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Evaluating uncertainty in accident rate estimation at hydrogen refueling station using time correlation model

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ABSTRACT

Hydrogen, as a future energy carrier, is receiving a significant amount of attention in Japan. From the viewpoint of safety, risk evaluation is required in order to increase the number of hydrogen refueling stations (HRSs) implemented in Japan. Collecting data about accidents in the past will provide a hint to understand the trend in the possibility of accidents occurrence by identifying its operation time However, in new technology; accident rate estimation can have a high degree of uncertainty due to absence of major accident direct data in the late operational period. The uncertainty in the estimation is proportional to the data unavailability, which increases over long operation period due to decrease in number of stations. In this paper, a suitable time correlation model is adopted in the estimation to reflect lack (due to the limited operation period of HRS) or abundance of accident data, which is not well supported by conventional approaches. The model adopted in this paper shows that the uncertainty in the estimation increases when the operation time is long owing to the decreasing data.

Introduction

Hydrogen is receiving increasing attention as a future energy carrier in Japan. It is expected that widespread usage of hydrogen energy will result in energy savings, strengthen energy security, and reduce the environmental impact of energy consumption. One of the primary uses for hydrogen at present is in fuel cell vehicles (FCV's). FCVs were introduced into the Japanese market in 2014, and the Government of

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Japan is planning to have approximately 40,000 FCV's in Japan by 2020 [1].

Various projects that focused on introducing FCV and Hydrogen Refueling Station (HRS) have been implemented. One such major project is the Japan Hydrogen & Fuel Cell Demonstration Project [2], which conducted FCV research activities from 2002 to 2010. For HRS, the "Concurrent Operation of Hydrogen Stations with Different Types of Fuel and Different Methods - The First Demonstration Study in the World" project was implemented with the objective of researching actual efficiency and any problems associated with HRS.

In addition to these projects, several laws have been revised [3] to facilitate implementation of hydrogen energy. For example, the High Pressure Gas Safety Act was revised to expand the varieties of steel used for facilities such as pipelines, lowering the safety factor for pipelines, and devise rules relevant for liquid HRS. Further, an HRS and a gas station can be installed at the same place according to the Fire Safety Act. The Building Standards Act has also been revised to enable the storage of sufficient hydrogen stock to provide hydrogen in cities. These laws enabled FCVs and HRSs to be introduced and utilized in the market.

There is a possibility of abnormal events occurring at an HRS due to increased activities and operations performed at the HRS. In Japan, as HRSs store and dispense hydrogen are at a relatively high pressure, they are controlled by the High Pressure Gas Safety Act. Accident information such as hydrogen leakage at an HRS is available in the high-pressure gas incidents database of The High Pressure Gas Safety Institute of Japan [4]. This database contains a compilation of high-pressure gas accidents, including the accident information for HRSs. In the law, explosions, fires, spouting or leak, rupture or damage, and loss or burglary are defined as "accidents" [5]. One of the characteristics of HRS accidents in Japan is that a high percentage of leak accidents occur at the joint section of the pipe [6]. Note that even a small leakage has to be reported based on the guidelines described in the High Pressure Gas Safety Act. This is because in the case of hydrogen fuel, even a small leak can lead to catastrophic events. In this study, "accident" refers to that defined in the High Pressure Gas Safety Act. Considering the accident statistics of natural gas stations, there are concerns that HRS accidents may increase as more HRSs are implemented in the future [7].

Focusing on the HRS operation time from its start may reveal important characteristic of accident occurrence. In other words, collecting data about accidents in the past will provide a hint to understand the trend in the possibility of accidents occurring by identifying its operation time. However, the estimation of accident rate is only as good as the data availability. Under such circumstances, addressing uncertainty in the statistical data through time series effect is important.

Relevant safety studies

There are recent quantitative risk assessment (QRA) studies on hydrogen refueling stations and storage infrastructure to consider the application of accident scenario modelling [8]. The first step in the risk analysis is to conduct hazard and operability (HAZOP) study to liquid hydrogen fueling station [9]. Failure mode and effects analysis (FMEA) is then reported for hydrogen fueling systems to understand component failures and their effects on the system. These two techniques are used in a study that performed the FMEA and HAZOP to identify possible accident scenarios for liquid hydrogen fueling station [10]. Pasman and Rogers [11] performed risk assessment for compressed and liquefied hydrogen transportation and tank station by means of Bayesian networks. Nakayama et al. [12]. Carried out the preliminary hazard identification to a hybrid gasoline-hydrogen fueling station with an on-site hydrogen production system using organic chemical hydride.

Studies have also been performed on HRS accident and leak frequency by major organizations such as Sandia National Laboratories [13]. There are few research papers discussing on the application of accident scenario frequency modelling in risk analysis [14–16]. Accident rate estimation can provide a key input to Quantitative risk assessment (QRA) to quantify risks numerically. Matthijsen et al. [17] performed risk assessment of hydrogen filling stations with the generic data taken from Ref. [18]. LaChance et al. [19]. Performed QRA to determine separation distances for hydrogen refueling stations. Tsunemi et al. [20]. Estimated consequence and damage caused by an organic hydride hydrogen refueling station numerically.

Risks are measured from the combination of frequencies and consequences of the scenarios. Estimation of accident rates provides a key input to reliability and risk assessment quantification. Unfortunately, however, hydrogen failure data is extremely limited. One possible way is to use surrogate failure data from other settings such as commercial nuclear power plants, chemical plants, and offshore oil and natural gas platforms [18]. A study uses the fault tree analysis (FTA) to determine frequency of the accident scenarios based on generic failure data [21]. Another way is to employ a Bayesian statistical approach to estimation of failure rate from prior accident data. A study developed a Bayesian model to estimate leak frequency leading to accidents in various components used in a hydrogen refueling stations [13].

Objective

Accident rate estimation plays a vital role in the determination of the occurrence frequency of the accidental scenarios. The work can conclude whether the refueling station taken into consideration is safe enough from frequency point of view or any additional refined studies are required. However, a drawback in the analysis could be lack of experience and the scarcity of the relevant data collection [21]. The data scarcity drawback can be solved by understanding the uncertainty in the estimation due to data unavailability.

Compared to the risk analysis, the accident data uncertainty has not been so well-established, partly due to low probabilities involved and partly due to the complexity of such accidents [15]. For this purpose, we have introduced a study on the accident data uncertainty based on time correlation model. This is also one of the reasons for using operation time as the basis of analysis in this paper. This paper estimates the uncertainty and accident rate by time correlation model that are fundamental to the challenge of lack of data, and not been addressed in previous models. This new way of dealing with and interpreting accident information can be utilized to evaluate new systems such as HRS in the future.

Accident data evaluation at HRSs based on operation time

The accident data for HRS is collected and counted based on the events listed in the high-pressure gas incidents database [4]. The number of accidents at an HRS over time from the start of its operation is determined. "HRS operation start" denotes the start of operation of the HRS used in either test research, or commercial operation. The operation start time of the HRS does not include the time the HRS infrastructure was built. Operation time is the period between the operation start month and the accident occurrence month. This paper uses "month" as the unit of time measurement.

Thirty-four HRSs operating from 2002 to 2014 in Japan, including onsite and offsite type, for test research and commercial use, were investigated. The operation start time for all HRSs is considered together at the same time in the analysis. The overall number of accidents recorded for these HRSs is 26. Out of these 26 accidents, 23 accidents resulted in leakage, 3 accidents resulted in explosion. Further details on the operating time and accident information for each of the 26 accidents is provided in Appendix A.

Firstly, the accident data for each HRS were investigated with respect to operation time and summed for total accidents, as shown in Fig. 1.

The graph in Fig. 1 can be categorized into the following three cases:

- Case I: Events occurred in the short period. Looking across the operation time, some event occurred in short period (i.e., 10 accidents in the first 24 months).
- Case II: Events occurring at the intermediate operation time. This includes 10 accidents that occurred between the 25th month and the 85th month.
- Case III: Events occurring at the later operational time. This includes 6 accidents that occurred between the 86th month and the 144th month.

Note that the length of operation for each station differs; hence, the number of stations differ at each operation time (Fig. 2). For example, there are 15 stations at the 50th month, but only 7 remaining at the 100th month. Fig. 2 shows the number of existing stations at each operation month. It can be concluded from the below chart that the data availability is decreasing with increasing operation period.

The next step is to divide accident counts by the number of existing stations. Dividing the accident count by the number of existing stations results in the mean accident count shown in Fig. 3. The trend in Fig. 3 is an increase in accidents in the later operation time, but this is because the number of stations has decreased. The accident data is available up to 122 months based on the high-pressure gas incident database [4]. However, this paper analyses data up to 144 months.

There are several drawbacks in the data represented in Fig. 3. These are:

1. The data availability is decreasing over time due to less number of existing stations. This introduces large uncertainty in the estimation at the late operational period.
2. The data collected from multiple HRSs is that each station has dissimilar operation period. The availability of data varies for two stations with different operating hours. For e.g. a station operated for 1 year will have limited data compared to the station operated for 10 years. This implies that the data are all mixed and not based on common requirements. This leads to a large uncertainty in the result after modelling theory is applied.
3. There is no accident data between some months. For e.g. there is no accident data between 25th month to 38th month.

Method of uncertainty evaluation

Application of intrinsic CAR model to estimate uncertainty

In order to address the above issue, conditionally autoregressive (CAR) model [22] is applied. Conditional autoregressive (CAR) model is a graphical or network model designed to specifically model spatially auto correlated data

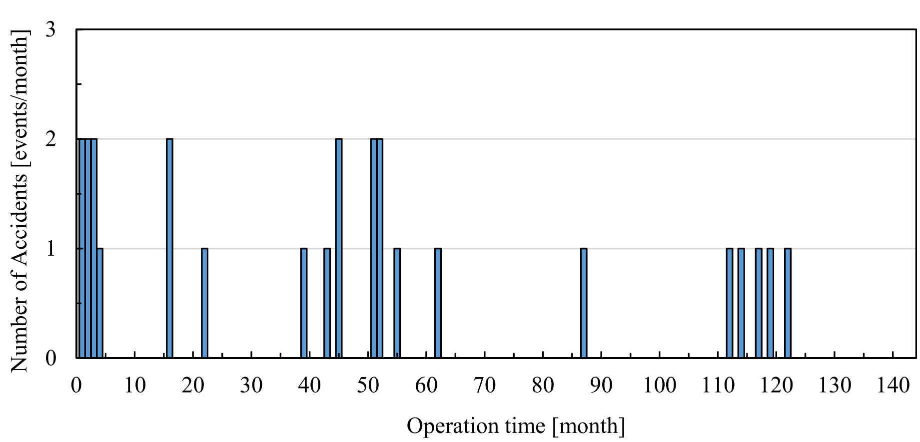

Fig. 1 – Accidents in HRS by operation time (total count).

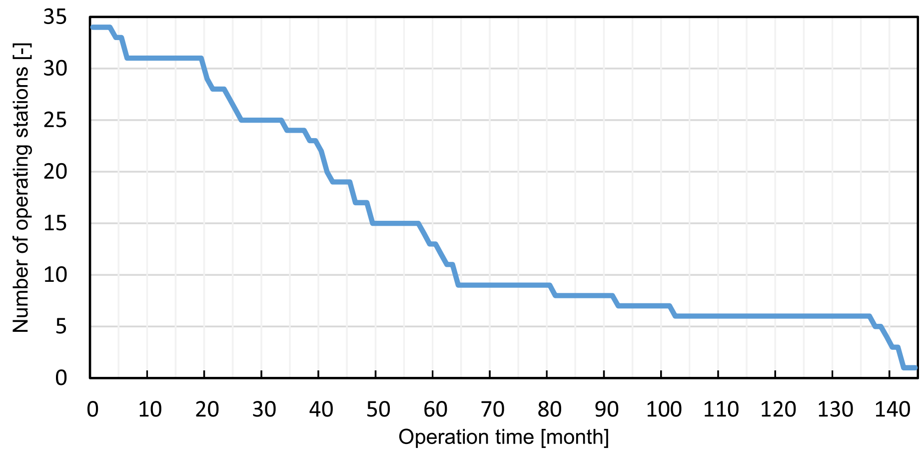

Fig. 2 – Number of stations operating in each month.

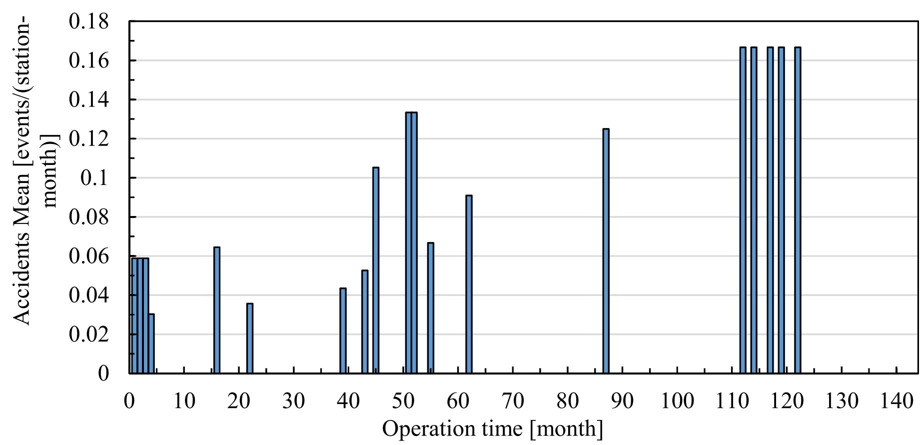

Fig. 3 – Accidents in an HRS by operation time (mean).

based on neighborhood relationships [23]. Due to its benefit to describe spatial correlations, it is suitable for application to accident data such as in Fig. 3. As observed in Fig. 3, there are missing data for several months which can lead to uncertainty in accident rate estimation. Prediction of random variable in off-sample (missing) areas using is unambiguous since it is not obvious how to specify the adjacent structure of just the in-sample (observed) areas ignoring the off-sample areas. As illustrated by Banerjee et al. [24] for the case of a CAR model fitted to point level (rather than area) data, prediction at a missing location can be achieved by constructing a CAR model for the full set of observed and missing location. In this paper, a CAR model is specified for the full set of spatial random variable in the in-sample and off-sample areas, and simply treat the response data in the off-sample areas as missing. This leads to a modified set of full conditional distributions for the spatial random effects in off-sample areas in the Markov Chain Monte Carlo (MCMC) scheme used to estimate the posterior distribution [22]. This paper utilizes this method to estimate uncertainty in the accident data. The accident rate is estimated to have similar value to the adjacent month by utilizing the intrinsic Gaussian CAR model. The variable under observation are assumed to follow Poisson, and autocorrelation is modelled by a set of random effects that are assigned a CAR prior distribution [25].

Accident rate description using time correlation model

The problem that arises when using time series data collected from multiple HRSs is that each station has dissimilar operation period. The availability of data varies for two stations with different operating hours. For e.g. a station operated for 1 year will have limited data compared to the station operated for 10 years. It is intuitively supposed that when computing accident data shown in Fig. 2, the result of the early operation period is reliable, however the estimation of the late operation period is not very convincing.

In order to address the above issue, CAR model is applied. Firstly, in the case of the 34 HRSs with accident data, the start operation time for all stations are considered together. However, the numbers of accidents for the stations are not summed; instead, they are treated separately for each station. Accident occurrence is modelled using Poisson distribution for each month per station. Poisson distribution has been found advantageous for describing count data (i.e., 0, 1, 2 …) for each month and each station [26]. Thus, accident rate on ith month for jth station is considered as a random variable following the Poisson distribution:

$$Y_{i,j} \sim Poisson(\lambda_i) \tag{1}$$

where.

$Y_{i,j}$: accident occurrence for each month per station.

i: operation time index.

j: station index.

λ_i: expected value of the Poisson distribution of the accident rate for each month.

In addition, to make changes with time, the mean of the Poisson distribution is considered and described using two parameters, β and r_i. The β parameter considers the overall-time accident rate whereas the r_i parameter considers only the individual month's accident rate. It takes the form of the generalized linear model shown in Eq. (2), where the left-side function is called the logarithmic link function and the right side is called the linear predictor.

Here, the expected value of the accident rate λi is described by generalized linear model below:

$$Log(\lambda_i) = \beta + r_i \tag{2}$$

where.

Log (λi): logarithmic link function of λi.

Β: global parameter and.

r_i: local parameter.

The characteristic of this model is such that the accident rate may change; however, the value is relatively similar to the adjacent month. Time correlation was set to the statistical model by utilizing the intrinsic Gaussian CAR model. In this model, each local parameter r_i does not take a value independently. To connect each local parameter r_i, their prior distribution must be described by Eq. (3). The local parameter r_i follows the prior distribution given that μ_i is true. μ_i is calculated as equal to the mean of two values, r_{i-1} and r_{i+1}, of the adjacent operation time. Parameter s represents the overall dispersion. If s is small, r_i does not vary widely and the accident rate is smooth overall. Conversely, if s is large, r_i varies widely and the accident rate fluctuates significantly. Eqs. (3) and (4) are applied to estimate the accident rate using the time correlation model. In the simplest form, the density of an intrinsic CAR model for $\mathbf{r} = (r_1 \ldots r_n)$ is

$$p(r_i|\mu_i, s) = \sqrt{\frac{n_i}{2\pi s^2}} \exp\left\{-\frac{(r_i-\mu_i)^2}{2s^2/n_i}\right\} \tag{3}$$

$$\mu_i = \frac{r_{i-1}+r_{i+1}}{2} \tag{4}$$

where.

μi is the mean of the value of the two local parameters $r_i - 1$ and $r_i + 1$.

s is the parameter representing overall dispersion. It is the precision parameter that determines the amount of smoothing and it is commonly estimated from data.

In other words, the prior distribution of the ith local parameter r_i should be a normal distribution with mean μ_i and standard deviation $s/\sqrt{n_i}$.

The prior distribution ("non-informative prior") of the other parameter is set as follows:

$$\beta \sim N(0, 0.0001)$$

$$s \sim Unif(0,\ 10000)$$

where.

N (μ,τ): normal distribution with mean μ and inverse square of its standard deviation τ.

Unif (a,b): uniform distribution with lower bound a and upper bound b.

Flow of accident rate analysis using the conditional autoregressive model

The flow of accident rate analysis using the conditional autoregressive model is shown in Fig. 4. The analysis flow is divided into the two parts. Part 1 is related to organizing data in the format suitable to the model. Part II performs statistical analysis based on the model described in Section 3.2.

Part I: Input data preparation for statistical analysis software - Unlike accident rate analysis using traditional method, data processing is not needed in the conditional autoregressive model. This means the statistical data shown in Fig. 3 can be directly used as an input data to CAR model without any data processing. The prior distribution for the dataset is represented in Fig. 3. The prior (input) data reported is given as an input to the model. However, the important thing to note is that there are several problems associated with the prior data. There are some months with no accident and operation period is different for each HRS.

Part II: Statistical analysis using WINBUGS software - Using the prior (input) data, the accident rate for each month is estimated. To calculate the accident rate through updating of the prior distribution with the accident data, WinBUGS uses Markov Chain Monte Carlo simulation, and it needs an initial value for each parameter. The model in WINBUGS is written in a series of commands. The statistical model used in this paper will overcome the problems by:

1. Estimating accident rate for each month by the condition that the adjacent accident rate is similar to each other
2. Estimating uncertainty associated with data over operation period

The model output is obtained from the WINBUGS and is represented in the form posterior distribution. The posterior distribution is further analyzed to understand the uncertainty associated with the data. Fig. 5 shows a posterior output from the model and thereafter several comparisons and conclusions are made.

Results - accident rate estimation and uncertainty analysis

The interpretation from the outcome of this model is important. The accident rate estimation provided by the time correlation model is based on the interpretation of the reality. The accident rate estimation using the lognormal type function or Weibull function estimates the accident rate change

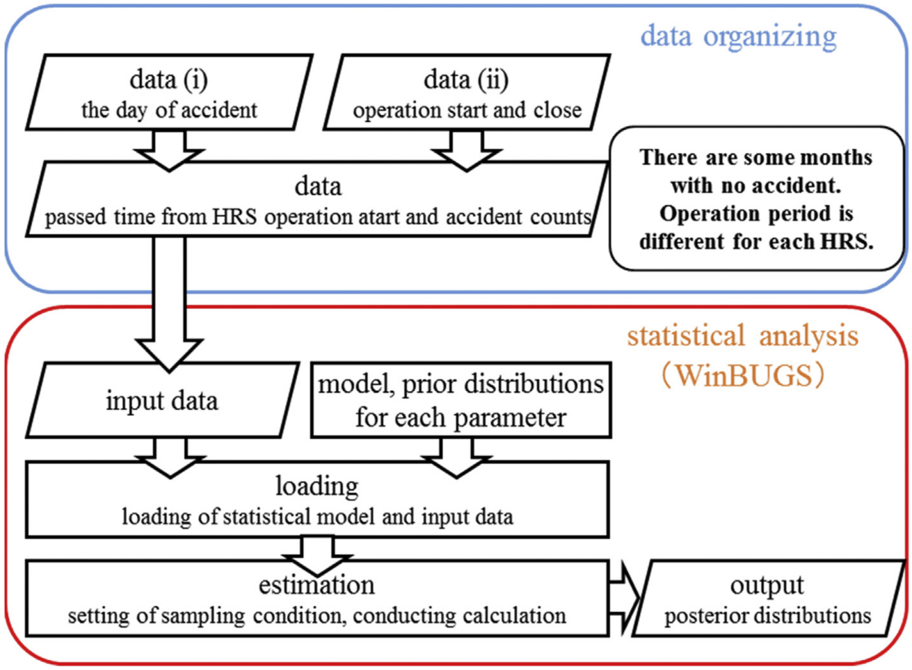

Fig. 4 – Flow of analysis using conditional autoregressive model.

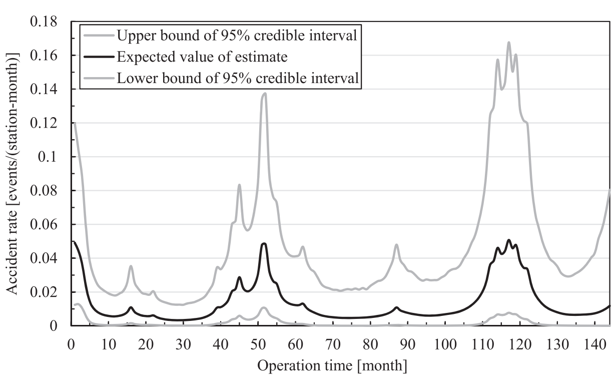

Fig. 5 – Results - Accident rate in an average HRS across its operation time, estimated using the intrinsic Gaussian conditional autoregressive model.

over time. This model estimates the accident rate per month, and is constrained by the condition that the adjacent accident rate is similar to each other.

In Fig. 5 the results of accident rate for each month have been plotted. The distribution shows the expected (mean) value of the accident rate for each month. In addition to the mean value, the upper bound and lower bound of 95% credible interval are plotted in the same distribution. The three peaks obtained in Fig. 5 can be related to the 3 cases described in section 2. Peak 1 is a result of events occurring in the short period. i.e., seven accidents in the first four months. Peak 2 is a result of events occurring at intermediate operation time. Finally, Peak 3 is a result of events occurring at late operational time. This model approximates accident data for some months that originally does not have any accident data. The estimated accident data for each month is adjacent to its predecessor month thereby obtaining non-discrete distribution.

In addition to the uncertainty estimation, the graph in Fig. 5 has two main differences compared to Fig. 3. Firstly, the bar graph in Fig. 3 shows only discrete values whereas in Fig. 5, the graph is continuous without any gaps in the data between each stations. Secondly, no-accident months exist in Fig. 3, whereas in Fig. 5, each month has a positive value. Thirdly, in Fig. 3, the bar graph does not define the probability of accident occurrence.

It can also be noticed that the credible interval is narrower during the start operation period of the HRS. Remarkably, the credible interval tends to expand as the operation time elapses. This is because the amount of available data decreases as the operation time increases, as mentioned in Section 2. There is a wider distortion between the expected value and lower/upper bound credible interval at the late operational period for e.g. after 80th operating month. The wider the credible interval, the higher uncertainty in the accident rate estimation. In order to demonstrate this numerically, we have assigned an error factor (EF) which is the difference between the upper bound and lower bound. Error factor as defined in the red book on probability estimation is given by Ref. [18]:

$$EF = \sqrt{\frac{x'0.95}{x'0.05}} \tag{5}$$

where.

$x'_{0.95}$ = upper bound of 95% credible interval.

$x'_{0.05}$ = lower bound of 95% credible interval.

The result of the error factor starting from 1st month till 144th month is shown in Fig. 6. The lower bound and upper bound of accident rate for each month can be calculated from Fig. 5. The plotting of error factor vs operation month is shown

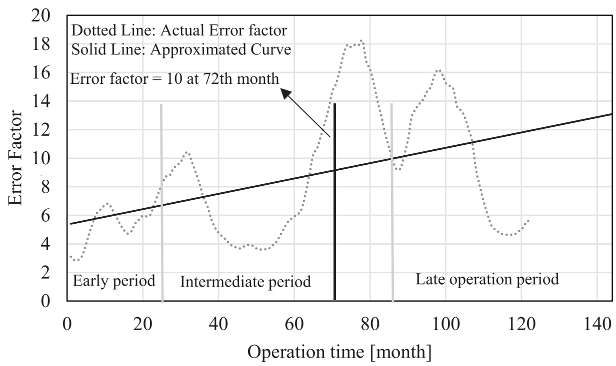

Fig. 6 – Result and Interpretation – Evaluation of Uncertainty by means of Error Factor.

in Fig. 6. As the original data has random data for each month with some months having no data, the graph is non uniform. The operation time is divided into early, intermediate, late operation period based on the 3 cases categorized in section 2. An interpretation of the results is developed using approximate curve as shown by solid line. The solid line is taken as the linear smooth curve from the plotted points. This shows an increasing trend for error factor over the operation month. The error factor can be related to decreasing data over the longer operation period. The average error factor is less than 10 from the beginning of the operation period until the mid-operation month i.e. till 72th month approximately. However in the late operation period, it can be noticed that the error factor shoots well above 10 pointing towards higher uncertainty in the data as a result of no enough data available during that period.

Furthermore, using CAR model offers some advantageous such as it can directly use accident data of HRS with different lengths of operation month without any data processing. In CAR model, the total number of HRSs is not considered. Even though the number can be more or less than reality, the result is not significantly affected. However, less information than target may cause uncertainty in the estimation.

Conclusions

This paper examined the manner in which accident rate is modelled and described for HRSs. Unlike conventional statistical models in which the accident rate changes according to overall time function, CAR model estimates the accident rate per month, and is constrained by the condition that the adjacent accident rate is similar to each other. Another result is that of the intrinsic Gaussian CAR model, which represents the uncertainty in the estimation due to lack of data. The CAR result succeeded in showing that the uncertainty in the estimation increases when the operation time is long owing to the decreasing data.

A model with accident rate following the intrinsic Gaussian conditional autoregressive model has following advantages:

- Suitable to show the estimate uncertainty is increasing owing to lack of data
- Estimates the accident rate per month and thus the graph is continuous without any gaps in the data between stations
- Support in decision making for new process systems

In a final remark, the CAR model is different from the other lifetime distribution models because its main aim is to reveal the estimate's uncertainty. A new system such as HRS has very little accident information, and so future predictions are inevitably unreliable. One approach to rectify this problem is to wait until enough data have been collected, or utilize the accident data of similar systems to increase its reliability. However, the Gaussian conditional autoregressive model does not aim to reduce the uncertainty; rather it discusses the effect of lack of information on the estimation. This new way of dealing with and interpreting accident information can be utilized to evaluate new systems such as HRS in the future.

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Appendix

Appendix A – Detailed explanation of 26 accidents collated from database [4].

ID	Accident Code (KHK-ID)	Accident Name	Failure Date	Number of elapsed months
1	2005–120	Hydrogen leakage from filling hose	13-05-2005	2
2	2005–222	Hydrogen leakage at hydrogen station	28-07-2005	4
3	2005–415	Explosion of hydrogen at hydrogen station	07-12-2005	1
4	2006–216	Hydrogen leakage at hydrogen station	17-06-2006	39
5	2006–433	Hydrogen leakage in compressed hydrogen gas	24-10-2006	3
6	2007–532	Hydrogen gas leakage accident	17-10-2007	55
7	2007–557	Hydrogen gas leakage accident	07-08-2007	51
8	2007–574	Hydrogen gas leakage accident	28-09-2007	51
9	2010–122	Hydrogen leakage from filling hose during filling operation	12-05-2010	2

(continued on next page)

Appendix A – (*continued*)

ID	Accident Code (KHK-ID)	Accident Name	Failure Date	Number of elapsed months
10	2010–135	Inhalation of hydrogen station, hydrogen leakage from discharge valve mounting part	15-06-2010	87
11	2011–066	Hydrogen leakage from dispenser joint due to earthquake	12-03-2011	3
12	2012–090	Hydrogen leakage from the cap nut of the connection part of the card	09-04-2012	16
13	2012–224	Hydrogen leakage from hydrogen station pressure gauge	10-07-2012	62
14	2012–226	Leakage from hydrogen station dispenser and hose attachment	18-07-2012	16
15	2012–314	Leakage from valve mounting part of hydrogen stand	17-10-2012	22
16	2012–339	Hydrogen leakage from the valve connection	05-11-2012	114
17	2012–362	Hydrogen leakage from the check screw ground thread portion of compressor discharge	30-10-2012	112
18	2013–037	Hydrogen leakage from the accumulator base valve	06-02-2013	119
19	2013–063	Leakage from liquid hydrogen receiving lower valve at hydrogen station	09-03-2013	117
20	2013–115	Leakage from overflow preventing valve connection of hydrogen station	22-05-2013	1
21	2014–173	Hydrogen leakage from the shutoff valve	03-07-2014	52
22	2014–182	Hydrogen leakage from filling hose after completion of filling test	17-07-2014	52
23	2014–299	Hydrogen leakage from the connecting part of the compressor unit	24-10-2014	43
24	2014–349	Explosion during inspection of opening of accumulator	09-12-2014	45
25	2013–356	Hydrogen leakage from suction valve of compressor	31-07-2013	122
26	2013–376	Rupture of hydrogen filled hose during filling test	03-12-2013	45

KHK – The High Pressure Gas Safety Institute of Japan.

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