Field Repairable System Modeling with Missing Failure Information

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SUMMARY & CONCLUSIONS

Many systems, ranging from military vehicles to drink dispensers used in restaurants, are repairable. Operation and failure data from this type of system are often collected by manufacturers and customers. The data are used to monitor system performance as well as for reliability prediction and system improvement. However, due to errors in collecting the data, including human errors, raw field data are rarely suitable for reliability modeling. Data cleanup and certain assumptions have to be made in order to use existing statistical modeling technologies. This is the main challenge the authors have encountered when they tried to model a fleet of fielded repairable systems. An example is a situation where multiple machines are located at the same site, and data on the site's location, instead of the failed machine's ID, are collected. Without knowing which particular machine had the failure, the existing non-homogeneous Poisson process (NHPP) modeling method cannot be applied [1-3]. This type of missing data is called *masked data* for repairable systems. In this paper, a method for modeling masked failure data is proposed and its application is illustrated using a case study. The proposed method can be used to predict the number of failures and the confidence bounds at a given operation time.

1 INTRODUCTION

With the advance of computer technology, field usage information of many products can be easily collected by manufacturers. For example, a printer can automatically record the number of pages it printed; a drink dispenser knows how many cycles it is used every day. This information can be sent to the manufacturers via the internet, a communication network, or collected by technicians at the service time. However, due to human errors and equipment failures, field data are rarely complete and sufficient for reliability modeling purposes. Sometimes, the useful information required for reliability modeling is missing. For example, for a single repairable system, it may be found that no failure information is available for a given time period, or the wrong failure information was found in the record. When this happens, the so called "gap data analysis" [1] can be used. Another common scenario is when there are multiple systems for a given customer or at a given site. When a failure occurs, only the customer or the site ID is recorded, and the serial number of the machine that had the failure is not recorded. For example, three drink dispensers are used in a restaurant. Each dispenser can automatically record the number of cycles of use at the end of each day. Whenever a failure occurs, a technician is sent to the site. From the date of repair, the usage information of each machine can be obtained from a central database. The table below shows this scenario.

Failure No.	Service Date	Caused By	Usage at Service (cycle)		
			M1	M2	M3
1	1/1/2012	{M1}	112	180	150
2	3/2/2012	{M1, M2}	389	350	400
3	5/8/2012	{M1, M2, M3}	568	600	607
4	8/8/2012	{M1, M3}	896	888	910
5	9/18/2012	{M2}	1008	1208	1310
6	11/19/2012	{M3}	1345	1508	1600
7	1/18/2013	{M2, M3}	1657	1890	1867

Table 1 – Example of Masked Failure Data

The notation {M1, M2, M3} means that the repair is done for either machine M1, M2, or M3. The "Usage at Service" column shows the number of cycles recorded by each machine at the time of repair. Many modeling methods for repairable systems have been proposed [2, 3]. However, all of them require knowing exactly which machine had the failure. The existing methods cannot handle the special case in Table 1.

In this paper, we will provide a method for estimating the reliability model for repairable systems with masked failure data. This method is based on one of the existing models and maximum likelihood estimate (MLE) theory.

2 BACKGROUND

Many models have been proposed for repairable system modeling. Among them, the log-linear model and the power law model are the most popular [2, 3]. In this paper, we will

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use the power law model to illustrate our new method. However, the proposed method is very general and it can be extended to other models.

2.1 The Power Law Model

In the power law model, the failure intensity of a repairable system is described by a power function as in [2]:

$$\lambda(t) = \lambda\beta t^{\beta-1} \tag{1}$$

where:

- λ is the scale parameter and β is the shape parameter.
- t is the usage of the system. It can either be the time or number of cycles.

When β is less than 1, the failure intensity decreases with time; when β is larger than 1, the failure intensity increases with time; when β is equal to 1, the system has a constant failure intensity.

At a given time t, the predicted number of failures can be calculated as:

$$\hat{N}(t) = \int_0^t \lambda\beta x^{\beta-1}dx = \lambda t^{\beta} \tag{2}$$

If there are two machines with usage of T_1 and T_2 at a given date for a given site, then the predicted number of failures of this site is:

$$\hat{N}_{site}(date) = \hat{N}(T_1) + \hat{N}(T_2) = \lambda\left(T_1^{\beta} + T_2^{\beta}\right)$$

given that the two machines have the same failure intensity functions. Clearly, if $\beta \neq 1$, then:

$$\hat{N}(T_1) + \hat{N}(T_2) \neq \hat{N}(T_1 + T_2)\,, \tag{3}$$

since:

$$\lambda\left(T_1^{\beta} + T_2^{\beta}\right) \neq \lambda\left(T_1 + T_2\right)^{\beta}$$

Therefore, for the data in Table 1, we cannot simply add together the usage cycles of the three machines to obtain the failure time for an equivalent system, since we do not know if β is 1 or not. If they can be added together (i.e., β =1), then the data in Table 1 can be simplified to:

Failure No.	Service Date	Usage at Service (cycle)			Total Site Usage
		M1	M2	M3	
1	1/1/2012	112	180	150	442
2	3/2/2012	389	350	400	1139
3	5/8/2012	568	600	607	1775
4	8/8/2012	896	888	910	2694
5	9/18/2012	1008	1208	1310	3526
6	11/19/2012	1345	1508	1600	4453
7	1/18/2013	1657	1890	1867	5414

Table 2 – Repairable System with Constant Failure Intensity

For the data in Table 2, the existing modeling method can be used since it becomes a single *equivalent* system with known failure times. The 1st and the last column in Table 2 can be used for modeling.

For a single system with known failure times, the MLE method can be used to estimate the model parameters in Eqn. (1). We will explain this next.

2.2 The MLE Solutions

It is known that the reliability and failure intensity functions have the following relationship:

$$R(t) = e^{-\int_0^t \lambda(x)dx} = e^{-\lambda t^{\beta}} \tag{4}$$

For a repairable system, the time to next failure is conditional on the previous failure time. Let $0 < t_1 < t_2 < \cdots < t_n$ be the n consecutive failure times of the system. The conditional reliability of the system at time t given that the i^{th} failure occurs at t_i (i= 1, 2, …) is:

$$R(t \mid t_i) = e^{-\lambda(t^{\beta} - t_i^{\beta})} \tag{5}$$

and the corresponding conditional probability density function (*pdf*) of the i^{th} failure time t_i is given as:

$$f(t_i \mid t_{i-1}) = \lambda\beta t_i^{\beta-1} R\left(t_i \mid t_{i-1}\right) \tag{6}$$

For a failure-terminated data set with n failures, the likelihood function of a data set is:

$$L\left(\lambda,\beta \mid data\right) = f(t_n \mid t_{n-1}) f(t_{n-1} \mid t_{n-2}) \cdots f(t_1) \tag{7}$$

For a time-terminated data set with a termination time of T, the likelihood function is the following product:

$$L\left(\lambda,\beta \mid data\right) = f(t_n \mid t_{n-1}) f(t_{n-1} \mid t_{n-2}) \cdots f(t_1) R(T \mid t_n) \tag{8}$$

When $T = t_n$, Eqn. (8) becomes Eqn. (7). So Eqn. (7) is a special case of Eqn. (8), mathematically. Taking the natural logarithm on both sides of Eqn. (7) and (8) yields:

$$\ln(L) = n\ln\lambda + n\ln\beta + (\beta-1)\sum_{i=1}^{n}\ln t_i - \lambda T^{*\beta} \tag{9}$$

where T^* is either the last failure time t_n or the termination time T. The MLE estimate $\hat{\lambda}$ and $\hat{\beta}$ can be obtained by maximizing the log-likelihood function ln(L).

If there are multiple systems/machines, the total log-likelihood function will be the sum of the individual log-likelihood function of each system.

From the above equations, it is clear that in order to apply the MLE method we need to know the exact failure time of each failure for each system, as required in Eqn. (8). For the masked failure data in Table 1, the above method cannot be applied directly, since for a given failure at a site, we may not know which machine had the failure. If we can simplify the data to Table 2 by assuming that the failure intensity is constant, then we can use Eqn. (9) to solve for λ by setting $\beta = 1$. However, for most repairable systems, the failure intensity is not constant.

In Section 3, we will propose a practical method for modeling the masked failure data given in Table 1.

3 MODELING MASKED FAILURE DATA

For non-repairable systems, methods for modeling masked failure data have been proposed [4-8]. In this section, we will introduce a new method for analyzing masked failure data for repairable systems. MLE will be used to estimate the model parameters. Methods for obtaining the confidence bounds of some reliability metrics are also discussed.

3.1 The Likelihood Function for Masked Failure Data

Let $C_i = \{1, 2, 3, \cdots, J\}$ be the set of J machines that are possibly responsible for the i^{th} failure at a site. If the failure is caused by machine j, then the conditional *pdf* given in Eqn. (6) is used for machine j. For all other machines in C_i, the conditional reliability function given in Eqn. (5) should be used since they are working at failure time t_i. For machines not in C_i, the conditional reliability function should be used for the same reason. Therefore, for the i^{th} failure, the likelihood function is:

$$L_i = \left\{ \sum_{j \in C_i} \left[f(t_{j,i} \mid t_{j,i-1}) \prod_{k \in C_i, k \neq j} R\left(t_{k,i} \mid t_{k,i-1}\right) \right] \right\} \times \prod_{k \notin C_i} R\left(t_{k,i} \mid t_{k,i-1}\right) \tag{10}$$

The above equation assumes minimal repair. If there are multiple sites, then for the i^{th} failure at site l, the likelihood function becomes:

$$L_{l,i} = \left\{ \sum_{j \in C_{l,i}} \left[f(t_{l,j,i} \mid t_{l,j,i-1}) \prod_{k \in C_{l,i}, k \neq j} R\left(t_{l,k,i} \mid t_{l,k,i-1}\right) \right] \right\} \times \prod_{k \notin C_{l,i}} R\left(t_{l,k,i} \mid t_{l,k,i-1}\right) \tag{11}$$

where $C_{l,i}$ is the set of machines that is possibly responsible for the i^{th} failures of site l. Therefore, the overall likelihood function for all the observations is:

$$L = \prod_{l=1}^{S} \prod_{i=1}^{N_l} L_{l,i} \tag{12}$$

where

- S is the total number of site
- N_l is the number of records at site l

Taking the logarithm on both sides of Eqn. (11), we get:

$$\begin{aligned} \Lambda_{l,i} = \ln(L_{l,i}) &= \ln \left\{ \lambda \beta e^{\sum_{k=1}^{M_l} -\lambda t_{l,k,i}^{\beta} + \lambda t_{l,k,i-1}^{\beta}} \sum_{j \in C_{l,i}} t_{l,j,i}^{\beta-1} \right\} \\ &= \ln \lambda + \ln \beta + \sum_{k=1}^{M_l} \left(-\lambda t_{l,k,i}^{\beta} + \lambda t_{l,k,i-1}^{\beta} \right) + \ln \left(\sum_{j \in C_{l,i}} t_{l,j,i}^{\beta-1} \right) \end{aligned} \tag{13}$$

where M_l is the total number of machines at site l. The total log-likelihood function is:

$$\Lambda = \ln L = \sum_{l=1}^{S} \sum_{i=1}^{N_l} \ln\left(L_{l,i}\right)$$

By maximizing Eqn. (13), the MLE solution for λ and β can be found.

3.2 Confidence Bounds for Parameter Estimates

When MLE solutions are obtained, we can use the Fisher information matrix to get the variance and covariance matrix for the model parameters, as detailed in [9]. The Fisher information is based on the second order derivatives of the log-likelihood function with respect to the model parameters. It is defined as:

$$F = -\begin{bmatrix} \dfrac{\partial \Lambda^2}{\partial^2 \lambda} & \dfrac{\partial \Lambda^2}{\partial \lambda \partial \beta} \\ \dfrac{\partial \Lambda^2}{\partial \lambda \partial \beta} & \dfrac{\partial \Lambda^2}{\partial^2 \beta} \end{bmatrix} \tag{14}$$

For the log-likelihood function of each failure given in Eqn. (11), the second order derivatives are as follows:

$$\frac{\partial \Lambda_{l,i}^2}{\partial \lambda^2} = -\frac{1}{\lambda^2}$$

$$\frac{\partial \Lambda_{l,i}^2}{\partial \lambda \partial \beta} = \sum_{k=1}^{M_l} \left(-\ln t_{l,k,i} \times t_{l,k,i}^{\beta} + \ln t_{l,k,i-1} \times t_{l,k,i-1}^{\beta} \right)$$

$$\begin{aligned} \frac{\partial \Lambda_{l,i}^2}{\partial \beta^2} = &-\frac{1}{\beta^2} + \lambda \sum_{k=1}^{M_l} \left(-\ln^2(t_{l,k,i}) \times t_{l,k,i}^{\beta} + \ln^2(t_{l,k,i-1}) \times t_{l,k,i-1}^{\beta} \right) \\ &+ \sum_{j \in C_{l,i}} \left(\ln^2(t_{l,j,i}) \times t_{l,j,i}^{\beta-1} \right) \left(\sum_{j \in C_{l,i}} t_{l,j,i}^{\beta-1} \right)^{-1} \\ &- \left[\sum_{j \in C_{l,i}} \left(\ln(t_{l,j,i}) \times t_{l,j,i}^{\beta-1} \right) \right]^2 \times \left(\sum_{j \in C_{l,i}} t_{l,j,i}^{\beta-1} \right)^{-2} \end{aligned}$$

The above formulas are good only for failures. If the data set is time terminated and the last observation of the site l is the end time, then the 2nd order derivatives for the $N_l th$ observation will be:

$$\frac{\partial \Lambda_{l,N_l}^2}{\partial \lambda^2} = 0$$

$$\frac{\partial \Lambda_{l,N_l}^2}{\partial \lambda \partial \beta} = \sum_{k=1}^{M_l} \left(-\ln t_{l,k,N_l} \times t_{l,k,N_l}^{\beta} + \ln t_{l,k,N_l-1} \times t_{l,k,N_l-1}^{\beta} \right)$$

$$\frac{\partial \Lambda_{l,N_l}^2}{\partial \beta^2} = \lambda \sum_{k=1}^{M_l} \left(-\ln^2(t_{l,k,N_l}) \times t_{l,k,N_l}^{\beta} + \ln^2(t_{l,k,N_l-1}) \times t_{l,k,N_l-1}^{\beta} \right)$$

where t_{l,k,N_l} is the time for the $N_l th$ observation which is the termination time for machine k at site l. Adding the above derivatives of all observations, we can get each element of the Fisher information matrix. From the Fisher information matrix, we can obtain the variance and covariance matrix of the model parameters, as given below:

$$\begin{bmatrix} Var(\hat{\lambda}) & Cov(\hat{\lambda},\hat{\beta}) \\ Cov(\hat{\lambda},\hat{\beta}) & Var(\hat{\beta}) \end{bmatrix} = F^{-1} \tag{14}$$

Once the variance of each parameter is obtained, we can compute the asymptotic confidence bounds of the model parameters [9]. For example, based on the asymptotic distribution (lognormal) of $\hat{\lambda}$, the two-sided confidence bounds of $\hat{\lambda}$ are:

$$\left[\hat{\lambda}\exp(z_{\alpha/2}\sqrt{\mathrm{var}(\hat{\lambda})}\,/\,\hat{\lambda}),\ \hat{\lambda}\exp(-z_{\alpha/2}\sqrt{\mathrm{var}(\hat{\lambda})}\,/\,\hat{\lambda})\right] \tag{15}$$

where $z_{\alpha/2}$ is the $\alpha/2$ quantile of the standard normal distribution.

3.3 Confidence Bounds for Functions of Model Parameters

Eqn. (2) gives the expected number of failures $N(t)$ up to time t for a single machine. If we know how many failures a site will have for a given period of time, then we can allocate the repair budget and resources more accurately. Once we know the variance and covariance matrix of the model parameters, we can calculate the variance and confidence bounds for the functions of the model parameters. The variance of $N(t)$ can be approximated by:

$$Var\left[\hat{N}(t)\right] = \left(\frac{\partial \hat{N}(t)}{\partial \lambda}\right)^2 Var(\lambda) + \left(\frac{\partial \hat{N}(t)}{\partial \beta}\right)^2 Var(\beta) + 2\frac{\partial \hat{N}(t)}{\partial \lambda}\frac{\partial \hat{N}(t)}{\partial \beta}Cov(\lambda,\beta) \tag{16}$$

The confidence bounds are:

$$\left[\hat{N}(t)\exp\left(z_{\alpha/2}\frac{\sqrt{Var\left(\hat{N}(t)\right)}}{\hat{N}(t)}\right),\ \hat{N}(t)\exp\left(-z_{\alpha/2}\frac{\sqrt{Var\left(\hat{N}(t)\right)}}{\hat{N}(t)}\right)\right] \tag{17}$$

For other functions of the model parameters such as the cumulative mean time between failures (MTBF) and failure intensity, we can calculate their variances and confidence bounds in a similar manner. The details of the calculations are not provided here [1].

3.4 Example

An example based on a consulting project the authors did is given here to illustrate the proposed method for modeling the masked failure data for repairable systems. The data for three sites with similar machines are collected and given in the following tables. We want to model the data and predict the number of failures for each site.

Failure No.	Caused By	Usage at Service (cycle)
		A1
1	{A1}	27
2	{A1}	82
3	{A1}	100
4	{A1}	154
5	{A1}	196
6	{A1}	208
7	{A1}	236
8	{A1}	481
9	{A1}	601
10	{A1}	608
11	{A1}	678
12	{A1}	683
13	{A1}	738
14	{A1}	753
15	{A1}	761
16	{A1}	886
17	{A1}	968
18	{A1}	969
19	{A1}	993
End Time		1054

Table 3 – Site A Failure Data (1 Machine)

Failure No.	Caused By	Usage at Service (cycle)	
		B1	B2
1	{B2}	88	38
2	{B1}	93	113
3	{B1, B2}	104	131
4	{B1, B2}	139	135
5	{B1, B2}	143	138
6	{B1, B2}	143	147
7	{B1, B2}	152	217
8	{B1, B2}	176	223
9	{B1, B2}	227	230
10	{B1, B2}	265	241
11	{B1}	271	270
12	{B1}	300	340
13	{B2}	345	373
14	{B2}	394	404
End Time		400	425

Table 4 – Site B Failure Data (2 Machines)

All machines have the same design. The notation {C1, C2, C3} means that the failure may be caused by C1, C2, or C3.

Since Site A in Table 3 has only one machine, all the failures are caused by A1. The power law model is used for this data. The proposed method in Eqn. (11) is applied to estimate the MLE solutions for model parameters. The estimated parameters are:

$$\hat{\lambda} = 0.0140, \quad \hat{\beta}=1.0396$$

The variance and covariance matrix is:

$$\begin{bmatrix} Var(\hat{\lambda}) & Cov(\hat{\lambda},\hat{\beta}) \\ Cov(\hat{\lambda},\hat{\beta}) & Var(\hat{\beta}) \end{bmatrix} = \begin{bmatrix} 6.901E-06 & -3.398E-05 \\ -3.398E-05 & 3.887E-04 \end{bmatrix}$$

For a site with multiple machines, the expected number of failures is the sum of the expected number of failures of each machine at that site. Let's use site B to show how the expected number of failures and variance are calculated. Since there are two machines at Site B, clearly:

Failure	Caused By	Usage at Service (cycle)

No.		M1	M2	M3
1	{C1, C2, C3}	3	16	25
2	{C1, C2}	15	25	27
3	{C1, C2, C3}	22	49	40
4	{C1, C2, C3}	54	91	47
5	{C1, C2, C3}	62	97	73
6	{C1, C2, C3}	96	102	118
7	{C1, C2, C3}	118	110	146
8	{C1, C2, C3}	132	141	152
9	{C1, C2, C3}	141	196	161
10	{C1, C2, C3}	156	204	180
11	{C1, C2, C3}	209	232	183
12	{C1}	214	240	225
13	{C2}	230	267	228
14	{C3}	240	293	229
15	{C2, C3}	259	295	239
16	{C1, C3}	279	297	240
17	{C2}	302	315	247
End Time		303	317	260

Table 5 – Site C Failure Data (3 Machines)

$$\hat{N}_{siteB}(t) = \hat{N}_{B1}(t_1) + \hat{N}_{B2}(t_2) = \lambda(t_{B1}^{\beta} + t_{B2}^{\beta}) \quad (18)$$

where t is the total cycles of Site B at a given calendar time or failure time; t_{B1} and t_{B2} are the cycles for machine B1 and B2, and $t = t_{B1} + t_{B2}$. The variance of $\hat{N}_{siteB}(t)$ is:

$$\begin{aligned} Var\left[\hat{N}_{siteB}(t)\right] &= \left(t_{B1}^{\beta} + t_{B2}^{\beta}\right)^2 Var(\lambda) \\ &+ \left(\hat{N}_{B1}(t)\times\ln t_{B1} + \hat{N}_{B2}(t)\times\ln t_{B2}\right)^2 Var(\beta) \quad (19) \\ &+ 2\left(t_{B1}^{\beta} + t_{B2}^{\beta}\right)\left(\hat{N}_{B1}(t)\times\ln t_{B1} + \hat{N}_{B2}(t)\times\ln t_{B2}\right) Cov(\lambda,\beta) \end{aligned}$$

Using the MLE solutions $\hat{\lambda}$ and $\hat{\beta}$ in Eqns. (18, 19), we can get the estimated $\hat{N}_{siteB}(t)$ and its variance. Eqn. (17) can then be used to get the confidence bounds of $\hat{N}_{siteB}(t)$. For each site, the results are given in the following plots, where the X-axis is the total number of cycles for each site, and the Y-axis is the predicted number of failures.

For each machine, the usage rate in each month can be estimated based on history data, and then used to calculate the number of failures for a given time period based on the estimated model parameters.

4 CONCLUSIONS

In this paper, we proposed a new method to estimate the model parameters from masked failure data of repairable systems. Traditionally, the failure time and the machine ID of each failure are required in order to solve the parameters of a model. However, this information is often missing. The method proposed in this paper can be used when masked failure data is encountered.

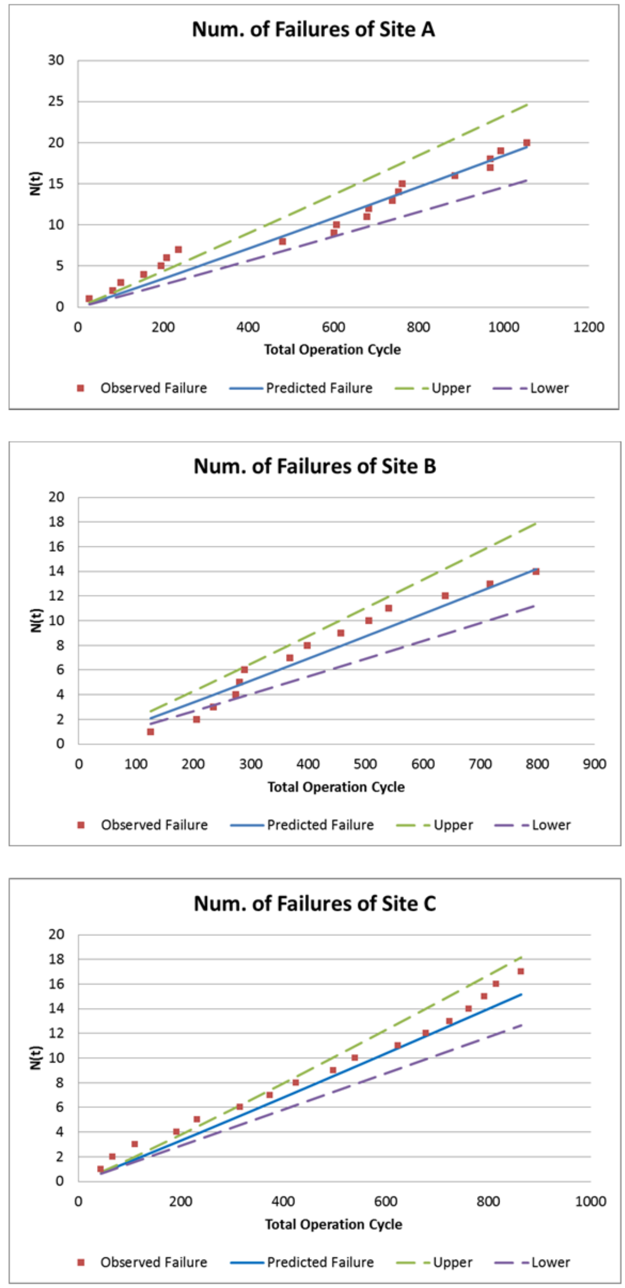

Figure 1 – Predicted Failure and Confidence Bounds for Each Site

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