [9]. If the soiling rate r is constant and the loss grows linearly ($1 - SR \approx r \cdot t$), the loss accumulated over the interval T equals $p \cdot E_0 \cdot r \cdot T^2/2$ ($E_0 = P_{nom} \cdot H \cdot PR$). Equating it to C_{cl}, we obtain the optimal interval:

$$T^* = \sqrt{\frac{2C_{cl}}{pE_0 r}} \qquad (9)$$

For average values (C_{cl} = 5.32 mln UZS, p = 650 UZS/kWh, E_0 = 5920 kWh/day, r = 0.8 %/day), $T^* \approx 18.6$ days is obtained. However, under real conditions r is not constant: dust storms increase it sharply, while rain partially cleans the panel. Therefore, the proposed algorithm does not set T* in advance;

instead, it calculates L_k daily from the measured SR and thereby adapts to actual conditions.

Meteorological constraints. The following additional conditions are introduced into the cleaning decision:

–if precipitation R > 5 mm is expected within the next 48 hours, cleaning is postponed (natural cleaning is used);

–if a dust storm is expected the next day (PM10 forecast > 250 μg/m³), cleaning is postponed until after the storm;

–if the relative humidity φ > 60% (risk of dew), dry brush cleaning is prohibited, since wet dust forms a muddy layer;

–safety condition: if $SR < SR_{min} = 0.80$ and no precipitation is expected, cleaning starts immediately.

Algorithm steps. The control cycle is executed every day after sunset:

1. the daily SR value is determined from the measurements taken during the day;
2. the daily loss is calculated and added to L_k;
3. the weather forecast (precipitation, PM10, humidity) is obtained;
4. if $L_k \geq C_{cl}$ or $SR < SR_{min}$ and the meteorological constraints are satisfied, a cleaning command is generated;
5. based on the image analysis results, cleaning starts from the most soiled rows; the robot operates at night or early in the morning (when φ < 60%);
6. after cleaning, L_k is set to 0, and SR recovery is verified by the next day's measurement. If SR remains below 0.95, a cleaning inefficiency alarm is issued.

The advantage of the algorithm lies in its simplicity: it is easily implemented on an industrial controller (PLC) or a microcontroller and automatically changes its behavior when the cleaning cost C_{cl} changes (for example, when the water tariff increases).

Experimental setup and research methodology

To test the proposed system in practice, an experimental setup was designed, the composition of which is given in Table 2.

Table 2

Composition of the experimental setup

Component	Function	Recommended element
Reference modules (2 pcs)	Measuring the currents of the clean and soiled modules	300-550 W monocrystalline module of the same type as at the plant

Component	Function	Recommended element
Current sensors	Measuring the short-circuit current	Shunt + ADS1115 (16 bit) or INA226
Temperature sensors	Measuring the module temperature	DS18B20 (on the back side of the module)
Pyranometer	Measuring solar irradiance	Second-class pyranometer or calibrated reference cell
Dust sensor	Measuring PM10 and PM2.5	Optical laser sensor (e.g., SDS011)
Weather sensors	Humidity, wind, precipitation	BME280, anemometer, rain gauge
Camera	Capturing panel images	5-8 MP IP camera or drone
Control unit	Data acquisition and algorithm execution	ESP32 / Raspberry Pi or industrial PLC
Actuator	Panel cleaning	Waterless brush robot or motorized brush on the test bench

Data are collected every 5 minutes and transmitted to the server via the MQTT protocol. The algorithm is implemented in the Python programming language, and the TensorFlow library is used for the CNN model.

To evaluate the efficiency of the algorithm, the operation of a 1 MW PVPP from June 1 to August 31 (92 days) was simulated based on the model presented above. The input meteorological data were generated to approximate the summer climate of the Fergana Valley: the average daily PM10 concentration was 96.5 μg/m³ (dust storms on days 19, 48 and 72, with the concentration increasing 3.5 times); the average relative humidity was 33.4%; the average wind speed was 3.2 m/s; significant precipitation occurred only twice, on day 10 (6.5 mm) and day 64 (8.0 mm); the average daily irradiation on the panel plane was 7.26 kWh/m².

In the economic calculations, the electricity selling tariff was taken as p = 650 UZS/kWh, and the cost of a single cleaning of a 1 MW area (including water, electricity, wages and robot wear) as C_{cl} = 5.32 mln UZS. Five cleaning strategies were compared: A - no cleaning; B - every 30 days; C - every 14 days; D - every 7 days; E - the proposed adaptive algorithm. All strategies were tested with the same meteorological data.

Results and discussion

The proposed adaptive algorithm (E) provided the highest net revenue among the compared strategies, 301.0 mln UZS, with only 4 cleanings performed. Figure 1 shows the daily variation of the soiling ratio for three strategies.

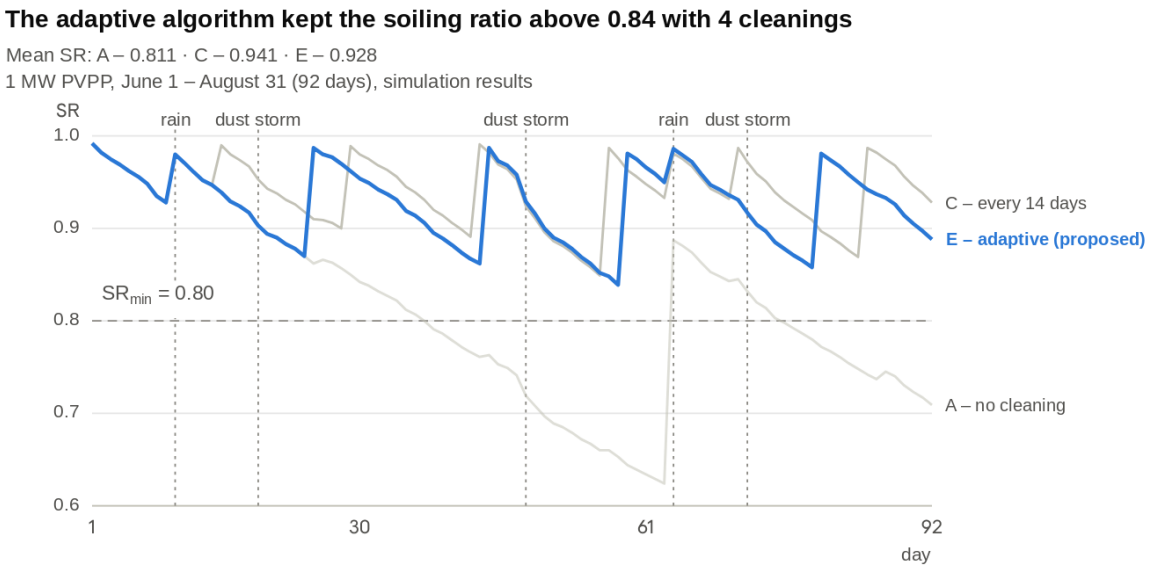

Figure 1. Variation of the soiling ratio over 92 days

In the uncleaned case (A), SR dropped to 0.624 by day 63, i.e., 37.6% of the plant's power was lost. The rain on day 64 restored SR to 0.887, but not completely. Dust storms (days 19, 48 and 72) appear in the graph as sharp drops.

The 14-day schedule (C) performed cleaning on day 14 even though SR was still 0.947, i.e., the loss was only 5.3%, which is an example of excessive cleaning. The adaptive algorithm, by contrast, waited until day 24 and started cleaning only when the accumulated loss became equal to the cleaning cost (SR = 0.870). Subsequent cleanings were performed on days 43, 58 and 79 (Table 3). After the dust storm on day 48, the algorithm did not react immediately but waited until sufficient loss had accumulated.

Table 3

Cleaning events under the adaptive algorithm (strategy E)

	Cleaning day	Interval, days	SR before cleaning	SR after cleaning	L_k, mln UZS	Weather events in the interval
	24	24	0.870	0.987	5.65	day 10 - rain; day 19 - dust storm
	43	19	0.862	0.987	5.38	-
	58	15	0.839	0.981	5.41	day 48 - dust storm
	79	21	0.858	0.981	5.41	day 64 - rain; day 72 - dust storm

Table 3 shows that the average interval between cleanings was 19.8 days, which is close to $T^* \approx 18.6$ days calculated by formula (9). However, the intervals

are not equal: in the period with a dust storm the algorithm performed cleaning after 15 days, while in periods when rain partially cleaned the panels it waited 21-24 days. Thus, the algorithm automatically adapts the cleaning time to actual weather conditions.

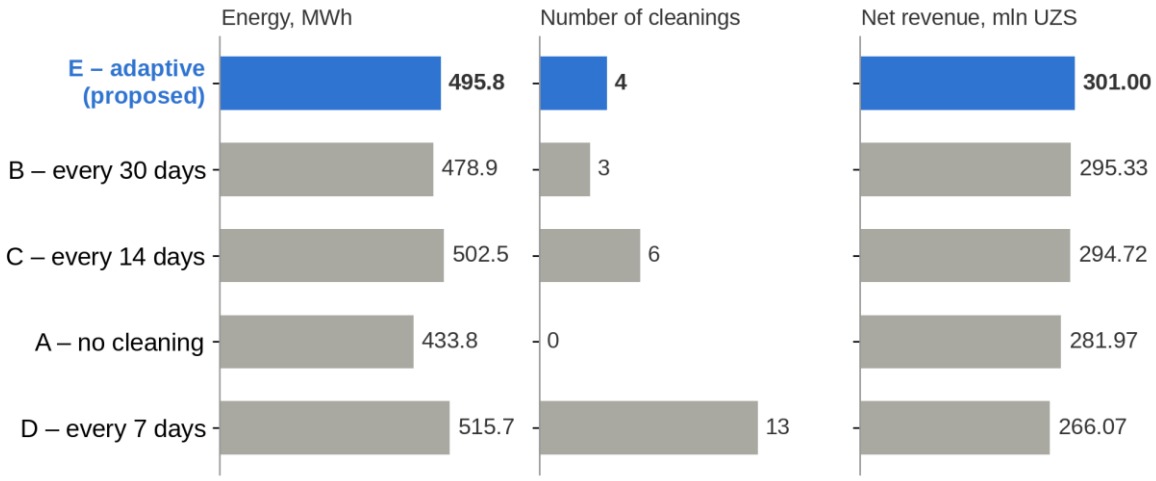

Figure 2. Results of the cleaning strategies over 92 days (1 MW PVPP)

Figure 2 shows that cleaning every 7 days (D) yields the most energy, but the cost of 13 cleanings exceeds the additional energy revenue and the net revenue is the lowest. Therefore, when evaluating a cleaning strategy, the main criterion should be net revenue rather than the amount of energy [3].

Compared with the uncleaned case, the adaptive algorithm provided an additional 62.0 MWh (+14.3%) of energy. Compared with the 14-day schedule, it generated 6.7 MWh less energy, but by saving 2 cleanings it increased net revenue by 6.28 mln UZS (2.1%).

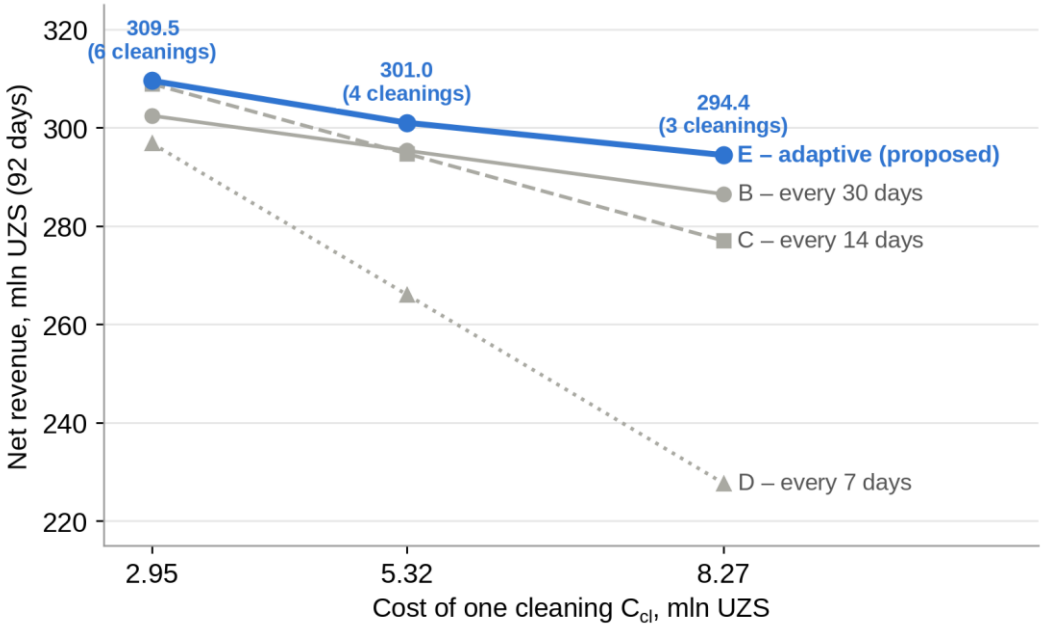

Figure 3. Net revenue versus cleaning cost C_{cl} (92 days)

Figure 3 shows an important property of the algorithm: each fixed schedule performs well only within a certain cost range (the 14-day schedule for cheap cleaning, the 30-day schedule for expensive cleaning), whereas the adaptive algorithm itself changes the number of cleanings depending on the cost (6 → 4 → 3) and gives the best result in all cases. This property is particularly important in practical conditions where water and electricity tariffs vary.

Although the difference in net revenue is 2-3% for 92 days, for large plants (100 MW and above) and over a one-year period it becomes a significant amount. In addition, reducing the number of cleanings also reduces water consumption, robot wear and the risk of mechanical damage to the panel coating.

It should be noted that the results were obtained on the basis of the model: the model parameters (k_d, β, γ, κ) must be identified at a real plant. In addition, the weather forecast was assumed to be ideal; in practice, forecast errors may slightly reduce the effectiveness of the algorithm.

Conclusion

As a result of the research, an adaptive control system has been developed that automatically detects soiling of solar panels and selects the cleaning time according to weather conditions. The simulation results showed the following:

1. If the panels are not cleaned, the energy loss due to soiling reaches 18.8% in the summer season.
2. The proposed algorithm increases energy generation by 14.3% compared with the uncleaned case.
3. Compared with the fixed 14-day schedule, the number of cleanings decreases by 33%, and net revenue increases by 6.28 mln UZS.

At the next stage, the system will be tested on the experimental setup and at an operating plant.

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