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Research Article

Developing a New Decision Support System to Manage Human Reliability based on HEART Method

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Abstract

Human performance and reliability monitoring have become the main issue for many industries since human error ratios cannot be mitigated to the zero level and many accidents, malfunctions, and quality defects are happening due to the human in production systems. Since the human resources implement a different range of tasks, the calculation of human error probability (HEP) is complicated, and several methods have been proposed to identify and quantify the HEP. This fact expresses the necessity of a Decision Support System (DSS) to calculate the HEP and propose optimal scenarios to increase human reliability and decrease its related cost such as quality defect and rework cost. This study develops a DSS that calculates the HEP based work specifications and proposes optimal scenarios to deal with error occurrence probability. The scenarios are provided using an AHP according to experts' opinions about the cost and time of corrective actions. The proposed DSS has been applied to a real case, and the provided results show that the proposed DSS can provide effective scenarios to deal with human error in production systems.

Keywords: HEP, HEART; Decision support system; Artificial neural network; Reliability

1. Introduction

Human error is a source of concern, and lack of attention to this fact can impose an unexpected cost on production systems. Although many production systems have been automated using digital machines, human error has not been eliminated considerably, and humans have a high impact on errors in many industries. There are many examples in this regard, in chemical production systems, 60-90% of error happens because of human error (Reason, 2006).

Human errors can be divided into two categories according to their impact on production systems:The low and high impact categories. Low impact leads to produce poor quality and defected production (Le et al., 2012). But in critical industries such as nuclear or chemical industries, human errors in the high impact category can cause a fatal failure and impose a high risk to production systems (V. Di Pasquale et al., 2013). Human errors also decrease productivity and increase the undesirable costs such as idle cost, backorder cost, and quality cost.

Human reliability is an important issue for researchers, managers, and decision-makers. HRA methods are subjective and the data concerning the human factor is imprecise. Human reliability shows how reliable the workers implement specific action correctly. Also, there is another definition which considers the length of time that a worker can implement without any failure (Pyy, 2000).

The first time (Swain 1990) investigate the HRA after the Second World War to assess a weapon system. After that many industries such as nuclear power plant, power plant, and transportation utilized the HRA methods. (Calhoun et al., 2013; Guo et al., 2012; Zubair and Zhijian, 2013).

The HRA methods were developed with the quantitative methods in the first generation and the qualitative methods in the second one (Boring, 2007) (Hollnagel, 1998b). Some methods such as technique for human error rate prediction (THERP) (Swain and Guttmanm, 1983), success likelihood index methodology (SLIM) (Embrey et al., 1984), a technique for human error analysis (ATHEANA) (Cooper et al., 1996), human error assessment and reduction technique (HEART) (Williams, 1986), cognitive reliability and error analysis method (CREAM) (Hollnagel, 1998a), simplified plant analysis risk human reliability assessment (SPAR-H) (Gertman et al., 2005) are the known methods of HRA.

In recent year, dynamic HRA has attracted the researchers' attention, since many parameters affecting the human reliability are not deterministic and the exact algorithm cannot be used to calculate the HEP. In this regard, (Chang and Mosleh, 2007a, 2007b, 2007c, 2007d, 2007e) presented the Information Decision and Action in Crew (IDAC) context for HRA. The aim of the proposed model was to predict the reaction of the operating crew in control room of nuclear power plants. Trucco and Leva (Trucco and Leva, 2007) provided a probabilistic cognitive simulator (PROCOS) to calculate the human errors using the quantification susceptibilities of the first-generation HRA. (Valentina Di Pasquale et al., 2015) proposed the Simulator for Human Error Probability Analysis (SHERPA) to obtain the error probability for a specific scenario in production systems. In these models, the effect of performance shaping factors (PSFs) have been investigated, and the HEP has been calculated considering PSFs.

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The HRA methods have time-consuming routines. Indeed the managers should have enough time to calculate and validate the HEP in the first step and provide optimal scenarios to mitigate the HEP in the second step, but most managers need to confront human error quickly to reduce the probable damage and cost. Decision support system on HRA can be developed to help manager dealing with human error in production systems. (LaSala et al., 1995) proposed The Reliable Human-Machine System Developer (REHMS-D) using a new human reliability method and a six-stage system, the REHMS-D decision support methods help the designer by the synthesis of system or process human functions. (Akyuz and Celik, 2015) developed an approach to conducting human reliability analysis (HRA) via the knowledge-based system to reduce the operational defects caused by human errors. The proposed approach supports shipboard organizations to monitor, recognize, prioritize and perform the corrective actions to reduce the human error in ship operational. (Stojiljkovic et al., 2016) proposed a DSS to facilitate the decision-making process by experts to mitigate the human errors, in the electric power companies. They provided a database for error and injuries and used absolute probability judgment (APJ) method to calculate the HEP. (Bumblauskas et al., 2017)proposed a conceptual framework for Smart Maintenance Decision Support System (SMDSS) based on corporate data from several companies. The SMDSS provides some recommendation to improve asset lifecycles.

To the best of author's knowledge, there are no outstanding researches in which a DSS for HRA has been developed to identify the work specification according to historical data and calculate the HEP considering PSFs and finally propose optimal scenarios to mitigate the HEP. In this paper, we propose a framework that helps operators and managers to face human error. This framework can categorize the work types by an artificial neural network (ANN) and historical Data, in the first step, and calculate the PSFs impact on HEP according to their importance factor in the second step, and propose the optimal scenarios to mitigate the error probability in the third step. The performance of the proposed DSS is examined using some case studies in a production system.

The rest of the paper is organized as follows: Section 2 presents the knowledge-based on HEART method. Section 3 proposes the Artificial Neural Network. Section 4 describes the error producing conditions. Section 5 presents some information about HEP mitigation activities. Section 6 presents the proposed DSS. Section 7 provides a case study to evaluate the DSS, and finally, section 8 concludes the paper.

2. Knowledge based data for HEART

Some HRA methods have proposed some aspects of work type that the error probability can be calculated by using them. For example, HEART method can estimate the HEP based on some work type aspects. This method was presented to evaluate human works with predetermined values for HEP calculation (Williams, 1988). HEART has been developed based on two parameters. The first is a generic task type (GTT) and the second is error producing condition (EPC). The GTT categorizes the works and proposes the generic error probability (GEP) for each category, then EPC evaluates the effect of performance shaping factor on HEP and make the HEP value closer to reality.

The HEART process to calculate HEP begins by selecting a generic task type that is matched to the work conditions, to find the GEP values as the first parameter. Since the GEP is based on the nature of the generic task to be performed, they are regarded as the same value as adopted in HEART with given nominal likelihood within probabilistic limits. HEART proposes eight generic tasks that each of them has a value for GEP to provide the HEP. The GTT and their related GEP are shown in Table 1.

Table 1
The proposed GTT presented by HEART

Generic Task Type	Value
unfamiliar, perform a despot with no real idea of likely consequence	0.55
Shift or restore the system to a new world original state on a single attempt without supervision or procedure	0.26
A complex task requiring a high level of comprehension and skill	0.16
The fairly simple task performed rapidly or given scant attention	0.09
Routine, highly practiced, a rapid task involving a relatively low level of skill	0.02
Restore or shift the system to original or new state following procedures with some checking	0.003
Completely familiar, web design, highly attractive, routine task occurring several times per day, perform to highest possible standards, by highly motivated, highly trained, and experienced personnel.	0.0004
Respond correctly to system command even when there is an augment or automated supervisory system providing an accurate interpretation of system state.	0.00002
The miscellaneous task for which no description can be found	0.03

After calculating the GEP, the effect of performance shaping factor should be considered using EPC. The EPC includes some factors such as available time, worker experience, fatigue, environmental conditions, worker age, etc. that can severely affect human performance and increase the HEP. There are some works that have the specifications of two or more generic tasks. Therefore this is complicated to select one generic type. To solve this problem, we implement the ANN to calculate the HEP using specification of GTT. In this paper, we extract all the specifications of GTT and show them in Figure 1.

Specification for GTT	
$\begin{cases} familiar \\ unfimiliar \end{cases}$	$\begin{cases} highly\ practiced \\ normal\ practiced \\ low\ practiced \end{cases}$
$\begin{cases} complex \\ simple \\ routine \end{cases}$	$\begin{cases} with\ procedure/\ description \\ without\ procedure/\ description \end{cases}$
$\begin{cases} requring\ high\ attention \\ requring\ low\ attention \end{cases}$	$\begin{cases} with\ electronic\ control \\ without\ electronic\ control \end{cases}$
$\begin{cases} rapid\ speed \\ normal\ speed \end{cases}$	$\begin{cases} well\ designed \\ not\ well\ designed \end{cases}$
$\begin{cases} requring\ high\ skill \\ requring\ low\ skill \end{cases}$	$\begin{cases} requring\ high\ train \\ requring\ high\ motivation \end{cases}$

Fig. 1. The GTT specification Category

Using the provided specification of GTT shown in Figure 1 and their related GEP, ANN can calculate the HEP for all work types. The ANN performance in HEP calculation has been proposed in the next subsection.

3. Artificial Neural Network

Artificial neural networks (ANN) can evaluate a huge amount of information via an interconnected network with several nodes in many layers (Graupe, 2007). The network architecture which mimics the one present in the neurons of the human bodies, influence the information flow, Since ANN is an imitation of nature and the human body, it consists of several steps such as recognition, verification, optimization, and prediction. ANN attempts to identify the effect of parameters (inputs) on a result (output) in different systems. After selecting the input parameters, the learning process implemented by training and testing step. Also, it can be done after standardizing and eliminating the outliers of the input parameters (Passino, 2005). The schema of the ANN has been shown in Figure 2.

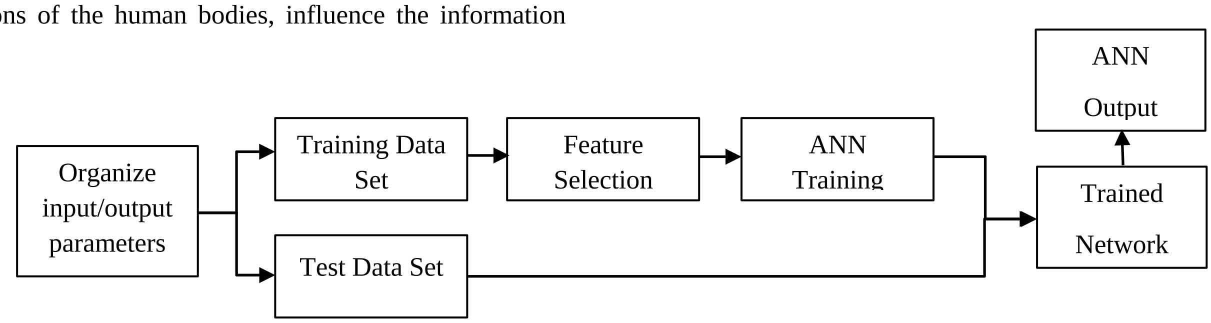

Fig. 2. The schema of ANN

In the learning process different networks can be selected and examined by changing the nodes and layers number, the transfer functions' shape, and the learning algorithm to obtain their performance. Equation (1) is used to evaluate the accuracy of different networks, which minimizes the overall error between the targets and calculated values.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i' - y_i)^2}{\sum_{i=1}^{N}(y_i' - \sum_{i=1}^{N} y_i'/N)^2} \quad (1)$$

In Equation (I) y_i' and y_i are the actual and estimated output values (HEP), and N is the number of input data (GTT specification) points. In ANN we have some test vectors and the provided results of ANN have been compared to them. The square error insures that ANN has proper performance to predict the HEP value.

In this paper, we use the ANN to obtain the HEP value based on GTT specifications. We use the specification of GTT mentioned in Figure 1 as inputs and the HEP value as output to train the neural network. The proposed ANN consists of three layers: the input, the hidden, and the output layer. It has 22 inputs (number of GTT) with one output (The HEP value). To overcome the over fitting problem, the hidden node number should not be very large. With some practical guideline, this number is selected to be the same as the number of input nodes. Using this trained network we can estimate the HEP for all work types based on GTT specifications. The ANN input is a vector of GTT specifications as shown in Figure 3.

Familiar	Unfamiliar	Complex	Simple	Routine	Req high attention	Re low attention	Rapid speed	Normal speed	Req high skill	Req low skill	Highly practiced	Normal practiced	Low practiced	With procedure	Without procedure	With elec control	Without elec control	Well designed	Not well designed	Req high train	Req high motivation
1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0

Fig. 3. The schema of ANN input

As shown in Figure 3 work specifications are shown using a vector. For example, Figure 3 shows a work that has five specifications such as familiar, simple, normal practiced, with electronic control, and well designed. This vector used as an input and its related HEP used as an output to train the ANN.

4. Error Producing Condition and HEP calculation

After providing the HEP, the relevant error producing conditions (EPCs) of the works should be identified to calculate the negative influence of other conditions such as mental and environmental conditions on HEP. HEART proposes 38 EPCs to make HEP value closer to reality. Some EPCs of HEART have been shown in Table 2. Each EPC has a multiplier that increases the HEP based on this value. The overall HEP is calculated using Equation (2).

$$\textit{Overall human error probability} = \textit{Nominal human error} * \textit{EPC multipier1} * \textit{EPC multipier2 ..etc} \qquad (2)$$

As could be seen in Table 2, some EPCs have overlap and selecting the proper EPC is difficult, to confront this difficulty we extract the specification of each EPC and develop an ANN to calculate the multipliers value based on EPCs specifications. The ANN for EPCs multipliers values is similar to GTT identifier ANN and uses the same structure to code the EPCs specifications. Using the multiplier provided by ANN the overall HEP can be calculated by Equation (II).

5. HEP Mitigation Scenarios Evaluation

In this section, we describe how the proposed DSS collects and evaluates the possible scenarios to mitigate human error and makes the production process safe for human and machines. As shown in Equation (II) the HEP consists of two factors, the nominal human error value and the EPCs impact on the nominal error value. Nominal HEP depends on the nature of the work and cannot be changed or reduced, but some action can be done to mitigate the EPCs impact on HEP. For example, the EPC "the shortage of time available for error detection or correction" has the multiplier equal to 11. That is to say, this EPC can increase the error probability by 11 times. To mitigate this EPC, we can extend the work time for error detection or correction, this activity greatly reduces the HEP and increases human reliability. The implementation of activities for dealing with EPCs need cost and time, considering this fact, we should select the optimal mitigation activities according to some factors such as time and cost. If we confront more than one EPC for a specific work, the impact of EPCs is also considered as a factor to evaluate the mitigation activities. In this paper, we extract the mitigation activities for each EPC to find the optimal activity for HEP mitigation. To find the optimal activity, the needed cost and time for predetermined activities, are suggested by the experts and based on the provided data, the optimal activity is selected to implement for HEP mitigation. Some example of activities to mitigate the EPCs impact has been shown in Table 3.

Table 2
EPC description and value

NO.	Error producing condition	Multiplier value
1	Unfamiliarity with the situation which potentially important for but which only occurs infrequently or which is novel	17
2	A shortage of time available for error detection and correction	11
3	a low signal to noise ratio	10
4	A means of suppressing, overriding information or features which is too easily accessible	9
5	No means of conveying spatial and functional information to operators in a form which they can readily assimilate	8
6	A mismatch between an operator's model of the world and then Imagine by the designer	8

7	No obvious means of reversing and unintended action	8
8	A channel capacity overload, particularly one caused by simultaneous presentation of none- redundant information	6
9	A need to unload a technique and apply one which requires the application of an opposing philosophy	6
10	the need to transfer specific knowledge from task to task without loss	5.5
11	Ambiguity in the required performance standards	5
12	The mismatch between perceived and real risk	4
13	Poor, ambiguous or ill-matched system feedback	4
14	No clear direction and timely confirmation of an intended action from the portion of the system over which control is to be exerted	3
15	Operator inexperienced	3
16	An impoverished quality of information conveyed by procedures and person-person interaction	3
17	Little or no independent checking or testing of output	3
18	The conflict between immediate and long-term objectives	2.5
19	No diversity of information input for veracity checks	2.5
20	A mismatch between the educational achievement level of an individual and the requirement of the task	2
21	An incentive to use other more dangerous procedures	2
22	Little opportunity to exercise mind and body outside the immediate confines of the job	1.8
23	Unreliable instrumentation	1.6
24	A need for Absolute judgments which are beyond the capabilities or experience of an operator	1.6
25	Unclear allocation of function and responsibility	1.6

Table 3
Suggested activity to reduce the EPC effect

EPC No.	Activities to mitigate the EPCs
12	Education of operators Developing business intelligence system Developing control procedures
13	Improve the feedback system Remove feedback defect Using more experienced operator
15	Education inexperienced operators Using experienced operators Using productive procedures or instruments
23	Using automated instruments instead of manual instruments Instrument improvement or replacement Changing the work's instrument or procedures
24	Using automated detectors Removing heel man judgments Adding another worker for judgments

The activities used to mitigate the impact of EPCs, vary according to the production system conditions. As shown in Table 3 if we want to reduce the impact of 12th EPC we can educate the operators to correct their perceptions or develop a computer-based business intelligent system to correct the perceived risk or use a more experienced worker with the higher power of perception. The implementation of the mentioned activities are costly and time-consuming, and each activity has a specific mitigation rate for HEP. Based on specifications of activities for HEP mitigation such as cost, time and mitigation rate, a method can be used to select the candidate activities for HEP mitigation such as AHP, TOPSIS, and PROMETHEE.

In this paper, we use the AHP to obtain the priority of candidate activities and select the activity with high priority to mitigate the HEP.

The AHP is a multi-criteria decision making (MCDM) method. This method was developed by (Saaty, 1980) to solve complex decision-making problems. AHP calculates the relative weight of nodes within a group by decomposing the problem into a hierarchy of comprehended sub-problems in which can be analyzed separately. The relative importance of alternatives are evaluated based on sub-problems, and the alternative with high importance can be select as an optimal decision. In this paper, the AHP technique is used to prioritize the importance of mitigation activities based on expert opinions.

6. The Framework of DSS for Human Error Probability Calculation

Regarding the description of DSS modules, the DSS schema has been shown in Figure 4. The DSS consists of seven modules to find the GTT category, EPC and HEP for works, assess the proper activities for HEP mitigation, and select the best activity to reduce the error probability. "GTT prediction module" and "Prioritize the mitigation action module" need the experts' opinion, and the "GTT Knowledge-based DB" uses the HEART method data for GTT identification.

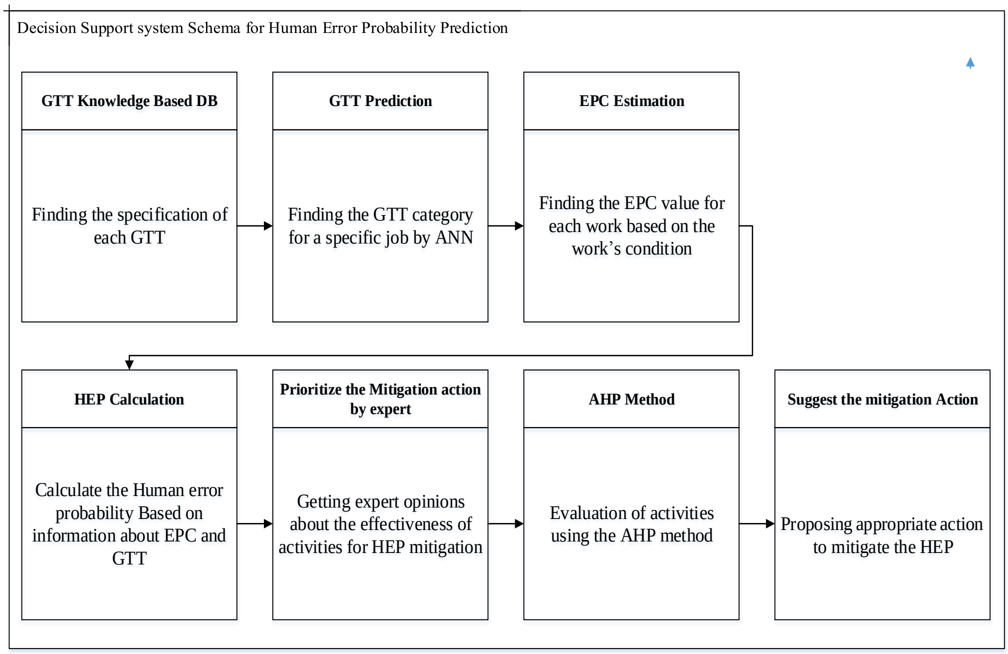

Fig. 4. The schema of presented DSS

7. Case Study and DSS Implementation

In this section, we propose some instances from a lathing workshop and use the proposed DSS to provide the HEP of some work types and present the optimal activity to mitigate the error probability of human. Since we have a limited budget and time, we should find the most effective scenarios to reduce the total HEP in lathing workshop using the proposed DSS. The description of the works has been proposed in Table 4.

Table 4
The description of each Instance

Instance No.	Description
1	The worker put the piece and close it on the lathing machine without any procedure
2	Cutting the machine at the desired speed at a relatively low rate manually
3	Drilling the piece with a specific diameter that needs a low level of skill

In the first step, we use the ANN and the knowledge-based database from HEART method. We develop ANN to categorize the proposed works and obtain the HEP for each of them. The average error of the trained neural network is equal to 0.0003. The nominal HEP provided by ANN for the presented works is shown in Table 5.

Table 5
The nominal HEP provided by ANN

Instance No.	Description	Nominal HEP provided by ANN
1	The worker put the piece and close it on the lathing machine without any procedure	0.03
2	Cutting the machine at the desired speed at a relatively low rate manually	0.06
3	Drilling the piece with a specific diameter that needs low a level of skill	0.04

In the second step, we train another ANN to estimate the EPC multiplier for each work, according to the EPC of HEART method. The average error of this ANN is equal to 0.352. The provided EPC multiplier for each proposed work is shown in Table 6, according to nominal HEP and EPC value for each work, the overall HEP is obtained as shown in Table 6.

Table 6
The EPC and overall HEP provided by ANN

Instance No.	Description	EPC provided by ANN	Overall HEP
1	The worker put the piece and close it on the lathing machine without any procedure	1.73	5.2%
2	Cutting the piece at the desired speed at a relatively low rate manually	2.53	15.2%
3	Drilling the piece with a specific diameter that needs a low level of skill	2.12	8.5%

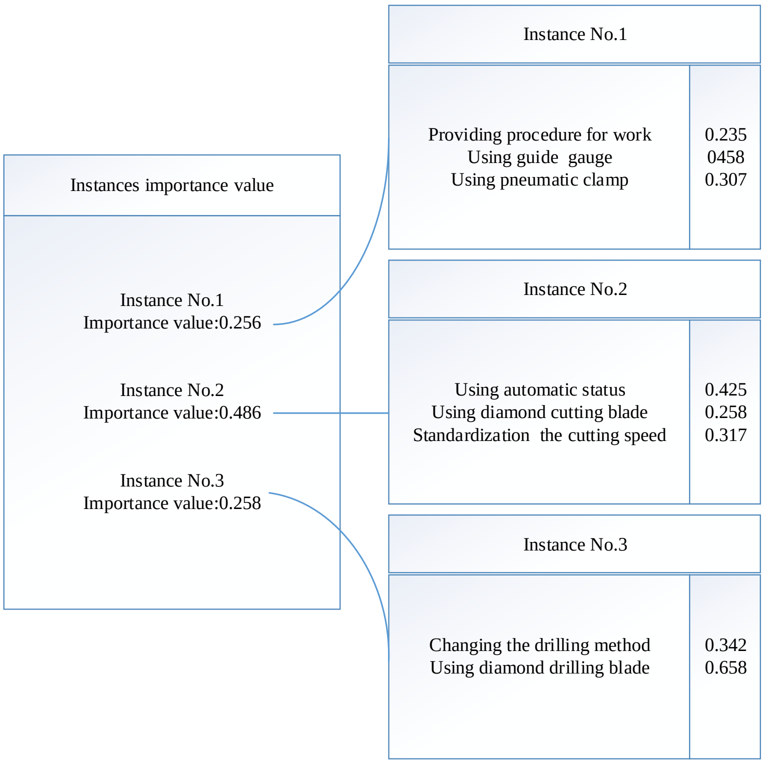

Fig. 5. The Importance value provided by AHP

In the third step, we collect expert opinions about activities that mitigate the HEP for each proposed work and implement the AHP method to provide the importance value for mitigation activities. The mitigation activities with their importance value are shown in Figure 5.

As could be seen the DSS prioritizes the proposed works and their related activities for HEP mitigation. The DSS suggestion for HEP mitigation is to use "automatic status" in "cutting the piece at the desired speed" since this action has a high priority in HEP mitigation based on cost, time and HEP mitigation rate. "Standardization the cutting speed" is the second activity for HEP mitigation. If we have extra cost and time, we can implement more than one activity for HEP mitigation.

Using the proposed DSS, we can determine the HEP for different works in production systems and provide some activities to mitigate the error probability according to expert opinions considering some factor such as time, cost and mitigation rate

8. Conclusion and Future Research

In recent years, several methods have been developed to evaluate human reliability. These methods formed the human reliability analysis (HRA) procedure, in which consists of human error identification, categorization, and quantification. HRA methods are mostly based on expert judgment, and this fact can create tolerance in the HRA results. In this paper, we proposed a method to reduce the error caused by expert judgment using the ANN method and the historical data about human error probability (HEP) and the HERAT method information about GTT and EPC. In this paper, we also proposed a step-by-step DSS to suggest some actions to mitigate the human error according to experts' opinions considering some factors such as time, cost and mitigation rate. The performance of the proposed DSS was examined, and the provided results indicated the model could obtain some suggestions to reduce the human error.

To the best of our knowledge, this study is the first one dealing with finding HEP value using ANN with HEART method and proposing a DSS for HEP mitigation scenario selection. Therefore, a promising avenue for future research is to study other HRA methods in order to propose a comprehensive method. Further, other prioritization procedures can be examined for scenario evaluation.

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