Availability Importance Measure for Various Operation Condition

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ABSTRACT

The concept of availability importance measures can be used to identifying critical components from the availability performance point of view. The availability of an item depends on the combined aspects of its reliability and maintainability performance indices. These indices are considerably affected by operational and environmental conditions such as; ambient temperature, precipitation, wind, etc. Thus, different subsystems or components' availability in various conditions changes the performance priority of the system. In this way, the paper used the availability importance measure considering the operating environment for a mining fleet consisting of one shovel and six trucks. The reliability and maintainability characteristic of machines considering all influence factors (covariates) is analysed using by Cox regression model. The availability importance measure in two scenarios demonstrated that subsystem criticality changes in various conditions and the appropriate decisions should be made on different operational conditions.

Keywords

Importance measure, operation condition, reliability, maintainability.

1. INTRODUCTION

The increasing demand for material is forcing mining companies to increase their output. To meet production targets, large-scale equipment with high performance is needed.

Availability is a comprehensive metric for repairable systems performance management, which combines reliability and maintainability [1]. Since reliability and maintainability [2] characteristics of equipment are considerably affected by the operating environment (temperature, precipitation, etc.) thus, availability can change through the different conditions.

As previously noted, availability is an important indicator of a repairable system. When the availability of a system is low, efforts are needed to improve it. In a system whose performance depends on the performance of its components, some of these components may play a more important role than others. Therefore, identifying the crucial components is an optimal way to improve system availability [3]. Importance measure is an effective approach that provides a guideline for performance improvement. Availability importance measure is an index that shows the contribution of components available on the system availability. The index provides a numerical ranking of components that highly ranked components have the greatest effect on system availability [4].

Up to this time, many studies have investigated component contribution on system performance. At first, Birnbaum proposed a quantitative definition that measures the contribution of component reliability to system reliability. Then, Gao *et al.* [5] have proposed a maintainability importance measure to identify critical components from a maintainability perspective. Gao *et al.* [6] and Wu and Coolen [7] have proposed a cost-effective manner to improve system reliability using the concept of Birnbaum importance measure. Availability importance measure that identifies the importance of each component on system availability investigated by some authors. Thus, the best strategy selection through decreasing failure rate or increasing repair rate is proposed [4]. Finally, Qarahasanlou *et al.* have presented availability importance measure considering operation environmental factors on RAM characteristics. The study shows different operation conditions can change the availability of components [8].

The previous research shows that the reliability, maintainability, and availability importance of components have been conducted using time series data such as Time Between Failures (TBF's) and Time To Repairs (TTR's). However, RAM characteristics of components can be affected by operation environmental factors (covariates); thus, accurate estimation of system performance requires both time series data and covariates. Furthermore, since various operation conditions may have different influences on component availability performance, thus availability importance of components may change through different operation conditions, which has not been addressed in the previous studies. In this paper, the availability of the system is calculated using both time and covariate data. After that, the concept of availability importance measure is used to identify critical components from the availability point of view in various conditions.

The paper is structured as follows: Section 2 introduces a methodology for reliability and maintainability analysis considering operation conditions after introducing availability and availability importance measures. Section 3 presents a case study describing component importance analysis in various conditions in Iran's Golgohar iron mine. Section 4, finally, concludes the paper.

2. THEORETICAL BACKGROUND AND DEFINITIONS

2.1 Reliability and maintainability analysis

The traditional reliability approach is based on the lifetime distribution of event records of a population of identical items. In this approach, the population characteristics [e.g., mean time to failure (MTTF) and probability of reliable operation] are estimated using historical failure time data. This popular technique was proposed as a standard tool for the planning and operation of automatic and complex mining system reliability/maintainability in the mid-1980s [9]. The approach does not require condition and operating environment data, a limitation in dynamic operating and environmental conditions. Therefore, covariate-based hazard models (regression models) approaches were developed [10]. A pioneering covariate-based hazard model is the proportional hazard model (PHM), introduced by Cox (1972). The common form of PHM is log-linear and is expressed as Equation (1) [11].

$$\lambda(t,z)=\lambda_0(t)\psi(\alpha z)=\lambda_0(t)\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right) \tag{1}$$

The component reliability influenced by covariates is expressed as Equation (2).

$$R(t,z)=(R_0(t))^{\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right)} \tag{2}$$

The mean time to failure (MTTF) can be given by Equation (3) [6]. In this Equation, $\lambda\,(t,z)$ and $R\,(t,z)$ are the failure and reliability functions, respectively, z is row vector consisting of the covariate parameters (indicating the degree of influence which each covariate has on the failure function), α (column vector) is the unknown parameter of the model or regression coefficient of the corresponding n covariates (z), $\lambda_0(t)$ and $R_0(t)$ are baseline hazard rate and baseline reliability, respectively, dependent on time only and $exp\sum_{i=1}^{n}(\alpha_i z_i)$, exponential function commonly used for covariates term [12].

$$\begin{aligned}\mathrm{MTTF}&=\int_0^\infty R(t,z)\,dt=\int_0^\infty (R_0(t))^{\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right)}dt\\&=\int_0^\infty\left(\exp\left(-\int_0^t\lambda_0(x)\,dx\right)\right)^{\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right)}dt\end{aligned} \tag{3}$$

The proportional repair model (PRM) is proposed to predict repair rate considering the operating environment. PRM can be expressed as Equation (4) [2].

$$\mu(t,z)=\mu_0(t)\phi(\beta w)=\mu_0(t)\exp\left(\sum_{i=1}^{m}\beta_i w_i\right) \tag{4}$$

The component maintainability influenced by covariates is expressed as [2].

$$M(t,z)=1-(1-M_0(t))^{\exp\left(\sum_{i=1}^{m}\beta_i w_i\right)} \tag{5}$$

The mean time to repair (MTTR) can be given by [13].

$$\begin{aligned}\mathrm{MTTR}&=\int_0^\infty(1-M(t,z))\,dt=\int_0^\infty(1-M_0(t))^{\exp\left(\sum_{i=1}^{m}\beta_i w_i\right)}dt\\&=\int_0^\infty\left(\exp\left(-\int_0^t\mu_0(x)\,dx\right)\right)^{\exp\left(\sum_{i=1}^{m}\beta_i w_i\right)}dt\end{aligned} \tag{6}$$

Where $\mu(t,w)$ and $M(t,w)$ are the repair and maintainability function, respectively; β is the regression coefficient of the corresponding m covariates (w); and $\mu_0(t,w)$ and $M_0(t,w)$ are the baseline repair rate and baseline maintainability (cumulative distribution function of TTRs), respectively. The main assumption in the PHM/PRM is that the covariates are time-independent variables (PH assumption [2].

There are several approaches to evaluating the proportional hazards (PH) assumption of the PHM: a graphical procedure, a goodness-of-fit testing procedure, and a procedure involving the use of time-dependent variables [14]. However, the PH assumption may not be valid in some cases. This means the effect of the environment on reliability performance is time-dependent. In this case, we can use the stratified Cox regression model (SCRM). The stratified Cox model modifies the PHM, allowing for control by ‘‘stratification’’ of a predictor that does not satisfy the PH assumption. Predictors assumed to satisfy the PH assumption are included in the model, but the stratified predictor is not. For example, suppose the population can be divided into r strata for failure (/g strata for failure), based on the discrete values of a single covariate or a combination of discrete values of a set of covariates. Then, the hazard rate of an asset in the *s*th stratum can be expressed by Equation (7) [14].

$$\lambda_s(t,z)=\lambda_{0s}(t)\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right),\qquad s=0,1,\ldots r \tag{7}$$

As with the original SCRM, there are two unknown components in the hazard model: the failure regression parameter α_i and the baseline failure function λ_{0s} (t) for each stratum. The baseline failure functions for “r” strata could be arbitrary and assumed completely unrelated. The repair rate of an asset in the g’th stratum can be expressed as Equation (8) [11].

$$\mu_g(t,z)=\mu_{0g}(t)\exp\left(\sum_{j=1}^{m}\beta_j w_j\right),\qquad g=0,1,\ldots u \tag{8}$$

Where β_j is the regression parameter and $\mu_{0g}(t)$ the baseline repair function for each stratum. The baseline repair functions for ‘‘u’’ strata could be arbitrary and assumed completely unrelated.

2.2 Availability performance

Availability of a system depending on its component uptime (reliability performance), downtime (maintainability performance), and the system structure (i.e., configuration) [15]. Suppose that 1 and 0 denote system up and downstate, respectively. Therefore, availability is the probability that the system is operational at time t. This measure can be represented mathematically by [16]:

$$A(t)=\Pr(X(t)=1) \tag{9}$$

A(t) is a point or instantaneous availability. However, a common measure of availability is steady-state availability. Steady-state availability is defined as the long-term fraction of time that an item is available. The system's steady-state availability (As.s) is the limit of the point availability as time tends to infinity [17].

$$A_{s.s}=\lim_{t\to\infty}A(t) \tag{10}$$

Typical system structures are series, parallel and series-parallel. In the present paper, the series-parallel structure is discussed. For other structures, see references [4] and [18]. Steady-state availability of a series-parallel system that consists of n independent component in series and m independent component in parallel can be found in Equation (11).

$$A_s(t) = \prod_{k=1}^{n}\left(1-\prod_{l=1}^{m}\left(1-A_{kl}(t)\right)\right) = \prod_{k=1}^{n}\left(1-\prod_{l=1}^{m}\left(1-\frac{MTBF_{kl}}{MTBF_{kl}+MTTR_{kl}}\right)\right) \quad (11)$$

2.3 Availability Importance Measure

Importance analysis, as one of such tools, can be used to prioritize components in a system by mathematically measuring the importance level of each component on the system performance [4]. Availability importance measure can identify the weakest area of the system from an availability point of view. Availability importance measure is the partial derivative of the system's availability for the component availability, which is mathematically expressed by Equation (12):

$$I_A^i = \frac{\partial A_S}{\partial A_i} \quad (12)$$

I_A^i is availability importance of component i, A_s and A_i is the system and ith component availability, respectively. In a system, components with high I_i^A have the greatest effect on the system availability [4]. From Equations (11) and (12), the availability importance measure of ijth component in a series-parallel system can be found in Equation (13) [4].

$$I_A^{ij} = \frac{\partial A_s}{\partial A_{ij}} = \frac{\partial\left(\prod_{k=1}^{n}\left(1-\prod_{l=1}^{m}\left(1-A_{kl}(t)\right)\right)\right)}{\partial A_{ij}} = \prod_{\substack{k=1\\k\neq i}}^{n}\left(1-\prod_{l=1}^{m}\left(1-A_{kl}\right)\right)\times\prod_{\substack{l=1\\l\neq j}}^{m}\left(1-A_{kl}\right) \quad (13)$$

I_A^{ij} To determine the relative ranking of components, this index () should be normalized. represent the absolute value of importance measure, which may not be as significant as component relative ranking [19]. Therefore, normalized availability importance measure for component ij of a series-parallel system can be defined as [18]:

$$NI_A^{ij} = \frac{I_A^{ij}}{\sum_{k=1}^{n}\sum_{l=1}^{m} I_A^{kl}} \quad (14)$$

After detecting critical components, the best strategy for availability improvement through increasing TBF or decreasing repair time should be identified. For this purpose, reliability and maintainability-based availability importance measures are appropriate metrics. Indeed, reliability and maintainability-based availability importance measure shows the influence of reliability and maintainability of component i on the availability of the whole system and can be represented by Equations (15) and (16), respectively [4].

$$I_{A,MTBF_{ij}}^{ij} = I_A^{ij}\times A_{ij}\times\frac{MTTR_{ij}}{MTBF_{ij}(MTBF_{ij}+MTTR_{ij})} \quad (15)$$

$$I_{A,MTTR_{ij}}^{ij} = I_A^{ij}\times A_{ij}\times\frac{1}{(MTBF_{ij}+MTTR_{ij})} \quad (16)$$

Normalized reliability and maintainability-based availability importance measure are defined by Equations (17) and (18), respectively [18].

$$NI_{A,MTBF}^{ij} = \frac{I_{A,MTBF}^{ij}}{\sum_{k=1}^{n}\sum_{l=1}^{m} I_{A,MTBF}^{kl}} \quad (17)$$

$$NI_{A,MTTR}^{ij} = \frac{I_{A,MTTR}^{ij}}{\sum_{k=1}^{n}\sum_{l=1}^{m} I_{A,MTTR}^{kl}} \quad (18)$$

3. CASE STUDY

Mining companies are using large-scale equipment with high investment. To meet the production target, high performance of this equipment is needed. Here, we present a case study to illustrate the proposed methodology. This mine is an open pit, and the shovel-truck fleet is used for material handling. Therefore, a shovel-truck system illustrated in Figure 1 is selected as a case study. This fleet is considered a system, loading and hauling are considered a subsystem, and each machine is considered a component. Table 1 represents the model of the machines and corresponding codes.

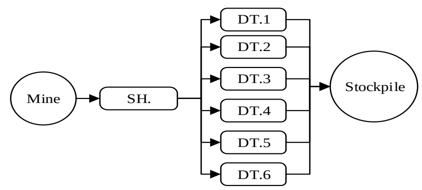

Figure 1- Block diagram for shovel-truck fleet

Table 1- components of the mining system and their code

Equipment	Model	Code
Shovel	Liebherr R9350	SH.
Dump Trucks	Terex-TR100	DT.1,2,3 and 4
Dump Trucks	Caterpillar-777D	DT.5 and 6

After identifying the system, subsystem, and component, required data were collected over 18 months. For each machine, TBF, TTR, and corresponding covariate were sorted, classified, and quantified. Identification and quantification of all influence covariates are curtailed tasks. For instance, the classification and quantification of covariates for haulage subsystem failure are shown in Table (2). In addition, identified covariates for shovel and dump truck subsystem failure and repair are appeared in Table (3).

Table 2- Classification and quantification of failure covariates for haulage subsystem

Covariate	Classification	Quantification
Shift (Zsh)	Morning	1
	Midday	2
	Night	3
Working Place (Z_{WP})	Bench 10-12	1
	Bench 13-15	2
	Bench 16-18	3
Math with loader (Z_{ML})	Excavator	1
	Shovel	2
	Suitable	1

Number of times service (Z_{NS})	Moderate	2
	Unsuitable	3
Rock kind (Z_{RK})	Ore	2
	Waste	1
Team (Z_{Team})	Team A	1
	Team B	2
	Team C	3
	Team D	4

Table 3- Failure and repair covariates for subsystems

Failure covariates		repair covariates
Dump trucks	Shovel	
Shift	Shift	Shift
Rock kind	Rock kind	Precipitation
Number of services	Number of services	Temperature
Match with loader	Match with loader	Wind
Team	Team	
Working place	Precipitation	
Precipitation	Temperature	
Temperature		

3.1 Reliability and Maintainability Performance Analysis

In this case, graphical and theoretical models are used for checking PH assumption. In Cox PHM or PRM, Weibull distribution widely used for baseline hazard rate λ_0 and baseline repair rate μ_0. So, for ensuring the Akaike Information Criterion (AIC) is used for goodness to fit baseline hazard rate and baseline repair rate for all subsystems. In the present study, test z for eliminated covariates was found to have no significant value from the subsequent calculations. The corresponding estimates of a regression coefficient were obtained and tested for their significance based on test z and (/or) p-value (obtained from the table of normal unit distribution). Used the p-value of 5% as the upper limit to check the significance of covariates. To avoid any bias in the results of PRM and PHM, the assumption of the proportional repair model and proportional failure model must be checked; Stata accommodates a statistical test of the PH assumption using the Schoenfeld residuals. The results of the PH assumption for DT.1 are shown in Table 4. In the theoretical model, if the p-value is bigger than 0.05, the PH assumption is established, and covariates are time-independent.

Table 4- The results of theoretical model for PH assumption for subsystem DT.1

Covariates	Rho	Chi2	Df	P-value
Temperature	-0.04	0.91	1	0.3395
Precipitation	0.008	0.07	1	0.7962
shift	0.056	1.51	1	0.2196
Rock type	0.042	0.81	1	0.369
Number of service	0.063	1.27	1	0.259
Proportional loading	-0.05	1.26	1	0.262
Operation team	-0.009	0.04	1	0.838
Working place	0.038	0.75	1	0.385

Since the PH and PR assumption results show all covariates (continues and category) for failure and repair data are time-independent, thus PHM and PRM are selected as a suitable model for analysis. For instance, the results of selecting effective covariates for PHM of DT.1 are shown in Table 5.

Table 5- The results of PHM for hazard ratio (HR) and select effective covariates for DT.1

Covariates	HR	P-value	95% Conf. Interval	
Temperature	1.005	0.426	0.993	1.017
Precipitation	0.891	0.038	0.800	0.994
shift	0.929	0.216	0.827	1.043
Rock type	0.816	0.626	0.361	1.845
Number of service	0.056	0.000	0.047	0.075
Match with loader	1.212	0.049	1.000	1.469
Team	0.948	0.226	0.869	1.033
Working place	0.848	0.32	0.769	1.046

According to Table 5, the hazard ratio calculated for each covariate, the third column, shows the value of the z test statistic. The most important column is the last column, which determines the effective covariates. If the calculated p-value for the z-test is greater than 0.05, the null hypothesis will be accepted (covariate not affected); otherwise, the covariate is effective. According to Table 5, precipitation, the number of services, and match with loader are selected as effective covariates for DT.1. Finally, each component's reliability and maintainability functions are shown in Table 6 and Table 7, respectively. The MTBF and MTTR in the last columns were calculated according to Equation (3) and (6) and using Wolfram Alpha software with mean values of the covariate.

Table 6- Best-fit distribution for baseline, covariates, and MTTF calculation for failure data

Equipment	Baseline hazard rate (λ_{0s})		$\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right)$	MTBF (Suitable)	MTBF (Unsuitable)
	Best Fit	Parameter			
DT.1	Weibull	Shape=2, Scale=0.8	$\text{Exp}(-2.5Z_{NS}+0.19Z_{ML}-0.108Z_{P})$	2.2	26.41
DT.2	Weibull	Shape=2.03, Scale=0.57	$\text{Exp}(-2.6Z_{NS})$	1.82	23.55
DT.3	Weibull	Shape=2.2, Scale=1.7	$\text{Exp}(-2.6Z_{NS}-0.2Z_{ML}+0.108Z_{Sh})$	8.8	186.3
DT.4	Weibull	Shape=2.1, Scale=0.7	$\text{Exp}(-2.6Z_{NS}-0.09Z_{Team}+0.011Z_{T})$	2.2	25.7
DT.5	Weibull	Shape=1.9, Scale=2.2	$\text{Exp}(-2.6Z_{NS}+0.14Z_{Team}+0.02Z_{T})$	5.2	80.3
DT.6	Weibull	Shape=1.9, Scale=1.4	$\text{Exp}(-2.6Z_{NS})$	4.9	75.4
SH	Weibull	Shape=1.9, Scale=8.8	$\text{Exp}(-1.9Z_{NS}+0.\ 9Z_{MT}+0.17Z_{T})$	2	15.12

Table 7- Best-fit distribution for baseline, covariates, and MTTR calculation for repair data

Equipment	Baseline repair rate (μ_{0s})		$\exp\left(\sum_{i=1}^{n}\alpha_i z_i\right)$	MTTR
	Best Fit	Parameter		
DT.1	Weibull	Shape=0.6, Scale=10	-	15.05
DT.2	Weibull	Shape=0.64, Scale=1.7	$Exp(-0.28Z_{Sh})$	4.56
DT.3	Weibull	Shape=0.67, Scale=3.5	$Exp(-0.02Z_T)$	8.22
DT.4	Weibull	Shape=0.6, Scale=4.8	-	7.22
DT.5	Weibull	Shape=0.7, Scale=1.7	$Exp(-0.023Z_T)$	4.08
DT.6	Weibull	Shape=0.7, Scale=1.35	-	1.71
SH	Weibull	Shape=0.6, Scale=9.6	-	14.44

3.2 Availability importance measure

After calculating RM characteristics and identification component interaction in a logical model, availability importance measure can be used to find the critical component of the system from an availability perspective. In this paper, we consider covariates that can change the availability of the system in dynamic conditions. Therefore, critical components in different conditions should be identified. For this purpose, two scenarios for the number of times service (suitable (Z_{NS}=1), unsuitable (Z_{NS}=3)) is considered. For each scenario, availability importance measure (I_A), reliability-based availability importance measure ($I_{A,\ MTBF}$), and maintainability based availability importance measure ($I_{A,\ MTTR}$) are calculated using Equations (13), (15), and (16) then normalized by Equations (14), (17) and (18) (NI_A- $NI_{A,\ MTBF}$- $NI_{A,\ MTTR}$), the calculation are represented in Table 8 and Table 9.

As shown in Tables 8 and 9, the list of components in decreasing order in the suitable condition is Sh., DT.6, DT.5, DT.3, DT.2, DT.4, and DT.1. The list of components in decreasing order in the unsuitable condition is Sh., DT.6, DT.3, DT.5, DT.2, DT.4, and DT.1. This indicates that various condition components may have different availability and correspondingly different importance from an availability point of view. From a reliability and maintainability perspective, each scenario has its own ordered list of components. From a reliability point of view in the suitable condition, the list of components in decreasing order is Sh., DT.2, DT.6, DT.5, DT.4, DT.3, and DT.1. However, in the unsuitable condition, again in descending order, the list of components is Sh., DT.2, DT.4, DT.1, DT.6, DT.5, and DT.3. Thus, various condition components have a different priority for resource allocation problems.

Table 8- Availability importance measure of mining fleet in the suitable condition

Equipment	Availability	I_A	NI_A	$I_{A,\ MTBF}$	$NI_{A,\ MTBF}$	$I_{A,\ MTTR}$	$NI_{A,\ MTTR}$
DT.1	0.128	0.0037	0.0036	0.000185	0.00342	0.000027	0.0028
DT.2	0.285	0.0045	0.0044	0.000501	0.00926	0.000200	0.0209
DT.3	0.517	0.0066	0.0065	0.000188	0.00347	0.000201	0.0210
DT.4	0.233	0.0042	0.0041	0.000339	0.00627	0.000103	0.0108
DT.5	0.560	0.0073	0.0072	0.000344	0.00636	0.000438	0.0458
DT.6	0.741	0.0123	0.0122	0.000483	0.00894	0.001385	0.1449
Sh.	0.122	0.9738	0.9620	0.052014	0.96227	0.007202	0.7537

Table 9- Availability importance measure of mining fleet in the unsuitable condition

Equipment	Availability	I_A	NI_A	$I_{A,\ MTBF}$	$NI_{A,\ MTBF}$	$I_{A,\ MTTR}$	$NI_{A,\ MTTR}$
DT.1	0.637	0.0000008	0.0000008	7.22E-09	4.36654E-07	1.27E-08	7.3218E-07
DT.2	0.838	0.0000018	0.0000018	1.06E-08	6.44055E-07	5.50E-08	3.1802E-06
DT.3	0.958	0.0000071	0.0000071	1.54E-09	9.30580E-08	3.48E-08	2.0142E-06
DT.4	0.781	0.0000014	0.0000014	9.09E-09	5.49841E-07	3.23E-08	1.8691E-06
DT.5	0.952	0.0000062	0.0000062	3.55E-09	2.14521E-07	6.97E-08	4.0306E-06
DT.6	0.978	0.0000135	0.0000135	3.88E-09	2.34757E-07	1.71E-07	9.8948E-06
Sh.	0.511	0.99999942	0.9999692	1.65E-02	9.99998E-01	1.73E-02	9.9998E-01

4. CONCLUSION

Availability improvement with minimum effort is an interesting issue. Dynamic operation environment is changes component technical characteristics and correspondingly component influence on system availability. Thus, to avoid wrong results, all influence factors on system characteristics must be identified. In this paper, the RAM characteristics of the system are analyzed using both time and operating condition variables (covariates). After that, using availability importance measure, component priority in various working conditions is identified. To illustrate the proposed methodology, a shovel-truck fleet that consists of one shovel and 6 dump trucks is selected. Availability importance measure in two different conditions (suitable and unsuitable) shows that DT.5 has the greatest effect in suitable conditions than DT.3. However, in an unsuitable condition, DT.3 has the greatest effect on system availability. Comparing reliability and maintainability-based availability importance measure for sh., DT.1, DT.2, and DT.4 show that, in the suitable condition, reliability improvement is the best strategy. However, in unsuitable conditions decreasing repair time is more appropriate.

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