DEVELOPING AN INTELLIGENT SYSTEM FOR MODELING THE DAM BEHAVIOUR BASED ON STATISTICAL PATTERN MATCHING OF SENSORY DATA

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ABSTRACT

Structural condition and health monitoring is an important issue for dam safety. Dams are usually large and located in remote areas. A computerized monitoring system is very useful for detecting any abnormal behaviour in a dam. Although manual inspection is performed periodically, automatic acquisition of data from the sensors and instruments installed in a dam provide valuable information about its performance. The volume of data acquired from the sensors could be huge. Validating the sensor data, correlating them to the observation from manual inspection and interpreting the data to evaluate the performance of a dam presents a great challenge. This article presents a number of data driven models based on statistical pattern recognition technique. The models have been developed for representing the sensor data in a dam to capture the relationship between the parameters related to the cause and effect. The present models are based on statistical methods such as multi-linear regression analysis. Although such models have been used in the past, a number of limitations have been identified with the existing methods. This paper presents a more robust set of statistical pattern recognition models, where physical parameters such as water level, temperature and deformation play the key roles. The results show a marked improvement from the existing model where some of the governing parameters are artificially created. A case study using the data obtained from a Canadian dam will be presented to demonstrate the effectiveness of the proposed methods. The system developed using the proposed method can be used for validating the sensor data in immediate future, identifying anomaly in dam behaviour, and aiding in decision-making.

KEY WORDS

Dam safety, Structural Health Monitoring, Data Modeling, statistical pattern recognition, Decision Support Systems.

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INTRODUCTION

Dams play an important role in water management. They meet the demand of drinking and industrial water supply. In some cases they can provide indefinitely renewable hydro-electric power. They control floods and increase dry-weather flows. They can also maintain a wetland environment that is favorable to biodiversity.

But besides being a great source of wealth, dams can also become a source of accidents. Although an average of less than 1% of dams have suffered accidents over a long period of time, the resulting damage and loss of life mean that such accidents are unacceptable.

In order to prevent such accidents, dam safety must be seriously taken into account when engineers design, build, operate and maintain the dams. For example, some instruments can be installed during the dam construction to measure the small structure motions at regular intervals. Then dam engineers can analyze those data collected from those instruments to detect some failure mode and estimate the potential risk. Some risks and suggestions will be reported to the dam authorities. Then the authorities will take into account those suggestions and allocate the required resources to ensure the dam safety.

Although many methods in a wide disciplines, including hydro-technical, structural and geochemical, can be used in dam safety monitoring, we mainly focus on the statistical analysis of instrumental data and build the computer-based model to find the correlation between cause and quantified effects, automatically identify the potential abnormal behavior and provide some software to help dam engineers analyze the data effectively.

In this paper, a number of statistical methods based on multi-linear regression (MLR) technique have been presented. One such model is Hydrostatic-Season-Time (HST) model (Ferry and Willm, 1958), which have been used in the past. While the effect of temperature is incorporated implicitly through the season parameter, it may not truly account for the effect of temperature variation. Thus the effectiveness of HST model in dam monitoring is limited. In order to overcome the limitations of the HST model, several new models have been developed which account for the effect of temperature and thermal inertia explicitly. An extensive study has been conducted to evaluate the performance of those models and the proposed new models are found to have superior performance over the traditional HST model.

MODELS FOR DAM MONITORING

THE HST MODEL

The hydrostatic-Season-Time method was first proposed by Electricity de France for analyzing pendulums (Ferry and Wilm, 1958) and now it becomes a good tool for interpreting the behavior of concrete dam. It takes account of various factors which affect the dam structure deformation. The traditional HST model is currently used by many dam owners around the world. Recently, Feknous et al. (2001) have used the HST model to monitor the dam data owned by ALCAN.

In basic HST model, the displacement of a pendulum is represented by superposition of three effects: hydrostatic conditions (effects of the reservoir level), the Season effect and irreversible effect (time drift), given by

$$M(z,\tau,t) = A_0 + H(z) + S(\tau) + T(t), \tag{1}$$

where, A_0 is a constant term representing the bias, $M(z,\tau,t)$ is displacement at time t, $H(z)$ is response due to hydrostatic load, $S(\tau)$ is the response due to the seasonal effect, and $T(t)$ is the effect of time or irreversible effect. The effect of temperature is not explicitly accounted for in the HST model. It is implicitly incorporated in the season parameter $S(\tau)$. In the HST model, the H, S and T functions are represented as follows:

$$H(z) = a_1 z + a_2 z^2 + a_3 z^3 \tag{2a}$$

$$S(\tau) = b_1 \sin(\omega\tau) + b_2 \cos(\omega\tau) + b_3 \sin^2(\omega\tau) + b_4 \sin(\omega\tau)\cos(\omega\tau) \tag{2b}$$

$$T(t) = c_1 t \tag{2c}$$

$H(z)$ is represented by a cubic polynomial of the hydrostatic head, $S(\tau)$ is represented by a sum of four sine functions of ω, where $\omega = 2\pi/365$ and τ denotes the *i*th day in a year, and $T(t)$ is represented in terms of a monotonic time function.

One of useful properties of HST model is that it separates the effects of input variables which affect the output variable. For example, if in summer the reservoir level is lower, the seasonal effect probably outweighs hydrostatic effect. By separating hydrostatic and seasonal effects, some paradoxical behaviors can be better understood.

THE HSTT MODEL

In the HST model, the season effect takes account of the temperature variations and structure thermal inertia. It assumes that the same period patterns repeat every year. In reality this assumption may not be true. In the HSTT model as proposed here, temperature information is explicitly used in regression model, which is a direct extension of HST model.

$$M(z,\tau,t) = H(z) + S(\tau) + T(t) + T'(t), \tag{3}$$

where the notations of $M(z,\tau,t)$, $H(z)$, $S(\tau)$ and $T(t)$ are the same as those in (1) and $T'(t)$ denotes the temperature effects, which can be represented in terms of linear function.

THE HTT MODEL

As explained earlier, in the HST model, S is an artificial parameter that takes account of the temperature variations and structure thermal inertia. Since the seasonal tempretature variation follows a similar pattaren represented by the artificial parameter, S, it may be possible to use temperature directly instead of using S. The proposed HTT model is build upon that idea, where components of the HTT model are described in Equation (4).

$$M(z,\tau,t) = H(z) + T(t) + T'(t), \tag{4}$$

where the notations of $M(z,\tau,t)$, $H(z)$, $T(t)$ and $T'(t)$ are the same as those in (2).

TRAINING AND SIMULATION APPROACH

The models presented here have been tested using a set of data provided by British Columbia (B.C.) Hydro from one of its concrete gravity dams. The data is available for the years 1998 and 1999 and it contains the records of hydrostatic pressure, dam displacement at a number locations in the dam, and the ambient temperature. All the models used in the results below have been trained on the data from the entire year 1998. The output results have been simulated on the data from the entire year 1999.

The physical variables used for the exercise are:

a) Head water level
b) Temperature
c) Displacement

The abbstract variables Season (S) and Time (T) have been generated according to Equations 2(b) and 2(c) for the date ranges used.

SAMPLE RESULTS

Performance indicators on the simulation data (1999 data), for the three models are given in the table below:

Table 1 : Performance indicators

	HST	HSTT	HTT
R^2	0.872	0.904	0.692
MSE	0.000002	0.000001	0.000004
STDEV Error	0.001354	0.001170	0.002100

Figures 1, 2 and 3 show the simulation of displacement using models HST, HSTT and HTT respectively. It can be seen in Figure 1 and from Table 1 that HSTT is able to perform better at predicting the displacement over the year 1999 based on the knowledge gained in the year 1998. In Figure 2 and from Table 1 we see that, HST is able to match the pattern fairly accurately, although it fails to explain some variations in the original displacement measurement data. HTT model does well over all, except in the months of January and December, where it seems to drift away from the original measurement.

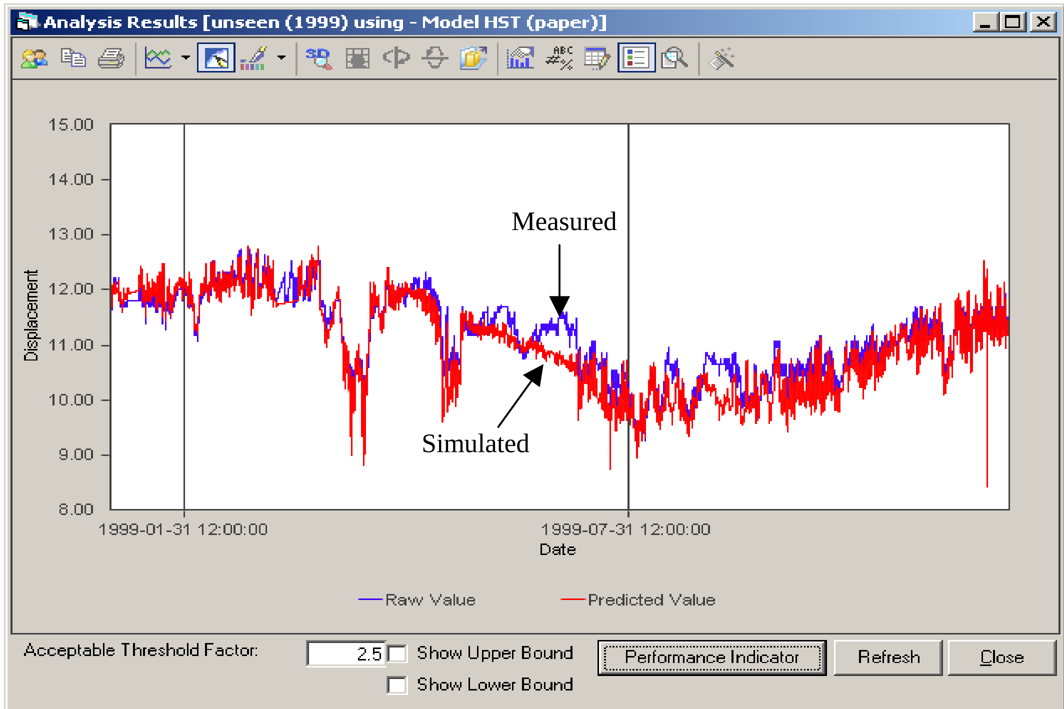

Figure 1: Displacement prediction using HST model

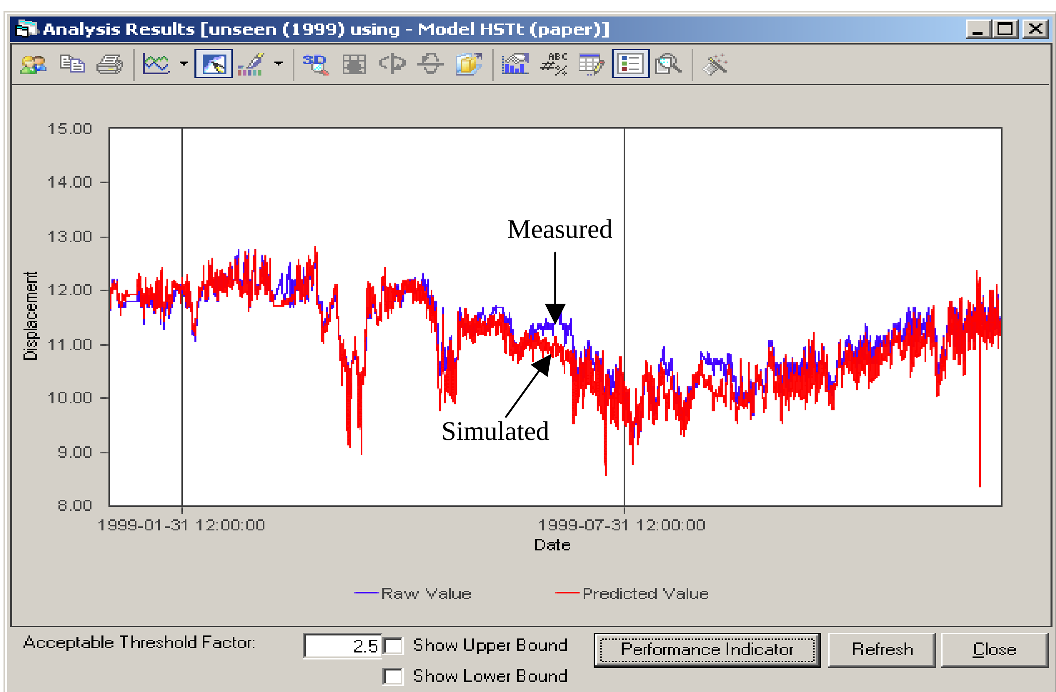

Figure 2: Displacement prediction using HSTT model

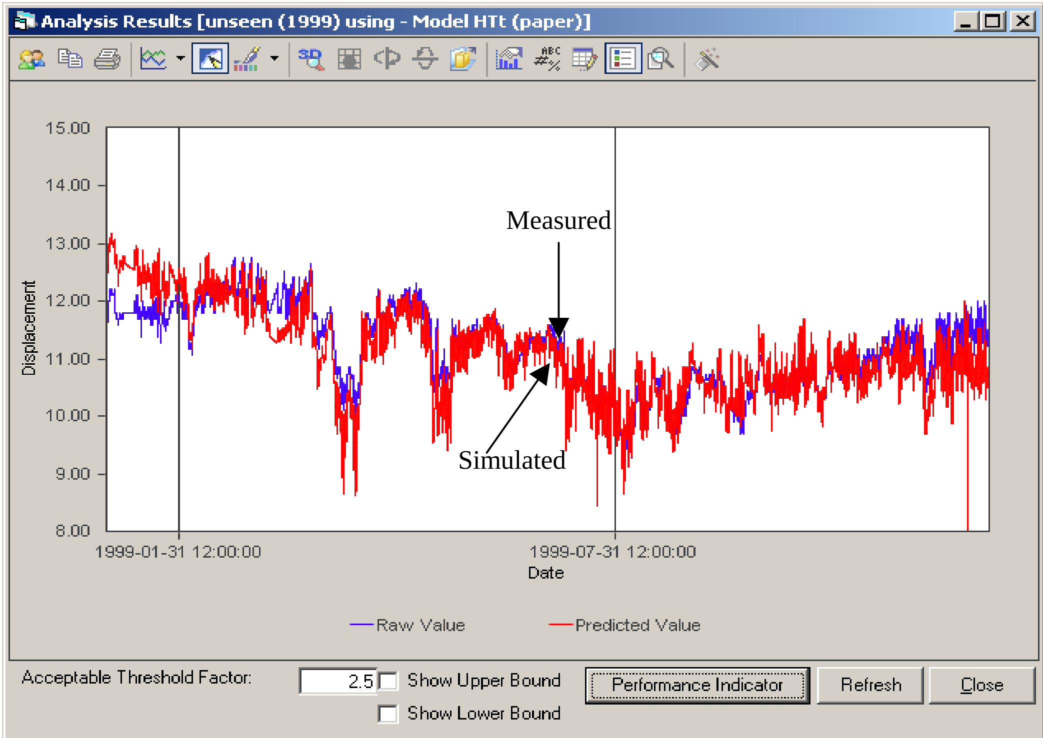

Figure 3: Displacement prediction using HTT model

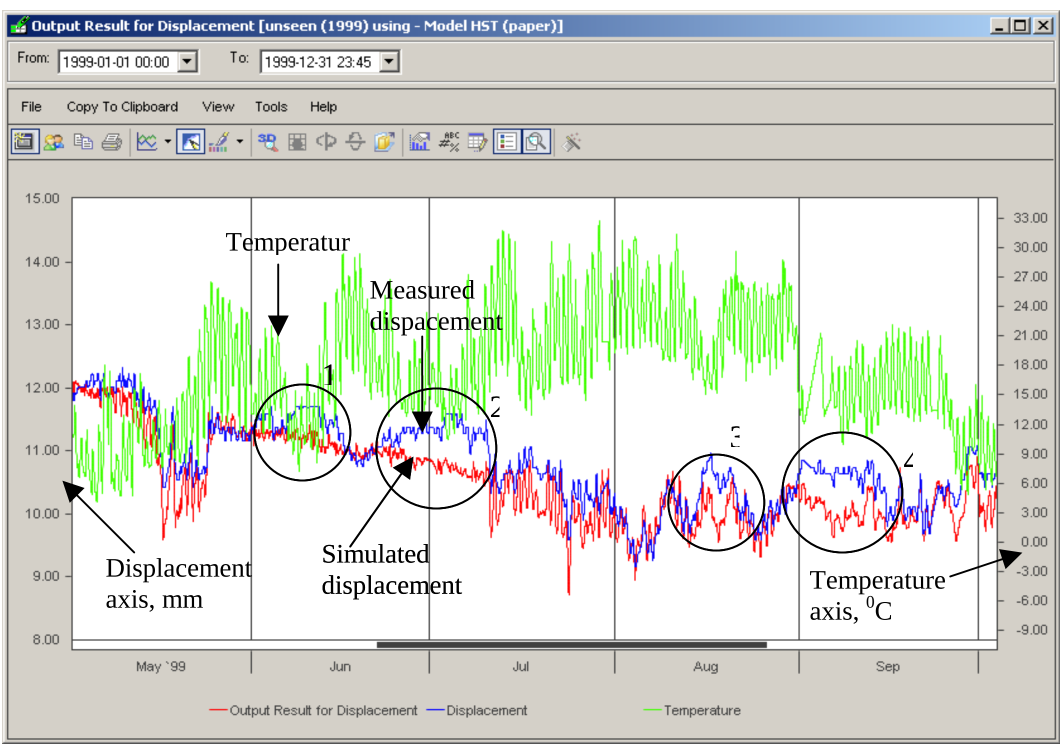

Figure 4: Displacement prediction using HST model – magnified

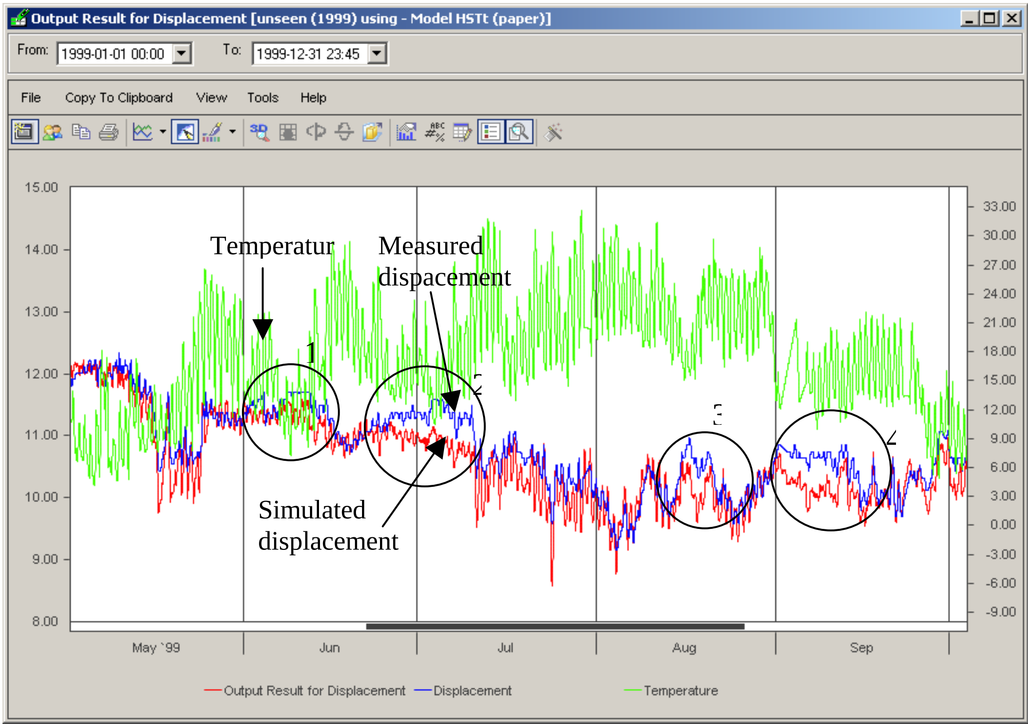

Figure 4: Displacement prediction using HSTT model – magnified

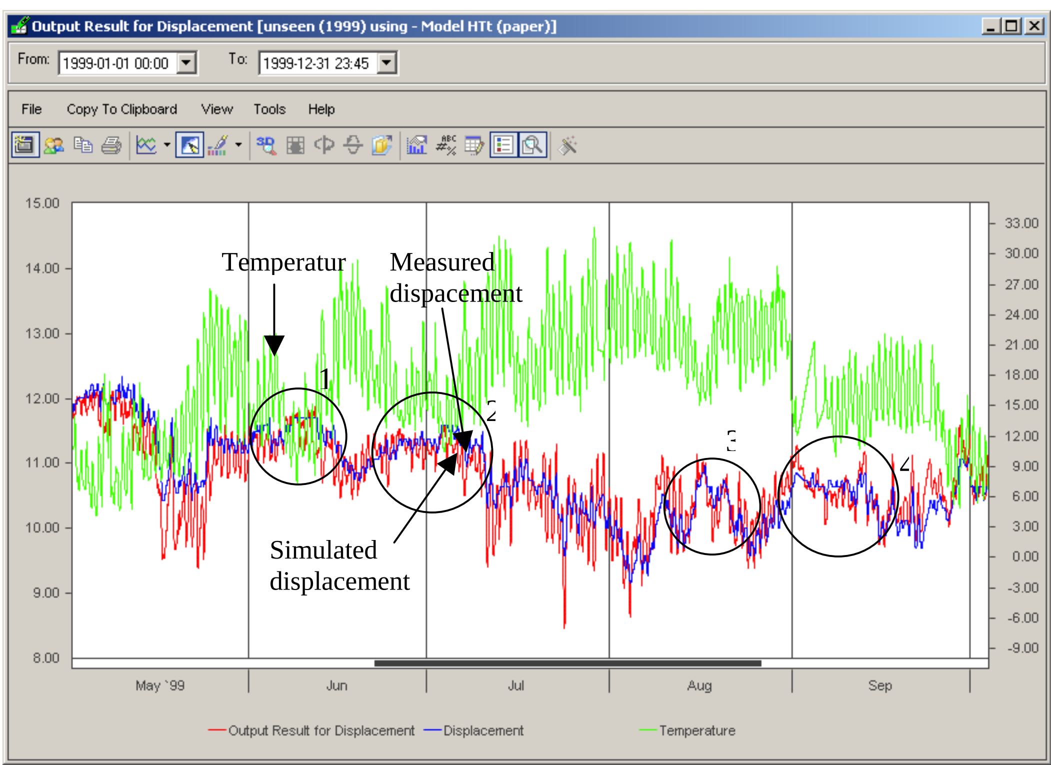

Figure 4: Displacement prediction using HTT model – magnified

Taking a closer look in certain regions of Figure 1,where HST fails to match the original data, we can see in Figures 5 and 6 that, the HSTT and HTT models better explain the deviations in the original curve. Taking a look at the corresponding temperature curve, overlayed in each of the graphs, we can see that, the deviations in the displacement were probably a cause of variations in the temperature.

In that, the HSTT model and the HTT model, particularly try to reject the disturbance due to variations in the temperature where as, the HST model has no information about the actual temperature conditions affecting the displacement. This may in turn be misconstrued as an anomaly, when really it is a reversible effect of temperature on the structure.

The Regions 1 through 4 as marked using circles on Figures 4, 5 and 6 show that there is some deviation in the simulated values of the displacement from the measured ones. The deviation in these regions is more noticeable in the HST model (Figure 4), while the HTT model (Figure 6) almost eliminates it. However, Table 1 shows that the HTT model achieves less favourable performance on the whole range as indicated by the R^2 values. It may be due to the fact that there is a delay between the ambient temperature and the observed displacement response of the dam (Boneli et al. 2001, Penot et al. 2005). This delay is caused by the thermal inertia of the dam structure. HSTT model, although incorporates the temperature as an input, it also includes the season parameter which perhaps indirectly accounts for the delay effect in this case.

DISCUSSION AND CONCLUSIONS

- HST model has been the most widely used model for modeling effects of head water loading on the displacements in concrete gravity dams.
- One of the shortcomings of this model is that it tries to substitute a season variation in temperature as against the real temperature measurement.
- This proves to be a handicap in the model performance where it seems to portray the reversible effects as anomalies.
- HSTT/HTT models incorporate the real temperature affecting the structure on that given day and hence are in a better position to explain and reject the variations in the displacment due to reversible effect of temperature.
- HSTT/HTT models lend better power to the analysis of the dam’s health and hence in making better and correct decisions.
- It is possible that there is a delay between the temperature load and the displacement response because of the thermal inertia of the dam structure. HSTT/HTT models can incorporate such delay to improve the performance of these methods.

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