SUPPORTING DECISION MAKING WITH AN ARIZ-BASED MODEL FOR SMART MANUFACTURING

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ABSTRACT

Smart manufacturing has transformed the way decisions are made. By accelerating the delivery of data to the various decision points, more rapid decision-making processes can be realized. A generic Decision Support System (DSS) utilizes an efficient technique, which integrates the algorithm for inventive problem solving (ARIZ) and supervised machine learning into a model for supporting various automated decision making processes. The proposed model is to examine the theoretical framework of ARIZ by devising an ARIZ-based DSS model. It incorporates supervised ML algorithms to assist decision making processes. Three case studies from the manufacturing sector are evaluated. The results indicate the capability of the proposed DSS in achieving a high accuracy rate and, at the same time reducing the time and resources required for decision making. Our study has simplified the data processing and extraction processes through an automated ARIZ-based DSS model; therefore enabling a non-technical user the opportunity to harvest the vast knowledge from the collected data for efficient decision making.

Keywords: Decision Support System, ARIZ, Machine Learning, Smart Manufacturing, Production Management

1.0 INTRODUCTION

Smart manufacturing is expected to radically change the business strategies and decision making processes with knowledge-embedded facilities. Through advances in digital technologies, fast sensors and and gateways are available to generate and collect a large number of data samples in a short duration over the Internet for various applications, e.g. condition monitoring and predictive maintenance of machine and product quality monitoring and improvement. In addition to data concerning manufacturing processes, management related data (e.g. marketing, sales, finance, customers) can be readily collected and stored [41]. As the databases become more available organizational-wide, rapid decisions can be made at the closest level they impact the most. As such, the increasingly smart manufacturing environment challenges the bureaucracy by distributing decision making to various levels in the organizational hierarchy from the executive office to the production floor.

Digital transformation in manufacturing led by advances in computing architecture, e.g. Internet of Everything and artificial intelligence (AI), has also changed the way decisions are made from heuristics-based decision-making to analytic-driven decision support. Ever since the popularity of AI methodologies from the early 2000s, automating decision making, especially in decentralized decision-making environments, is important to ensure smooth functionality of critical business processes. In line with the notion of "automating automation" in *Science* [9], this paper presents a solution to support the decision making process in smart manufacturing environment using an AI-based decision support system (DSS).

In general, a DSS acts as a tool to facilitate decision-makers in making informed decisions by utilizing the most out of the available information. The usefulness of AI-related DSSs in manufacturing and other domains is becoming more apparent, as exemplified by numerous recent studies reported in the literature. To assist decision making of engineers in manufacturing environments, a new method to model the manufacturing cost-tolerance and to optimize the tolerance values along with its manufacturing costs was presented in [43]. Several artificial neural network (ANN) models are used to model the complex cost-tolerance relationship, while a genetic algorithm (GA) is used to optimize the tolerance values based on the best ANN model. Three case studies are used to validate the proposed method, indicating its usefulness to enable the design and process planning engineers in proposing manufacturing related decisions irrespective of their experience. On the other hand, to enable 3D printing facilities to make real-time, online reprinting decisions in a ubiquitous manufacturing environment, fuzzy logic-based methods were developed in [11]. Firstly, fuzzy-valued parameters are defined to determine the uncertainty, while slack is derived to decide whether to restart an early terminated 3D printing process. Then, two optimization models, namely, a fuzzy mixed-integer linear programming model and a fuzzy mixed-integer quadratic programming model, are developed to consider both uncertainty and early termination factors. Based on empirical evaluation, the proposed fuzzy approach is able to shorten the average cycle time by 9%, facilitating real-time decision making in handling reprinting situations.

A knowledge-driven tool was designed for supporting the design of sustainable systems such as products, manufacturing systems or services systems [1]. The tool supports the design process by helping the use of appropriate methods for improving sustainability of the resulting systems. The effectiveness of the tool in supporting design for sustainability has been successfully demonstrated in six case studies. On the other hand, a DSS for the emergency department in making rapid and reliable decisions for crisis management was described in [33]. The tool highlights the importance of experience feedback pertaining to historical records, covering both success and failure cases. Several dimensions including factors related to organization, communication and problem-solving capabilities are considered, in order to assist decision makers in making informed decisions under the pressure of time, stress, and emotional impact in critical situations. In [27], a computational model was introduced to perform analysis between additive manufacturing and subtractive manufacturing. The model is able to assist decision makers in determining the most energy efficient metallic part production. A multi-criteria decision-making tool proposed in [51] acted as a guideline for designers in additive manufacturing design. The tool offers solutions that contain design oriented and material-machine combinations from various databases.

Generally, the literature on DSS supports a rich collection of approaches for solving some targeted decision problems. The goal of this paper is to design and develop a generic DSS model that aids decision-makers in various decision-making processes. To accomplish this goal, an effective technique that integrates the algorithm for inventive problem solving (ARIZ) [34] and supervised machine learning (ML) model into a framework for decision support is presented, which is denoted as an ARIZ-based DSS model. The main objectives of this paper are as follows.

1. To examine the theoretical framework of ARIZ, and investigate how it can be extended to develop a DSS model;

2. To devise an ARIZ-based DSS model, which incorporates supervised ML algorithms to assist decision making processes;

3. To evaluate the DSS model via three case studies, i.e. steel plate manufacturing industry, semi-conductor manufacturing and a real-world communication device manufacturing, and demonstrate that the DSS model can efficiently support the decision-making problems with high accuracy.

The organization of this paper is as follows. In section 2, the background of ARIZ and ML models for decision support is discussed. The proposed ARIZ-ML methodology and its implementation as a DSS model is explained in section 3. Three case studies to evaluate the usefulness of the developed DSS model are presented in section 4, with the results analyzed and discussed. The implication of the ARIZ-based DSS model for smart manufacturing is discussed in section 5. Conclusion and suggestions for future work are presented in section 6.

2.0 BACKGROUND

In this section, a list of abbreviations is stated in this section. The basic components constituting our proposed DSS model are discussed. After that, we continue with the background of ARIZ and its application to problem solving. Then, an overview of supervised ML and DSS methodologies is presented.

Table 1: Abbreviation and Explanation

AI	Artificial Intelligence	p	Type of fault for SPF - Pastry	PL	Classifier PairLearners
TRIZ	Theory of Inventive Problem Solving	z	Type of fault for SPF - Z_Scratch	LB	Classifier LeveragingBag
ARIZ	Algorithm for incentive problem solving; a meta TRIZ model	k	Type of fault for SPF - K_Scatch	OSB	Classifier OnlineSmoothBoost
DSS	Decision Support System	s	Type of fault for SPF - Stains	OB	OzaBag
ML	Machine Learning	d	Type of fault for SPF - Dirtiness	OBA	OzaBagAdwin
GUI	Graphic User Interface	b	Type of fault for SPF - Bumps	SB	Stop build; an execution action by manufacturer
SPF	Benchmark dataset - Steel Plates Faults	o	Type of fault for SPF - Other_Faults	LSL	Lower Specification Limit; lower bound acceptance design guidelines
SECOM	Benchmark dataset - Semiconductor Manufacturing Process	P	Classification result - Pass	USL	Upper Specification Limit; upper bound acceptance design guidelines
PQI	Product Quality Improvement	F	Classification result - Fail	SMT	Surface Mount Technology
NPI	New Product Introduction			MA	Model Assembling

2.1 Algorithm for Inventive Problem Solving (ARIZ)

In actual day-to-day manufacturing environments, typically minimal changes to a system or process are preferred, or permitted, for improvement purposes. In other words, only limited parameter modifications of a system or process are allowed, prohibiting the introduction of new parameters or components into the system or process. In this scenario, the ARIZ [2, 34] model, also known as the "*mother of all Theory of Inventive Problem Solving (TRIZ) tools*" [52], offers a viable approach to problem solving. Since the first version of TRIZ was introduced in 1968, numerous revisions have been made to make TRIZ more precise and capable of solving a variety of technical problems. A TRIZ-based system in developing innovative talents is a recent study [20]. ARIZ is a meta TRIZ model, which comprises the theory of inventive problem solving developed by Altshuller [2]. ARIZ integrates the power of various pieces of TRIZ-based problem-solving tools into a consolidated approach [52].

In [16], a study on comparative study to establish the differences and complementaries between the design methods is proposed. ARIZ is used to identify the impact on design activities conducted. ARIZ shows the advancement to guide designers on the transformation from an identified conflict towards the generation of a concept that resolved the conflict. In a recent study [4], ARIZ is adopted to tackle warehousing problems, especially in searching innovative solutions. In general, ARIZ includes inventive principles and scientific effects analysis to address complex problems that other tools fail to tackle via innovative structured solutions. This central analytical tool has a sequential multi-step algorithm for solving a wide variety of technical problems, with minimal changes to the underlying system or process.

On the macro level, there are three levels of processes, each comprises three sub-steps, in ARIZ [34]:

1. *Restructuring of the Original Problem*
2. *Removing the Physical Contradiction*
3. *Analyzing the Solution*

Level 1 begins with a systematic analysis of the system or process and its resources. Once the basic function of the system or process is identified, the problem is reformulated into a "*mini-problem*". Intensification of conflicts is carried out next. Thereafter, the idealized problem undergoes further processing in Level 2. The ultimate goal of Level

2 processing is to arrive at the concept of a solution for the problem through removal of contradictions, applying a knowledge base and changing the idealized problem, if necessary. Finally, at Level 3, the quality of the solution is reviewed. This involves re-evaluating all the steps taken and re-examining the solution to leverage the knowledge gained from the newly created concept. The notion is to maximize the usage of the solution; generalizing the solution into a method that can be applied to other problems, if any.

In [52], a case study of ARIZ to solve a problem on leakage at the joints between equipment and container in a manufacturing process was conducted. The study successfully introduced useful solutions to enable the fluid to flow perfectly through the system (such as increased depth of the threads or increased pitch between threads) which effectively resolved the problem without making the system more complex. In [38], an ARIZ-based model to accelerate the solution of an engineering design task of a sterilizer for a company manufacturing medical and healthcare materials was investigated. The redesign introduced minimal changes to the sterilizer (e.g. a modified sterilizer with a modular component layout) at a low cost, which significantly improved the quality of the sterilization processes.

In [6], an ARIZ-based solution for supply chain problems via integration of ARIZ with discrete event simulation in electronic devices for an automotive manufacturing company was proposed. The ARIZ-based model offered an ideal innovative tool to solve complex problems resulting in cost reduction and operation efficiency improvement, such as optimizing the manpower required in the raw material store. In [14], an ARIZ-based life cycle engineering model for eco-design of an inflight meal service was presented. The ARIZ-based model achieved environmental improvements via product redesign with material change and component reduction of an in-flight hot meal system. It modified a foil disposable item to a plastic lid recyclable item, and integrated cutlery items with the container lid, in order to minimize waste of resources, maximize product value, and minimize cost. Motivated by the study in [14], an effective evaluation method was introduced to combine three dimensions of analysis into a single decision support tool. The study proposed an ARIZ-based DSS to integrate multiple dimensions of parameters into a single decision support tool. More ARIZ-based integration studies can be found in on an eco-innovation biomimetic design tool and [5] on arowana gender identification among others.

2.2 Supervised machine learning

In supervised learning, a computational model "*learns*" through a set of labelled data. As an example, an ML-based model is able to identify defective product after it is trained on a set of samples containing both normal and defective products. As the training process reiterates, the model continuously adjusts its error rate according to the input data until a tolerable accuracy score is achieved. Thereafter, the trained model can be applied to new products through generalization of the knowledge learned from the current data. There are two modes of training: online and offline. Online training offers an incremental learning method where the knowledge based on the ML model is updated in a sequential order as data samples become available. Conversely, offline training receives a set of training data, and updates the model based on the given data samples only. In our ARIZ-based DSS, both offline and online training models are adopted, in order to make the best out of both approaches.

A common application of supervised ML is to group data samples into different categories based on a set of features. The process is known as classification. While it is straightforward for human to perform classification, machines require complex algorithms to perform the same task. In [46], several ML methods, such as random forest and support vector machine, were used to form an intelligent fault diagnosis system for inferring fault status in steel plate manufacturing industry. The goal of the system is to improve manufacturing production line by reducing faulty plates.

In a recent work [49], a ML-based model assesses the financial performance of intelligent manufacturing enterprises to improve financial management model and optimize those costs involved. In another work, building a prediction model using ML and optimiser in smart machinery is published [21]. The model has objective in achieving improved quality products by decreasing time with stable surface roughness and superior geometric accuracy. In this study, a correlation-based optimiser [18] is used to optimize the features of ML model by omitting less important features. This feature selection approach is able to identify a good feature set that is highly correlated with the classification class, yet uncorrelated with each other. Experiments showed that the approach identifies and screens irrelevant, redundant, and noisy features, and identifies relevant features which does not strongly depend on other features. This correlation-based approach has been extended to tackle cancer [23], gene expression [44] and electroencephalography signal [42] studies.

2.3 Decision support systems

Decision-makers receive information from multiple sources, analyze and evaluate the information before arriving at a finalized conclusion. A typical decision-making process can be divided into four phases [47]: the *intelligence* phase (problem identification), *design* phase (development of candidate solutions), *choice* phase (selection of a solution), and *implementation* phase (put to action). These phases offer the foundation for the construction of our DSS model.

Based on the dominant technology component, the DSS models can be classified into five types [40]: communication-driven, document-driven, knowledge-driven, data-driven, and model-driven. In general, a typical DSS obtains information from a data *repository* or *database management system*. Strategies of leveraged and effectively integrated AI with data-driven manufacturing in empowering manufacturers have been highlighted in [50]. Our proposed DSS model obtains data stream of manufacturing as its inputs. ML-based model acts as its decision model to identify manufacturing defects after being trained with given inputs, which contain samples on both normal and defective products. In this study, we use the ARIZ model to integrate multiple dimensions of parameters (features for classifier) to form a single decision support tool, ARIZ-based DSS model. It provides intelligence to augment training online operations. Through the Graphical User Interfaces (GUIs), human decision-makers are provided with functionalities to analyze the input and output decision-related data. They are guided throughout the decision processes via three steps of GUI, as explained in the next section.

In [26], a DSS was employed to aid decision-makers in automobile manufacturing industry with repurposing used batteries. The system provided matching used batteries to scenarios, and reduced technical misfit between the product and the scenario. In another study, DSS is facilitated to analyze the production and to create suggestions for optimization of products and processes [53]. The study discourses a comprehensive review on the ability of DSS for a sustainable manufacturing from the enterprise dimension economic, social and environmental.

Those days, predictive engineering was known as one of the pillars for an essence smart manufacturing [28, 29]. Machine tools were run by computer programmes, and required components were handled by automated material handling system with automated storage and retrieval system. Today, smart manufacturing system, as a form of production, utilises the concepts of cyber-physical systems in its implementation stage. In [45], a cloud-based manufacturing framework allows a wide sharing of manufacturing services and solutions. It has the outcome of intelligent decision-making support tools, which offers solution recommendation in cloud manufacturing system. Similarly, in our study, a GUI ML-based DSS is presented to support the decision making process by integrating ARIZ model for cyber-physical environment.

3.0 METHODOLOGY

In this section, the proposed DSS model underpinned by an ARIZ methodology is described. A realization of the model as a three-step implementation is given.

3.1 Proposed Model

Broadly, the proposed ARIZ-based DSS model consists of three levels that correspond to the three macro level processes of ARIZ (see Section 2.1). Level 1 aims at formulating a problem and transforming it into the desired form for further processing. In this research, our model is constructed to solve classification problems using ML methods. Therefore, it is appropriate to transform a general problem into a classification problem. From the manufacturing perspective, for example, Level 1 of the DSS model involves transforming the domain specific problem into a typical classification problem. At this stage, any critical parameters pertaining to the problem are identified. In supervised learning, these parameters form the input *features* of the ML classifier. The features are presented in the desired format for evaluation.

Next, in Level 2, any obstacles and contradictions are removed from the problem model. Level 2 deals with correlation-based model [18] optimization and knowledge accumulation through ML training. For data collection from real-world environment, not all data samples are useful. Some features can impact the classification process negatively, especially when they contain noise, false correlation, or are redundant. These features not only increase the computational load, but also potentially compromise the DSS accuracy. As such, during offline training, less important features are identified and removed through a process known as feature selection. After the feature selection process, the ML model is trained again using the optimized features set. This is similar to the ARIZ framework, where knowledge base is applied to improve the model.

In Level 3, the solution is critically analyzed. We examine the performance of the optimized solutions via online training. Only the best classifier, namely, the global winner in an ensemble is employed for online training. The classifier performance is assessed in terms of accuracy, i.e. the proportion of correct predictions over all predictions. The higher the accuracy score, the better the performance. Like ARIZ, an effective transfer of knowledge and rigorous evaluations of the model through ML training leads to an effective DSS model that can be applied to new input samples.

In short, the strengths of ARIZ in providing a systematic problem-solving approach accounts for the high performance of our proposed DSS model.

3.2 Model Implementation

The ARIZ-based DSS model comprises three major components labelled as Steps 1 through 3. These steps implement the three process levels of the DSS model described in Section 3.1. The information flow from one component to another in the ARIZ-based DSS model is shown in Figure 1.

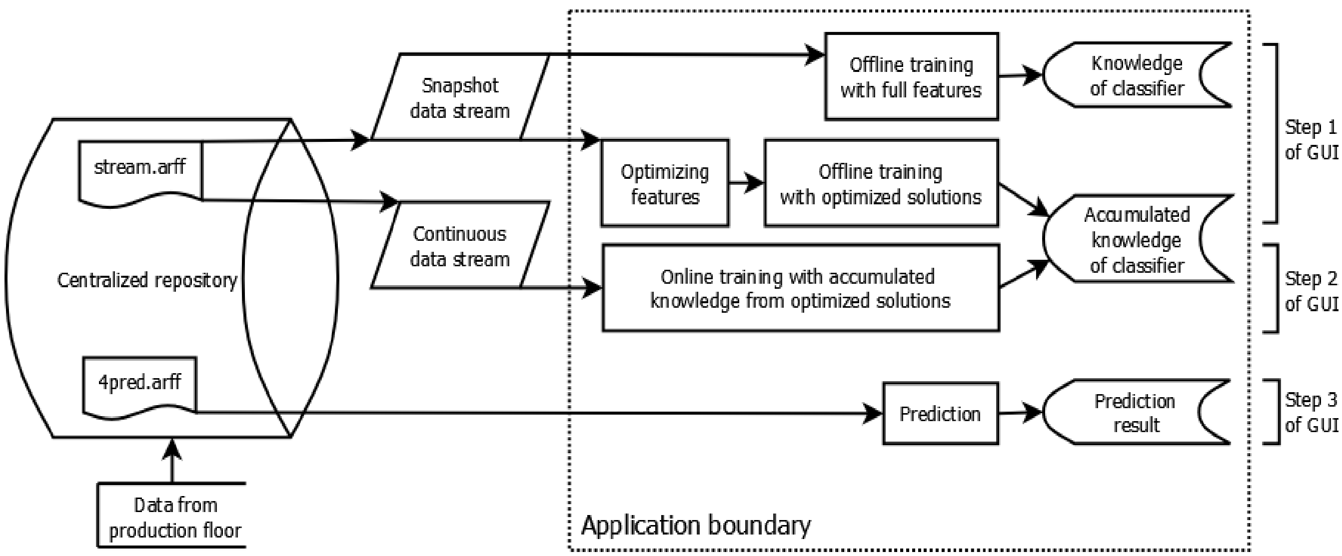

Fig. 1: Information flow in an ARIZ-based DSS model.

Initially, the system receives input from data samples of a data repository. For this implementation, the repository consists of text files in *.arff format. For a real-world implementation, the centralized repository receives updated data samples from a production floor, for instance. The data samples stored in the repository are fed into the DSS model in the form of snapshot data stream (static data) or continuous data stream (real time data), depending on the mode of training. The former enables offline training, while the latter facilitates online training.

To improve the model performance, an ensemble of classifiers is employed. By incorporating ensemble learning, our methodology performs better in terms of predictive measure than most single classifier models. The ensemble learning approach further incorporates a majority voting method to identify the winner of the ensemble model. Five different classifiers are employed in the ARIZ-based DSS model, namely, PairLearners (PL) [3], LeveragingBag (LB) [8], OnlineSmoothBoost (OSB) [10], OzaBag (OB) [39], and OzaBagAdwin (OBA) [7].

PL is modelled using a pair of learners, i.e. static and reactive, in predicting the outcomes based on all experiences as well as a short and recent window of time. The differences of accuracy from both learners determine when to replace the respective learner in answering the targeted concept of drift. The principle of PL has been adopted to form a pruning scheme recently. It is used to tackle the balance between accuracy and diversity in determining the naive and statistical pruning strategies [54] on 20 benchmark datasets from the UCI.

LB leverages on bagging by adding randomization to the input, and output of the classifiers. OB is constructed using online bagging and boosting algorithms. The self-adjusting concept on bagging Robust Online Self-Adjusting Ensemble (ROSE) [55] is inspired by LB and OB. ROSE changes over time to adapt the varying imbalance ratios using the self-adjusting concept to reflect the increasing difficulty in classifying minority class instances. The OSB prediction is better than random guessing with the respect to its smooth distribution concept. It is has been proposed with theoretical justification and experiments with 12 benchmark datasets, which achieves a relative small error rate as compared with those from other algorithms.

OBA presents bagging methods using different sizes of trees as well as a changeable detector to discard underperforming ensemble members. LB, OB and OBA are among the selected ensemble algorithms with online setting in deriving the recent mini-batching strategy [56]. The mini-batching strategy is used to improve memory access locality and performance of ensemble algorithms in handling stream mining under the multi-core environments.

These five different classifiers are adopted in the ARIZ-based DSS model, and the model works as follows:

- Training: At Step 1, two types of empirical results are generated using the five classifiers with default settings. The first is offline training, as shown in Figure 1. It consists of 30 experiments conducted on a full feature set with N-fold cross-validation, where N represents the data subset size. To quantify the results statistically, each fold is repeated N times. In Step 2 (second offline training), a total of 30 additional experiments are carried out on the optimized (reduced) feature set. The 10-fold cross-validation method is performed during each experiment. Using the accumulated knowledge of the classifier from offline training, i.e., the best classifier and optimized solutions, online training is carried out next. The bootstrap results with a 1 million re-samplings are used for evaluation, along with their 95% confidence intervals. During all training sessions, the input samples are in the form of a text file, named as stream.arff. They are labelled for supervised training purposes.

- Prediction: After completing the knowledge accumulation processes in Steps 1 and 2, the knowledge acquired is transferred to Step 3 where the prediction is carried out. A file named 4pred.arff acts as the input for Step 3. Unlike the training set, the data samples used for prediction are not labelled. The aim of the prediction module is to make a forecast of the target class (output) given the input data based on the trained model. As an example, suppose that the model has been trained to distinguish a defective product from a normal one. Drawing on the results of the trained model, the prediction module informs the user if the product is classified as faulty or normal given its current input features. Any user preferences can be specified in the input files, namely, stream.arff and 4pred.arff. Such interaction between the end-user and the system enables effective prediction for different data sets with different knowledge sources.

3.3 Software Development and User Interface

The ARIZ-based DSS model is built on the Java Swing platform. Additionally, an array of Open Source Software (OSS) is employed as its middleware. An user interface of the developed ARIZ-based DSS model is presented in Figure 2.

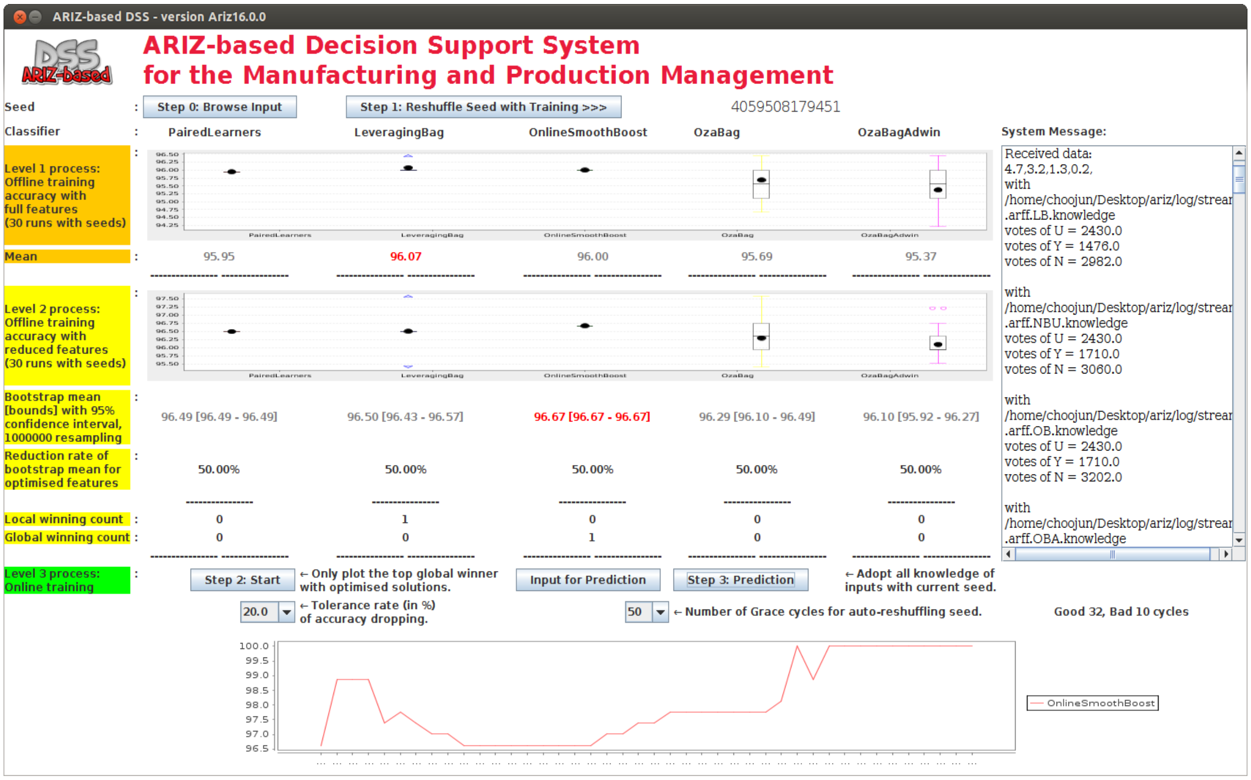

Fig. 2: User interface of the ARIZ-based DSS User model**.**

The user interface has been carefully designed to reflect the steps involved in the ARIZ-based DSS model (see Section 3.2). The training progression and results are displayed in the graphs located at the center of the layout. The results such as the mean, and upper and lower bound values on local (full features) and global (optimized) solutions are presented to the users. A user can interact with the DSS model, especially during online training by a click of a button. As an example, the user can configure the tolerance rate and the number of cycles in order to explore other feasible solutions. A user can also observe the performance as it progresses in real-time. It is worth noting that all the training and prediction processes are fully automated. The pseudo-codes of the overall model are summarized in Figure 3

Require: Receive training data stream from the formulated "*mini-problem*"
1: **for** each adopted ensemble classifier **do**
2: Perform offline training using the full feature dataset with cross-validation
3: **end for**
4: **for** each adopted ensemble classifier **do**
5: Optimize the number of features using the greedy-based correlation optimizer
6: Perform offline training using the reduced feature dataset with cross-validation
7: Save the trained knowledge base for online training
8: **end for**
9: Determine the best classifier, i.e., global winner, using majority voting based on comparative results of both full and reduced feature sets
Require: Receive continuous training data stream from the formulated "*mini-problem*"
10: **repeat**
11: Load the accumulated knowledge base of the global winner
12: Perform online training using the reduced feature dataset with cross-validation
13: **if** the pre-defined criterion of re-training is met **then**
14: Perform offline training, i.e., lines 1 to 9, on the accumulated data stream using the formulated "*mini-problem*" with classifiers
15: **end if**
16: **until** user terminates the process
Require: Receive the prediction data stream
17: Perform prediction using the accumulated knowledge base of the global winner

Fig. 3: The pseudo-code of ARIZ-based DSS model

In the subsequent sections, we present an evaluation of the ARIZ-based DSS model with two benchmark and one real-world manufacturing problem. All case studies demonstrate the efficacy of the ARIZ-based DSS model in undertaking classification problems.

4.0 CASE STUDIES

To ascertain the statistical stability of experimental results, the bootstrap method [19] is employed to numerically estimate histogram, variance, and confidence interval for an estimator by a large number of resamples from an original data set with a small size. Suppose that the sample size of the original data set is N. Then N times sampling with replacement is carried out to produce a resample. As such, the bootstrap method generates virtual resamples by duplicate sampling based on the empirical distribution inferred from the histogram of original data. Bootstrap is asymptotically more accurate than the standard intervals obtained using sample variance and assumptions of normality [59]. In this study, the bootstrap method helps to compute the confidence interval (CI) of performance metrics. It is beneficial for determining the confidence intervals of accuracy mean and its sampling distribution.

The bootstrap method has been used in many fields of science and engineering to evaluate the CI for an estimator. In a recent work [57], bootstrap has been extended with an uncertainty characterization method in a case study on surface-mounted permanent magnet synchronous motor. The study aims to minimize the variance while satisfying all design constraints via the percentile bootstrap interval. Bootstrap has been used for identifying the stochastic characteristics of leakage localization in another study [58]. Bootstrap CIs are constructed to predict the range of leak location, providing decision-makers with CI of the estimation and addressing the complex nature of electronic uncertainties. In [58], the experimental results with accurate coverage probability satisfactorily match the ground-truth CIs.

In the reported case studies, a total of 30 runs have been conducted for each model, and the bootstrap method with 100,000 re-samplings is adopted for estimating the associated 95% confidence intervals. In this section, we demonstrate the advantage of the proposed model, i.e. the efficacy in terms of performance accuracy. Experiments with full feature and optimum solutions on two benchmarking datasets and a real-world study are adopted.

4.1 Benchmark Steel Plates Faults (SPF)

In the first case study, we examine the manufacturing process of steel plates. Defective products impose a high cost for the steel product manufacturers [46], and a DSS model to help decision-makers in running an efficient manufacturing line is useful.

The case study comprises a diagnosis on the surface faults of plates in order to identify and classify different faults. The Steel Plates Faults (SPF) data set used is obtained from the University of California at Irvine (UCI) Machine Learning Repository. There are seven different types of faults: *Pastry* (p), *Z_Scratch* (z), *K_Scatch* (k), *Stains* (s), *Dirtiness* (d), *Bumps* (b), *Other_Faults* (o) (see Table 2). The fault description comprises 27 indicators (input features), which represent the geometric shape of a fault and its contour. The classification result is either *Pass* (P) or *Fail* (F). The experimental steps and the results are as follows.

Table 2: Characteristics of the SPF dataset

Experiment Name (by type of fault)	b	d	k	o	p	s	z
No. of Records	1941	1941	1941	1941	1941	1941	1941
No. of Features (Optimum Solution)	27(17)	27(7)	27(10)	27(10)	27(9)	27(5)	27(6)
Name of Target Class	Bumps	Dirtiness	K _Scratch	Other _Fault	Pastry	Stains	Z _Scratch
Potential Values of Target Class: Ratio of Records	{P,F}: 1539:402	{P,F}: 1886:55	{P,F}: 1550:391	{P,F}: 1268:673	{P,F}: 158:1783	{P,F}: 1869:72	{P,F}: 1751:190
No. of Experiment Runs on Each Classifier	30	30	30	30	30	30	30

The challenge of SPF is first transformed into a classification problem (Level 1). All 27 indicators are adopted as the input features while the target classes are the seven fault types, denoted as b, d, k, o, p, s, and z. We utilize the proposed ARIZ-based DSS model to train the classifiers in an offline training mode. A total of 1941 SPF data samples (with full features) are loaded into the model. The data samples act as the training set for the proposed DSS model and the targets are labelled as either *P* or *F*, denoting the plate acceptance level of *pass* or *fail*, accordingly. The classifier performances are evaluated based on the accuracy metric.

Generally, the five classifiers achieved over 40% of feature reduction with respect to all the SPF data samples during the optimization process in Level 2 (Table 3). In other words, the proposed DSS model is able to detect and remove more than 40% of the less important features from the data set. The remaining (important) features, are used for another offline training cycle to produce the optimum solution.

Table 3: Percentage of feature reduction on SPF and SECOM

Dataset	Experiment Name	PL	LB	OSB	OB	OBA
SPF	b	40.37	40.49	40.86	42.35	40.49
SPF	d	73.33	73.58	73.95	73.21	75.43
SPF	k	68.40	69.75	70.62	67.53	72.96
SPF	o	60.87	63.21	60.62	62.35	62.22
SPF	p	70.74	71.85	71.73	71.73	72.84
SPF	s	73.46	73.58	74.94	73.70	75.31
SPF	z	70.25	72.10	71.60	71.23	71.23
SECOM	-	80.94	80.90	81.21	81.04	81.50

Figures 4 to 6 provide graphical illustrations of the outputs in Level 3. In each figure, the circle dots represent the results of the full feature set, while the square boxes represent the bootstrap mean of an optimum solution (e.g. reduced features sets). The upper, middle, and lower lines correspond to the upper bound, mean, and lower bound, respectively, representing the 95% confidence intervals with a 1 million re-samplings. The proposed model achieves high performance accuracy rates on both the full feature set and the optimum solutions, i.e. above 90% for classifiers. Figure 4 depicts the performance of five classifiers. Classifiers PL and LB achieve the highest accuracy rates on seven fault types as compared with those of the other remaining classifiers. On a closer inspection (Figure 5), LB outperforms PL on all the seven fault types with over 99.3% accuracy rate each. The narrower boxes (representing the 95% confidence intervals of accuracy) on the optimum solutions indicates that LB is a stable classifier. In Figure 6, it is clear that LB is the winner in this problem, as shown by the highest accuracy rates it has achieved.

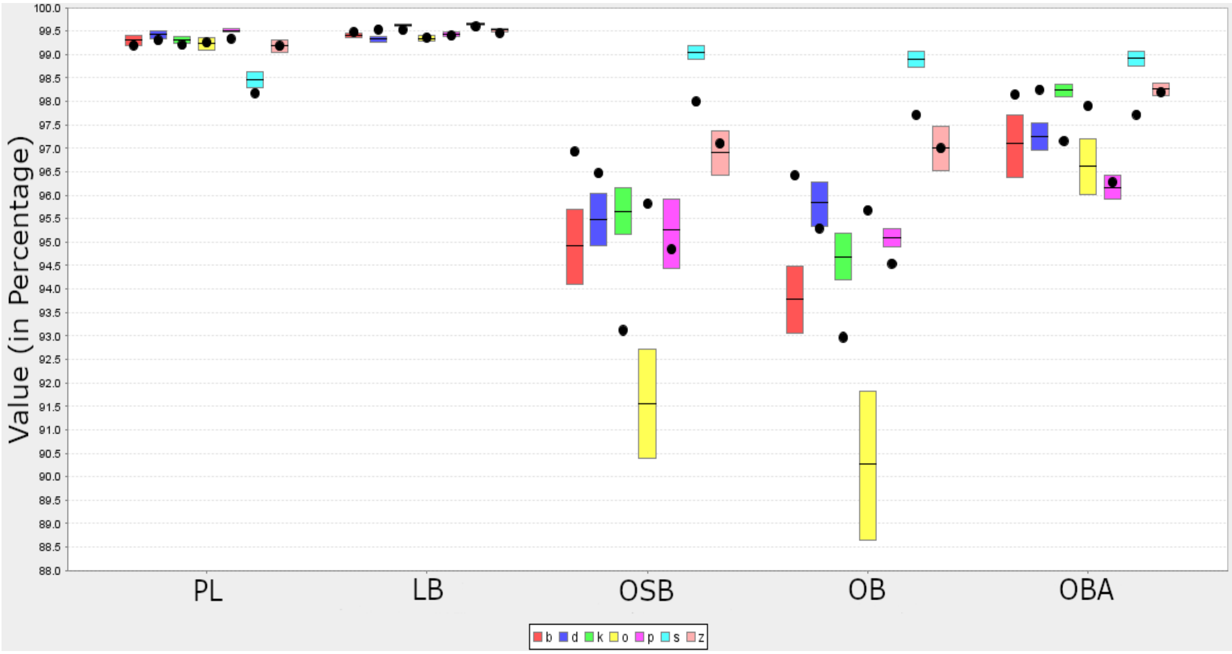

Fig. 4: SPF case study (performance by classifiers): Bootstrapped accuracy rates for full features dataset (black dot) and optimum solution (horizontal lines - filled with colors).

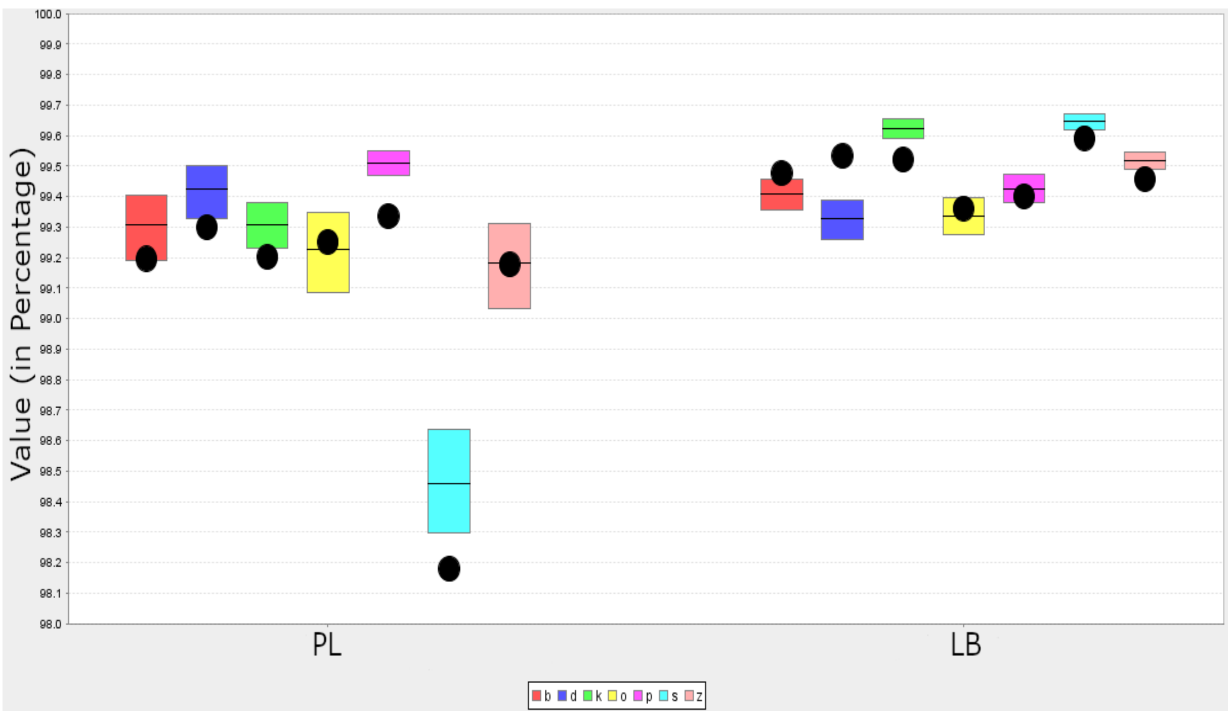

Fig. 5: SPF case study (performance for PairLearners and LeveragingBag): Bootstrapped accuracy rates for full features dataset (black dot) and optimum solution (horizontal lines - filled with colors)

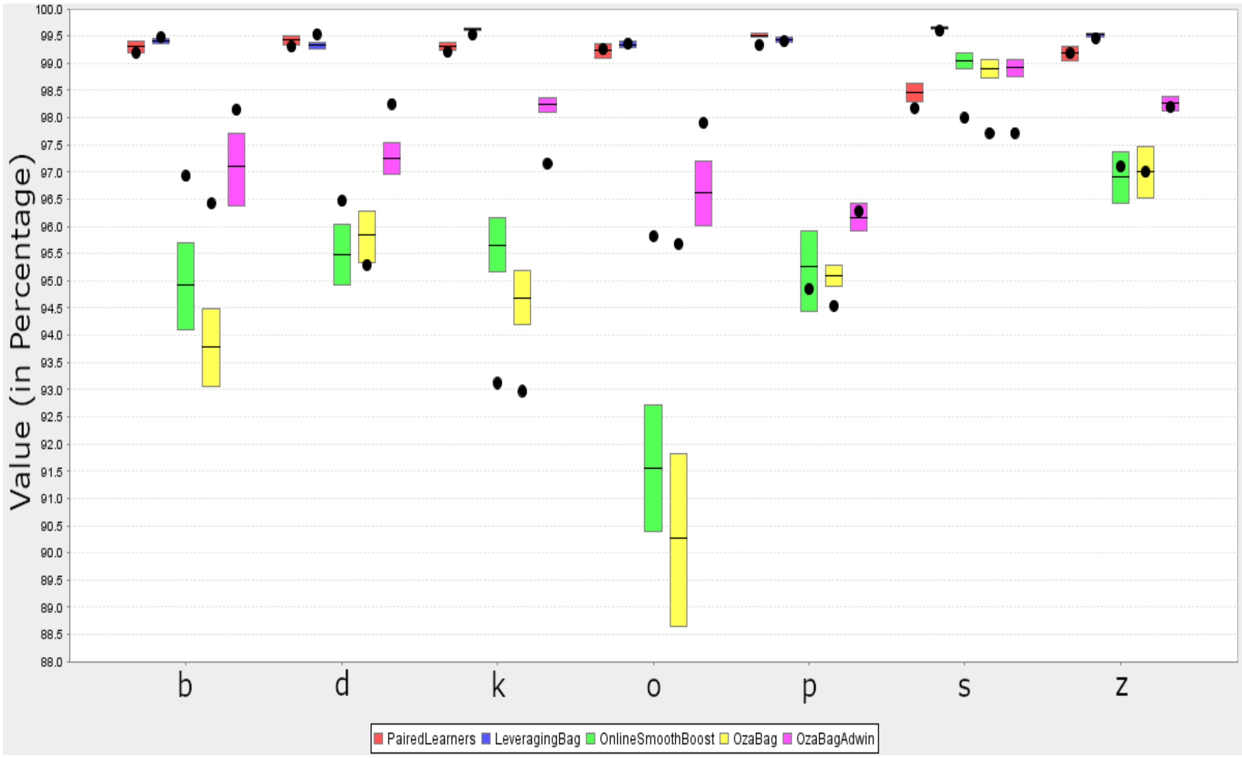

Fig. 6: SPF case study (performance by fault types): Bootstrapped accuracy rates for full features dataset (black dot) and optimum solution (horizontal lines - filled with colors).

Table 4 depicts the percentage of accuracy tolerance on the optimum solutions (with over 40% reduction in the number of features) as compared with those from the full feature set. A positive tolerance rate reflects an improvement in accuracy. In the worst case scenario of the best classifier (LB), for example, the model accuracy rate drops by merely 0.21% on the optimum solution as compared with that of the full feature SPF *b* set (see also Figure 5). Four out of the seven datasets using LB for training indicate improvements in accuracy on the optimum solutions as compared with those of the full feature sets. The overall lowest tolerance rate is 5.66% (OB classifier on the *o* dataset), while most of the classifiers yield improvement in accuracy based on the optimum solutions.

Table 4: Accuracy tolerance rate (in percentage) on the optimum solutions for SPF and SECOM

Dataset	Experiment Name	PL	LB	OSB	OB	OBA
SPF	b	0.11	-0.07	-2.06	-2.74	-1.06
SPF	d	0.12	-0.21	-1.03	0.57	-1.02
SPF	k	0.03	0.07	2.21	1.32	0.96
SPF	o	-0.03	-0.02	-4.44	-5.66	-1.30
SPF	p	0.18	0.03	0.45	0.59	-0.11
SPF	s	0.29	0.06	1.07	1.22	1.23
SPF	z	0.01	0.06	-0.19	0.01	0.07
SECOM	-	1.28	11.89	1.51	5.58	0.29

4.2 Benchmark Semiconductor Manufacturing Process (SECOM)

In a dynamic semi-conductor manufacturing plant, condition monitoring of its processes of equipment is of prime importance to ensure productivity efficiency. To facilitate condition monitoring, signals sensors located at various measurement points can be collected. However, these measured signals often contain irrelevant information and noise.

Useful information is buried in the pool of raw data. As a result, a large part of the signals collected are less useful. By considering each signal type as a feature, a feature selection method can be applied to identify the most relevant signals. The process engineer relies on these signals to determine the key factors contributing to yield loss due to excursions downstream in the process. The positive outcome of early intervention is an increase in production throughput and decrease in the per unit production cost. In this case study, the proposed DSS model is used to tackle the feature selection issue pertaining to condition monitoring of a semiconductor manufacturing process.

The SECOM data set is obtained from the UCI Machine Learning Repository. A summary of the data set is presented in Table 5. Each record shows a single production entity along with the associated measured features and its label as a pass (P) or a fail (F) outcome, which yields a test result. The proposed model has the capability of ranking the features with respect to the accuracy rate. A total of 1567 SECOM records are loaded into the proposed DSS model for training as in the Level 1 process. At Level 2, the full feature set first undergoes an optimization process to identify and remove the less important features. This is followed by another offline training cycle to produce the optimum solution.

Table 5: Characteristics of the SECOM dataset

Characteristics	Values
No. of Records	1567
No. of Features (Optimum Solution)	295(7)
Name of Target Class	Class
Potential Values of Target Class: Ratio of Records	{P,F}: 1463:104
No. of Experiment Runs on Each Classifier	30

As depicted in Table 3, all the classifiers achieve approximately over 80% reduction in the number of features. Again, PL and LB are the two best-performing classifiers (Figure 7). They achieve above 98.5% bootstrapped accuracy rates on the optimum solutions. The models perform well on the optimum solutions (Table 2) with LB recording the highest performance improvement (11.89%) on the optimum solutions as compared with those of the full feature set.

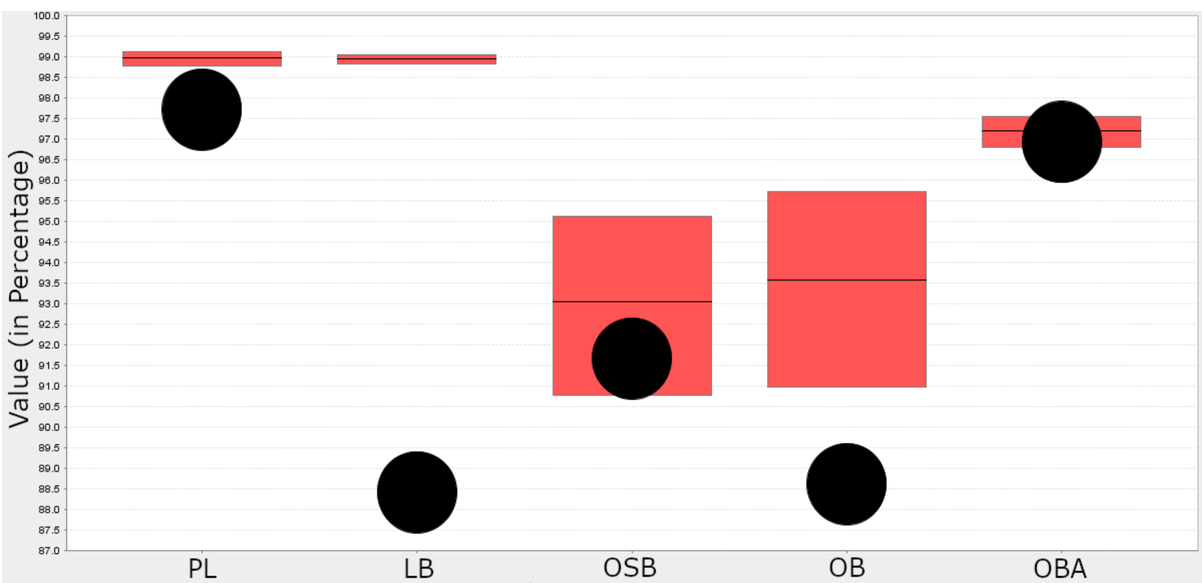

Fig. 7: SECOM case study performance: Bootstrapped accuracy rates for full features dataset (black dot) and optimum solution (horizontal lines - filled with color).

With the low accuracy tolerance rates and high performance accuracy rates, it is evident that training sessions are effective in filtering less important features while improving the overall performance.

4.3 Real-world Study on Prioritisation of Product Quality Improvement

Five important categories in manufacturing have been identified for recurrent analysis recently [30]. The Product Quality Improvement (PQI) is one of them, which focuses on reducing the costs of producing scrap (bad parts) by identifying the root cause for scrap and self-optimizing the assembly line. The same focus is aligned with the goal of a smart manufacturing company in our real-world case study. The company's production processes cater for a variety of models of communication device products, which involve six categorised PQI processes, i.e. Surface Mount Technology (SMT), Visual Inspection (VI), Model Assembling (MA), electrical test, functional test and final assembly, before the packaging and shipping processes.

In this case study, we focus on one of the six processes, i.e. electrical test. A particular device model, which has high valued and high failure rate, is chosen. A total of 196 test parameters, which cover a period of 32 months from 2017 to 2019, is identified. Actual defects are captured in the electrical test stations, where it is represented by the pass/fail status of assembled Printed Circuit Boards (PCBs). From the data compiled, a case was selected based on a historical event during production stop-build, i.e. the production was ordered to stop due to continuous failures detected on one parameter in an electrical test station. Then the historical data related to the particular parameter on the related product was retrieved for this study. The collected data set consists of no missing data, and they are labelled with unique Batch ID according to their sequence in passing pilot, production, pre-stop build and post-stop build phases, as shown in Table 6.

Table 6: Data labelling with Batch ID

Type	Record Sequence	No. of Records	Batch ID
Pilot	1 to 100	100	A
	101 to 200	100	B
	201 to 300	100	C
	301 to 400	100	D
Production	401 to 500	100	E
	501 to 600	100	F
	601 to 700	100	G
Pre-SB	701 to 800	100	H
	801 to 900	100	I
	901 to 1000	100	J
Post-SB	1001 to 1135	135	K

Figure 8 shows an example of real-world study. It contains normalised values of collected records for a test parameter. A total of 1135 records is plotted, where the first 400 records (A to D) are in the pilot phase. Subsequent 300 (E to G), 300 (H to J) and 135 (K) records are the production, pre-stop build (pre-SB) and post-stop build (post-SB) phases, respectively. There are 29 fails detected, i.e. values below the Lower Specification Limit (LSL) - red dotted line, at pre-SB phase. A stop build (SB) action is being called (an execution action by manufacturer) at the end of Pre-SB phase. Both LSL and Upper Specification Limit (USL) are the acceptance design guidelines on test results for manufacturing and testing purposes. We perform the linear normalisation based on both LSL and USL, i.e. $\frac{\text{test value}-LSL}{USL-LSL}$.

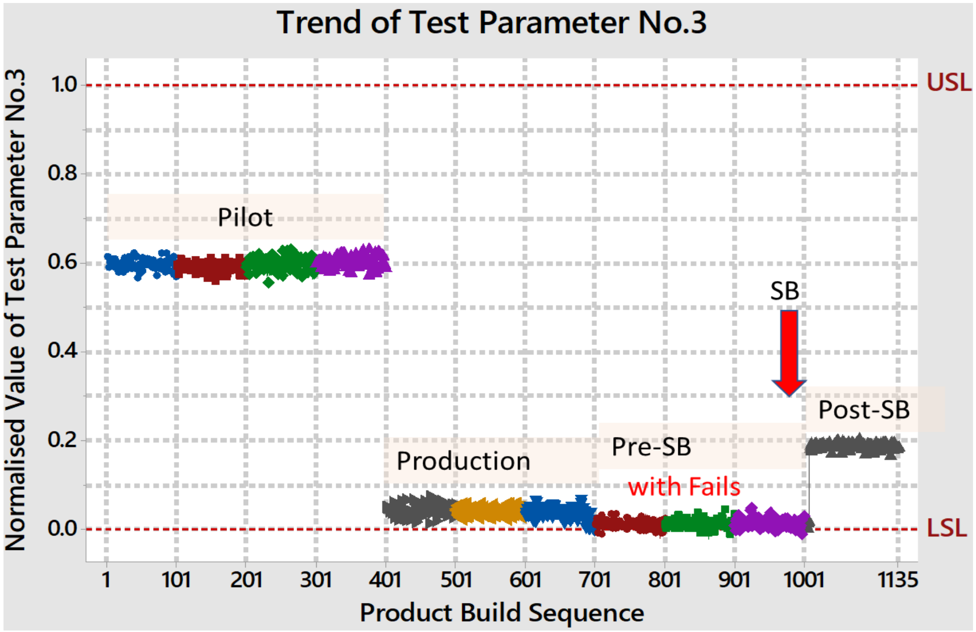

Fig. 8: Batch IDs of third test parameter

Upon SB occurrence, a human intervention is imposed. The human, i.e. manufacturing engineer occasionally, locates solution based on his/her past experiences in handling SB. In this case study, we propose the ARIZ-based DSS as an assistant to humans in making decision, as shown in Figure 9.

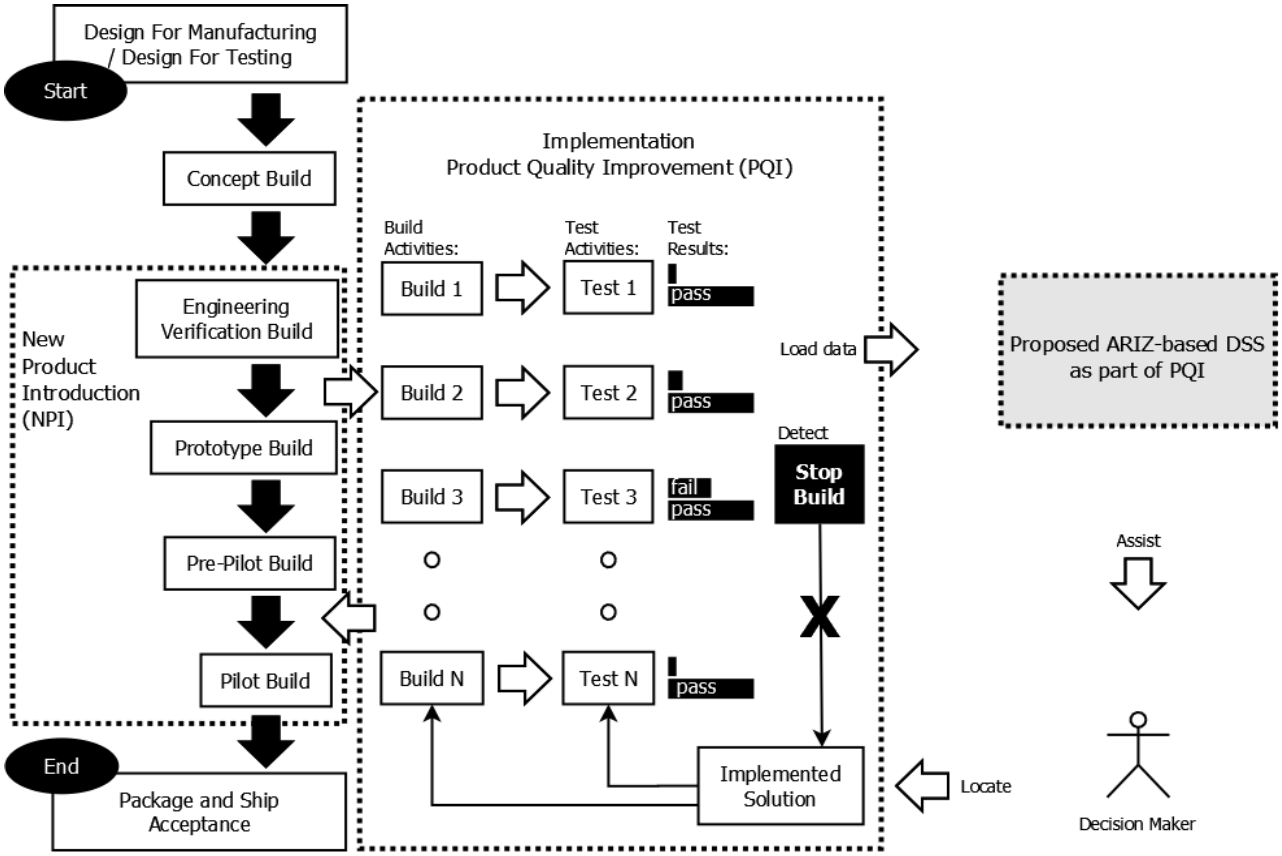

Fig 9: ARIZ-based DSS application network

The current study appeared to be reactive based on an event that has already occurred. The method is applied to the pilot builds in New Product Introduction (NPI) process and production builds. Note that the manufacturing company adopts the six PQI processes as their NPI process, which covers four main activities of a new product, i.e. engineering verification, prototype, pre-pilot and plot build before the product going into mass production builds. The NPI encompasses a big scope from manpower-material-machine-method planning, product prototyping to concurrent engineering processes. Their NPI has an objective to ensure smooth transfer from product design, i.e. either on manufacturing or testing, to mass production. Closure of issues at early stage during prototype or production stage is paramount in ensuring such transfer objective can be fulfilled. The impact of solving problem up front during design stage instead of during production is favourable. The proposed DSS model takes the role of assisting human in SB identification at early stage, i.e. preferably at either pre-SB or earlier phases under a non-experienced decision maker.

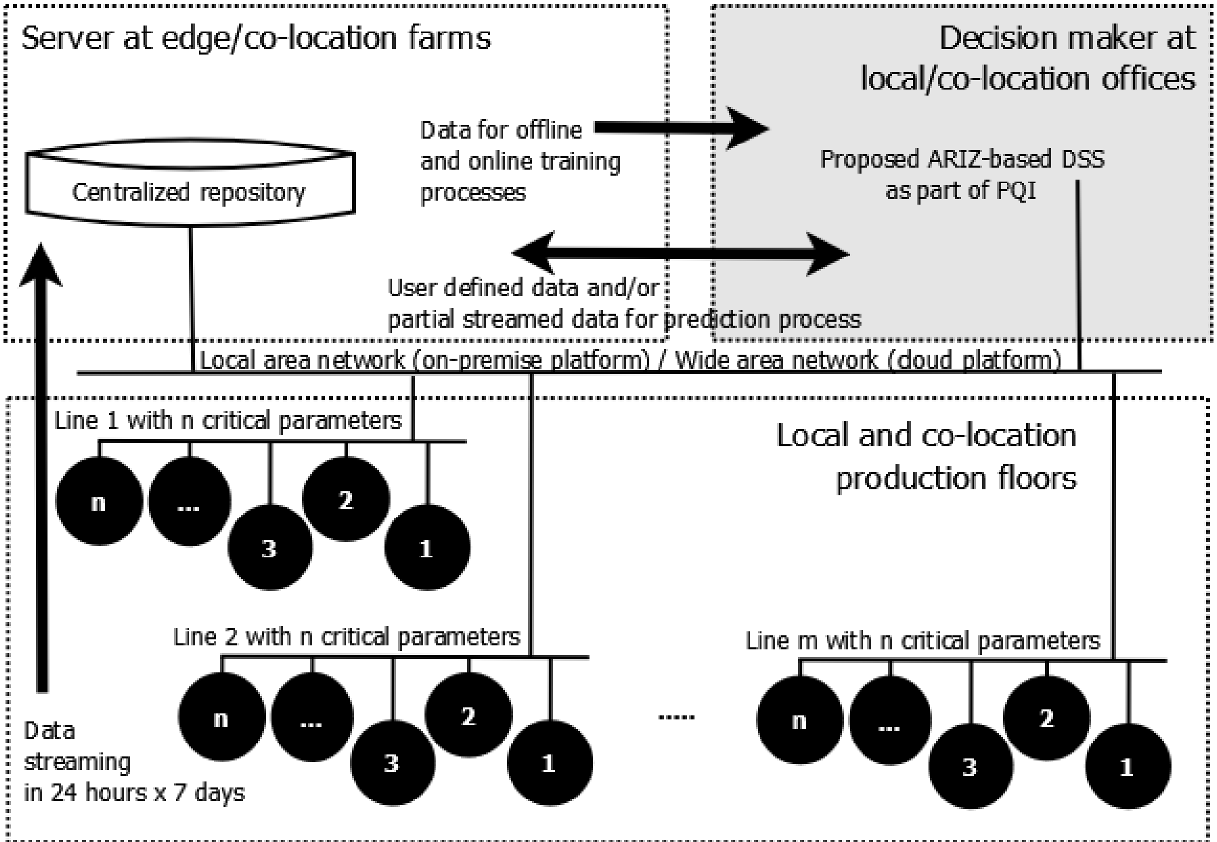

Fig. 10: ARIZ-based DSS application network.

Collected data cover 196 configurations of SMT and MA processes, including the actual test results of various build-and-test activities in PQI processes, as input features of classification problem (Level 1). Preprocessed data are loaded into the proposed DSS model after the data cleansing processes. Data are formed into 10 experiments (with 30 runs each) to identify SB occurrence, as summarised in Table 7. The classification result is either one of the encompassed batch IDs (target class), as highlighted in an individual experiment. In other words, each record is labelled with the identified batch ID before being used to train the classifiers.

Table 7: Characteristics of the Real-world Study

	Pilot			Production			Pre-SB			Post-SB
Experiment	1	2	3	4	5	6	7	8	9	10
No. of Records	200	300	4000	500	600	700	800	900	1000	1135
No. of Features	196	196	196	196	196	196	196	196	196	196
Name of Target Class	Class	Class	Class	Class	Class	Class	Class	Class	Class	Class
Potential Values of Target Class*	[A, B]	[A,B, C]	[A,B,C, D]	[A,B,C, D, E]	[A,B,C, D, E,F]	[A,B,C, D, E,F,G]	[A,B,C, D, E,F,G, H]	[A,B,C, D, E,F,G, H, I]	[A,B,C, D, E,F,G, H, I,J]	[A,B,C, D, E,F,G, H, I,J,K]
No. of Experimental Runs on Each Classifier	30	30	30	30	30	30	30	30	30	30

* Ratio of Records is 100 for each batch ID, except K has 135 records.

As depicted in Figure 11, the PL classifier achieves the highest bootstrapped accuracy rates in all 10 experiments, as compared with those of other classifiers. Its bootstrapped upper bound, mean and lower bound are based on the outcomes using the bootstrap method under the same 95% confidence intervals with a 1 million re-samplings. The results are higher than those from other classifiers. It implies that PL is good for detecting the pattern of root cause for scrap. In other words, it is able to reduce the costs of producing scrap on the targeted high valued and high failure rate device model. In addition, the PL classifier achieves high performance accuracy rates on the optimum solution. Note that black dots are achievements of the optimum solution with optimized feature sets, which are above those horizontal lines filled with colour.

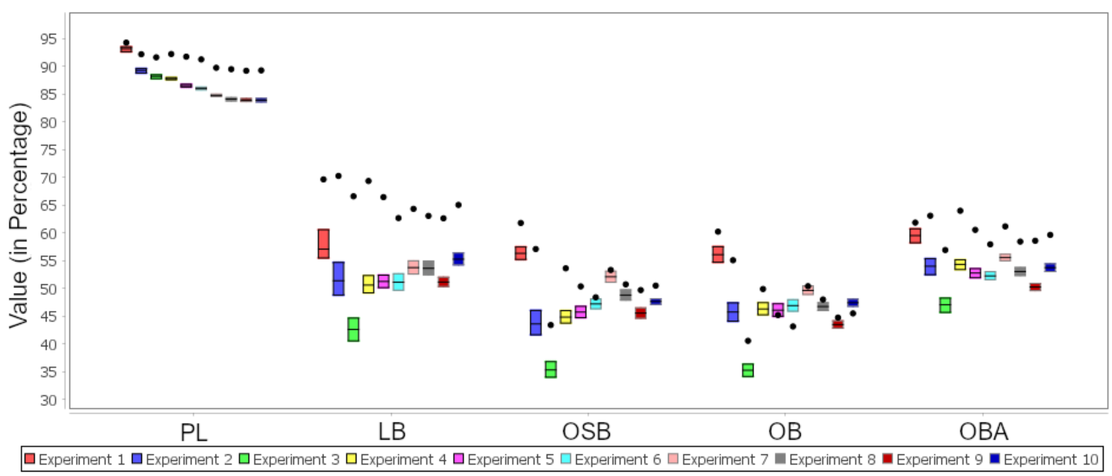

Fig. 11: Real-world case study performance: Bootstrapped accuracy rates for full features dataset (horizontal lines - filled with color) and optimum solution (black dot).

Table 8 reports the percentage of accuracy tolerance on the optimum solutions as compared with those from the full feature set (results of Level 2). Besides recording 89% and above bootstrapped accuracy rate, the PL classifier also achieves less than 6.5% positive accuracy tolerance rates across the experiments. The small tolerance rates indicate that the PL has a small risk in incorrectly detecting the pattern of root cause. The PL result is statistically significant at the 95% confidence intervals, indicating an improvement of accuracy with the optimum solution for experiments. In other words, fewer feature sets are concentrated with a higher degree of confidence in identifying the root cause before the occurrence of stop-build incidence.

Table 8: Accuracy tolerance rate (in percentage) for real-world Study

Experiment	1	2	3	4	5	6	7	8	9	10
PL	1.18	3.26	3.86	5.04	6.02	6.06	5.88	6.39	6.29	6.37
LB	21.97	36.69	56.22	37.01	29.62	22.57	19.67	17.60	22.43	17.66
OSB	9.70	30.88	22.86	19.58	10.08	2.51	2.35	3.95	9.10	5.96
OB	7.36	20.36	15.01	7.77	-1.90	-8.00	1.54	2.70	2.87	-4.04
OBA	3.92	16.82	20.94	17.77	14.71	10.90	10.10	10.15	16.57	10.96

Apart from that, the PL classifier achieves approximately 76% reduction in the number of features, as depicted in Table 9. It is worth noting that the actual root cause of SB occurrence in the results of the PL classifier, i.e. test parameters no.3, no. 4 and no. 5. is ranked as part of outcomes from Level 3. These test parameters have been ranked as the top three in experiments 4 to 6, and test parameter no.3 is the most influential one, as shown with the highest score of relative criticality rate. The peak of these rates (experiments 4 to 6) indicate the pre-occurrence of failures in production. Note that production with failures are detected in experiments 7 to 9, i.e., Pre-SB, as reflected in the actual data before SB. The ranking of these parameters, i.e. no.3, no. 4 and no. 5 in Table 9, reflects that the proposed DSS model is able to detect SB issues in an early stage, i.e. in prior pre-SB of PQI process.

Table 9: Test Parameters of Optimum Solution from PL Classifier

Experiment	1	2	3	4	5	**6**	7	8	9	10
Optimum Solution (Total)	46	42	40	30	24	24	22	22	19	46
Reduction in % (Out of 196)	-76.53	-78.57	-79.59	-84.69	-87.76	-87.76	-88.78	-88.78	-90.31	-76.53
Test Parameter	Ranking No.									
No. 3	7	4	3	**1**	**1**	**1**	4	4	5	7
No. 4	-	-	-	**2**	**2**	**2**	5	5	6	-
No. 5	16	37	14	**3**	**3**	**3**	6	6	7	16
Test Parameter	Relative Criticality Rate, $1 - \frac{\text{Rank no.}}{\text{No. of Reduced Parameter}} \times 100\%$									
No. 3 (in %)	85	90	93	**97**	**96**	**96**	82	82	74	85
No. 4 (in %)	-	-	-	**93**	**92**	**92**	77	77	68	-
No. 5 (in %)	65	12	65	**90**	**88**	**88**	73	73	63	65

The instability and fluctuation of accuracy rates achievement are observed among the classifiers, i.e. 1.18 to 6.39%, 17.60 to 56.22%, 2.51 to 30.88%, -8.00 to 20.36% and 3.92 to 20.94% for PL, LB, OSB, OB and OBA respectively. PL is the only classifier that shows the lowest fluctuation, i.e. 5.21%., as compared with other ensemble classifiers. PL is able to handle the concept drift issue, as reported in [3]. Specifically, the results in [3] indicated an outstanding performance (in term of accuracy rate under 95% confidence intervals) of the PL-based model, which performed better than other ensemble classifiers on five different evaluated experiments, including varied levels of class noise from 0% to 70% with an increment of 10%. The outcomes of our experimental study agree with the findings in [3].

The efficacy of proposed model is investigated at university. All experiments are conducted using the developed software on a single-thread based Intel Core i5 3.4 GHz processor with 8 GB of RAM. Figure 12 depicts the computational hours in computer laboratory. PL classifier consumes significant shorter period of time statistically, where its bootstrapped mean is lower than other classifiers across 10 experiments.

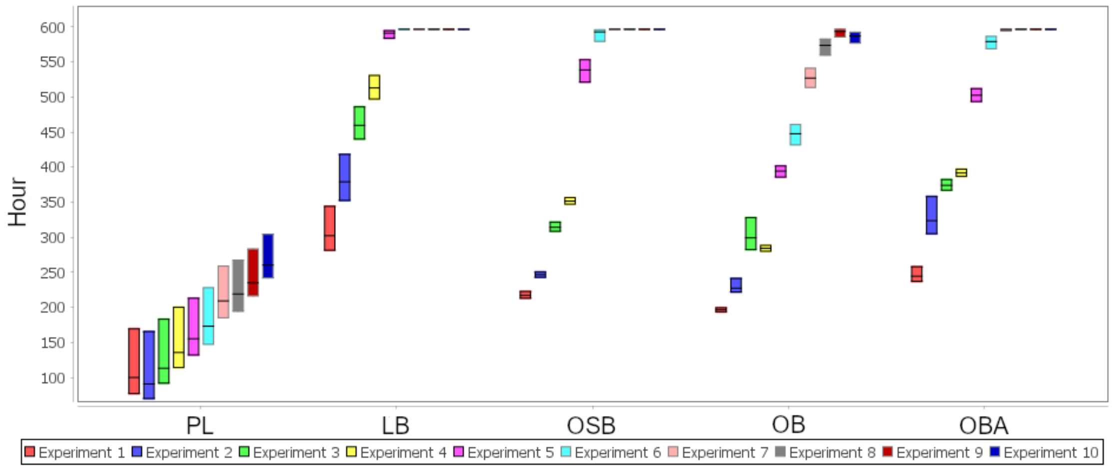

Fig. 12: Real-world case study performance: Bootstrapped computational hours for full features dataset (horizontal lines - filled with color).

5.0 DISCUSSION AND IMPLICATION

The implication of the ARIZ-based DSS model in facilitating smart manufacturing is analyzed, as follows.

5.1 Reduction of operational costs

In case studies, we have demonstrated the efficacy of the proposed ARIZ-based DSS model in terms of performance accuracy. In view of the above key capabilities of our DSS model, it achieves above 90% and 87% accuracy rates on two benchmark (SPF and SECOM) data sets. Importantly, it is able to maintain the accuracy rates from -5.66% to 5.88%, as reported in Table 4, when the number of features is reduced from 40.37% to 81.50%, as reported in Table 3. We emphasize that the success of ML training leads to an effective predictive model, which provides important information to the users. As an example, in the SPF case, mitigating the risk of production costs due to faulty steel plates is essential. Pits and blister, for instance, are the common causes in production of low carbon steel grades. The solution is to grind the surface of the steel product. But such action incurs additional production costs as well as time resources.

For the real-world problem the proposed DSS model is able to detect Stop-build (SB) issue at the early stage (at prior pre-SB), as discussed in Section 4.3. The results (Tables 8 and 9) are obtained under the optimum solutions. The features reduction rates are from 76.53% to 88.78% with the positive accuracy tolerance rates of 1.18% to 6.39%. Our DSS model can aid decision makers in running an effective and sustainable manufacturing production line by highlighting the potential failure of any targeted class in order to consider options for reducing the operation costs and other resources, while maintaining the production throughput and quality.

5.2 Improvement of decision quality

In the second case study, we have demonstrated our ARIZ-based DSS model pertaining to information filtering. As decision-makers rely more and more on the use of computers, the term “information overload” brings our attention to the seriousness of producing more information quickly and disseminating such information to a wide audience [17]. Intuitively, too much information can have deleterious effects on a decision-maker’s performance as cognitive resources are forced across multiple channels. Interruptions due to information overload has been found to influence decision makings. As analyzed in [48], a conclusion is drawn that for simple tasks, interruptions improve decision making performance, but reduce performance on complex tasks. Back to the SECOM case, our ARIZ-based DSS model simplifies decision making by filtering 80% of the less important features, presenting only the essential information to the decision-makers, and reducing the effect of information overload.

5.3 Process automation and flexibility

Human–machine interaction is one of the crucial aspects of smart manufacturing. It has been identified in the study [34]. An adaptive automation of Human-Machine interaction (HMI) based framework is proposed to accommodate varying levels of information abstraction to humans. The study aims is to provide a framework for human-involved manufacturing controllers as well as to gather the potential behavioral data of human supervisors and operators.

As a decision-maker provides the DSS model with training data, the underlying ML algorithms learn to make accurate prediction by subtly adjusting the error rates towards a tolerable range. Tolerance to errors of the learned ML model is important. The more training data, e.g. from machinery, the lower the error rate. Training is usually accomplished on a one-time basis in a consistent environment. Moreover, the training process is entirely automated in processing data from machine inside our ARIZ-based DSS model. In the SPF case, for instance, the model is trained once and applied to all types of steel production. Unless there is a change in the production requirements, there is no need to re-train the model. To tackle a new problem, the ARIZ-based DSS model has to be trained on a new data set, and this is only conducted once. Typically, the task to be learned is the target function, e.g., a function from the input environment pollution records, the output population health risk, or function from sensor inputs of a robot to find the next walking path. The ARIZ-based DSS model can be trained to handle the various tasks as aforementioned by collecting the relevant input-target data samples for learning purposes. Such flexibility pertaining to the developed ARIZ-based DSS model is appealing as it can be applied to a wide spectrum of HMI context without any modification to the underlying engine.

5.4 Machine-human interaction

After training, the ARIZ-based DSS model can be put to use. The decision-maker is able to interact with the model in various ways to improve the results, if necessary. A technically knowledgeable user can replace the proposed classifiers with other existing classifiers. In most cases, there is little need to interfere with the underlying classifier, since an ensemble approach is adopted in the ARIZ-based DSS model. In line with the “learning apprentice” approach [9], the model acts as a guide to aid humans, while learning by observing the human’s decisions and capturing them as additional information during the online training mode. Such approach opens up a new paradigm of knowledge transfer from humans to machines through combined expertise from different DSS users.

In the real-world study, we introduce a measurement of relative criticality in reflecting the warning signals before the SB occurrence. As shown in Table 9, peak values of relative criticality rate appear in experiments 4 to 6. The proposed DSS model reports the detected critical parameters, e.g. test parameters no.3 (most influential feature), no. 4 and no. 5, that cause failures. It helps in assisting humans in making decision to reduce the occurrences of the real SB.

5.5 Other applications

In line with the advent of Internet-of-Everything, edge computing, for instance, is a distributed computing paradigm in which computation is largely performed on distributed device nodes, called the smart devices or edge devices. With edge computing, data analytics with AI serves the data collection sources and cyber-physical systems, including smart sensors and actuators in the production floor at a closer range to the user. A closer range means a faster response. Such cloud infrastructure is common in smart manufacturing environments, e.g. studies in [31], [32], [45]. For most critical decisions, a timely response is essential. To this end, our ARIZ-based DSS model offers a feasible solution for processing data near the edge of a network in order to serve the organization in rapid decision making processes. Due to its adaptability, multiple deployment of ARIZ-based DSS instances (on production floor) is feasible, particularly in the High-Mix-Low-Volume (HMLV) manufacturing in serving the local and co-location environments, as shown in Figure 10. Each production line can perform local decisions as required by the production pace and needs, such as a change in the system or design.

In accordance with Industry Revolution 4.0, production floors are elevated to acquire a strategic approach to integrate sensor measurements into pre-existing data environments. Likewise, the manufacturing environment can take advantage of multiple ARIZ-based DSS model and install them at selective data points to accelerate digital transformation through effective decision making. Such a model also facilitates the distributed decision-making process in smart manufacturing.

6.0 CONCLUSIONS AND FUTURE WORK

Smart manufacturing has transformed the way decisions are made. By accelerating the delivery of data to the various decision points, more rapid decision-making processes can be realized. Unfortunately, according to *Nature* [28], leading industries including energy and aircraft, computing and semiconductor manufacturing face data gaps. Most organizations lack the knowledge in manipulating data to improve their products and processes [28, 35]. On this challenge, our study has simplified the data processing and extraction processes through an automated ARIZ-based DSS model; therefore enabling a non-technical user the opportunity to harvest the vast knowledge from the collected data for efficient decision making.

Indeed, the ARIZ-based DSS model promises efficient information gleaning that can be transformed into valuable knowledge to aid the decision making process. Such data centric approach can reduce uncertainty in decision making [13]. Reducing uncertainty and risk is essential noting that biases in judgement is not uncommon among decision-makers [36]. As illustrated in [37], individual decision-makers tend to rely on personal preferences under higher levels of risk even when there exists evidence that indicates superiority of other vertical attributes. One way to reducing the individual's perceived risk is by focusing on information that increases the accuracy of prediction [15], which can be achieved by the ARIZ-based DSS model, as demonstrated by its highly accurate performance in the three case studies.

In ensuring the proposed model efficiently supporting the decision makers, a list of requirements is needed for the implementation. The data samples used for training the proposed model need pre-processing. Input data have a direct influence on the training process, specifically in achieving high accuracy in the training process (Steps 1 and 2). The selected pre-processed snapshot or continuous data stream enables the employed classifiers to prepare and accumulate the required knowledge in the prediction process (Step 3). Valid and quality feedback during interaction between the end-user and system ensures an effective prediction for different data sets using different knowledge sources. For example, more real-world studies, i.e. a variety of defined PQI products and services as well as those categorized six processes, should be adopted as knowledge sources, and a consistent on-going analysis on these defined knowledge sources should be taken place.

ARIZ is useful to define the ideal final result and physical contradiction, e.g. in proposing candidate contradictions, in defining operational zone with time, and in identifying substance-field resources as highlighted in [16], there are several challenges in adopting ARIZ. Specifically in the implementation phase, the requirements disclosed to be solved could be in contradiction with the TRIZ laws of evolution. This challenge is applicable to our proposed DSS model, especially under the contradiction situation, leading to potentially unsatisfactory performance in the real manufacturing environment. Secondly, the use of ARIZ alone in our DSS model may not be sufficient to serve a full solution. New problems require additional information, e.g. ARIZ has no guideline in collecting cascaded requirements, which can result in a compromised solution. Therefore, an enhanced ARIZ concept with other complementary methods within the proposed DSS model is recommended in tackling complex real-world problems.

For future work, the ARIZ-based DSS model can offer a set of non-dominated solutions to the target problem after learning from a wide range of data. ML-based optimization approaches have continuously demonstrated promising results in this area [25]. As a result, it is plausible to expect an improvement in decision quality.

On the other hand, suboptimal decision making is costly, especially in a competitive manufacturing setting. In [22], it is found that people who are exposed to and can understand the common principle of a seemingly unrelated decision problem tends to exhibit improved ability in discovering solutions to other tasks of the same principle. In this light, the ARIZ-based DSS model can be extended to support group decision makings. The collaborative working environment encourages healthy information exchange, improved communication, and reduction in common biases. Moreover, the model can be configured to automate notifications which alert all decision-makers on a specific abnormality. As information is received in a timely manner, the decision-makers can focus on early intervention in order to minimize the risk of loss.

In summary, this paper presents the design, implementation, and evaluation of a generic ARIZ-based DSS model. By integrating a strong theoretical framework for problem solving based on ARIZ and robust ML methods, the proposed ARIZ-based DSS model can be applied to support a wide array of decision-making processes. The underlying methodology can be summarized into three levels: transforming a generic problem into a classification with feature optimization task, removing obstacles from the model, and finally, analyzing the results. Apart from simplicity, the ML classifier can be easily trained with existing data to achieve high accuracy rates. Moreover, decision-makers can adopt different types of classifiers from a plethora of open source algorithms. Other researchers can extend the proposed ARIZ-based DSS model in terms of functionalities in various ways.

In line with the notion "Automating automation" [9], an automated DSS model for supporting decision-making processes has been designed and developed in this study. By automating the decision-making process and providing a suitable environment for collaborative sharing, the risk of making ill-informed decisions will be reduced.

7.0 ACKNOWLEDGMENTS

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