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Prioritized relevant trend identification for problem solving based on quantitative measures

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ABSTRACT

This study proposed quantitative/mathematical ways to identify TRIZ solution models to given problems based on some similarity measures. The use of quantitative methods allows the users quickly and objectively obtaining solution models to a problem with priority based on existing trends and solved data base which is the accumulation of many expert knowledge and experiences instead of individual expert's judgment.

In this paper, the similarity concept was used to determine the relevant evolutionary trends and corresponding stages as solution models. A total of 124 known cases from literature and 10 author's own industrial cases verified the validity of the method in screening in n highest potential solution models for solution generation where n can be determined by the user. By conducting a 4-fold verification of 124 cases, the eight highest similarity solution models provided a hit rate exceeding 92% coverage of the original solutions. This substantially exceeded the hit rate of eight randomly selected solutions, which was less than 5%. Furthermore, problems and suggested trigger solutions were given to 20 TRIZ level 3 practitioners to test the effectiveness of those screened trigger solutions. On average, the eight most similar trigger solutions provided 4.2 effective specific solutions (52.6%) as opposed to that of the eight random trigger solution which is 1.5 effective specific solutions (18.69%). The eight worst similar solutions on average generated 0.86 solutions (10.79%).

The ideas can also be extended to identifying prioritized solutions objectively and quickly with any other TRIZ problem solving tools which contain large number of solution models such as effect database, principles, and standards. This establishes a paradigm shift new research direction for TRIZ-based scientific research contributing to TRIZ recognition in scientific fields. The contributions of this study include: (1) Integrating trends from Traditional and Darrell Mann's TRIZ to form a set of 52 trends in which each trend stage's characteristic attributes and evolutionary causes to the stages were completed. (2) A mathematical method was used to develop an objective and repeatable trend identification system in which the hit rate and feasible solutions substantially exceeded randomly selected solutions. (3) Providing a means to continually accumulate expert knowledge and experience by integrating more expert-solved cases to provide users a rapid, objective, and effective problem-solving system. This implies a continuous learning system which uses cumulative knowledge from many experts objectively instead of otherwise knowledge from individual experts. (4) Opening up a new research direction of identifying prioritized solution models using quantitative/mathematical measures instead of traditional qualitative reasoning.

1. Background and research purposes

TRIZ is the Russian acronym of theory of inventive problem solving. The well-known TRIZ model of problem solving is indicated in Fig. 1. This work focused on improving the encircled process step of converting from problem model to solution models, or trigger solutions. This is the step where TRIZ is able to provide solution ideas in generic directions.

The problem-solving process of the TRIZ has long been based on logical inference instead of more rigorous and repeatable quantitative/mathematical analysis. In particular, the process of matching problem models to their corresponding solution models (trigger solutions) by using TRIZ problem-solving tools has been reliant

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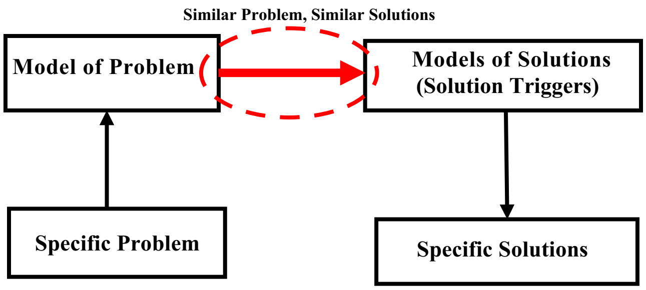


Fig. 1. TRIZ model of problem solving.

on expert experiences and judgments. Not only different experts may identify different solutions, the traditional methods may also obtain different solutions at different times even for the same person. The lack of repeatability, rigorous modeling, and mathematical/quantitative contents contributed to the lower-than-deserve acceptance of TRIZ research work by rigorous scientific journals.

Furthermore, the problem of identifying relevant solution models becomes an issue when the number of possible solution models becomes large. This applies to a number of problem solving tools such as effects, trends, and standards. For example, OxfordCreativity web site (OxfordCreativity Effect database, 2014) listed 222 suggestions for "Move Solid". (See Fig. 2.) Examining all possible solution models is very time consuming and highly inefficient – especially when many of the effects are unfamiliar to most people. Therefore, there are three major deficiencies involved with traditional TRIZ problem-solving tools: (1) Varying solutions often arise from various experts or particular problem-solving occasions. This generates solution models that are highly expert-dependent and non-repeatable. (2) Experts are often required to individually assess many possible solution models without priority. This is very time consuming. (3) Each instance of solution identification in problem solving is the decision of a team's expertise. There is no way to accumulate the identification knowledge/experience to future problem solving teams.

As some solution models are much more relevant than others, there is a need to objectively identify relevant solution models with priority to save problem solver's time.

The purpose of this research is to address the above-mentioned problems in TRIZ identification of solution models. As indicated in Fig. 1, by using quantitative measures the goals of solution priority, objectivity, repeatability, modeling rigor, and the speed of obtaining solution models, can be achieved. In the meantime, the system design allows for problem solving based on the integral results of continual accumulation of many experts' knowledge/experiences embedded in many expert-solved cases instead of knowledge/experience of an individual expert. In this paper, the above purposes applying on identifying solution models based on engineering trends are exemplified. In the future, the same concepts can be used to develop systems to identify relevant effects, standards, and principles, etc., for problem solving. This opens up a new research sub-field of using mathematical/quantitative methods in the TRIZ problem solving processes contributing to promoting TRIZ recognition in rigorous scientific research communities.

Based on an integration of the classic GEN3 and Darrell Mann's evolutionary trends (Mann, 2007) in TRIZ, this study identifies and prioritizes relevant trends and stages for solution models by calculating the similarities between the attributes/functions of a problem and the attributes/functions of a trend using mathematical tools constructed for the integrated set of evolutionary trends.

2. Relevant literature

2.1. Evolutionary trends

Trends of Engineering System Evolution was first proposed by Altshuller (1997) in the laws of development of technical systems,

Fig. 2. Too many possible solution models without priority.

which was further studied and organized by his students and other scholars. It is one of the most important TRIZ tools in traditional TRIZ. The contents comprised 11 main evolutionary trends and 26 sub-trends as shown in Fig. 3. Note that the trend of S-curve evolution itself is considered as one main trend.

Mann (2007) proposed 37 evolutionary trends and divided them into three dimensions, namely space, time, and interface as indicated in Fig. 4. In this study, only relevant technological trends were used. The two evolutionary trends related to sales and markets were excluded: market evolution and customer purchases focus. In addition, four evolutionary trends that were duplicated in space–time-interface dimensions were integrated: mono-bi-poly (similar), mono-bi-poly (various), mono-bi-poly (increasing difference), and boundary breakdown. Thus, 52 trends were compiled in this study, including the aforementioned traditional TRIZ trends and 31 of Mann's technological evolutionary trends. As the Trend of S-curve has only one stage, it is not used in the problem solving. This list of trends used in the research is attached in Appendix A.

2.2. Similarity comparisons

In order to define the similarity of any two elements, I and J, they can be represented as arrays of the same kind. Each column in the array I or J represents a particular attribute of the element and is denoted as i and j respectively. Dunn and Everitt (1982) listed a binary variable paired observation table as shown in Table 1. In the Table 1, i and j are two corresponding columns of I and J to be compared. They represent the same attribute column of the two arrays I and J. A matrix variable that equals to one represents that an observed value of an attribute exhibits certain defined characteristics. A matrix variable that equals to zero represents that the observed value does not exhibit the defined characteristics. Among the variables, a represents the number of attributes in which observed values i and j are both equal to one and that these two exhibit the defined characteristics, which results in successful positive matches; b represents the number of attributes in which observed values i and j are respectively $(0,1)$, which represents that i does not exhibit the defined characteristics while j exhibits the defined characteristics and thus matching is unsuccessful; c represents the number of attributes in which observed values i and j are respectively $(1,0)$, which represents that j does not exhibit the defined characteristics while i does. Again, the match is unsuccessful in this case; lastly, d represents the number of attributes in which i and j are both zero, which means that neither exhibit the corresponding defined characteristics, thereby resulting in negative matches.

Numerous similarity measurement methods exist to indicate the similarity between I and J (Choi, Cha, & Tappert, 2010; Donald, Keith, & Harold, 1989; Jackson, Somers, & Harvey, 1989; and Meyer, Garcai, Souza, & Souza, 2004). Ten mostly used measurements with their respective computational methods are listed as follows:

$$S_{JACCARD} = \frac{a}{a+b+c} \tag{1}$$

$$S_{Dice} = \frac{2a}{2a+b+c} \tag{2}$$

$$S_{Anderberg} = \frac{a}{a+2(b+c)} \tag{3}$$

$$S_{RUSSELL\&RAO} = \frac{a}{a+b+c+d} \tag{4}$$

$$S_{SOKAL\&MICHENER} = \frac{a+d}{a+b+c+d} \tag{5}$$

$$S_{PEARSON\&HERON-I} = \frac{ad-bc}{\sqrt{(a+b)(a+c)(d+b)(d+c)}} \tag{6}$$

$$S_{OCHIAI} = \frac{a}{\sqrt{(a+b)(a+c)}} \tag{7}$$

$$S_{OCHIAI-II} = \frac{ad}{\sqrt{(a+b)(a+c)(d+b)(d+c)}} \tag{8}$$

$$S_{YULEQ} = \frac{ad-bc}{ad+bc} \tag{9}$$

$$S_{ROGER\&TANIMOTO} = \frac{a+d}{a+2(b+c)+d} \tag{10}$$

In the above equations, the various formulas for S, represent various similarity measures, and the respective subscripts indicate the scholars who proposed the corresponding similarity equation.

Through the analysis performed in this study as well as experiments conducted by several graduate students in the authors' team, an improved Dice computational method was adopted, which is presented in Section 3.4.

3. Research methods and fundamental theories

This section explains the theories and methods developed for mathematical/quantitative approaches to identify TRIZ model of solutions with priorities. Section 3.1 explains the underling concepts for this work. Section 3.2 explains the modeling approaches for the problems, solutions and trends. Section 3.3 explains how to identifying trends and stages for solutions. Section 3.4 explains the overall tasks of this method of identifying trend solutions using similarity measures. Section 3.5 describes the computational details of how to identify the solutions in Section 3.4. Note that even though that the overall tasks is sophisticated, the user of the software system do not need to know anything about how the tools work to successfully use it. They are embedded in the software. The users need only to identify what attributes are relevant to the problem and what functions are needed to solve the problem.

3.1. Foundation concepts

The main foundation concepts of this novel work are based on:

1. Similar problems have similar solutions. Refer to Fig. 1. If the model of a problem is similar to the model of a solved problem, then, the solution model of the problem will be similar to the solution model of the solved problem. If the similarity index is higher than a pre-determined threshold, we can then use the solution of the solved problem weighted by the similarity to form the solution of the problem to be solved, There are two situations: (1) Using the solution models of the solved problems to form the solution model of the problem to be solved if the similarities between the to-be solved problem and the corresponding solved problems are all higher than certain threshold. (2) Considering the trend itself as a special "solved case". That is: If the problem model is similar to the model of a stage of a trend and jumping from the current stage to another stage of the trend can provide the needed improvements to solve the subject problem, then the later stage of the trend provides a solution model for the subject problem.

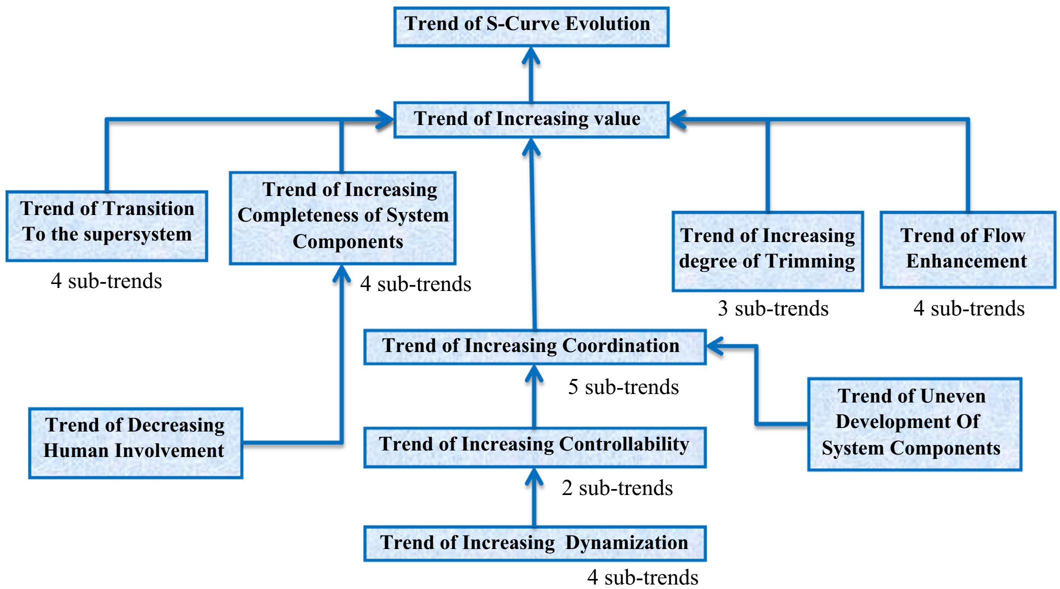


Fig. 3. Structural diagram of the evolutionary trends in traditional TRIZ family (GEN3).

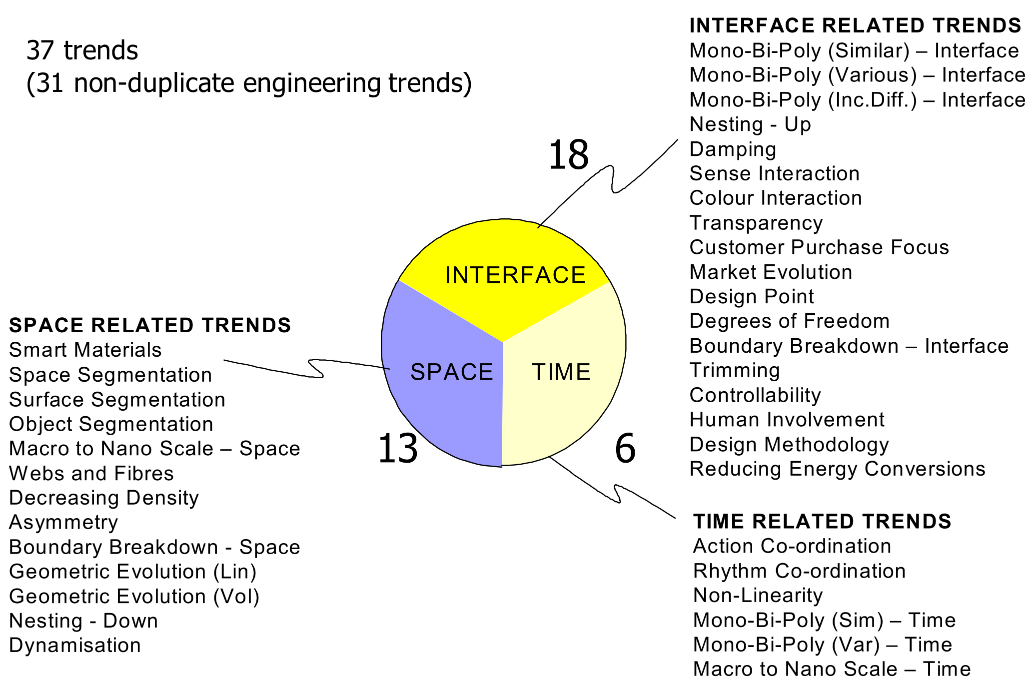


Fig. 4. Darrell Mann's trends collection.

Table 1
Paired observation table.

j	i: 1 (Presence)	0 (Absence)	Sum
1 (Presence)	a	b	$a+b$
0 (Absence)	c	d	$c+d$
Sum	$a+c$	$b+d$	$a+b+c+d$

2. In order to calculate similarity, the authors developed an array of attributes (attribute set) and an array of functions (function set) to model a problem as Problem Characteristic Array (PCA), a solution as Solution Array (SA), a case as Case Array (CA), and a trend as Trend Characteristic Array (TCA). By doing so, it is possible to calculate the similarity between two problems and the similarity between a problem and a trend stage.

3.2. Modeling of the problems, solutions, and trends

The formats of PCA/TCA/SA are explained in this section. They are to fully characterize a problem (PCA), a Solution (SA), a trend (TCA), and a case (CA) in the context of using trends to solve problems. PCA is the standardized problem model. SA is the standardized solution model. Note that CA = PCA + SA as a case will include the problem part and the solution part.

3.2.1. PCA for trend comparisons

Fig. 5 shows a PCA with binary bit array. A PCA contains an attributes part and a function part. Since function can also be represented as change or maintain the attribute(s) of an object, the function part of a PCA can be further divided into attribute subsection and function subsection to fully represent a function. For convenience, the authors denote the attribute part of the function as indirect functions and the function part as direct functions. In the attribute array, a "1" in a cell value indicating that the corresponding attribute is one of the characteristic attributes of the current problem. A "0" in an attribute cell indicating that the corresponding attribute is irrelevant to the problem. On the attribute sub-array of the function array, a "1" as the value of the cell indicating that to solve this problem some change/maintaining of this parameter is needed. A "0" in the cell location indicating that this attribute is irrelevant to the problem solving. On the function sub-array of the function array, a "1" as the value of the cell indicating that to solve this problem the corresponding function needs to be achieved. A "0" in the cell indicate that the corresponding function is irrelevant to problem solving.

3.2.2. The solution array and case array for trends

Fig. 6 shows expression used for SA in which $S_{T,i}$ represents the likelihood index of stage i of trend T to be a solution of the current problem. An $S_{T,i}$ equal to one represents that trend T stage i can be used as the possible solution to a problem. On the other hand, when $S_{T,i}$ is equal to zero indicating that the trend T stage i is irrelevant to the problem.

A Case Array (CA), is defined as the direct compilation of PCA and SA to be the model of the case. The first part is the problem characteristics array (PCA). The second part is the solution array (SA).

3.2.3. The Trend Characteristic Array (TCA)

Fig. 7 shows the Trend Characteristic Array (TCA). The stages of a trend can be expressed using TCAs. The attribute/function sets of the TCA are similar to that of the PCA/SA used with respect to the trends problem-solving tool. The first part of TCA is attribute array. The characteristic attributes of any stage of the trend are the attributes which are the features of the stage or changing or maintaining of the attribute can be achieved by jumping to some later stage of the trend. The second is function array. This part, in turn, includes change/maintaining attributes (as an indirect function) and the (direct) functions. A "1" in a stage of a trend's attribute array indicates that that attribute is a characteristic attribute of the stage. A "1" in a function field of a stage indicate that a function or attribute change can be achieved if a jump from another stage to this stage is performed. A "0" indicates irrelevant attribute(s) or function(s) to this stage of this trend. Each stage in the evolutionary trend consists of its corresponding attribute and function characteristics.

The TCAs do not need another solution arrays because the trend stage itself can be considered as a solution. In a sense, a trend by itself can be another form of a case. Therefore, they can be added to the case database for the solution process.

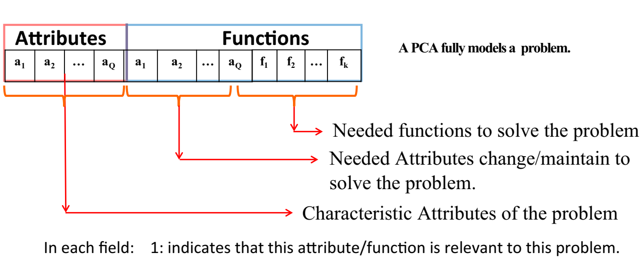


Fig. 5. Problem Characteristic Array (PCA).

3.3. Identifying trend stages for solutions

There are two ways of using similarity to locate appropriate trends and stages for solution models.

(1) Based on database of solved past problems with trend stages as solution model.

The concept of "***similar problems have similar solution models***" is the basis for this method. The method is explained in the ensuing section.

(2) Based on direct comparison of the Problem PCA with Trend Characteristic Array (TCA).

The second way of identifying SA of a problem using trends is to compare the similarities of PCA's attributes and functions directly with corresponding attribute/function parts of the evolutionary trends. If the characteristic attributes of the current problem PCA is similar to the characteristic attributes of certain stage of a trend and the needed function/attribute-change part of the current problem PCA is similar to the function/attribute-change capability part of another stage of the trend, the later stage of the trend may provide a solution model to the problem. This is detailed in Section 3.3.2.

3.3.1. Identifying solutions from solved cases

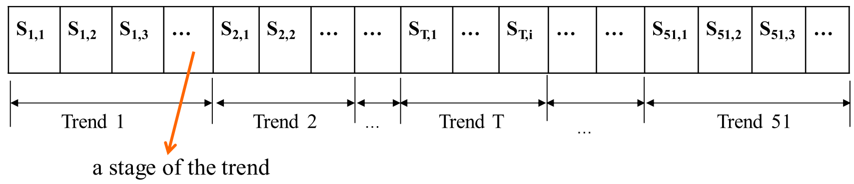
Identifying trend solutions from solved cases in case database is straight forward. Algorithm is as follows:

(1) Do for each case: Calculate the similarity value between the PCA of the current problem and PCA of each solved case in the database. If the similarity is no less than the set threshold, we consider the solve case is similar to the subject problem. The Solution array of this solved similar case is adopted as possible solution. The values of the fields in the Solution Array are then multiplied by the similarity to serve as a constituent Solution Array of the case.
(2) All the constituent solutions of the similar solutions are added up to form a solution array. The highest n trends/stages are selected for best n solutions of the solution array in the order of their cumulative field values.

3.3.2. Identifying solutions by similarity comparison with evolutionary trends

3.3.2.1. Comparison principles. Fig. 8 shows the concept of identifying trend and stage for model of solution in a regular trend which have apparent direction to evolve toward. Three steps are identified for the process. (1) Characteristic attributes of the problem PCA to be solved is compared against the TCA of an earlier stage of a trend on its attribute characteristic part. (2) If the similarity measure is higher than certain threshold 1, the needed function array part of the PCA is compared to the function array part of a later stage of the trend. If the similarity is higher than certain threshold 2, it indicates that jumping from an earlier stage to this later stage of the trend may solve the problem. Then, (3) the characteristics of the later stage of the trend can be used as the solution model of the problem.

Although most trends have a clear forward direction to evolve in evolutionary stages, therefore, only the later stages of the trend are check for potential solution. However, some trends do not have clear forward direction to evolve to. In this case, evolution toward either direction is possible. Therefore, with the same method, both



$S_{i,j}$: stands for the *j-th* stage of the *i-th* trend. A “1” at $S_{i,j}$ indicates that the *j-th* stage of the *i-th* trend is a solution of the problem. Otherwise, it is marked as “0”.

Fig. 6. The solution array with trends and stages indicated.

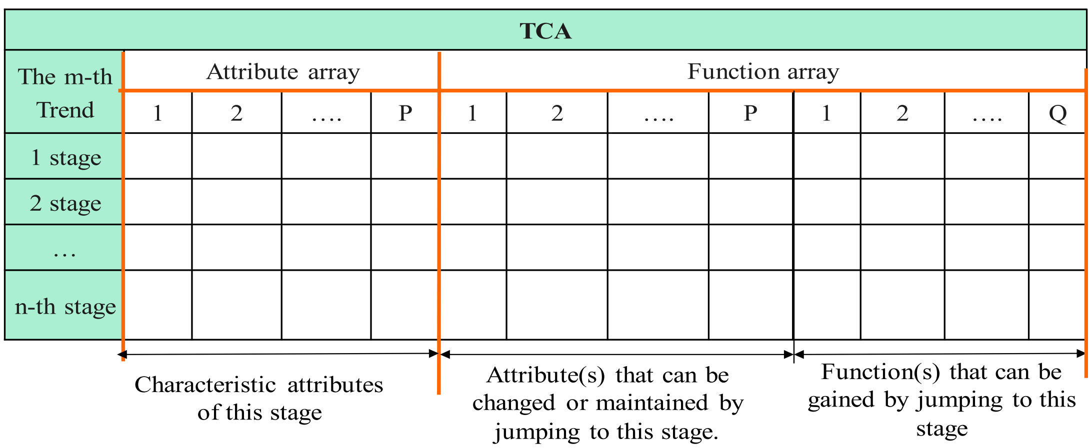


Fig. 7. The Trend Characteristic Array (TCA).

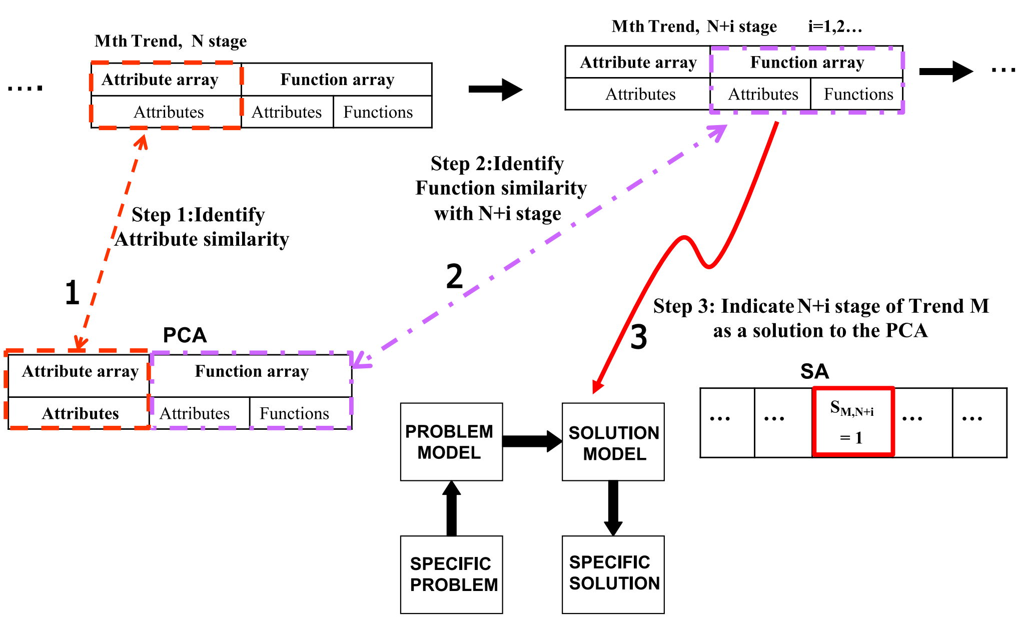


Fig. 8. Process of identifying the trend/stage for solution model.

directions of stage jump have to be checked for potential solutions. This is shown in Fig. 9. The detail steps of similarity comparisons are explained in the Sections 3.4 and 3.5.

3.4. The overall tasks of this research

The tasks of this research and their process sequence are illustrated in Fig. 10 and briefed below:

3.4.1. Compile generic attributes and functions

This step is to standardize the names for attributes and functions. All functions/attributes from Oxford creativity and CREAX web site are integrated for this purpose. Some additional ones from author's team research are also added. Wikipedia web site was referenced for the definitions of the generic attributes and functions. Detail definitions and list of attributes and functions used can be seen at (Chiu, 2013; Sheu, Chiu, & Lu, 2014).

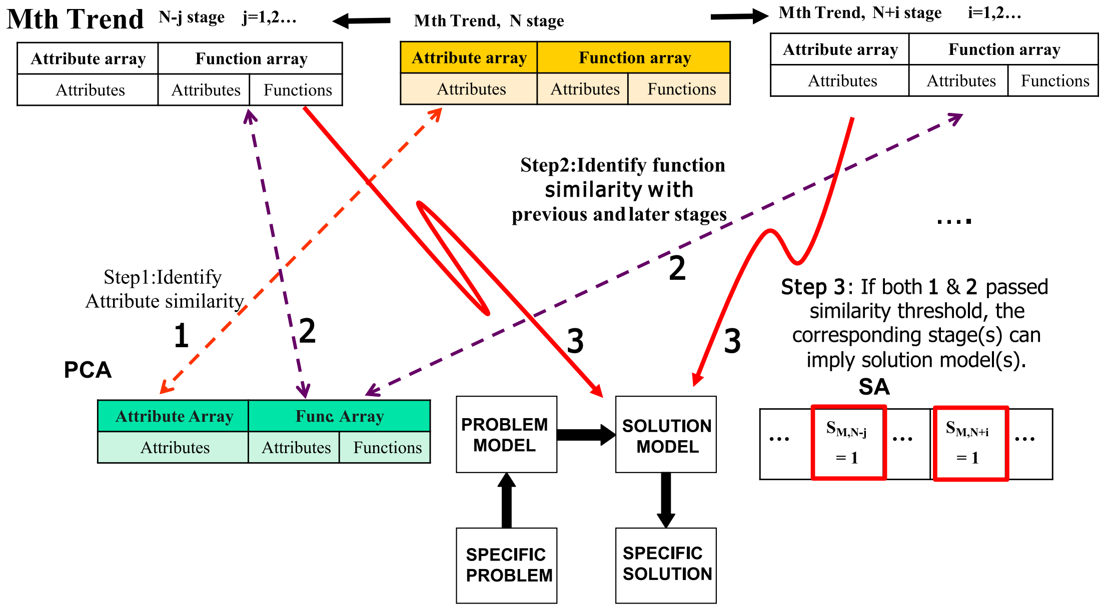


Fig. 9. Identifying solutions in trends without apparent evolutionary stages.

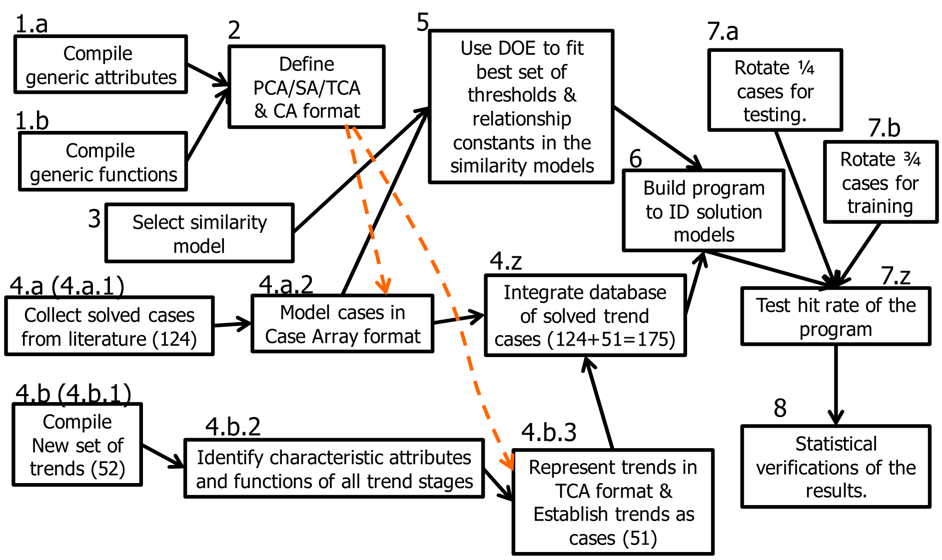


Fig. 10. Overall tasks of the research.

3.4.2. Define formats of Problem Characteristic Array (PCA)/Solution Array (SA)/Trend Characteristic Array (TCA)/Case Array (CA)

– Fig. 5–7 show the format of a PCA, SA, and TCA used in the context of using trend for problem solving.
– A Case Array is the combination of the PCA and its corresponding SA. Together, they can fully characterize a (solved) case.

The definitions of PCA/SA/CA/TCA in bit-array format allow us to calculate the similarities between problems/solutions/cases enabling the objective identification of trend/stage solutions to a problem. Methods of using PCA-CA comparisons and PCA-TCA comparisons to identify trend solution models with priority have been described in Section 3.2. See Section 3.5 for more details.

3.4.3. Determine similarity models

Given that there are many attribute and function types in the PCA and SA, in reality, most of the attributes and functions are irrelevant to the problem or solutions. Therefore, the matching between PCA/SA and TCA will be mostly of (0,0), (1,0), and (0,1) types. Only small numbers of the matches have (1,1) positive matches representing that both the problems and evolutionary trends are involved in such attributes or functions. It is apparent that, (1,1) conditions are much more significant than (0,0) matches necessitating that weights of positive matches to be larger than that of negative matches. This is further verified by authors' experiments of real case data. The commonly used Jaccard and Dice similarity indices in Section 2.2 were modified to become generalized Dice indices to form Eqs. (11) and (12) below.

Formulae for attribute similarity:

$$^{A}Sim = \frac{^{A}\alpha\,^{A}a + {}^{A}\beta\,^{A}d}{^{A}\alpha\,^{A}a + {}^{A}b + {}^{A}c + {}^{A}\beta\,^{A}d} \tag{11}$$

$0 \leqslant {}^{A}Sim \leqslant 1$; $^{A}\alpha$, $^{A}\beta$ are weighting values.

Symbol definitions: (Comparing the PCA with the *jth* stage of the *ith* evolutionary trend)

(1) ${}^{A}Sim$ represents the similarity coefficient of the attributes between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(2) ${}^{A}a$ represents the number of positive matches (1–1) in attributes between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(3) ${}^{A}b + {}^{A}c$ represents the number of non-matches (1–0 or 0–1) in attribute matches between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(4) ${}^{A}d$ represents the number of negative matches (0–0) in attribute matches between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.

Formulae for function similarity:

$$ {}^{F}Sim = \frac{{}^{F}\alpha^{F}a + {}^{F}\beta^{F}d}{{}^{F}\alpha^{F}a + {}^{F}b + {}^{F}c + {}^{F}\beta^{F}d} \tag{12} $$

$0 \leqslant {}^{F}Sim \leqslant 1$; ${}^{F}\alpha$, ${}^{F}\beta$ are weighing values.

Symbol definitions:

(1) ${}^{F}Sim$ represents the similarity coefficient of the functions between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(2) ${}^{F}a$ represents the number of positive matches (1–1) in needed functions between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(3) ${}^{F}b + {}^{F}c$ represents the number of non-matches (1–0 or 0–1) in needed functions between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.
(4) ${}^{F}d$ represents the number of negative-matches (0–0) in function matches between the problem to be solved and the *jth* stage of the *ith* evolutionary trend.

3.4.4. Collecting cases and establishing the case database

This includes steps in the 4.a and 4.b traces in Fig. 10. It includes two parts: Solved cases and Trend-as-cases.

Step 4.a.1 on solved cases:

124 cases of solved problems (CAs) were collected from all available trend cases in the articles of the TRIZ Journal and Darrell Mann's trend software and other sources of solved trend cases which are accessible to the authors.

The CAs were divided into 4 groups evenly and approximately randomly with the constraint that cases of the same trend are distributed as evenly as possible to each of the 4 groups in a round-ribbon manner. This is to make sure that each group has a good representation of the various trends solutions.

Step 4.a.2: Define the PCA for each problem

The purpose of this step is to define the functions and attributes of the overall problems and fill in function/attribute fields of the problem PCA according to the PCA definition stated before. The selections of characteristic attributes and desirable functions are based on discussions of author's research team.

The discerning criteria are based on the below questions:

– On the Attribute Array: If the change or maintaining of the subject attribute can cause the problem or can be caused by the problem, the attribute can be considered as relevant to the problem in the attribute field. If the attribute is a characteristic feature of the problem, the attribute can be considered as relevant to the problem. Other than these situations, the attribute is considered as irrelevant to the problem.
– On the in-direct function array: If change or maintaining the subject attribute can help to solve the problem, the subject attribute is considered as relevant indirect function of the problem. Otherwise, the subject attribute is irrelevant to the problem solving.
– On the direct function array: If the achievement of the subject function can help to solve the problem, the subject function is considered as relevant function to this problem. Otherwise, the subject function is considered irrelevant to the problem.

(a) It is clear that most attributes are not characteristic or relevant attributes of the problem thus easily screening out most attributes. They can be easily identified as "0" in the attribute fields.
(b) Usually, only a small number of attributes are clearly characteristic or relevant attributes of the problem. They can be easily identified as "1" in the fields.
(c) Small number of attributes may have unclear relevancy to the problem characteristics depending on different person's opinions. Discussions for consensus were used to determine if the value of those fields to be "1" or "0". In the future, certain fuzzy value may be assigned for this case based on some discussion or voting scheme. A later study indicated that use of fuzzy value did slightly improve the performance of identifying solution trends. This can be seen in a later thesis (Teng, 2015) and will be reported in a subsequent paper.
(d) Identification of the relevant functions to solve the problem is straight forward and only small number of functions can help to solve the problem.

It is because of (a), (b) and (d), a great majority of irrelevant trends can be easily screened out.

Step 4.b on trend-as-cases:

51 trends were converted into TCA for further comparisons based on the definition of the TCA as described in Section 3.2.3. This is for the trace of 4.b.1–4.b.3 in Fig. 10. Altogether, there were 124 solved cases and 51 trend-as-cases in the database for future problem solving.

Step 5 Setting parameter values

In the Step 5 of Fig. 10, the DOE (Design of Experiment) method was used to determine the best threshold levels and various parameters in the similarity equations, Eq. (11) and (12), with 124 solved cases from various literature and 51 compiled trends. The Taguchi method was used in the setting of these parameters to objectively obtain the optimal parameter combinations.

The process for parameters setting is as follows:

(1) Setting factor standards for a total of six factor parameters, which comprise threshold for attribute similarity (L_A), threshold for function similarity (L_F), (1–1) weighting ${}^{A}\alpha$ and (0–0) weight ${}^{A}\beta$ from the attribute similarity equation, Eq. (11), and (1–1) weighting ${}^{F}\alpha$ and (0–0) weight ${}^{F}\beta$ from the function similarity equation, Eq. (12).
(2) Proceed to conducting a Taguchi experiment with the parameters as inputs and the target of optimization is to maximize the case solution hit rates. The combination of the optimal parameter values is thus obtained as in Table 2 below.

Step 6: Build program to ID solution models

The detail algorithm and processes of the program is explained in Section 3.5

Step 7 and 8: Performance of the method and statistical verifications were given in Section 5 **below.**

3.5. The detail algorithm and processes of the program

3.5.1. Overall process of the similarity comparisons

The overall process of the identifying solution model is given in Fig. 11. It includes (1) the identification of solution models from the comparison between the problem PCA and the TCA's and (2) the identification of solution models from the comparisons between the problem PCA and the PCAs of the solved cases. The solutions from both parts are cumulated and prioritized based on the similarity measures for final prioritized solutions.

3.5.2. Part 1: Elaboration on the first part of Fig. 11

Similarity comparison process for the PCA to be solved and evolutionary trends (TCA).

Refer to Fig. 12.

Step 1: Set initial values

Set $i = 1$ and $j = 1$ representing calculation of the attribute and function similarities from the first stage of the first evolutionary trend.

Step 2: Determine whether $i <= I(51)$

The expression $I(51)$ represents that the model currently consists of 51 trends. During attribute and function similarity calculations, whether the current trend, i, under process is less than or equal to the maximum number of trends, $I(51)$, must first be determined. When the current trend i is less than or equal to the maximum number of trends, calculation continues. The process stops, if i is greater than the maximum number of trends representing that all trends have completed the similarity calculations. Proceed to Step 8 to prioritize and output the solutions.

Step 3: Determine whether $j <= J_i$

Where J_i represents the number of stages in the trend i; A j value greater than J_i represents that all stages have completed similarity calculations. If $j <= J_i$, the trend has not completed all stages of calculations and calculation on the attribute and function similarities of this trend can proceed. When the calculation proceed to the next trend, reset j to one, and begin from the first stage of the next trend, $i + 1$.

Step 4: Calculate ${}^{A}Sim$

Where ${}^{A}Sim$ represents attribute similarities between a problem and an evolutionary trend and is calculated using Eq. (11).

Step 5: Determine whether ${}^{A}Sim >= L_A$

Where L_A is a threshold for attribute similarity. During the similarity calculations of each problem and trend, the similarities must

Table 2
Parameter values derived from design of experiments.

Factor	LA	LF	${}^{A}\alpha$	${}^{A}\beta$	${}^{F}\alpha$	${}^{F}\beta$
Parameter value	0.6	0.7	6	0	8	0.2

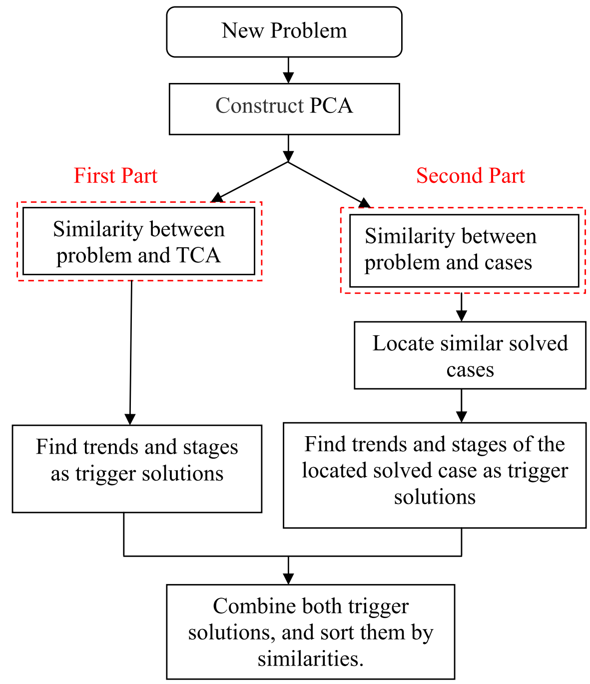


Fig. 11. Overall process of similarity comparisons.

be greater than a certain level to serve as the trigger solution to the problem. If ${}^{A}Sim$ qualifies, calculations proceed to Step 6, otherwise $j = j + 1$ and calculations proceed to the next stage of the trend and return to Step 3.

Step 6: Determine whether i is a normal trend or a non-specific-direction trend and calculate ${}^{F}Sim$

A trend of non-specific-direction is considered as a "checklist" trend representing that this is a trend without an apparent sequence in evolutionary stages. The variable ${}^{F}Sim$ represents the function similarity of the problem and evolutionary trend (Eq. (12)). If trend i is a normal trend with specific evolution direction, calculations only proceed to determine ${}^{F}Sim$ in the next stage $(j + 1)$; If trend i is a checklist trend, checking for possible solution should proceed to both directions toward stage J_i and stage 1 independently to calculate ${}^{F}Sim$ as described in the next step.

Step 7: Determine whether ${}^{F}Sim >= L_F$

Where L_F is the threshold for function similarity.

In the case of a "checklist" trend, an additional similar trace of similarity checking must be conducted. Let $j' = j - 1$ as the running index of this additional trace. For all $j' \geqslant 1$ check if the function similarity between the current stage and the PCA of the problem is larger than the threshold, the current trend stage is recorded as a trigger solution to the problems. When $j' \leqslant 1$, this additional trace is completed, proceed to the normal trace of similarity checking in the next paragraph.

Let $j = j + 1$. If the function similarity between the current stage, j, and the PCA of the problem is larger than the threshold, the current trend stage is recorded as a trigger solution to the problems, then j is checked for ending condition, $j \geqslant J_i$. If $j < J_i$, assign $j = j + 1$, calculations proceed to the next stage to determine if ${}^{F}Sim$ pass the threshold for possible solution trigger. If $j \geqslant J_i$, reset $j = 1$, proceed to the next trend $(i = i + 1)$ and return to Step 2.

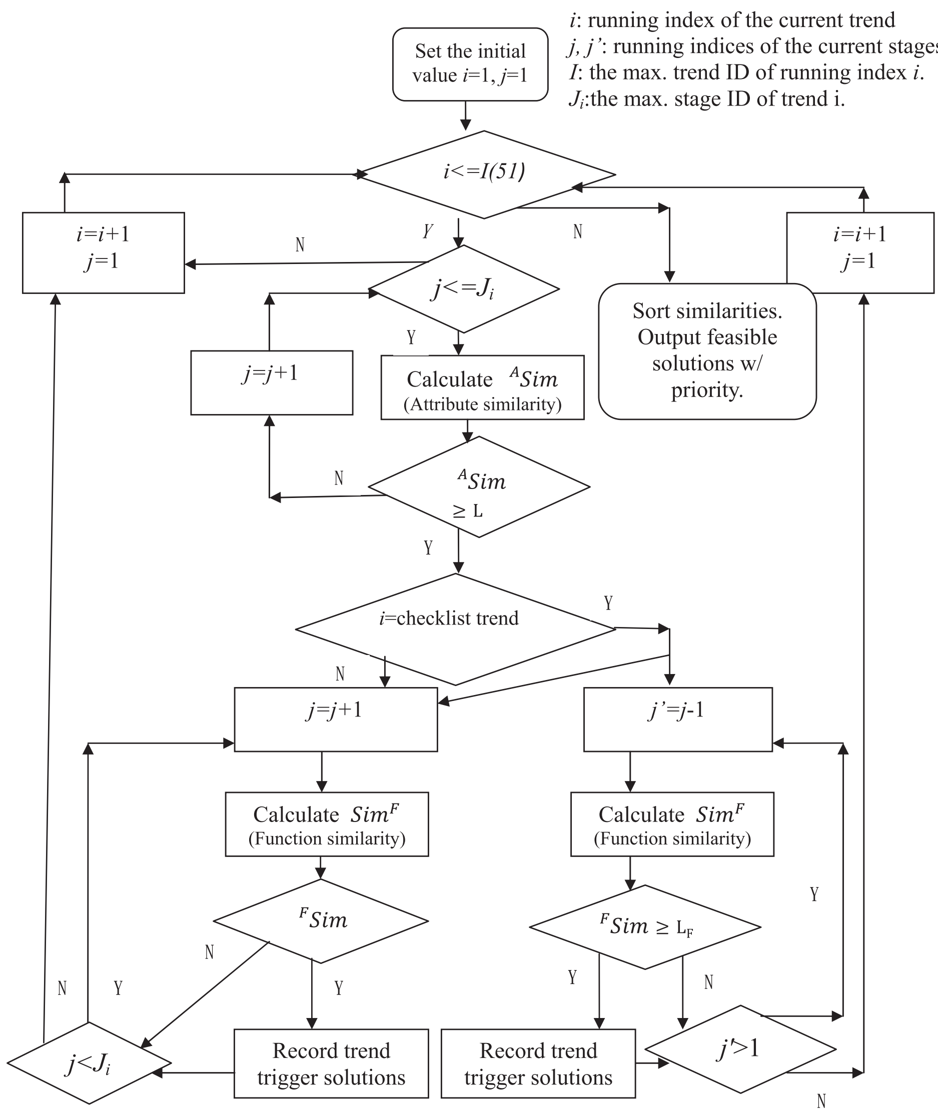


Fig. 12. Similarity comparison process for TCA and PCA.

Step 8: Prioritizing the solution models

When similarity calculations for all evolutionary trends are completed, the similarities of all feasible trigger solutions can be sorted (in descending order) followed by outputting the highest *k* (decided by the user) number of feasible trigger solutions or all trigger solutions greater than the qualifying standard as trigger solutions for the problem. Lastly, trigger solutions are converted to specific solutions to the problem by human operations.

3.5.3. Part 2: Elaboration on the Second part of Fig. 11

Similarity comparison process for PCA to be solved and known solution cases. Refer to Fig. 13.

Step 1: Setting initial values

Set $c = 1$, where c represents the running case number.

Step 2: Determine whether $c <\ = allc$

The variable *allc* represents the total number of all past solved cases. When calculating attribute and function similarities, the current case number c is checked to see if all cases have been examined. If the c is less than or equal to the total case number, calculations proceed to Step 3. On the other hand, if the case number is greater than the total case number indicating that all cases have been examined. Then, proceed to Step 5 to compile the solution models for outputs.

Step 3: Calculate ^{A}Sim and determine whether it is greater than L_A

Where ^{A}Sim represents the attribute similarity between the problem PCA and the current case using Eq. (11). The variable L_A represents the threshold for attribute similarities. Similarities between the problem and past cases must be greater than or equal to the corresponding threshold, $L_{A,}$ to be further identified as a similar case. Calculations proceed to Step 4, otherwise $c = c + 1$ and calculations proceed to the next case number and return to Step 2.

Step 4: Calculate ^{F}Sim and determine whether it is greater than L_F

The expression ^{F}Sim represents the function similarity between PCA and the current case. (Eq. (12)); L_F represents the threshold for function similarities. If the similarity is greater than or equal to the threshold value, the corresponding case solution, SA, is recorded as a potential solution to the problem with corresponding Similarity

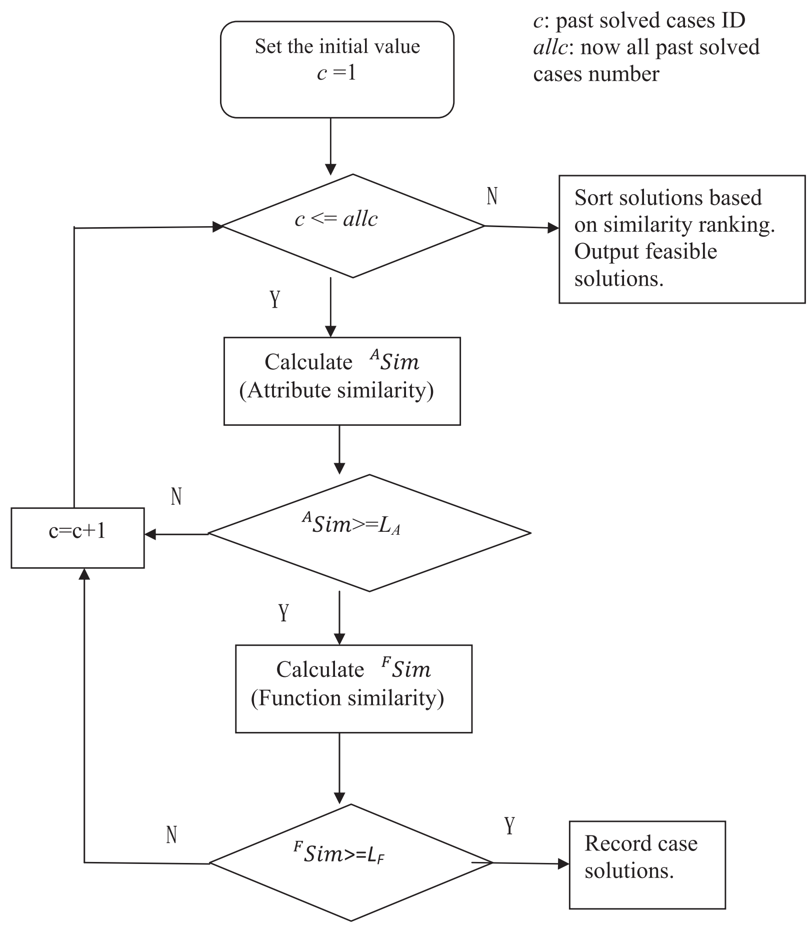


Fig. 13. Similarity comparison process for problem PCA and past solution cases.

measures recorded for later priority comparisons. Otherwise disregard this case. Then, let $c = c + 1$. Calculations proceed to the next case number and return to Step 2.

Step 5: Compile the solution models

If the similarity calculations for all past solution cases have been completed, the solutions indicated in the passing SA's can be weighted with their corresponding similarity values and combined to indicate all the feasible trigger solutions. The highest specified number of prioritized solution models can be output for recommended solution models.

4. Software construction

A simple operating interface for the mathematical problem solving tool in this study was constructed using the Matlab graphic user interface. The primary purpose was to enable users to rapidly search for new evolutionary trend solutions.

4.1. Inputting the PCA

Fig. 14 shows the input/out interface of the software system. The PCA of the current problem can be entered manually or by a batch file. The first array is the problem characteristic attribute array. The second array is the array for needed change-or-maintained attributes to solve the problem in the in-direct function area. The third array is the needed function array (direct function). The second and third array constitutes the full needed function array. Area 4 is the control parameters areas where all adjustable parameters are entered. A default set of parameters based on the previous DOE optimization is included in the system. Therefore, it is highly recommended to use the default set of the parameters.

Fig. 15 shows a sample input parameter setting. After the PCAs of the problems to be solved are entered into the software and before conducting similarity calculations, users can manually enter attribute (1) and function (2) thresholds and the number of output trend solutions (3). Two types of output methods can be selected. The first type is the desired number of output trends to be selected; thus, trigger solutions with multiple stages in the same trend is are all output for reference. The second type of output method is the desired maximum number of output solutions in stages considering each trend stage as a solution. The system will output the top designated number of solution stages, including their trend ID, which passed the similarity thresholds. The "clear" button is used to delete the entered PCA contents and restart data inputs.

To facilitate easier reading of existing database cases, users can also access the data by a batch file defaulted to be *case.xlsm*.

4.2. Outputting solutions

Upon completing the PCA data entry and possible parameter setting, the user can click the "computing-recommended solutions" button to proceed with computation. Areas 5, 6, 7 of the Fig. 14 are to display the calculated results. "Trends descriptions" button of area 6 can be clicked to view the contents of all the trends. By clicking on the area 7 of the Fig. 14, the detail output format of the prioritized the solutions can be shown as in Fig. 16. The users can convert the provided trigger solutions into specific solu-

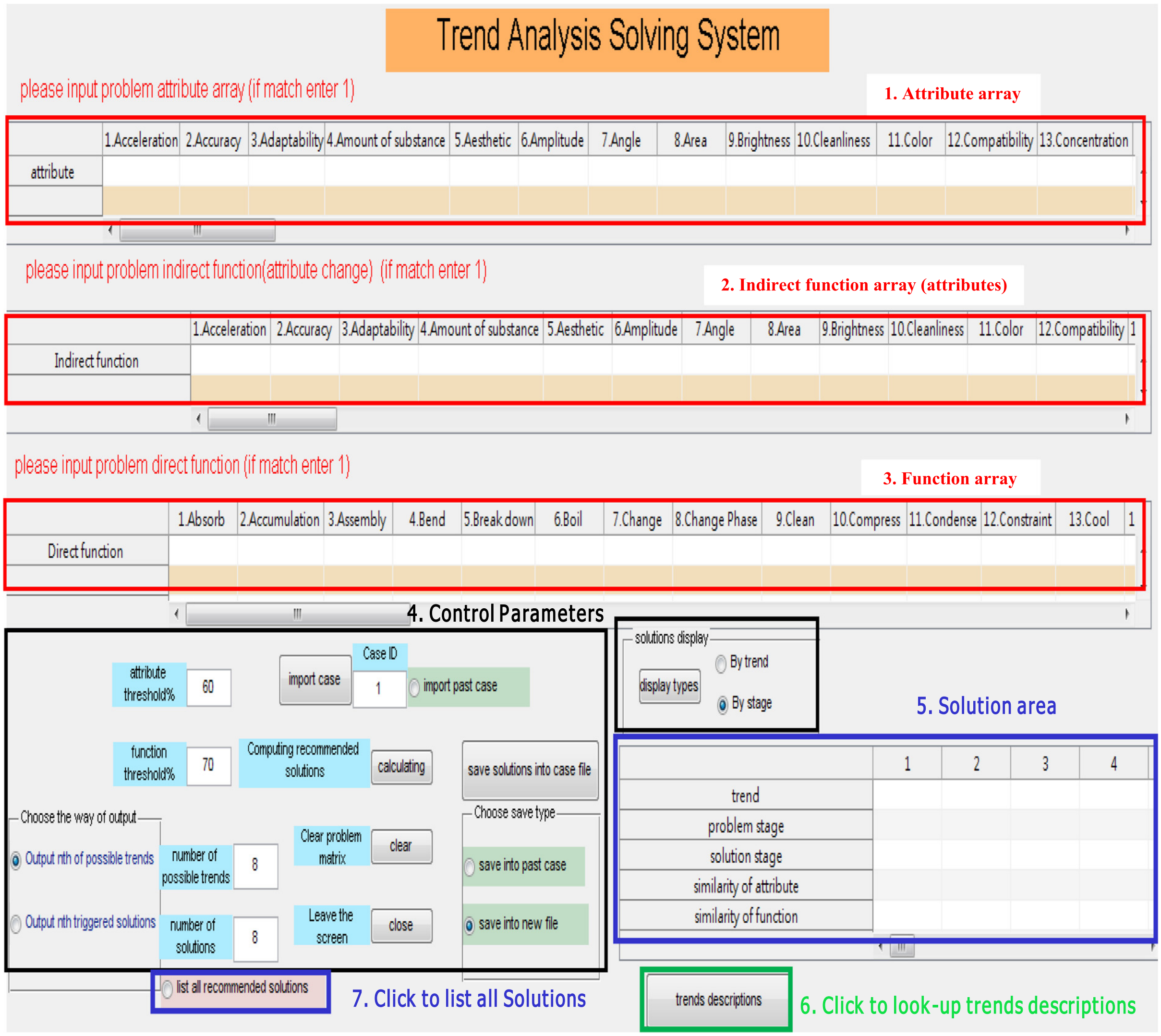


Fig. 14. Input/output window of the software by individual attribute/function data entry.

tions corresponding to the problem by themselves. See Fig. 17. The user can also examine all feasible trigger solutions greater than the threshold regardless of limitation on the maximum number of solution specified by clicking on the "list all recommended solutions" button. To record the solutions and facilitate case-file archives, the user can save the solutions individually and, if desired, add the new case into the existing database for future usage. Additionally, the user can click on the recommended solution models and the contents of the trend and stage information become available for reference.

5. Results and case verifications

The hit rate of the experiment is defined as the percentage when the proposed solution set is able to contain the original solution used in each case from literature.

5.1. K-fold cross-validation

To make a sound experiment, the *K*-fold (*K* = 4) cross-validation process was used to rotate test sets. That is, the 124 solved cases were divided equally into 4 data sets. The 4 groups of data sets take turns to serve as the test set of 31 problems each with the other 3 data set of 93 cases plus 51 trends as the case-base (training set) for experiments. A total of 31 × 4 = 124 problems as test cases with the 93 + 51 = 144 cases as each training set.

The results showed consistent good prediction of existing solutions regardless of which data set is used as test set.

The concept of *K*-fold validation is illustrated in Fig. 18.

The best, worst, and random output trigger solutions, were used to determine the effectiveness of the prioritization method proposed. By selecting the 8 highest priority solutions for each "unsolved" problem, the system was able to have 92.7% hit rate while random selection of solution models can only have 5% hit rate. To prove the effectiveness of the method in a reverse way, it is noted that the worst 8 solutions based on similarity measures also result in less than 1% hit rate.

To clearly verify the significant differences between best set, worst set, and random set of given number of trigger solutions, hypothesis testing was applied to the results in Table 3:

(1) Output methods of the eight best and random similarity trigger solutions

H_0: $\mu_{8\_best} <= \mu_{8\_random}$
H_1: $\mu_{8\_best} > \mu_{8\_random}$

Output results from the Minitab software:

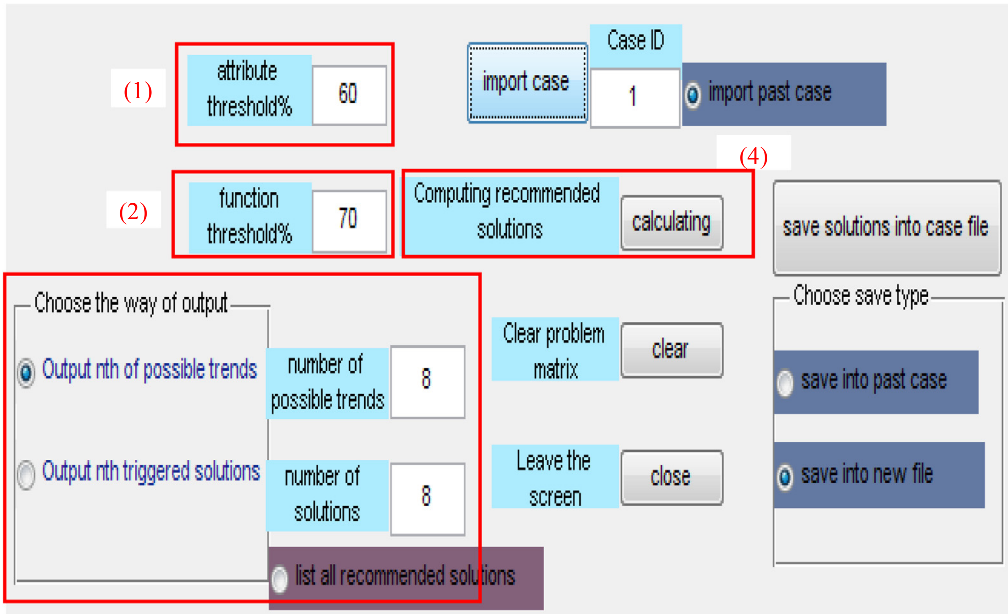


Fig. 15. Input parameters on the user interface.

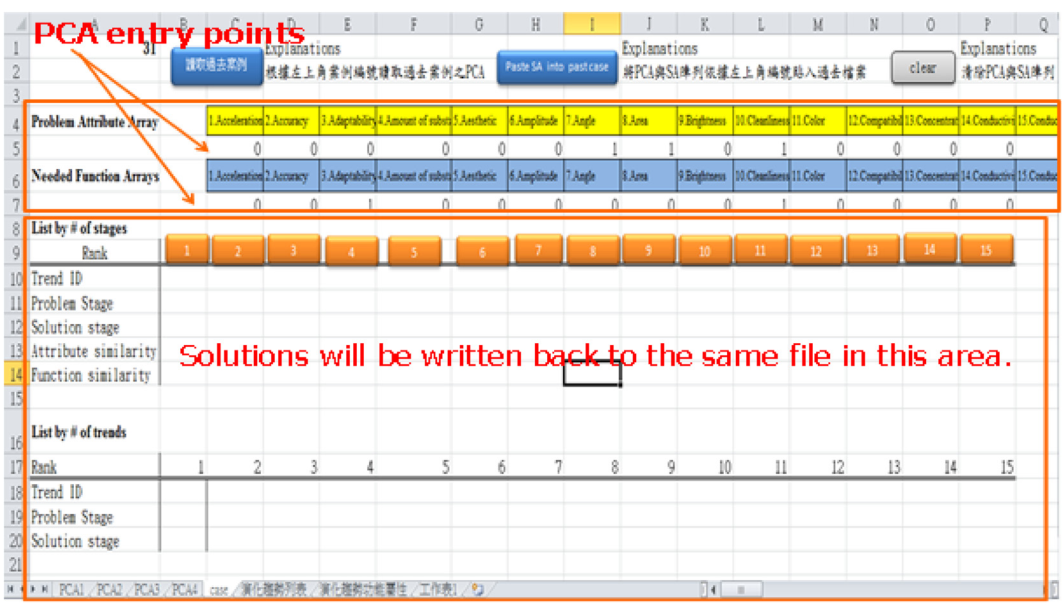


Fig. 16. PCA data and solution area expanded.

Two-sample t test and confidence interval: Eight best and eight random solutions

Two-sample t test for the eight best vs. eight random solutions

	N	Mean	StDev	SEM
Eight best	4	0.9274	0.0551	0.028
Eight random	4	0.0565	0.0551	0.028

Difference = $\mu_{8\_best} - \mu_{8\_random}$
Estimate for difference: 0.870968
95% lower bound for difference: 0.795271
t test of difference = 0 (vs. >): t value = 22.36
p = .000
DF = 6

The analysis results showed that $p = .000 < \alpha = .05$; therefore, H_0 was rejected in this study, which verified that the case solution similarity hit rate of the eight best trigger solutions were statistically higher than that of the randomly selected trigger solutions. This demonstrates the effectiveness of the similarity comparison method applied in this study.

(2) Output method of the eight best and worst similarity trigger solutions

H_0: $\mu_{8\_best} <= \mu_{8\_worst}$
H_1: $\mu_{8\_best} > \mu_{8\_worst}$

Output results from the Minitab software:

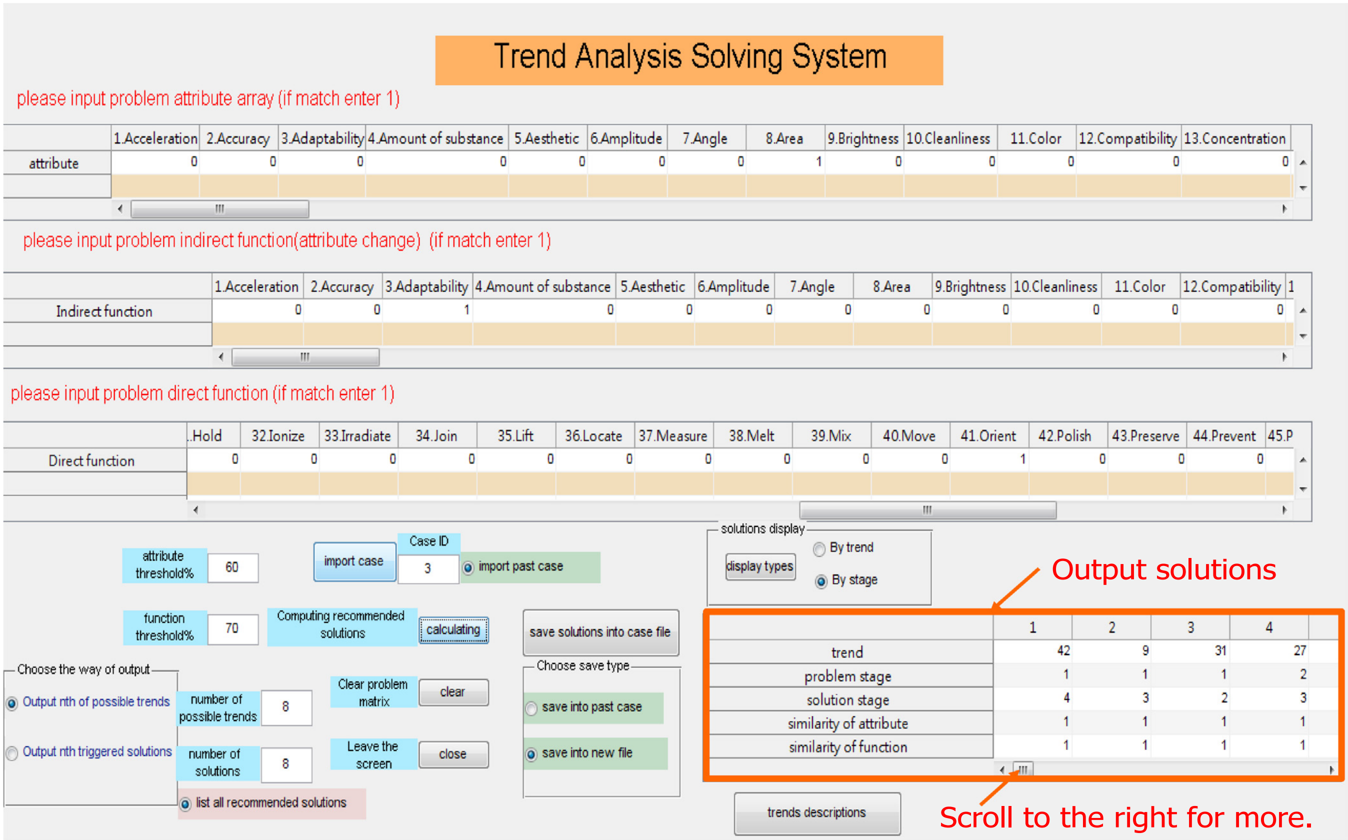


Fig. 17. Outputs for recommended solutions with priorities.

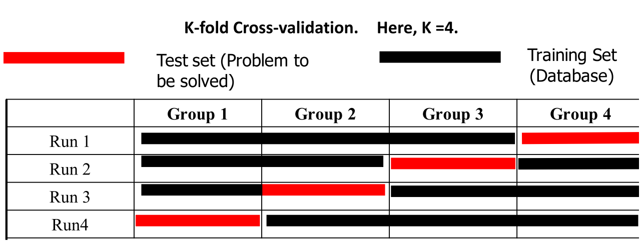


Fig. 18. The process of *K*-fold cross validation.

Table 3
The overall performance on hitting the original solutions obtained from *K*-fold cross-validation.

	k_fold (1)	k_fold (2)	k_fold (3)	k_fold (4)	Overall average
Best 8 solutions	0.935484	0.870968	0.903226	1	0.927
Worst 8	0	0.032258	0	0	0.008
Random 8 solutions	0	0.032258	0.129032	0.064516	0.056

Two-sample *t* test and confidence interval: Eight best and eight worst solutions

Two-sample *t* test for the eight best vs. eight worst solutions

	N	Mean	StDev	SEM
Eight best	4	0.9274	0.0551	0.028
Eight worst	4	0.0081	0.0161	0.0081

Difference = $\mu_{8\_best} - \mu_{8\_worst}$
Estimate for difference: 0.919355
95% lower bound for difference: 0.851809
t test of difference = 0 (vs. >): *t* value = 32.03
p = .000
DF = 3

The results showed that when $\alpha = .05$, $p = .000$, thus $p < \alpha$, which represents that H_0 was rejected. This proved that the case solution similarity hit rate of the eight best trigger solutions were statistically higher than that of the eight worst trigger solutions.

(3) Summary

The results from a one-tailed *t* test showed that regardless of the eight trigger solutions of random selections or worst similarities (may be under threshold), neither output methods were significantly better in problem solving performance to the eight trigger solutions of the highest similarities. Based on all the above statistical verifications, it is clear that the solving power of the eight trigger solutions of the highest similarities was superior to the outputs of other methods.

5.2. Comparison of capabilities from solution model to specific solutions

A survey of conversion from solution models to specific solutions was designed based on software output. For each test problem, eight trigger solutions of the highest similarities, eight of the lowest similarities and eight random selections constitute the test sets of solution models. This forms 3 comparison groups of solution models to each problem. The participants were 20 Level 3 specialists from Taiwan. Each participant was given some problem cases and corresponding several solution models randomly picked from the three comparison groups. The participants were not aware of which provided solution model belongs to which comparison group. Participants were asked to spend no more than 5 min to generate specific solution from each solution model. The results were then analyzed to determine which comparison group of solution models can generate the most number of sensible specific solutions to the problems.

Table 4 shows that the practitioners' abilities to convert to specific solutions using the eight trigger solutions of the highest similarities was approximately 52.6%, which represents that more than half of the trigger solutions output by the software can be converted into specific solutions within the 5 min maximum given time. However, only 18.7% of the randomly selected trigger solutions can be converted into specific solutions to the corresponding problems and only approximately 10.8% of the trigger solutions of the lowest similarities can be converted to specific solutions. Thus, this result verified that highest similarity trigger solutions have comparatively superior solving power than random and lowest similarity ones.

5.2.1. Sensitivity Analysis with respect to the number of output solutions selected

The results of the sensitivity analysis are shown in Fig. 19. The number of trend trigger solutions is positively correlated with case solution hit rates. With 4 best similarity solutions, the hit rate is already reaching 80%. Outputting the ten most similar trend trigger solutions resulted in 100% hit rate.

6. Additional problem-solving applications

In addition to the testing of existing 124 cases in from literature, the software has been used in solving more than 10 real-world cases successfully. Due to confidentiality and limited space, only the below case is illustrated. Another more sophisticated case can be found in Lan and Sheu (2013).

Case: Bricks for House Construction

In Taiwan, bricks are commonly used for house wall constructions. But, they are heavy to move. Their fire resistance and sound absorbance are not sufficient. People want the strength of the wall to be as strong as possible especially to resist/adapt to certain earth quake vibrations. These are areas bricks needs improvements.

The PCA for the case is listed below: (Only relevant items below are indicated as 1)

Relevant Attributes:
adaptability, conductivity-heat, density, hardness, mass, sound, strength, temperature, weight.
Functions needed:
Attribute Changes: adaptability, conductivity-heat, density, hardness, mass, sound, strength, temp, weight
Direct functions: absorb, joint, protect, resist.

Table 4
Survey verification results.

	Best similarity solutions given	Worst similarity solutions given	Random solutions given
Proportion of specific solutions successfully converted	0.5261	0.1079	0.1869

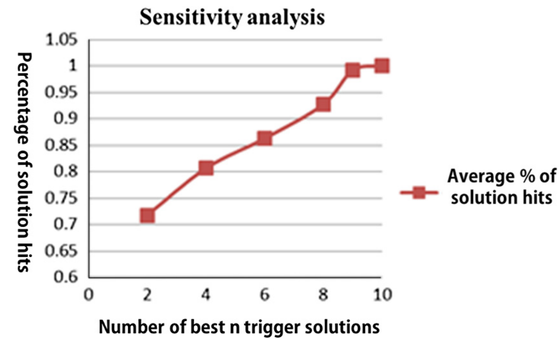


Fig. 19. Sensitivity analysis on the number of trigger solutions.

Using the system to computer the prioritized trends and stages as solution models. The relevant stages, whose values = 1, are listed below. The values of the rest stages are 0s indicating as non-prioritized/irrelevant stages.

Solution Array:

- Trend 42: Space Segmentation: $S_{42,2}$, $S_{42,3}$, $S_{42,4}$, $S_{42,5}$.
- Trend 31: Decrease Density: $S_{31,2}$.
- Trend 8: Smart Materials: $S_{8,4}$.
- Trend 43: Surface Segmentation: $S_{43,3,}$
- Trend 44: Object Segmentation: $S_{44,2}$, $S_{44,3.}$
- Trend 36: Substance Dynamization: $S_{36,6}$, $S_{36,7.}$
- Trend 4: Mono-bi-poly (similar sys.): $S_{4,2}$, $S_{4,3}$.
- Trend 5: Mono-bi-poly (Various sys.): $S_{5,2}$, $S_{5,3}$.

The identified relevant trends along with their generated and specific solutions are shown in Table 5. The ideas have been implemented. Some companies have added fire and sound retardation materials inside the bricks to provide extra functions and roughened the brick surface w/ 3D surface to enhance the holding effect.

7. Summary and conclusions

7.1. Summary

Integrated new evolutionary trends were used as an example in this study. A mathematical/quantitative solution model was constructed through similarity comparison to ultimately obtain the corresponding trend solutions. Engineering evolutionary trend surveys also showed that the proportion of specific solutions converted from the eight best solution models suggested by the system were substantially higher than those with lesser similarities. Thus, this comparison method was certainly effective for problem solving. The overall summary of this study is as follows:

(1) GEN3 and Darrell Mann's evolutionary trends were integrated along with similar trends in which the corresponding evolutionary stages were completely defined to complement the deficiencies in both evolutionary trends.
(2) A standardized function attribute table for evolutionary trends was established. Evolutionary causes for the integrated set of evolutionary trends were defined.
(3) Generic attributes and functions were organized as a reference for expressing PCAs and SAs and facilitating further research development.
(4) PCAs and SAs were developed to standardize problems and solution representations. It also enables mathematical calculations allowing generalization of mapping from model of

Table 5
Solutions for the brick case.

ID	Trend	Solution model (trend stage)	Solution ideas
42	**Space Segmentation**	Monolithic Solid	Make bricks hollow and place into it materials which are fire retardant and sound insulation. If materials of both characteristics are not available, put mixtures of fire retardant and sound resistant materials. Or, place the kind of materials in alternating layer to resist both fire and sound transmission.
		Hollow Structure	
		Structure with Multiple Hollows	
		Capillary Porous Structure	
		Porous Structure with active elements	
43	**Surface Segmentation**	Smooth surface	Make brick surface roughened or with 2D Rib Protrusions so that the joint between brick-cement-brick can be much stronger enhancing the strength of the wall.
		Surf. w/ 2D Rib Protrusions	
		3D Roughened Surf.	
		Roughened Surface + active elements	
		Segmented Solid	
		Particulate Solid	
		Fluid	
		Segmented Fluid	
		Gas	
		Plasma	
		Field	
		Vacuum	
8	**Smart Materials**	Passive Material	Add elastic additives to inside of the brick or to cement between the bricks so that it can absorb some shocks and be able to adapt to small amplitude of vibrations.
		One-Way Adaptive material	
		Two-Way Adaptive material	
		Fully Adaptive	
44	**Object Segmentation**	Monolithic Solid	Instead of using bricks and cements, use rocks, sands, cements, and fluid to build walls. The advantage are: - Easier to add steels for strength (re-enforced concrete) - Flexibility to add various additives for various functions. (for example: adapt to shock, heat/sound retardation).
		Segmented Solid	
		Particulate Solid	
		Fluid	
		Segmented Fluid	
		Gas	
		Plasma	
		Field	
		Vacuum	

problems to model of solutions facilitating the use of mathematical/quantitative methods to identify solutions objectively.

(5) A mathematical similarity concept was used to enable objective and rapid searches for the most likely trend and stages of the trigger solutions.
(6) Optimization methods were applied to determine similarity parameter settings.
(7) A computer-aided trend identification system was constructed to prevent laborious manual comparison processes and automatically and rapidly identify feasible solutions with priority to the provided problems.

7.2. Contributions of the work

The significance of this work compared with traditional expert identification of solution models are given below:

- Unlike traditional TRIZ methods which primarily based on qualitative reasoning, a new classes of using quantitative/mathematical methods such as similarity measures was proposed. This represents a paradigm shift from the traditional TRIZ research using qualitative methods for problem solving and opens up a new research direction of using mathematical/quantitative measures for TRIZ problem solving.

- With more quantitative and objective accumulation of expert knowledge in terms of solved cases, the proposed methods is able to achieve the below advantages:
  - Sense of priorities. To the best of the author's knowledge, no sense of priorities has been enabled in current TRIZ tools such as Trends, Effect database, and Su-field analysis. As some solution models are more relevant than others to each problem, sense of priority becomes important when there are so many solution models to choose from. The system is able to propose priorities for problem solving based on the principle of "Similar problems have similar solutions".
  - Knowledge expendability. The system's database cases can be extendable by adding more expert solved cases to the system. In a sense this system uses an extendable collection of experts' prior knowledge/experiences instead of relying on individual experts to identify solution models. As the number of verified cases grows, the robustness of the system to identify prioritized solution models is expected to increase.
  - Solution objectivity during identification of solution models. The process knowledge is based on the accumulation and integration of many expert solved problems instead of individual experts' problem solving.
  - Repeatability. Models of solution are repeatable by objective calculations during the process of problem model to solution model.
  - Speed. When there are many possible solution models to choose from, the expert examination of many solution models will be very time consuming. The computer aided system can calculate through all possible solutions quickly and reliably.
- With the use of rigorous modeling and quantitative/mathematical methods, the acceptance for TRIZ recognition by scientific communities may be enhanced.

Acknowledgments

The author would like to acknowledge the contributions from his graduate students in implementing and elaborating the author's original ides to make the system a reality: Tsung Hsing Lu and Yu Ting Huang. The reviews by Dr. Ellen Domb and Valeri Souchkov are greatly appreciated. The work was under the support of National Science Council (Now Ministry of Technology) of the Republic of China grant numbers: NSC 102-2221-E-007-083 and 99-2221-E-007-026-MY3.

Appendix A. Extended trend listing

Based on the compilation and integration of GEN3 and Darrell Mann's evolutionary trends, 52 engineering trends were identified. Note that the one trend of S-curve by itself cannot be used in the system. Therefore, there are 51 trends used in the problem solving process as listed below where Source designation of G representing GEN3 system and M representing Mann's system.

(1) Mono-bi-poly (increasing difference) → Source: GEN3/Mann (G/M)
(2) Increasing differentiation between main functions → Source: G
(3) Deeper integration → Source: G
(4) Increased similar integrated systems → Source: G/M
(5) Increased various integrated systems → Source: G/M
(6) Trend of increasing the completeness of system components → Source: G
(7) Stage of coordination → Source: G
(8) Smart materials → Source: M
(9) Webs and fibers → Source: M
(10) Action coordination → Source: M
(11) Rhythm coordination → Source: M
(12) Coordinating shapes (use as checklist) → Source: G
(13) Coordinating rhythms (2) (use as checklist) → Source: G
(14) Coordinating materials (use as checklist) → Source: G
(15) Coordinating actions (2) (use as checklist) → Source: G
(16) Parameters of coordination (use as checklist) → Source: G
(17) Device trimming & process trimming → Source: G/M
(18) Reducing number of energy conversion → Source: M
(19) Increasing conductivity of the flow (use as checklist) → Source: M
(20) Improving flow utilization (use as checklist) → Source: G
(21) Reducing the conductivity of the harmful/incidental flow (use as checklist) → Source: G
(22) Reducing the impact of the harmful flows (use as checklist) → Source: G
(23) Reducing human involvement → Source: G/M
(24) Increasing asymmetry → Source: M
(25) Boundary breakdown → Source: M
(26) Geometric evolution (linear) → Source: M
(27) Geometric evolution (volumetric) → Source: M
(28) Degrees of freedom → Source: M
(29) Increasing level of control → Source: G
(30) Increasing number of controllable states → Source: G
(31) Decreasing density → Source: M
(32) Controllability → Source: M
(33) Trends of uneven development of system components → Source: G
(34) Nesting (down) → Source: M
(35) Nesting (up) → Source: M
(36) Substance dynamization → Source: G/M
(37) Composition dynamization → Source: G
(38) Nonlinearities → Source: G/M
(39) Single-level to multilevel → Source: G
(40) Function dynamization → Source: G/M
(41) Field dynamization (use as checklist) → Source: G
(42) Space segmentation → Source: M
(43) Surface segmentation → Source: M
(44) Object segmentation → Source: M
(45) Evolution from macro- to nanoscale → Source: M
(46) Increasing use of senses → Source: M
(47) Increasing use of color → Source: M
(48) Increasing transparency → Source: M
(49) Reducing damping → Source: M
(50) Design point → Source: M
(51) Design methodology → Source: M

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