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ABSTRACT

This study proposes a new scheme for measurement of safety performance in work systems using segmented point process models that can capture the points of changes in the working conditions as well as changes in safety initiatives. Data, collected from an underground coal mine, were analyzed using homogeneous (HPP) as well as non-homogeneous (NHPP) point process models. Time between occurrences (TBO) and number of occurrences (NOC) were modeled followed by the development of loss functions. The methodology can be used to monitor safety performance and to check safety program effectiveness. The findings of the case study application showed that the injury occurrences data fit the models for (i) 'all incidents' and 'first aid' cases with one change point at 458 days, (ii) 'near-miss' case with one change point at 441 days, and (iii) 'minor' injury case with two-change points at 11 days and 375 days, respectively.

1. Introduction

A comprehensive measure of the safety performance is critical for effective safety management of hazardous facilities and operations. In addition to setting out safety objectives and targets for the safety management systems, a rational framework is needed for evaluation of safety performance in order to assess and improve the effectiveness of accident prevention programs over time.

Several measures exist for the measurement of safety performance. Accident rate has been used as a safety performance index and measuring performance by the number of studies (see Khanzode et al., 2012 for a comprehensive review). Similarly, *incident rate* has been used as a safety performance index. It has also been indexed in the form of risk.

Several methods exist for measuring the safety performance of a work system, such as, accident control chart, Safety Performance Evaluation (SPE) framework, System-Theoretic Accident Model and Processes (STAMP), risk indicator, and attitude scale, etc. Each method has its own merits and demerits. The attitude scale is rather subjective and provides only qualitative rather than quantitative measures on safety management. SPE framework improves the organizations' safety standards by continuous monitoring and review of their safety performance but several questionnaire surveys need to be conducted. Leveson (2015) proposed a new approach namely, System-Theoretic Accident Model and Processes (STAMP) to identify system-specific leading indicators that, in turn, could guide a risk management system. Øien (2001) proposed a risk indicator development methodology for identification of risk influencing factors (RIFs), assessment of potential change in RIFs, assessment of effect of change in risk, and selection of risk indicators. Although the proposed methodology is comprehensive, it lacks in implementation in real scenario. Past researchers have focused on identification of general leading indicators, like maintenance backlog, or on identification of system specific leading indicators that are characterized by hazard analysis techniques (Leveson, 2015; Sinelnikov et al., 2015; Koivupalo et al., 2015; Khawaji, 2012). But, unfortunately, there is a dearth of literatures that could provide the evidences of the usefulness of these general indicators in practical or real world applications (Khawaji, 2012).

Here we recommend the use of statistical approaches for safety performance analysis, notably by taking advantage of the resources offered by modeling. Statistical analysis of the work system safety performance measures facilitates safety management. Mingyan et al. (2011), Maiti et al. (2009) and Khanzode et al. (2011) have carried out statistical analysis for ascertaining safety performance in coal mines in China and India, respectively.

Maiti (2010) has proposed a new way of analyzing and evaluating work system safety based on probability models, control charts, loss functions and safety capability index. The development starts with the adoption of process approach to model safety. Effective combination of quality engineering concepts into safety study is the major attribute of the development.

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Nomenclature

HPP	Homogenous Point Process	λ	injury rate
NHPP	Non-Homogenous Point Process	t_k	development test time ($t_k > 0$)
ARI	arithmetic reduction of intensity	n_k	number of occurrence of incident
PLP	power law process	$L(\theta)$	likelihood function
TBO	time between occurrence	T	predetermined observation time
NOC	number of occurrence	i	change point location
α, β	model parameters (scale and shape parameter respectively) ($\alpha > 0$, $\beta > 0$)	$\lambda(t_i, \theta)$	conditional intensity process

All the above methods deal with a work system under stable conditions. They will not work well for work systems under changing environments. Changing work environment can be on account of changes in the workforce, changes in occupational safety and health systems, etc.

In all such cases the usual statistical approach defined above will not apply. The performance measures have to be treated as a stochastic process and the changes in the process on account of changes in the environment of the work system are to be incorporated to properly analyze the safety measures of the work system.

Such an approach has been applied to the data set of British coal mining disasters given in Maguire et al. (1952) and corrected by Jarrett (1979). The data set lists the times between 191 instances of mining disasters leading to ten or more deaths during the period 15th March 1951 to 22nd March 1962. Akman and Raftery (1986), Loader (1992), West and Ogden (1997), Raftery and Akman (1986), Achcar et al. (2007) and a number of other authors have analyzed this data set and conclusively showed that a change-point approach is suited to this data set. The change-point problem in software failure process was considered by Zou (2003) and some Non-homogenous Point Process (NHPP) software reliability models with change-point have been proposed. Muralidharan (2010) reviewed various point process model exclusively in parametric setup and provided the methods and applications of these models under different repairable policies.

Syamsundar and Naikan (2007) developed a point process methodology based on segmented point process models to model maintained systems with a fair degree of accuracy when the systems are operating under varying environment. This paper extends the work carried out in Maiti (2010) by applying segmented point process models developed in Syamsundar and Naikan (2007) to the safety performance measures when the work system safety is subjected to varying environment. This notion is considered here from the standpoint of how to develop its use in practice for safety performance analysis.

The motivation of this work came from the fact that there is a definite lack in the availability of the methods dealing with changes in performance with passage of time in the domain of work system safety performance measurement. The scope of this paper encompasses three main objectives. The first objective is to analyze the injury data set associated with a given industrial setting. Second objective is to develop loss functions for models used for analysis of work system performance. Final objective is to derive necessary conclusions from the results about the safety status of the work system.

This study is organized as follows. Section 2 describes the modeling of the work system safety performance and determination of the loss function. Section 3 provides the application of proposed methodology in an existing industrial situation. Section 4 discusses the key observations and the results followed by the conclusion and future scope of research.

2. Methodology

The purpose of the present paper is to assess the work system safety performance by modeling the injury or failure data using suitable point process models and also detect the presence of trend or pattern in the respective data. As given in Atwood et al. (1992) a trend means a steady increase or decrease over time, for example, a trend in a failure probability. A pattern means any deviation from an initial hypothesis, resulting from some cause more fundamental than mere randomness of the data; examples could be a step change in reporting rates, caused by issuance of a rule, or a high failure rate in one year, caused by discovery of a generic problem and a backlog of previously unrecognized degraded components.

This paper uses point process modeling to analyze and identify:

1. Trends and patterns associated with safety performance measures.
2. Developing loss functions for these measures.
3. Assess safety performance and take corrective and preventive measures if necessary.

A framework has been proposed for the development of work system safety performance scheme as shown in Fig. 1.

This section defines the segmented point process models as well as parameter estimation technique using the method of maximum likelihood, followed by the development of scheme for safety performance evaluation and decision making.

2.1. Segmented models for varying work system environment

In an industrial setting work systems designed for operation over long periods of time are subject to changes in the environment in which they operate. Changes in the environment bring about changes in the trend or pattern of performance of the systems.

Stochastically the changes in trend are modeled using non-homogeneous Poisson processes. For changing patterns in the maintenance processes of work systems, Syamsundar and Naikan (2007) have developed segmented point process models. In order to take into account the changes in the environmental conditions, a point process model is separated into segments at times where a change occurs in the process with each segment being modeled by a separate point process intensity model independent of the others forming segmented point process models.

Various point process models related to repairable and maintained systems can be easily extended to the case of work system safety performance without loss of generality.

2.1.1. Segmented models

The usual point processes used are the renewal process and the non-homogeneous point process. Renewal process (RP) is used for systems which undergo major changes and after change can be

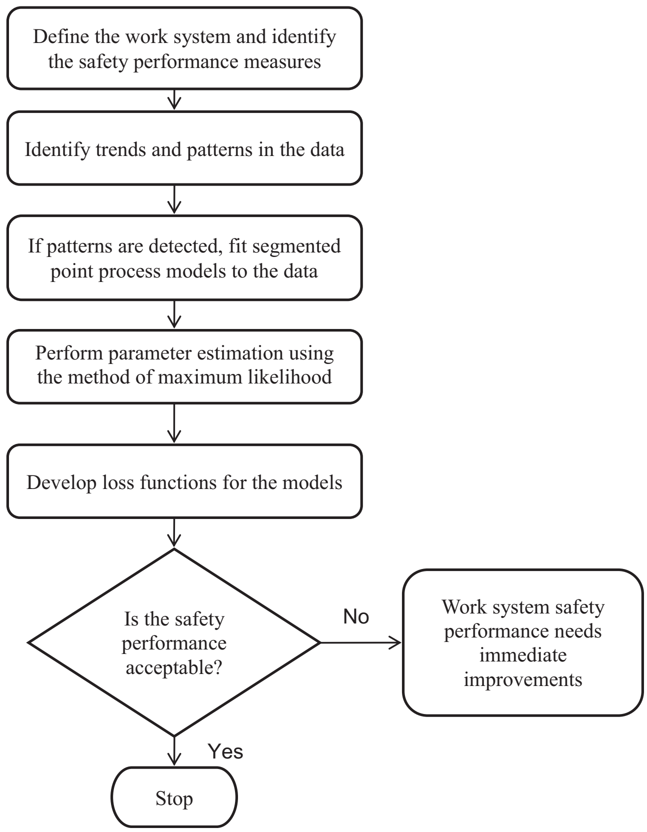

Fig. 1. Proposed framework for safety performance measurement.

termed same as a new system. Non-homogeneous point processes (NHPP) are used for systems which undergo minor changes and after change the intensity of their measure remains the same as before and are termed as same as old. A homogenous Poisson process is a special case of both the RP and NHPP.

When a work system performance undergoes sudden changes, the performance process intensity undergoes a change. Such systems cannot be modeled by means of a single monotonic intensity model as given above. Their domain the performance measure data of such systems can be broken up into sub domains separated by change points, each change point reflecting the time at which a change in the environment takes place. Each sub domain can be independently modeled by any of the models given above and these sub processes can be combined into a composite model to represent such systems. The composite failure intensity is a sum of the failure intensities of the individual sub domains.

Each sub-domain of the system performance measure can be independently modeled by a point process like the HPP or NHPP process and these sub processes can be combined into a composite model to represent such systems.

A segmented homogeneous point process model with multiple change points can be represented by a conditional intensity function given by;

$$\begin{aligned} \lambda(t_i,\theta) &= \lambda_1 && \text{for} \quad 0 \leqslant t \leqslant \tau_1 \\ \lambda(t_i,\theta) &= \lambda_i && \text{for} \quad \tau_{i-1} \leqslant t \leqslant \tau_i \\ \lambda(t_i,\theta) &= \lambda_{n+1} && \text{for} \quad \tau_n \leqslant t \leqslant T \end{aligned} \tag{1}$$

A generalization of the homogeneous Poisson process (HPP) which allows for changes or trend in the intensity of system failures is the non-homogeneous Poisson process (NHPP). A segmented non homogeneous point process with power law intensity can be represented by a conditional intensity function given by;

$$\begin{aligned} \lambda(t_i,\theta) &= \alpha_i\beta_i t^{\beta_i-1} && \text{for} \quad 0 \leqslant t \leqslant \tau_1 \\ \lambda(t_i,\theta) &= \alpha_i\beta_i (t-\tau_{i-1})^{\beta_i-1} && \text{for} \quad \tau_{i-1} \leqslant t \leqslant \tau_i \\ \lambda(t_i,\theta) &= \alpha_{n+1}\beta_{n+1} (t-\tau_n)^{\beta_{n+1}=1} && \text{for} \quad \tau_n \leqslant t \leqslant T \end{aligned} \tag{2}$$

Multiple peaks indicate that a number of changes have taken place in the process. Also, θ represents the history of the process or available data just prior to time t or the collection of all events observed on $[0,t]$ provide a general framework for the modeling of the event processes.

2.1.2. Parameter estimation and hypothesis testing for segmented models

Three key issues arise in the inference and estimation of these models. These are:

- Estimation of location of the change points or the times at which the changes occur i.e., the estimation of $\tau_i, i = 1,2,3,\ldots,n$.
- Estimation of the number of change points i.e., estimation of n.
- Fitting of the models in the different segments and estimation of the parameters of these models.

The method of maximum likelihood as given in Lindqvist (2006) is used estimation of parameters of these models.

2.1.2.1. Parameter estimation. For a system that has been observed for a period $(0,t_k)$, the data are the number of occurrences $n_1,n_2\ldots n_k$ with $n=\sum_{j=1}^{k}n_j$ in the non-overlapping intervals $(t_0,t_1],(t_1,t_2]\cdot(t_{k-1},t_k]$ with $t_0=0$. The likelihood for the Poisson process model is:

$$L(\theta) = \prod_{j=1}^{n} \frac{[\Lambda(t_{j-1},t_j;\theta)]^{n_j}}{n_j!} \exp[\Lambda(t_{j-1},t_j;\theta)] \tag{3}$$

As the number of intervals k increases and the size of the intervals approaches zero, there are exact reported recurrence times at $t_1,t_2\ldots t_k$ with $t_0 \leqslant t_1$, then using a limiting argument it follows that the likelihood in terms of the density approximation is

$$L(\theta) = \underset{j=1}{\overset{n}{d}} \lambda(t_j,\theta)\exp[-\Lambda(0,t_n;\theta)] \tag{4}$$

Two processes the Homogeneous Poisson Process (HPP) and the Non Homogeneous Poisson Process with a Power Law (NHPP-PLP), are used.

For a system with the HPP the intensity function is:

$$\lambda(t_j,\theta) = \lambda \tag{5}$$

where λ is the scale factor indicating constant intensity

For a system with the NHPP-PLP the intensity function is:

$$\lambda(t_j,\theta) = \alpha\beta t^{\beta-1} \tag{6}$$

where α is the scale factor and β the shape factor indicating increasing or decreasing trend

The likelihood function for a pattern with a deviation in the intensity at time points $\tau_1,\tau_2,\ldots,\tau_p$ where p is the number of changes in the intensity is given by:

$$L(\theta) = L(\theta_1)I(0 \leqslant t \leqslant \tau_1) * \ldots. * L(\theta_{p+1})I(\tau_p \leqslant t \leqslant t_n) \tag{7}$$

Estimation of the parameters is obtained at the maximum of this function obtained by equating its score to zero. The score is a vector of the first partial derivatives, one for each element of θ. A check is to be made as to whether the second partial derivatives are negative for obtaining the maximum. Estimates of variance of the parameters can be obtained by taking the inverse of the observed information matrix, and using these, the interval estimates of the parameters can be obtained. This method is presented in Lawless (2011).

2.2.1.2. Hypothesis testing. Goodness of fit tests based on the asymptotic distribution of the estimators or the log likelihood ratio are required to test the segmented models vs HPP or NHPP, for assessment of the model fit. However as these are not yet well developed alternate methods such as graphical fit and AIC ln L criterion are used to obtain models with best fit.

Graphical methods are used to check the accuracy of fit of the estimated expected cumulative failure intensities versus the observed cumulative failure intensities. The closer the fit of the model is to the observed cumulative failure process the more accurately the model describes the process.

A check for arriving at the model with the best fit is to look at the Log likelihood function values. The model whose function has the maximum value will provide the model with the best fit among the alternatives chosen.

A better check for correct fit is obtained by using a penalized likelihood criterion such as the Akaike Likelihood Criterion (AIC). Akaike (1998) observed that the tendency of the classical log likelihood ratio test is to favour the more complex models especially if the amount of data is large. To counter this he proposed to penalize the log likelihood of a model with the number of parameters in the model to obtain a better criterion for comparison. The criterion is given by:

$$AIC(k) = -2\ln L + 2k \tag{8}$$

where k = the number of parameters of the model.

The model with the minimum AIC estimate is considered as the model with the best fit. This is also stated in Chen and Gupta (2001).

Even in the absence of well-established goodness of fit tests for segmented models versus monotonic models, the above methods can still be used appropriately for checking the fit of the segmented models versus the HPP or NHPP models.

2.2. Loss function

To measure quality, Taguchi (1986) proposed the concept of a Quality Loss Function. The quality loss function is a continuous function that is defined in terms of the deviation of a design parameter from an ideal or target value. This function penalizes the deviation of a parameter from the specification value that contributes to deteriorating the performance of the product, resulting in a loss to the customer.

This loss function can be obtained for the safety measures and be used for cost benefit analysis of safety related investments. The objective of safety management is to reduce the monetary loss as well as severity associated with the work system.

2.2.1. Developing loss function for safety measures

For a *larger the better* type of characteristic X, a good approximation of the quality loss function L(X) is

$$\mathrm{L(X)} = \eta/\mathrm{X}^2; \mathrm{X} > 0 \tag{9}$$

Here,

X is the measured actual value of the product characteristic;
L(X) is the quality loss function;
$\eta$is a constant called the quality loss coefficient.

For a *smaller the better* type of characteristic X, a good approximation of the quality loss unction L(X) is

$$\mathrm{L(X)} = \eta/\mathrm{X}^2; \mathrm{X} > 0 \tag{10}$$

2.2.2. Expected loss function for safety measures

For a *larger the better* type of characteristic X, the expected value of the loss function L(X) can be expressed as

$$L_E = E\left[\frac{\eta}{X^2}\right] \tag{11}$$

Maiti (2010) showed that expected loss for *larger the better* (LTB) cases could be approximated as,

$$L_E = \frac{\eta}{\mu^2}\left[1 + 3\frac{\sigma^2}{\mu^2}\right] \tag{12}$$

Here the following notation is used:

$\mathrm{L_E}$ is the average quality loss per item;
μ is the mean of X;
σ^2 s the variance of X.

For a *smaller the better* type of characteristic X, the expected value of the loss function L(X) can be expressed as

$$L_E = E[\eta X^2] \tag{13}$$

Maiti (2010) showed that expected loss for *smaller the better* (STB) cases could be approximated using Eq. (7).

$$L_E = \eta(\mu^2 + \sigma^2) \tag{14}$$

As can be seen expected loss function consists of two terms (1) the variation, denoted by standard deviation, of performance about some mean and (2) the mean performance away from the target, denoted by the distance by which the mean performance is away from the target.

2.2.2.1. Homogenous Poisson process (HPP). For the Homogenous Poisson process, with parameter λ,

Mean = $1/\lambda$
Standard Deviation = $1/\sqrt{\lambda}$

The expected value of loss function, *for larger the better* (LTB) cases could be approximated as,

$$L_E = \eta\lambda^2[1 + 3\lambda] \tag{15}$$

The expected value of loss function, *for smaller the better* (LTB) cases could be approximated as,

$$L_E = \eta\left[\frac{1}{\lambda^2} + \frac{1}{\lambda}\right] = \frac{\eta(1+\lambda)}{\lambda^2} \tag{16}$$

2.2.2.2. Non homogenous Poisson process (NHPP). For the Non-Homogenous Poisson process, with a power law process baseline with parameters – scale α and shape β and Power Law Intensity = $\alpha\beta t^{\beta-1}$ the instantaneous;

Mean = $1/(\alpha\beta t^{\beta-1})$
Standard Deviation = $1/\sqrt{\alpha\beta t^{\beta-1}}$

The expected value of loss function, *for larger the better* (LTB) cases could be approximated as,

$$L_E = \eta\alpha^2\beta^2 t^{2(\beta-1)}[1 + 3\alpha\beta t^{\beta-1}] \tag{17}$$

The expected value of loss function, *for smaller the better* (LTB) cases could be approximated as,

$$L_E = \frac{\eta(1+\alpha\beta t^{\beta-1})}{\alpha^2\beta^2 t^{2(\beta-1)}} \tag{18}$$

2.2.2.3. Segmented homogeneous/Non-homogenous Poisson process (NHPP). For a segmented point process, the value of $\lambda_i/\lambda_i(t)$ varies for each segment of the homogeneous/Non-homogeneous Poisson Process respectively. The aggregate value of the loss function associated with the work system can be evaluated by adding all the individual loss functions for each segment.

The intensity function of a segmented non homogenous Poisson process with power law baseline can be expressed by,

$$\lambda_i(t,\theta) = \alpha_i\beta_i t^{\beta_i-1} \quad for \quad 0 \leqslant t \leqslant \tau_i \tag{19}$$

The expected value of loss function, *for larger the better* (LTB) case with the intensity (23) could be approximated as,

$$L_E = \sum_i \eta\alpha_i^2\beta_i^2 t^{2(\beta_i-1)}[1+3\alpha_i\beta_i t^{\beta_i-1}] \tag{20}$$

3. Case study

3.1. Work system description and data acquisition

The work system is an underground coal mine situated in eastern India, (Maiti, 2010). The mine contains four working seams. The number of underground employees is around 900 and the mine produces around 1000 metric tonne a day. The sequence of coal extraction at face is (i) inspection for safety related issues, (ii) drilling holes in the face, (iii) charging holes with explosive and blasting, (iv) fume clearance and inspection for loading, (v) loading of blasted coal with side discharge loader (SDL), and (vi) supporting roof and sides. The work personnel carry out different activities based on their designation such as driller, loader, short firer, SDL crew, maintenance crew, and roof bolting crew. Safety data were collected from the comprehensive incident database maintained by the mine management. Only injury records for 24 months were extracted from this database for this study.

The distribution of incidents is: all-injury, 197; minor, 29; first-aid, 132; near miss, 36.

3.2. Data analysis

To facilitate the analyses, following assumptions are undertaken:

1. This approach assumes that a work system's completeness of reporting is consistent over time, and that the completeness is independent of the event rate.
2. An implicit assumption is that there are no erroneous entries in the data set.
3. In order to minimize possible reporting biases; such as under reporting or re-classification to a lower level of severity, injury statistics are prepared from data collected directly on-site, from internal accident or medical-aid reports.

To facilitate the application of the methodology, we have adopted a database of time between occurrence (TBO) per month and number of incidents (NOC) per month for four cases i.e. *all incidents*, *first aid*, *near miss* and *minor* cases based on the extent of injury from the underground coal mine. The following sections analyze the respective TBO and NOC for all the four cases to identify trends and pattern in the data set.

3.2.1. Analysis of time between occurrences (TBO)

Case 1: All Incidents

In Fig. 2, the time (in days) between occurrence and number of injuries from the initial data set for all-incident cases are shown. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and log-likelihood are calculated for HPP-PLP with one change point (refer to Table 1). Here, the model HPP-PLP means that the data before the change point fits to HPP model and the data after the change point fits to NHPP-PLP model. In Fig. 3, segmented model for all incident cases is displayed with HPP-PLP single point change.

The intensity of incidents is constant up to 458 days i.e. 15 months after which it has fallen drastically (refer to Fig. 4). However there is an *increasing* trend in the intensity with time, though the intensity at the end of 25 months is still below the initial level of intensity (i.e., up to 15 months) as is evident from the intensity plot. This is mostly on account of a heavy increase in first aid incidents in the 23rd and the 24th months that too mostly due to SDL Crew. In absence of this change, the intensity would have shown a consistent drop in the last ten months. This sudden jump

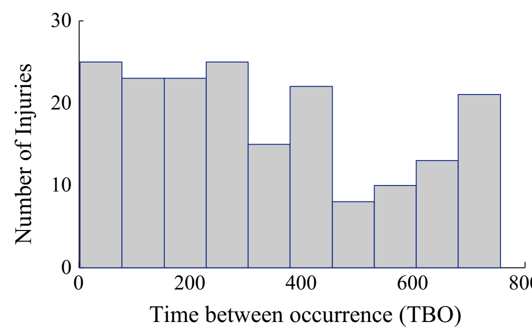

Fig. 2. Number of injuries for all-incidents case.

Table 1
Parameters of the models used for both TBO and NOC.

Point Process	Parameter	Estimated values for TBO	Estimated values for NOC
HPP-PLP with one change point (*All Incident Data*)	$\hat{\lambda}_1$	0.294	10.75
	$\hat{\tau}$	458	12
	$\hat{\alpha}_2$	0.005	2.076
	$\hat{\beta}_2$	1.598	1.356
	ln L	−434.435	−356.256
HPP-PLP with one change point (*First Aid Incident Data*)	$\hat{\lambda}_1$	0.200	6.75
	$\hat{\tau}$	458	11
	$\hat{\alpha}_2$	0.001	0.317
	$\hat{\beta}_2$	1.780	1.805
	ln L	−353.442	−337.716
HPP with change point model with two change points (*Minor Incident Data*)	$\hat{\lambda}_1$	0.454	2
	$\hat{\tau}_1$	11	10
	$\hat{\lambda}_2$	0.046	0.866
	$\hat{\tau}_2$	375	–
	$\hat{\lambda}_3$	0.019	–
	ln L	−112.532	10.422
HPP with change point model with one change point (*Near Miss Incident Data*)	$\hat{\lambda}_1$	0.065	2.3
	$\hat{\tau}_1$	441	10
	$\hat{\lambda}_2$	0.022	1.133
	ln L	−141.487	20.701

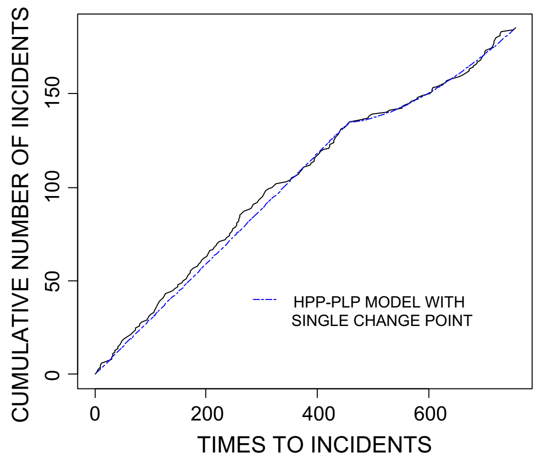

Fig. 3. Segmented model for All-incident cases.

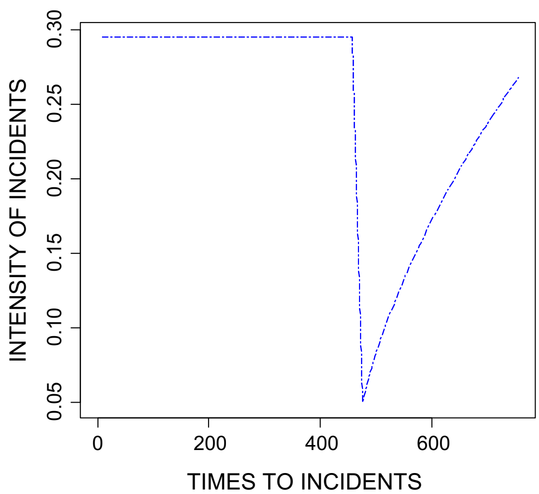

Fig. 4. Intensity plot for all incident cases.

needs to be investigated, reasons noted and remedial measures should be suggested.

Case 2: First Aid incidents

In Fig. 5, the time (in days) between occurrence and number of injuries from the initial data set for first-aid incident case is shown. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and

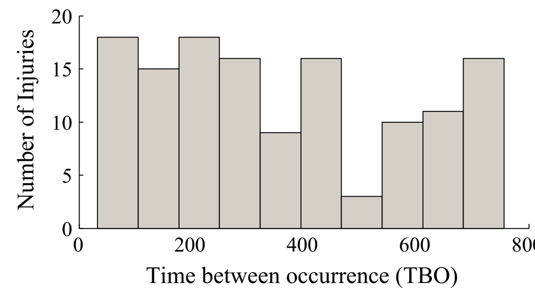

Fig. 5. Number of injuries for first-aid incident case.

log-likelihood are calculated for HPP-PLP with one change point (refer to Table 1). In Fig. 6, segmented model for first-aid cases is displayed with HPP-PLP single point change.

The intensity of incidents is constant up to 458 days i.e. 15 months after which it has fallen drastically (refer to Fig. 7). However there is a sharply *increasing* trend in the intensity with time, and the intensity at the end of 695 days i.e., on crossing the 23rd month, has crossed the initial level of intensity (i.e., up to 15 months) as is evident from the intensity plot. This is mostly on account of a heavy increase in first aid incidents in the 23rd and the 24th months that too mostly due to SDL Crew. In absence of this change, intensity would have shown a consistent drop in the last ten months. This sudden jump needs to be investigated, reasons noted and remedial measures should be suggested.

Case 3: Minor Incident

In Fig. 8, it illustrates the time (in days) between occurrence and number of injuries from the initial data set for minor incident case. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and log-likelihood are also computed for HPP with two change points (refer to Table 1). In Fig. 9, segmented model for minor incident cases is displayed with HPP-HPP-HPP model with two changes point.

The intensity of incidents (refer to Fig. 10) is constant and high up to 11 days as a number of minor injury incidents have taken place at short intervals but thereafter dropped to a low constant level around 9.73 times less. This has persisted so till up to 375 days i.e., the next one year thereafter dropped still further to an intensity which is a further 2.37 times lower. Thus there is an improving trend in minor injuries which is encouraging.

Case 4: Near Miss

In Fig. 11, it illustrates the time (in days) between occurrence and number of injuries from the initial data set for near-miss incident cases. Table 1 describes that the estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$),

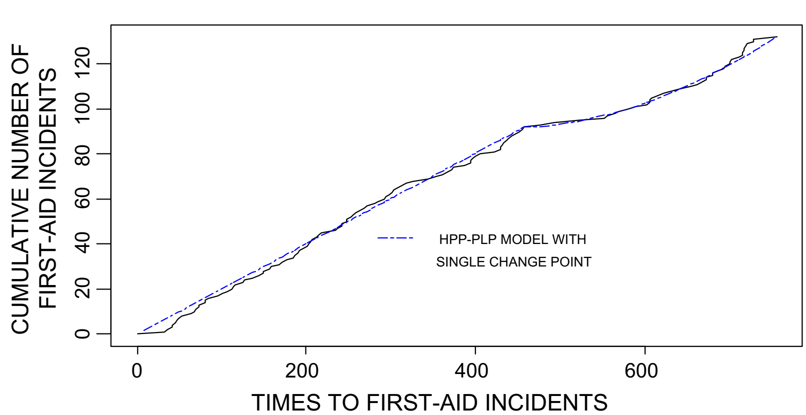

Fig. 6. TBO segmented model for first aid case.

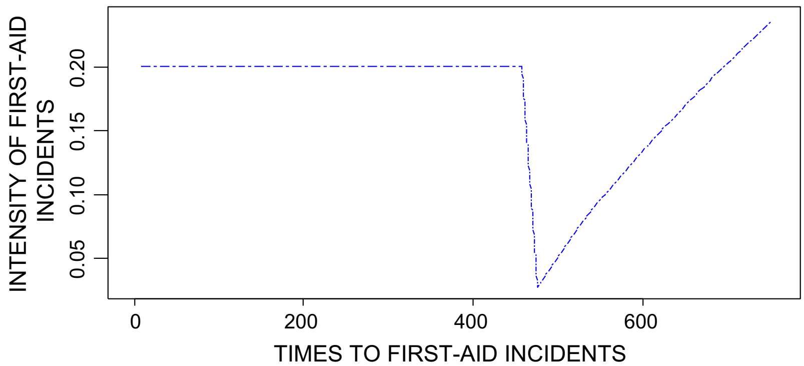

Fig. 7. TBO intensity plot for first aid case.

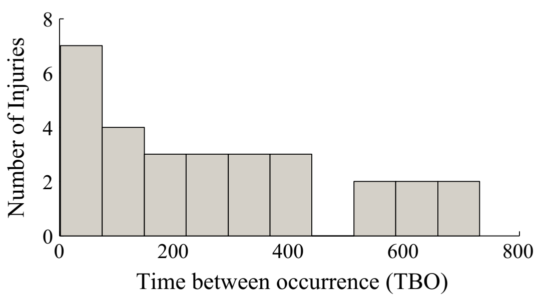

Fig. 8. Number of injuries for minor incident case.

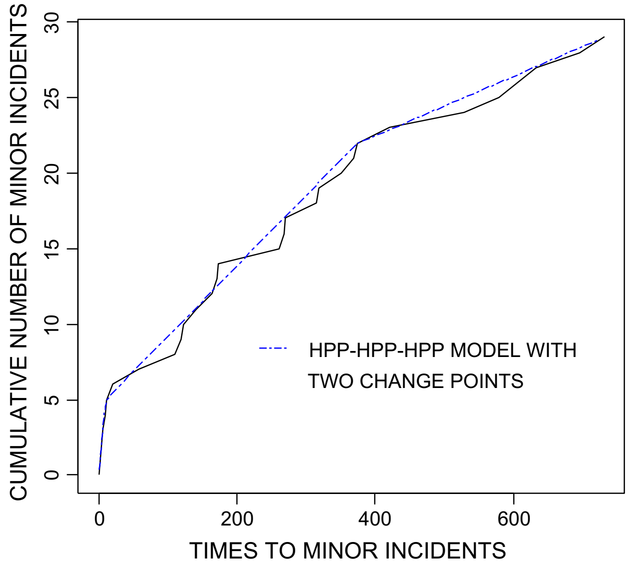

Fig. 9. TBO segmented model for minor incident case.

shape parameter ($\hat{\beta}_2$), and log-likelihood are also computed for HPP with one change point (refer to Table 1). In Fig. 12, segmented model for near-miss incident cases is displayed with HPP-HPP model with one change point.

The intensity of incidents (refer to Fig. 13) is constant and high up to 441 days i.e., 14.5 months and thereafter dropped to an intensity which is a 2.92 times lower. Thus there is an improving trend in near misses which is encouraging. However as seen from the first aid injuries in the 23rd and 24th months the near misses

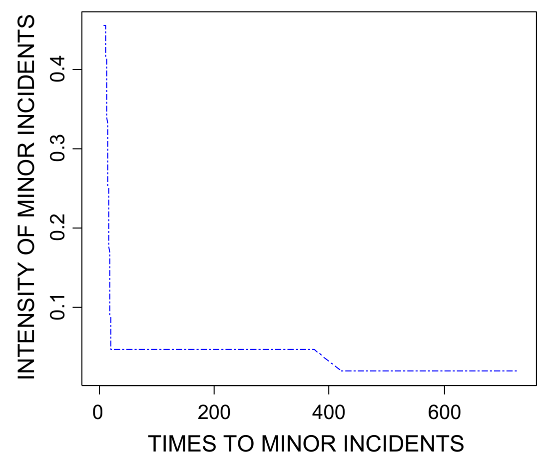

Fig. 10. Intensity plot for minor-incident case.

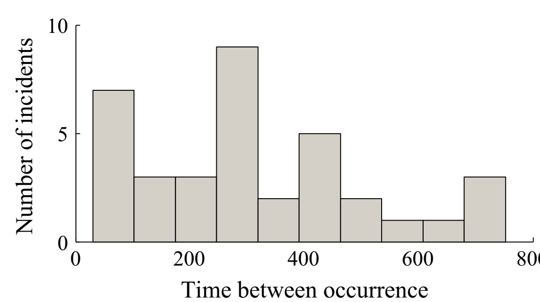

Fig. 11. Number of injuries for Near-miss incident case.

are getting converted to first aid injuries which is more detrimental.

3.2.2. Analysis of number of occurrence (NOC)

Case 1: All Incident data

In case of analysis of number of occurrence, all incidents data set is provided in Table 2. Table 1 describes that the estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and log-likelihood are also computed for HPP-PLP with one change point. In Fig. 14, segmented model for all incident cases is displayed with HPP-PLP model with one change point.

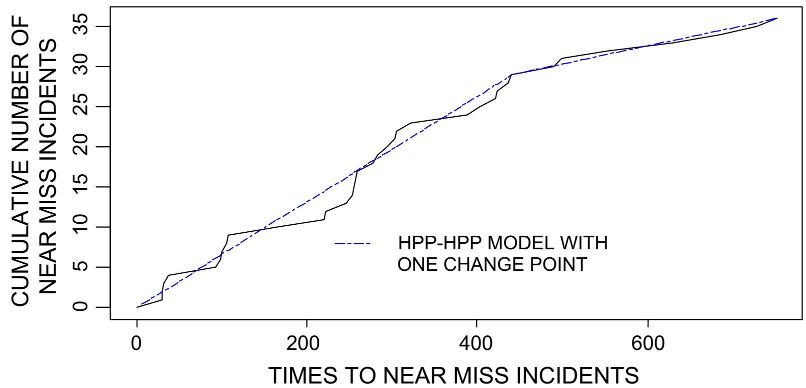

Fig. 12. Segmented model for near-miss case.

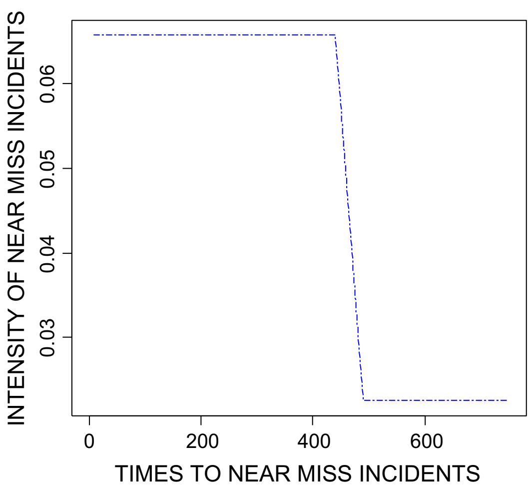

Fig. 13. Intensity plot for near-miss case.

The intensity of incidents (refer to Fig. 15) is constant up to 12 months after which it has fallen drastically. However, there is an increasing trend in the intensity with time, though the intensity at the end of 25 months is still below the initial level of intensity (i.e., up to 12 months) as is evident from the intensity plot. This is mostly on account of a heavy increase in first aid incidents in the 23rd and the 24th months that too mostly due to SDL Crew. Had this not been there the intensity would have shown a consistent drop in the last 13 months. This sudden jump needs to be investigated, reasons noted and remedial measures suggested.

Table 2
Data sets for all incidents and first aid incidents.

Month		NOC: All incidents	NOC: First aid incident data
From	To		
0	1	11	–
1	2	11	8
2	3	9	9
3	4	14	6
4	5	8	6
5	6	12	8
6	7	9	9
7	8	10	7
8	9	16	8
9	10	12	8
10	11	10	6
11	12	7	6
12	13	10	7
13	14	9	5
14	15	14	12
15	16	2	2
16	17	4	1
17	18	2	1
18	19	7	4
19	20	7	6
20	21	5	3
21	22	4	4
22	23	13	10
23	24	23	21
24	25	3	2

Case 2: First Aid

In case 2, first aid incidents data set is provided in Table 2. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and

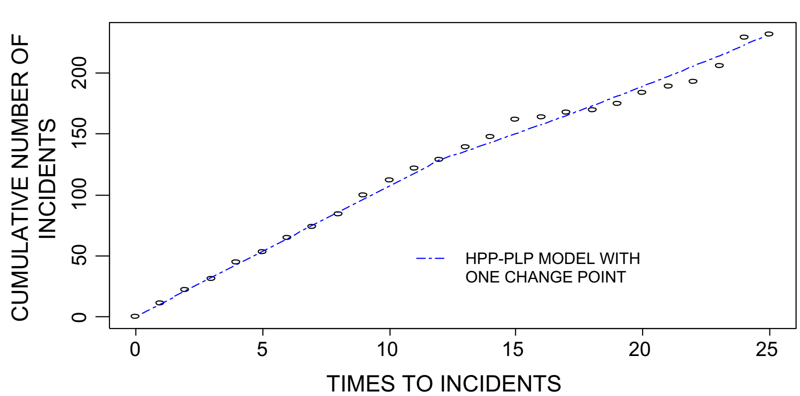

Fig. 14. Segmented model for all-incident case.

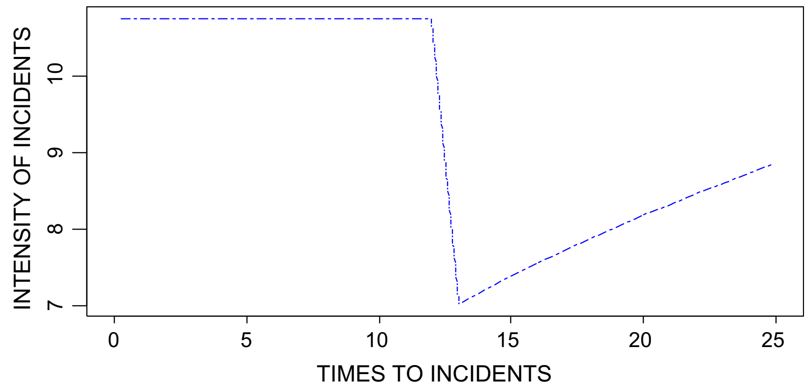

Fig. 15. Intensity plot for all-incident case.

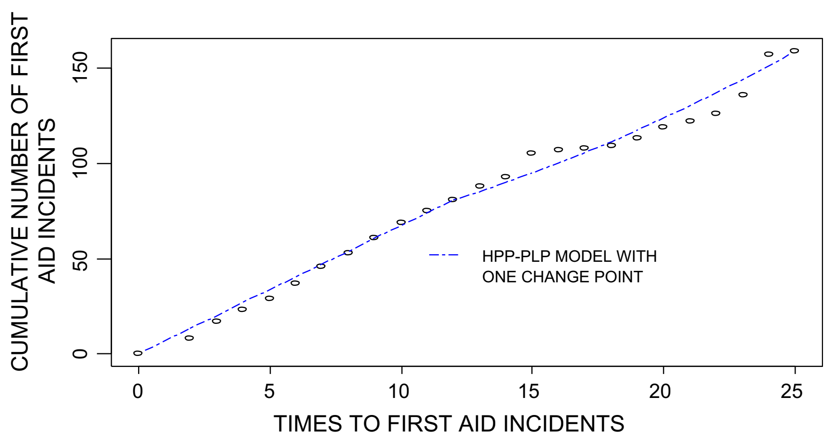

Fig. 16. NOC segmented model for first aid case.

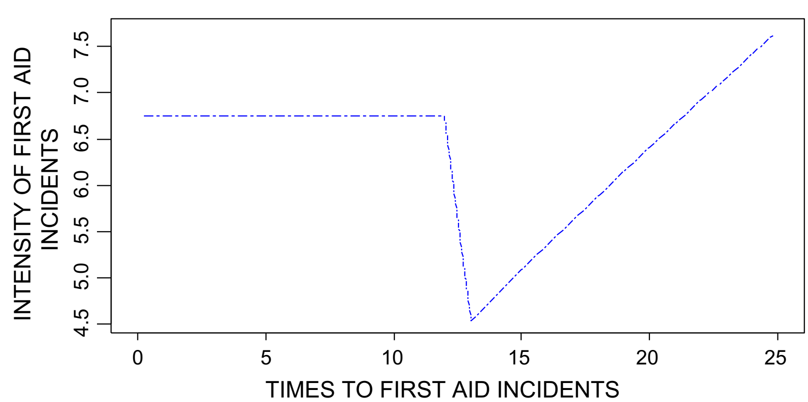

Fig. 17. NOC intensity plot for first aid case.

Table 3
Data sets for minor and near miss incidents.

Month		NOC: Minor incidents	NOC: Near miss incidents
From	To		
0	5	14	10
5	10	6	13
10	15	6	8
15	20	3	5
20	25	4	4

log-likelihood are also computed for HPP-PLP with one change point (refer to Table 1). In Fig. 16, segmented model for first aid incident cases is displayed with HPP-PLP model with one change point.

The intensity of incidents (refer to Fig. 17) is constant up to 12 months after which it has fallen drastically. However there is a sharply increasing trend in the intensity with time, and the intensity on crossing the 21st month, has crossed the initial level of intensity (i.e., up to 12 months) as is evident from the intensity plot. This is mostly on account of a heavy increase in first aid incidents in the 23rd and the 24th months that too mostly due to SDL Crew. Had this not been there the intensity would have shown a consistent drop in the last ten months. This sudden jump needs to be investigated, reasons noted and remedial measures should be suggested.

Case 3: Minor Incident Data

Similarly, in case 3, minor incidents data set is provided in Table 3. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and log-likelihood are also computed for HPP-PLP with one change point (refer to Table 1). In Fig. 18, segmented model for minor incident cases is displayed with HPP-HPP model with one change point.

The intensity of incidents (refer to Fig. 19) is constant and high up to 10 months and thereafter dropped to an intensity which is a 2.31 times lower. Thus, there is an *improving trend* in minor incidents which is encouraging.

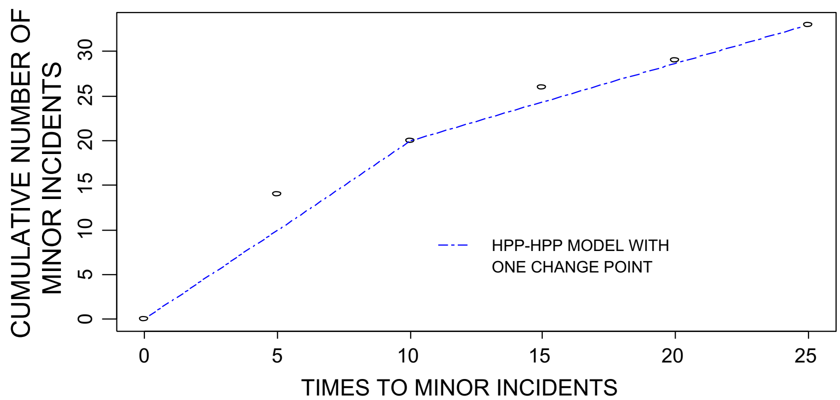

Fig. 18. NOC segmented model for minor incident case.

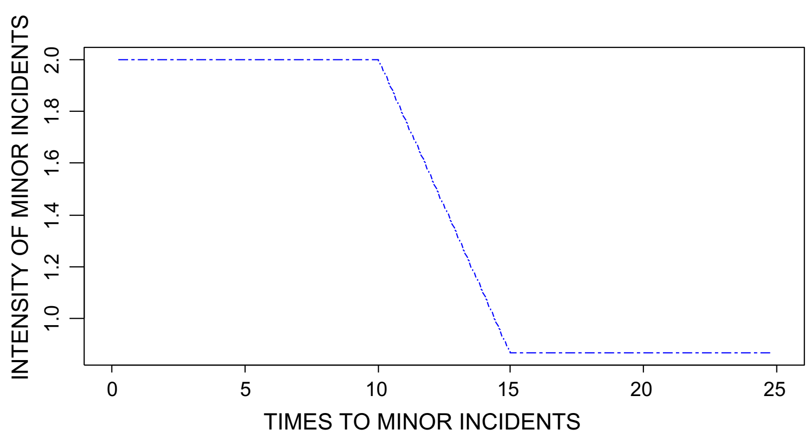

Fig. 19. Intensity plot for minor incident case.

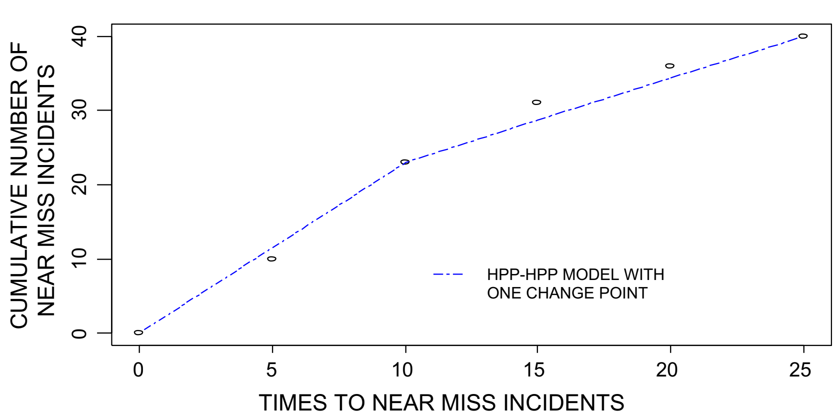

Fig. 20. Segmented model for near-miss incident case.

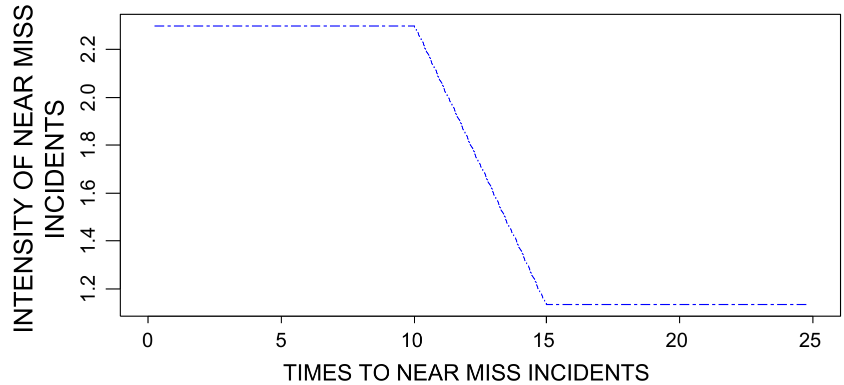

Fig. 21. Intensity plot for near-miss incident case.

Case 4: Near Miss

In case 4, near-miss incidents data set is provided in Table 3. The estimates of the parameters like injury rate ($\hat{\lambda}_1$), change point location ($\hat{\tau}$), scale parameter ($\hat{\alpha}_2$), shape parameter ($\hat{\beta}_2$), and log-likelihood are also computed for HPP with one change point (refer to Table 1). In Fig. 20, segmented model for near-miss incident cases is displayed with HPP-HPP model with one change point.

The intensity of incidents (refer to Fig. 21) is constant and high up to 10 months and thereafter dropped to an intensity which is a 2.03 times lower. Thus, there is an *improving trend* in near misses which is encouraging.

3.3. Expected loss function and expected loss for the safety measures TBO and NOC

The lower the time between occurrence, TBO, the greater the number of undesired events (such as injuries) and greater is the loss. For safety analysis, Time between occurrence, TBO is a *larger the better* (LTB) type variable, L(TBO) is a quadratic decreasing function.

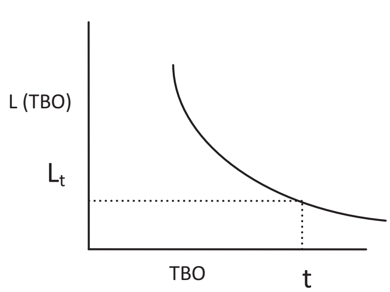

Fig. 22. Loss Function for TBO.

Loss function for the time between injury, L(TBO) can be expressed as,

$$L(\mathrm{TBO}) = \eta\left[\frac{1}{\mathrm{TBO}^2}\right] \tag{21}$$

The higher the number of occurrences, NOC, the greater the number of undesired events (such as injuries) and greater is the loss. Number of occurrence (NOC) is a *smaller the better* (STB) type variable.

$$L(\mathrm{NOC}) = \eta[\mathrm{NOC}]^2 \tag{22}$$

Here η is loss coefficient associated with the minimum/maximum TBO/NOC acceptable to the work system considered. For example, if minimum TBO accepted is t with corresponding loss L_t, then η is equal to $L_t t^2$. (See Fig. 22)

The expected loss functions and expected loss values as a function of $\eta_{(.)}$ the respective loss co-efficients are obtained for all four cases for both TBO and NOC data and reported in Table 4. The expected loss value can be interpreted as '*the average loss for an incident to the category of injury considered*'.

These values can be used by the mine management once the constants are known for each of the cases. The expected loss can be converted into monetary terms which can further be used for cost benefit analysis of safety related investments.

4. Discussion and conclusions

This research deals with the development of safety performance measurement scheme in a work system using segmented point process models having change points. Interestingly, the TBO as well as NOC data fit to single or multiple change points models in combination of HPP and PLP (Eqs (5) and (6)). For example, for

Table 4
Expected loss functions and expected loss for injury cases.

Sl. No	Injury type	TBO case		NOC case	
		Expected Loss Function	*Expected Loss*	*Expected Loss Function*	*Expected Loss*
1	All-Injury (a)	$L_a = \eta_a\begin{bmatrix}\lambda^2[1+3\lambda] \\ +\alpha^2\beta^2 t^{2(\beta-1)} \\ [1+3\alpha\beta t^{\beta-1}]\end{bmatrix}$	$(0.16 + 7.87e{-}05t^{1.2} + 2.1e{-}06t^{1.8})\ \eta_a$	$L_a = \eta_{ao}\left[\frac{(1+\lambda)}{\lambda^2} + \frac{(1+\alpha\beta t^{\beta-1})}{\alpha^2\beta^2 t^{2(\beta-1)}}\right]$	$(0.1 + 0.13t^{-0.7} + 0.36t^{-0.36})\ \eta_{ao}$
2	First –Aid (f)	$L_f = \eta_f\begin{bmatrix}\lambda^2[1+3\lambda] \\ +\alpha^2\beta^2 t^{2(\beta-1)} \\ [1+3\alpha\beta t^{\beta-1}]\end{bmatrix}$	$(0.06 + 7.84e{-}06t^{1.56} + 6.59e{-}08t^{2.34})\ \eta_f$	$L_f = \eta_{fo}\left[\frac{(1+\lambda)}{\lambda^2} + \frac{(1+\alpha\beta t^{\beta-1})}{\alpha^2\beta^2 t^{2(\beta-1)}}\right]$	$(0.17 + 3.04t^{-1.6} + 1.74t^{-0.8})\ \eta_{fo}$
3	Minor (m)	$L_m = \eta_m\sum_i\lambda_i^2[1+3\lambda_i]$	$0.49\ \eta_m$	$L_m = \eta_{mo}\sum_i\frac{(1+\lambda_i)}{\lambda_i^2}$	$3.24\ \eta_{mo}$
4	Near Miss (n)	$L_n = \eta_n\sum_i\lambda_i^2[1+3\lambda_i]$	$0.0057\ \eta_n$	$L_n = \eta_{no}\sum_i\frac{(1+\lambda_i)}{\lambda_i^2}$	η_{no}

Table 5
Key findings through the analysis.

	Data Types	Fitted Model	Injury Event Pattern: Change Point	Trend
TBO	All incident data	HPP and PLP	1 change point at 458 days.	Constant up to 458 days. Then there is a sharp decline followed by increasing pattern (refer to Fig. 5).
	First aid data	HPP and PLP	1 change point at 458 days.	Constant up to 458 days. Then, there is a steep decline followed by increasing pattern (refer to Fig. 8).
	Minor data	HPP	2 change points at 11 days and 375 days.	Constant as high as up to 11 days. Then there is a steep dropping which is followed by constant pattern up to 375 days. Then it is followed by decreasing pattern. Finally, it becomes constant over time (refer to Fig. 11).
	Near-miss data	HPP	1 change point at 441 days.	Constant up to 441 days and then certain dropping. After that, constant level is retained back (refer to Fig. 14).
NOC	All incident data	HPP and PLP	1 change point at 12 months.	Constant up to 12 months. Then there is a sharp decline followed by increasing pattern (refer to Fig. 16).
	First aid data	HPP and PLP	1 change point at 11 months.	Constant up to 11 months. Then there is a sharp decline followed by increasing pattern (refer to Fig. 18).
	Minor data	HPP	1 change point at 10 months.	Constant up to 10 months. Then there is a sharp decline followed by constant pattern (refer to Fig. 20).
	Near-miss data	HPP	1 change point at 10 months.	Constant up to 10 months. Then there is a sharp decline followed by constant pattern (refer to Fig. 22).

all incident data the HPP model (Eq. (5)) fit to the first part of TBO data before the change point and the NHPP PLP model (Eq. (6)) fit to the second part of TBO data after the change point (Figs. 3 and 4). For minor incident cases, three HPP models with two change points fit to the TBO data (Figs. 9 and 10). It is noteworthy to mention here that at each change point there is a change in the intensity and it can be explained with the same model with different parameter estimates or using a different model altogether.

This work is intended to present an analysis on the overall trend and pattern of injury data for an industrial setting. In Table 5, key findings are listed down for better insights. Table 5 indicates, for the mine system studied, data types (TBO and NOC), their fitted models, and injury event patterns. For example, HPP-PLP model with one change point is fitted to both the TBO and NOC data for all-incident as well as first-aid cases. Similarly, HPP model with one change point is fitted to the TBO data for near-miss and NOC data for both minor and near-miss cases. Interestingly, HPP model with two change points is fitted to the TBO data for the minor incident cases.

It should be noted here that the period within change points and the injury patterns (i.e., increasing, decreasing or constant) can be used as safety performance measure and to design appropriate safety improvement strategies, respectively. However, this analysis can be easily extended to other systems' safety study without loss of generality. Regarding the modeling of the system, the usual point processes used are the renewal process and the NHPP. NHPP-PLP is used for systems which undergo minor repairs and the system failure intensity remains the same after rectification of the hazards, i.e., the improvement process brings the system to a functioning state but does not change its failure intensity.

Consideration of these findings may enable managerial solutions and workplace organization interventions for the prevention of injuries and safety performance improvement. The methodology can be used by mine management, or higher authorities in targeting locations in a mine or mines in a region, respectively for reducing injury incidents, or unsafe acts or conditions or all of them together. Based on the model results, there is a need for development of a decision making scheme for the work safety performance evaluation, monitoring and improvement. For successful implementation of the proposed method, it requires sufficient number of unsafe observations for variety of industrial situations. The loss function can also be used for cost benefit analysis. Otherwise, the management has to conduct experts' opinions study to determine how much improvement is achievable and required. As a reflection, reinforcing the implications of this study, we must notice that segmented point process models (NHPP-PLP) are statistically more equipped and poses better interpretability than HPP for work system safety analysis.

The study though provides valuable tools for modeling, analyzing and improving work system safety performance; the proposed methodology does not focus on *risk reducing* measures. Hence, the study has to be extended by (i) incorporating risk reducing factors in a suitably designed framework, and (ii) developing loss function incorporating multiple safety performance measures that are usually being measured and analyzed by safety professionals.

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References

Achcar, J.A., Loibel, S., Andrade, M.G., 2007. Inter failure data with constant hazard function in the presence of change-points. REVSTAT–Stat. J. 5 (2), 209–226.
Akaike, H., 1998. Information theory and an extension of the maximum likelihood principle. In: Selected Papers of Hirotugu Akaik. Springer, New York, pp. 199–213.
Akman, V.E., Raftery, A.E., 1986. Asymptotic inference for a change-point poisson process. Ann. Stat., 1583–1590
Atwood, C.L., Gentillon, C.D., Wilson, G.E. (1992). Data and Statistical Methods for Analysis of Trends and Patterns (No. EGG-RAAM-10563). EG and G Idaho Inc, Idaho Falls, ID (United States).
Chen, J., Gupta, A.K., 2001. On change point detection and estimation. Commun Stat Simul Comput 30 (3), 665–697.
Jarrett, R.G., 1979. A note on the intervals between coal-mining disasters. Biometrika 66 (1), 191–193.
Khanzode, V.V., Maiti, J., Ray, P.K., 2011. A methodology for evaluation and monitoring of recurring hazards in underground coal mining. Saf. Sci. 49 (8), 1172–1179.
Khanzode, V.V., Maiti, J., Ray, P.K., 2012. Occupational injury and accident research: a comprehensive review. Saf. Sci. 50 (5), 1355–1367.
Khawaji, I.A., 2012. Developing System-Based Leading Indicators for Proactive Risk Management in the Chemical Processing Industry. Massachusetts Institute of Technology [Doctoral dissertation].
Koivupalo, M., Sulasalmi, M., Rodrigo, P., Väyrynen, S., 2015. Health and safety management in a changing organisation: case study global steel company. Saf. Sci. 74, 128–139.
Lawless, J.F., 2011. Statistical Models and Methods for Lifetime Data. Vol. 362. John Wiley & Sons.
Leveson, N., 2015. A systems approach to risk management through leading safety indicators. Reliab. Eng. Syst. Saf. 136, 17–34.

Lindqvist, B.H., 2006. On the statistical modeling and analysis of repairable systems. Stat. Sci., 532–551

Loader, C.R., 1992. A log-linear model for a Poisson process change point. Ann. Stat., 1391–1411

Maguire, B.A., Pearson, E.S., Wynn, A.H.A., 1952. The time intervals between industrial accidents. Biometrika 39 (1/2), 168–180.

Maiti, J., 2010. Development of worksystem safety capability index (WSCI). Saf. Sci. 48 (10), 1369–1379.

Maiti, J., Khanzode, V.V., Ray, P.K., 2009. Severity analysis of Indian coal mine accidents–a retrospective study for 100 years. Saf. Sci. 47 (7), 1033–1042.

Mingyan, A., Zesheng, D., Lianjun, Z., 2011. Statistical analysis of coal mine accidents in China during 2007–2010. J. Saf. Coal Mines 42, 177–179.

Muralidharan, K. (2010). A review of repairable systems and point process models. In: ProbStat Forum, vol. 1, pp. 26–49).

Øien, K., 2001. Risk indicators as a tool for risk control. Reliab. Eng. Syst. Saf. 74 (2), 129–145.

Raftery, A.E., Akman, V.E., 1986. Bayesian analysis of a Poisson process with a change-point. Biometrika, 85–89.

Sinelnikov, S., Inouye, J., Kerper, S., 2015. Using leading indicators to measure occupational health and safety performance. Saf. Sci. 72, 240–248.

Syamsundar, A., Naikan, V.N.A., 2007. Segmented point process models for maintained systems. Int. J. Reliab. Qual. Saf. Eng. 14 (05), 431–458.

Taguchi, G. (1986). Introduction to Quality Engineering: Designing Quality into Products and Processes.

West, W.R., Ogden, T.R., 1997. Continuous-time estimation of a change-point in a Poisson process. J. Stat. Comput. Simul. 56 (4), 293–302.

Zou, F.Z., 2003. A change-point perspective on the software failure process. Softw. Test. Verifi. Reliab. 13 (2), 85–93.