A New and Efficient Intelligent Collaboration Scheme for Fashion Design[1]

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Abstract –Technology mediated collaboration process has been extensively studied for over a decade. Most applications with collaboration concepts reported in the literature focus on enhancing efficiency and effectiveness of the decision making processes in objective and well-structured workflows. However, relatively few previous studies have investigated the applications of collaboration schemes on problems with subjective and unstructured natures. In this paper, we explore a new intelligent collaboration scheme for fashion design which by nature relies heavily on human judgment and creativity. Techniques such as multi-criteria decision making, fuzzy logic and artificial neural network (ANN) models are employed. Industrial inputs and data are used for the analysis. Our experimental results suggest that the proposed scheme exhibits significant improvement over the traditional method in terms of the time cost effectiveness, and a company interview with design professionals has confirmed its effectiveness and significance. Insights are generated.

Index Terms – design scheme, multi-criteria decision making, fuzzy logic, artificial neural network

I. INTRODUCTION

The past 10 years have seen the advances in information systems which include the development of collaboration schemes [1],[3] and intelligent decision systems [2],[8]. Such schemes enable multi-party participation in organizational activities through sophisticated information management [40], [41]. In fact, studies on computer aided decision making tools can be dated back to the 1960s [31], [17], and became termed as decision support system (DSS) in the 1970s [18]. In the 1980s, most of the research works on DSS aimed at determining optimal design parameters and development processes for implementing the systems [9]. The use of a DSS will generally increase the effectiveness of decisions and/or the efficiency of the decision making process and its development can be a part of many business process re-engineering projects [15], [20]. For instance, Bui and Jarke [4] developed Co-op, a system for cooperative multiple criteria group decision support with a goal of enhancing the quality of decisions. Kraemer and King [23] introduced the concept of collaborative DSS which they defined as interactive computer-based systems to facilitate the solution of ill-structured problems by a set of decision makers working together as a team.

Many works have been devoted to studying the technology mediated intelligent decision (TMID) systems and also their applications in collaborative commerce [2], [15], [19], [28]. Among them, design-related collaboration has also been studied while it appears to be rather complicated. According to [11], the element of human judgment is critical to the success of design and cannot be delegated to formal methods or simple machine intelligence. The design process is described as a set of issues and responses to those issues, with a tissue of weak and strong bonds linking these responses. In [27], this model of argumentation is confirmed to be able to provide a remarkably robust description of design collaboration in a variety of settings. Furthermore, in [12] and [13], this model is adopted to analyze design collaborations in software engineering and mechanical engineering. On the other hand, Mitchell [26] pointed out that "design is not description of what is, it is exploration of what might be", which indeed explains why many conventional approaches failed to solve problems related to design process.

Developments in the computer technologies over the past two decades have made the implementation of the artificial intelligence (AI) techniques feasible. As a result, it has been proven that several artificial intelligence techniques can be used as effective tools in solving problems where conventional approaches fail or perform poorly [32], [35], [42], [55]. An excellent example to demonstrate this argument can be found in the field of engineering design in which specific characteristics and requirements are given. Soft computing approaches, such as fuzzy logic, artificial neural networks and genetic algorithms (GA) can be used in engineering design for (i) representing and modeling the design knowledge, (ii) finding the optimal quantitative solutions, (iii) retrieving the pre-existing design knowledge, and (iv) learning new knowledge [31], [37]. These soft computing approaches can hence be powerful tools for developing versatile TMID systems related to technical design. Unlike the works in the literature ([40], [41], [42]) which focus on AI theory and models, our work focuses on the application of these technologies, and the enhancement of efficiency by the proposed TMID scheme.

Fashion design, being a specific area of industrial design, shares some features as the technical designs mentioned above and there are a few published works which employ soft computing approaches to enhance the performance of fashion design. For instance, Kim &

Cho [21] used GA in the identification of fashion style to facilitate the design process. However, there is little prior study which illustrates how effective the soft computing approach is in enhancing fashion design. Moreover, how team work in fashion design can be supported by a TMID system is also under-explored. As a consequence, in this paper, we propose a new TMID system for the fashion design process. Alteration to the traditional fashion design process is proposed and the artificial neural network (ANN) approach is employed in the analysis, where no discipline specific knowledge is required. Our experimental findings have revealed that the proposed TMID system can improve the process' efficiency and the quality of decision in the respective fashion design process. This illustrates a promising research ground of employing TMID in the creative design related industry. As a remark, the major differences between this paper and other related works in the literature are listed in Table 1.

Table I

MAJOR DIFFERENCES BETWEEN OUR MODEL AND OTHER TMID SYSTEMS

	For unstructured problems	**For creative design**	**Discipline specific knowledge required**
Our TMID	Yes	Yes	No
Kim & Cho [21]	No	Yes	Yes
Walczak et al.[37]	No	No	Yes
Lauria et al. [57]	No	No	Yes

II. TRADITIONAL FASHION DESIGN PROCESS & PROPOSED TMID MODEL

In this section, the traditional fashion design process is studied and related data are collected from a fashion product company. The new design process which employs the TMID system is also proposed.

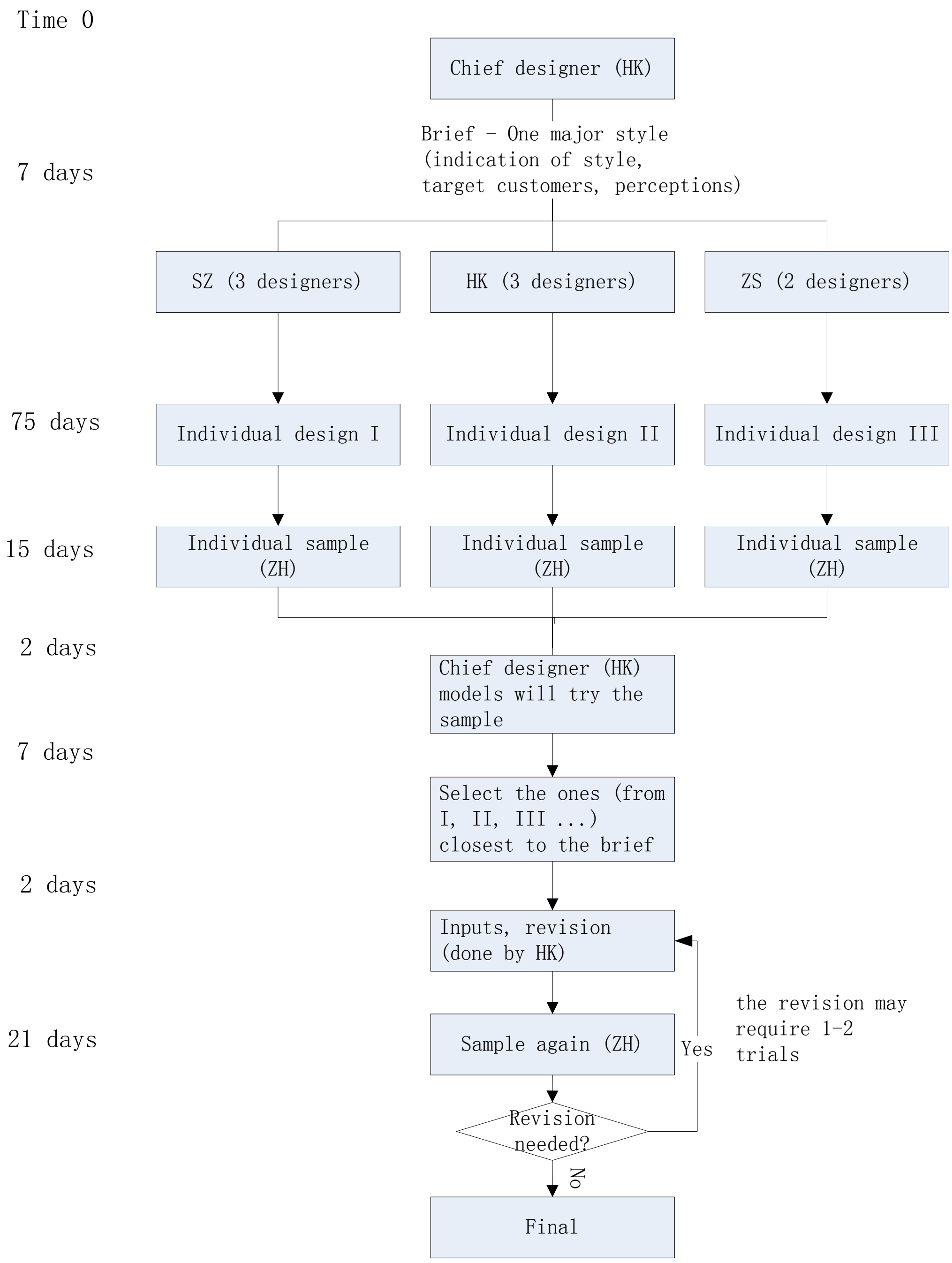

Fig. 1. Traditional design process in a fashion knitwear company.

A. The traditional fashion design process

In this research, the design process with real data of a Hong Kong based fashion knitwear company called Pearls & Cashmere (PC)[5] is studied. As a prototype of the fashion design process, a study on the real data of this company can provide important insights for the

[5] PC is a real knitwear company (see Appendix for the details of this company).

development of the TMID system. Fig. 1 illustrates the whole design process currently employed in PC. In the fashion design process, the chief designer oversees the overall design workflow. In PC, there are three design teams located in the Mainland China and Hong Kong (HK). The chief designer in HK first gives his descriptions of the design brief to the design teams. The design teams in different locations would then work out their designs and present them to the chief designer for evaluation. The chief designer then makes a choice among various designs. Revisions are required when the chief designer is not satisfied, and the revision work is performed by the HK team only.

Time and quality of design are two major performance measures for this fashion design process (and they also affect the whole related fashion supply chain's performance [30], [39], [53], [56]). The expected time for each step of the design process, which is obtained from a survey with PC, is summarized in Fig. 1. As we can observe from Fig. 1, the most time consuming part is the individual design step of the designers. During this step, each individual designer will attend fashion shows and exhibitions, and hold discussion meetings with customers so as to get some ideas on the design. Other time consuming parts include the preparation of individual samples, revisions of design work and the communication of design description and proposals between the chief designer and the individual designers in different locations. It is clear that the traditional design process is far from perfect. In addition to the drawbacks mentioned above, a team who is not involved in the original design may also need to conduct the revision. Although this arrangement may reduce the time of delivery of design description and design proposals between different locations, the time required for getting a revised design is lengthy. There is also a lack of communication among the original designer and other designers.

To overcome these existing challenges, which also improves the design process both in terms of the required time and the quality of design, a TMID system is proposed which aims at: simplifying the design process, supporting computer-aided design evaluation, and enhancing the collaboration between designers by various tools.

B. The model of fashion design process with Multi-Attribute Utility Function (MAUF)

We propose to formulate the fashion design decision making problem as a multicriteria optimization problem in which the performances of individual objectives are considered. In fact, many design decision making problems reported in the literature employ this model formulation (see, .e.g, [29], [33], [43]). Most of these problems rely on the sum of the weighted preferences of individual designs with the weighting factors being assigned to individual attributes of designs depending on the respective importance. The objective function under such methods is often called a Multi-Attribute Utility Function (MAUF), which is widely used in multi-objective decision-making problems [35]. As a result, the MAUF can be used as a ranking system in the selection of the most preferable design among many alternatives in fashion design process. Moreover, color and texture are two critical factors in the fashion design process. The MAUF identifies the color differences from their corresponding numerical values. The color representation is an abstract mathematical model describing colors in numbers, typically in three or four values or color components. These representations are called color spaces. Images in computer are usually stored and displayed in the RGB color space [7]. When evaluating color differences in the MAUF, the differences should correspond to Euclidean distances. In other words, the same Euclidean distance should reflect the same difference between colors when judging by human eyes, regardless of what the colors are. However, a color space like the RGB color space does not guarantee Euclidean metric of its color difference, because the human eye is more sensitive to certain colors than the others. In RGB space, the tricolors have equal weighting. A better color space should take this into account in order to measure the color difference. There are other color spaces, which are defined for different demands. For example, the LUV space [7] is designed to approximate perceptually uniform color spaces. In this space the simple Euclidean distance $dist = \sqrt{(L_1 - L_2)^2 + (U_1 - U_2)^2 + (V_1 - V_2)^2}$ is defined between two colors, (L_1, U_1, V_1) and (L_2, U_2, V_2), and this distance can be used to denote the color difference. The mapping between RGB and LUV spaces is given by [7]:

$$\begin{pmatrix} L \\ U \\ V \end{pmatrix} = \frac{1}{\sqrt{6}} \begin{pmatrix} \sqrt{2} & \sqrt{2} & \sqrt{2} \\ 2 & -1 & -1 \\ 0 & \sqrt{3} & -\sqrt{3} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}. \tag{1}$$

The texture description in our TMID system is based on the fibers from which the texture is made of, and the corresponding proportion of the fiber blended in the texture. Suppose a texture is made of *n* kinds of fibers, the texture description is in a format of $(p_1, p_2, \cdots p_n)$, where p_i is the proportion of fiber *i*. With this definition, the MAUF which models a designer's preference can be given in the following format:

$$U_{designer}(L,U,V,p_1,\cdots,p_3) = w\sqrt{(L-l)^2+(U-u)^2+(V-v)^2} + w_1|p_1 - f_1| + \cdots + w_n|p_n - f_n|, \tag{2}$$

where (l, u, v) is the hypothetical center of the designer's color preference, and $(f_1, f_2, ..., f_n)$ is the hypothetical center of the designer's texture preference. In (2), Euclidian difference color and absolute difference for fiber's preference with weight parameters are utilized. These help illustrate the ordinary MAUF functions. The overall MAUF of a ranking system can be given by (3) below,

$$U_{guide} = W_1 U_{customer} + W_2 U_{chief} + W_3 U_{designer} + W_4 U_{exhi}, \tag{3}$$

where $U_{customer}$, U_{chief} and U_{exhi} correspond to the parts of the utility function contributed by the customer, the chief designer, and the idea from exhibition, respectively. These all are called sub MAUFs and each W_i is the corresponding weight of the respective sub-MAUF.

Such multi-criteria decision support methods are common in modeling collaborative design problem, and there exist many more varieties of MAUFs which can also model the problem. However, the traditional MAUF approach has some drawbacks[6] and in order to overcome these challenges, AI approaches are proposed in this paper in modeling the MAUF. To be specific, we propose to use ANN and fuzzy logic model in modeling the MAUF in the

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[6] These methods typically rely on the specification of importance weights to accomplish trade-offs among the competing objectives. However, these methods often have difficulties in terms of the selection of all possible Pareto optimal solutions, and the direct specification of importance weights can be arbitrary and ad hoc [47]. Besides these difficulties, using MAUF in modeling TMID systems also often requires expert knowledge of the under studied design process (e.g., we need to know the tradeoffs between colors and textures, or even expertise knowledge on colorimetry) in order to come up with a reasonable model to represent them. When modeling using MAUF, people usually assume linear models of importance weights while in reality, the underlying system may not act in a linear manner.

fashion design process. The ANN model has the capability of approximating arbitrary functions, and with the help of fuzzy logic, such model can successfully model the human preferences of fashion designers. The newly proposed TMID system with fuzzy ANN model of the fashion design process is depicted in Fig. 2, and Fig. 3 shows each step of the TMID system in details.

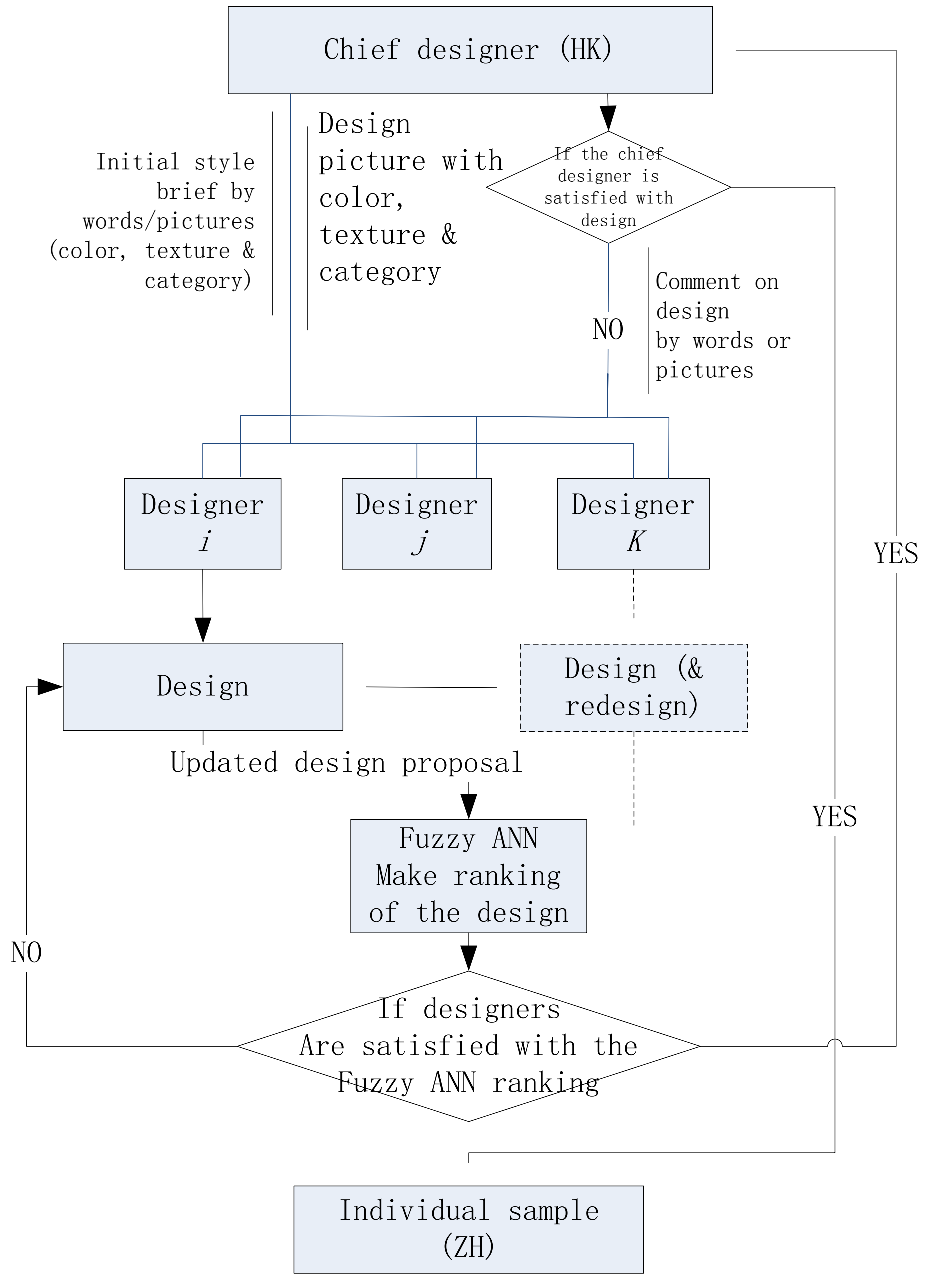
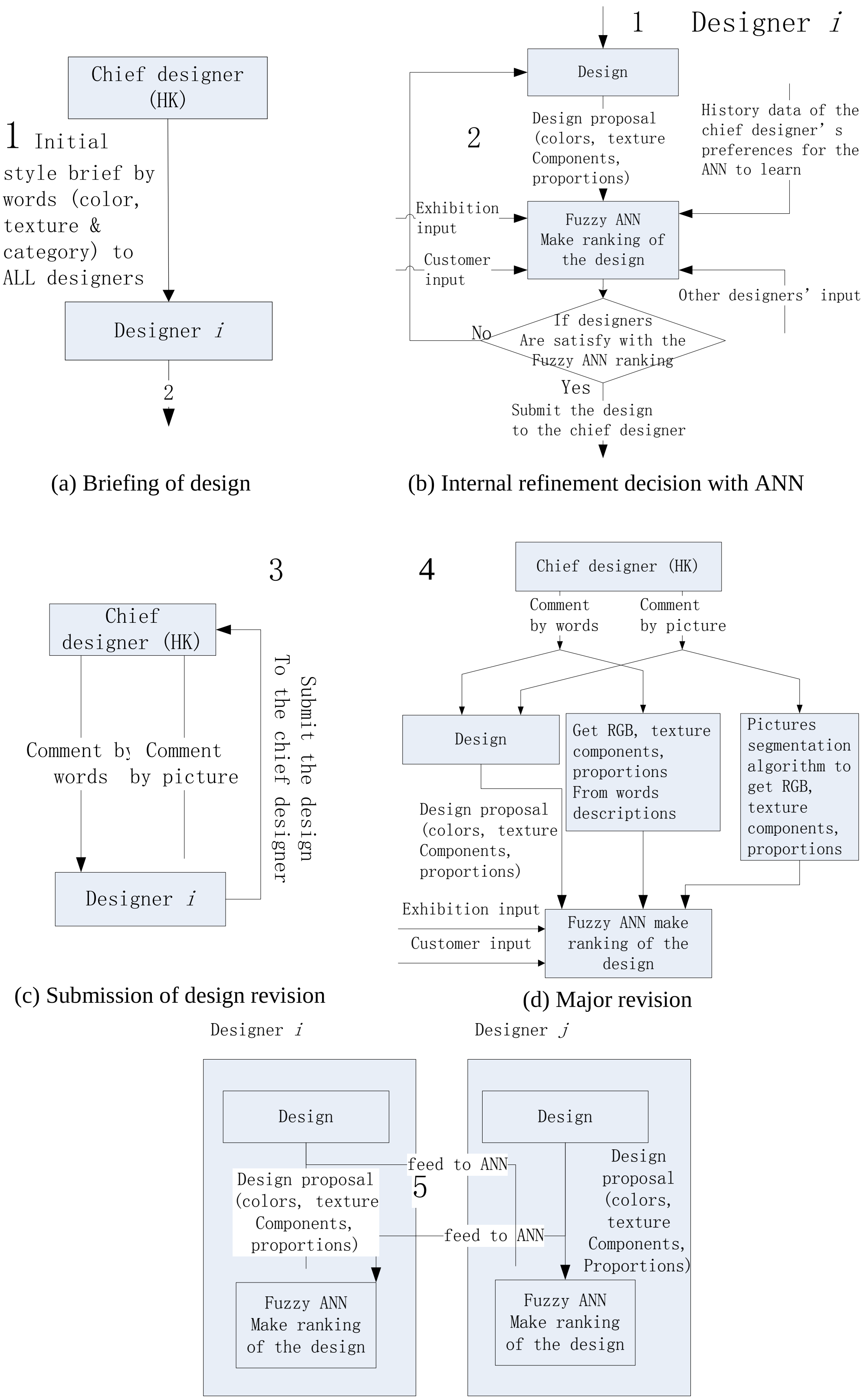


Fig. 2. The proposed fashion design process with the TMID system.



(a) Briefing of design

(b) Internal refinement decision with ANN

(c) Submission of design revision

(d) Major revision

(e) Internal details of ANN preference learning mechanism

Fig. 3. The details of the proposed fashion design process with the TMID system.

In Fig. 3(a), as the first step of the process, the chief designer gives the briefing of design either via descriptions of category in “words”, or via color and texture of the design. The key parameters, color and texture, can be translated into numerical values and thus be modeled in the TMID system. Fig. 3(b) shows the second step, in which the fuzzy ANN approximation of MAUF is employed to rank the designs from individual designers by the preferences of the chief designer, the inputs from fashion exhibition and the requirements from customers. The individual designer determines his/her design which will be sent to the chief designer based on this ranking. The design is revised if he/she is not satisfied with the ranking (this revision is called Internal Refinement). Fig. 3(c) illustrates the process when an individual designer sends his/her design to the chief designer. The fashion design process is completed if the chief designer finds that this design meets all his/her expectation, or the chief designer will provide his/her final comment to the individual designer either by words or picture so that the designer may follow in the revised design (this revision is called Major Revision). In Fig. 3(d) the chief designer’s comments are translated into numerical parameters and fed back to a fuzzy ANN ranking system to refine the chief designer’s preference. During the ranking process, if the preferences of another designer are available, they can also be used as the inputs to the fuzzy ANN system, so that the ranking is incorporated into the other designer’s preference, as shown in Fig. 3(e).

III. DECISION SUPPORT WITH MULTI-ATTRIBUTE UTILITY FUNCTION & ANN

As mentioned in the previous section, MAUF and ANN are employed in our TMID system to perform automatic ranking of designs. The evaluation of fashion design consists of several attributes (such as colors and textures of the design). Decision-makers often find it difficult to handle the tradeoffs among multiple objectives in reaching a decision. These types of multi-objective decision making problems are generally solved by the multi-attribute utility theory (MAUT). The basic hypothesis of MAUT is that if there is a decision making problem, there is a real valued multi-attribute utility function (MAUF) defined among the set of feasible alternatives (e.g., the design proposals), which is to be maximized, then the alternative having the maximum value of MAUF is treated as the optimal solution. In order to evaluate a design, the preferences of the chief designer, other designers, exhibition inputs and customer inputs can all be included in the MAUF [24], [35], [22].

Many researchers are devoted to the determination of MAUF and this area has been well-established in recent years. Steuer [34] considered the utility function as the basis in which different settings (solution alternatives) to a multi-criteria problem are determined (where a higher value of the utility score implies a more preferred solution alternative). In the context of multiple objectives, an MAUF is often formed to rank a set of solution alternatives. A tradeoff among the objectives is usually made to evaluate the utility value associated with the solution alternative. This tradeoff incorporates the contribution of each optimization objective into an overall system performance evaluation. ANN has also been applied in solving the MAUF [5], [33] and it has been proven that any continuous MAUF can be mapped into an ANN three-layer perceptron [14]. Fuzzy logic is also often combined with ANN system [50]-[53], so that the approximation capability of ANN is introduced to the fuzzy system, and the fuzzy system provides benefits on the interpretation of results and interaction with user. In our work, a simple fuzzy ANN system is adopted for the approximation of the MAUF. Details about the fuzzy ANN system are discussed in the subsequent sections.

As the TMID system is developed to support human decisions, it has to imitate the human judgment on designs. While human judgments are often not clear and crisp, fuzzy logic is utilized to overcome this problem [38]. In this research, we employ fuzzy preference together with the MAUF in evaluating and ranking the fashion design proposals. The fuzzy ANN is a Mamdani type fuzzy ANN, and the number of its input node equals the input of the MAUF. The output node provides the result of the MAUF. The empirical experiment is conducted on the performance of the fuzzy ANN with a hypothetical MAUF below.

$$U_{guide} = \vec{w}\begin{pmatrix} U_{customer} \\ U_{chief} \\ U_{designer} \end{pmatrix}, \tag{4}$$

where $\vec{w}$ is the weight vector. ANN has been used in the approximation of MAUF and it has been proven that the three layer feed-forward ANN has the ability of approximating any form of MAUF, or any assumption of the weight factors [45], [46]. As changing the weights in MAUF has no obvious impact on the ANN approximation for the MAUF, considering the popular knowledge that the customers' preferences for a fashion product play a more important role than the designers' ones, and the chief designer has the authority over other designers, $\vec{w} = (0.7, 0.2, 0.1)$, which follows the above assumptions, is used in (4).

In this analysis, the hypothetical MAUF (as in (2)), the center of color (l,u,v) and the center of texture $(f_1, f_2, \cdots, f_n)$ must be given. As these centers represent the ideal design details of a fashion product, which could be of any value. In this analysis, some random centers are given to the MAUFs just for illustrating the approximation ability of ANN.

The hypothetical MAUF of the customer is centered with color (100, 20, 30) and texture (0.6, 0.4, 0); the hypothetical MAUF of chief designer is centered with color (80, 10, 10) and texture (0.5, 0.5, 0); the hypothetical MAUF of designer is centered with color (90, 10, 0) and texture (0.4, 0.5, 0.1). With (4), we have all the theoretical data for any given design proposal with the color and texture parameters as shown in Table II.

Table II

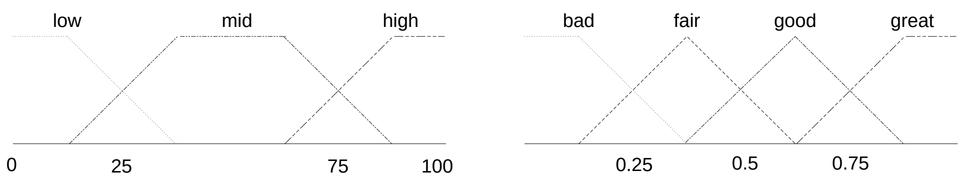
THE ANN APPROXIMATION OF MAUF

Chief Designer's preference history						
	Color representation			Textile composition (*100%)		
Rank	*L*	*U*	*V*	p_1	p_2	p_3

	(Lightness)	(*u* coordinate)	(*v* coordinate)	Component 1	Component 2	Component 3
0.618527	238	208	240	0.129874	0.15474216	0.715384
0.311424	124	80	202	0.952498	0.01354855	0.033953
0.232765	12	93	32	0.635219	0.03504115	0.32974
0.342413	168	43	139	0.203284	0.12864596	0.66807
…						

With sufficient past data (400, suppose that we have enough ranking records from the chief designer) of design proposals and the above setup of weight parameters, the analysis of ANN approximation is conducted. If we measure the approximation accuracy by the Mean Absolute Percentage Error (MAPE) which is given by $\frac{1}{N}\sum_{n=1}^{N}\frac{|R_n - A_n|}{R_n}$ wher*e* R_n *is* the expected ranking value given by MAUF and A_n is the ANN approximated ranking value, the ANN can approximate the theoretical MAUF with MAPE of 0.96%. It is obvious that when there is insufficient past data, the accuracy of the ANN approximation of MAUF would drop, but in either case, the ANN often outperforms the traditional MAUF model [45], [46].

In the decision process under the framework of multipurpose decision-making, fuzziness is inevitably found in the human decisions and this property can be modeled by fuzzy sets theory [6]. There are also many studies on the fuzzy neural systems [50] which combine the benefits of fuzzy logic and ANN systems. In our study, a relatively simple fuzzy ANN system is employed to illustrate the benefit of such technologies. Though there are no advanced features such as the automatic adaptation of membership functions, it illustrates the effectiveness of such technologies. Fig. 4 illustrates an example of the fuzzy membership function which describes the chief designer's preference, and one of the inputs L. In real fashion design practice, as what we learnt from the company PC and many other similar firms, the designers often evaluate a design by linguistic words instead of numbers, and there could be multiple correlated aspects of evaluations such as color-matching and touch-feeling, etc. We employ only one overall ranking evaluation for the sake of simplicity. The preference is described with a degree of membership ranging from 0 to 1. Although there could be many fuzzy terms such as 10 in this range, too many terms will decrease the understandability of the system and may not benefit the decision-making process. In reality, designers use often three or four terms, as such, the chief designer's preference is divided into 4 fuzzy terms *bad*, *fair*, *good*, *great*, and is transformed with the functions shown in Fig. 4. The four terms are evenly distributed along the numerical rank and the shapes of the membership functions are fixed during the running of the system. Such fuzzy preference could be improved if fuzzy neural systems like the ones in [51], [52] are employed to tune the parameters of the membership functions in the learning process, and this could be the future extension of our current research. The extreme values of preferences, which are smaller than 0.125 or greater than 0.875, are considered as absolutely *bad* or *great*, and fields in between the two terms are equally divided into *fair* and *good*. The centers of the 4 terms are located at preference values 0.125, 0.375, 0.625, 0.875. To reduce the computational burden, triangle-shape membership functions are used instead of the bell-shape ones. With this setting, an experiment was conducted. The structure of the fuzzy ANN system is depicted in Fig. 5, and the system is implemented by the neural network framework *Neuroph* [54]. The input parameters are given in (2). In the training stage, the crisp inputs of color and composition go into the input layer, and the target preferences, which are given by (1) and (2), go into the output node. The target preferences are then fuzzified into the four fuzzy terms as shown in Fig. 4. The fuzzy ANN is then trained with supervision by the input and fuzzy output. Once the fuzzy ANN is trained, it can be used to approximate the designers' preferences. The result shows that the fuzzy ANN algorithm can fit the chief designer's theoretical MAUF with a 40% MAPE (increased 2% compared to the non-fuzzy one) with limited data (Table III). It is also observed that with sufficient data sets (with more than 100 data samples), the accuracies of the fuzzy and non-fuzzy algorithms are almost the same. This reveals that the fuzzy preference does increase the accuracy under certain circumstances, although the effect is not always significant, fuzzy preference is still useful in applications for modeling the human fuzzy nature. At the same time, the fuzzy ANN results are more understandable than the non-fuzzy one, and the fuzzy ANN is especially useful when the data sample size is small. As the fashion design process inherently involves many human reasoning and judgments, and this makes the fuzzy approach particularly suitable for the implementation of the TMID system for fashion design. For the case with the membership functions in Fig. 4, there are borderline cases where the "degree of membership" falls equally between two fuzzy sets, this phenomenon is especially likely to happen when the preferences of designers are not evenly distributed like what is presumed by the membership function in Fig. 4, and this could reduce the accuracy of the system. Table 4 shows the errors that are introduced by these borderline cases, in which the preference values falling in the 0.05 interval around the mid points (0.25, 0.5, 0.75) of terms are considered as the borderline cases. In most cases, less than 25% of the errors are introduced by these borderline cases, and such cases are especially rare in the scenario with more training data. Of course, such errors are highly related to the data feature and adopting a fuzzy ANN system with automatic adaptation of membership functions (like in [50]) or making the training set to include such borderline cases deliberately could alleviate such errors.



(a) MF of *L* (b) MF of chief designer's fuzzy preference

Fig. 4. The membership functions.

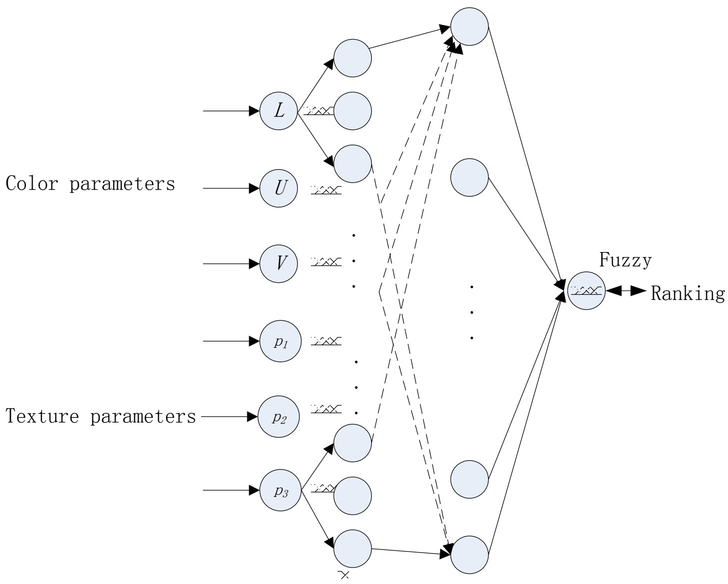


Fig. 5. The fuzzy ANN structure.

Table III

COMPARISON OF ACCURACY OF FUZZY AND NON-FUZZY ALGORITHMS IN TERM OF MAPE

No. of Data Sets	Fuzzy ANN	ANN

4	40%	42%
40	16.4%	17.7%
100	0.83%	0.84%
200	0.91%	0.91%
300	0.95%	0.96%
400	0.94%	0.96%

Table IV

ERRORS INTRODUCED BY BORDER CASES OF FUZZY MEMBERSHIP FUNCTIONS

No. of Data Sets	Error introduced by border cases of MF (%)
4	25%
40	22%
100	6%
200	11%
300	0%
400	0%

IV. SIMULATION STUDIES

To study the effectiveness and performance of the proposed TMID system, simulation experiments [36] of the design processes with and without the TMID system are conducted (depicted by Fig. 1 & Fig. 2 respectively). The simulations strictly follow the design processes and compute the respective time costs for each scenario. The overall time costs are then accumulated and the number of revision rounds is also obtained. As there is significant uncertainty in the parameters which model the fashion design process, Monte Carlo simulation method is used. In the following, Section A presents the simulation of design process with hypothetical datasets. The times spent on design and revision are defined to follow specific probability distributions, the improvement of the design quality is also modeled by some pre-defined probability distribution functions. In this simulation study, all the possible hypothetical combinations of the parameters in the design process are studied so as to give an overall picture of the relationships between the parameters and the time cost. After this, another simulation experiment with real data is discussed in Section B to further verify the results. Fig. 6 illustrates the pseudo codes for the simulations of the design process with and without the TMID system.

Traditional process	TMID process

Generate initial design time t_{id}
Generate initial satisfactory S for each designer's design work
 	
Loop when $S \leq 90\%$
    Generate revision time
    Increase S
    Add up total time
End loop
 	
Report total time and rounds
	Generate initial design time t_{id}
	Generate initial satisfactory S for each designer's design work
	
	Loop when $S \leq 90\%$
	    Generate self-revision rounds
	    Loop every self-revision rounds
	        Generate self-revision time
	        Increase S
	    End loop
	    Increase S
	    Add up total time
	End loop
	Report total time and rounds

Fig. 6. The pseudo codes for the simulations of the design process

A. Simulation with Hypothetical Data

The two fashion design processes, namely the traditional design process and our proposed fashion design process with the TMID system, are simulated. Hypothetical data sets are used in this simulation study. A preliminary field study has indicated that the time cost of the design process appears to follow normal distributions. As a result, the total time cost is modeled as a normally distributed random variable. The mean of the normal distribution is given by the field data as shown in Fig. 1, which also illustrates the time cost in every step of the traditional design process. Normally it is assumed that the time cost in the new design process with the TMID, as in Fig. 2, is the same as the corresponding time cost in Fig. 1, except those factors that are affected by the TMID, such as the time spent on the initial design both in Fig. 1 & Fig. 2. In our experimental setup, we assume t_{id} follow a normal distribution of *Normal*(65.2, 5), so that $p(55.4 < t < 75.0) = 95.0\%$, with 75 days as the upper limit and 55 days the lower limit. The stopping criterion for the design process is modeled by a factor on the quality of design, or the satisfactory degree, denoted by $S \in [0,1]$.

The chief designer selects a design from the design proposals and the final result is selected whenever S > 90%. Thus, S of every initial design must be defined. In practice, most designs need at least one revision, so it is reasonable to make S to follow a distribution that the probability of the initial design S > 90% is small enough. In our setup, S follows the normal distribution of *Normal*(50%, 0.2), and the probability that the initial design meets the stopping criteria $p(S > 90\%) = 2.3\%$ is a small one. This obeys our assumption that most of the design will be revised. For every round of revision, the degree of satisfaction S is increased by $S' = S + (1-S)I$, which is a simple model similar to [29], where ($1-S$) is the "unsatisfactory" factor which will be reduced by I, I is the factor representing the increase of satisfaction level, which is a quality improvement factor of each revision. It follows a normal distribution of *Normal*(u, 0.2^2) with mean u and standard deviation 0.2, $I \in (0,1)$, u = 70% is used for the initial test. The time spent in revision of design follows the distribution of *Normal*(7, 1^2), with a mean of 7 days as shown in Fig. 1.

Based on these assumptions, the total design time for a traditional fashion design process in Fig. 1 is given by,

$$T = t_{id} + t_{sample} + t_{cd} + N(\max t_r + t_{sample} + t_{cd}), \tag{5}$$

where the total time T is the sum of t_{id} (the time of initial design), t_{sample} (the time for individual sample), t_{cd} (the time for the chief designer to make decision and comment on design, and the time spent in sending the designs), N is the number of revisions, t_r is the time spent on revision. The total design time for the new TMID process (in Fig. 2) is given by,

$$T' = t_{id} + N'(\max(nt_r) + t_{sample} + t_{cd}). \tag{6}$$

where n is the number of revisions before the designer sends the design to the chief designer, N' is the number of rounds of sending design to the chief designer for comments in the new process with TMID, which is different from N in (5). The number of rounds n is also influenced by the satisfaction degree of the designer. Since a sequence of the discrete events like revisions can often be modeled as a Poisson process, we employ the Poisson distribution

$P(\lambda)$ in the simulation experiments [48]. The simulation is conducted with the Monte Carlo method [25], with 1,000 evaluations for each parameter setting. Table V presents the simulation results. In this simulation, the two systems share the same parameter of the initial *S* and the increasing factor *I*. When there are new parameters introduced to the TMID process, we denote the increasing factor for self-revision by I', and the number of rounds for self-revision by *n*. The simulation stops when S > 90%. The parameters' settings are given in Table V. The results are presented by the average value of the total time cost in days and the number of rounds. The statistical 95% confidence intervals for the simulation results of time and rounds are also given. The experimental results have shown that with the help of the TMID system, the total time for the design process is reduced by around 17 days which is equal to 12% of the original one, and the number of rounds is also reduced slightly.

Table V

COMPARISON OF THE SIMULATION RESULTS OF THE TRADITIONAL FASHION DESIGN PROCESS AND THE FASHION DESIGN PROCESS WITH THE TMID SYSTEM (HYPOTHETICAL DATA)

	Initial satisfaction degree *S*	Increasing factor *I*	Increasing factor for self-revision I'	Self-revision rounds *n*	Simulation results (average)			
					Time	95% confidence interval	Rounds *N*(N'')	95% confidence interval
Traditional process	*Normal*(0.5, 0.2)	*Normal(0.7, 0.2)*			137.5	±1.2	2.3	±0.034
Process with TMID	*Normal*(0.5, 0.2)	*Normal(0.7, 0.2)*	*N(0.1, 0.1)*	Poisson λ=3	120.9	±1.5	2.1	±0.023

Table VI

THE PERCENTAGE SAVING OF TIME COST IN FASHION DESIGN: THE TMID SYSTEM COMPARED TO THE TRADITIONAL PROCESS, WITH DIFFERENT *I*

	I	Time saving (%)
TMID	0.1	-76.3%
	0.2	-60.6%
	0.3	-48.7%
	0.4	-37.9%
	0.5	-29.6%
	0.6	-20.9%

	0.7	-15.2%
	0.8	-0.1%
	0.9	0.01%

Many parameters in (5) and (6) influence the performance of the simulated design process. Further studies on the impact of these parameters on the total time cost and number of rounds of the design process with or without the TMID system are conducted. We first fix the distribution of revision rounds to be $n \sim P(\lambda = 3)$, and the increasing factors for self-revision are set to be $I' \sim N(10\%, 0.1)$ and $I' \sim N(30\%, 0.1)$, respectively. Table 6 illustrates a part of the results with $I' \sim N(10\%, 0.1)$, $S \sim N(30\%, 0.2)$ and I ranging from 10% to 90%. The percentages of saving of time cost are given in Table 6, where negative value means the time cost is reduced whereas a positive value means the time cost is increased. We can observe from Table 6 that in most cases the TMID reduces the time cost significantly, except for some rare cases where I is very high such as 0.8 or 0.9, the time costs of the two systems are almost the same. This reveals that the time cost saving of the TMID system is especially useful when I is small.

Fig. 7 & Fig. 8 illustrate the comparisons in detail with all possible combinations of I and S, with I ranging from 10% to 80% and S ranging from 10% to 90%. In Fig. 7 & Fig. 8, we observe that with the increase of S and at a fixed I = 20%, the time and the number of rounds are decreased for both processes. The percentage improvement of the time cost is given by $(t_{cdss} - t_{traditional}) / t_{traditional} \times 100\%$, where $t_{traditional}$ is the time cost of the traditional design process and t_{cdss} is the time cost of the design process with the TMID system. Among all the computed values, most t_{cdss} values are smaller than the $t_{traditional}$ values until S is increased to 80%, and in all cases the number of required rounds of the TMID system is smaller than that of the traditional system. Fig. 9 & Fig. 10 further show the result with S = 70% and increasing I; for this case, t_{cdss} is only better than $t_{traditional}$ in terms of the time cost when I < 30%, although the number of required rounds does reduce.

In Fig.s 7-10, we find that the TMID system is especially helpful when the initial S is not very high and I is low. In most cases, with the help of the TMID system, the average number of revision rounds of the new TMID fashion design process is lower than that of the traditional process. The major contribution of the proposed TMID system is hence on speeding up the revision process. When the initial satisfactory level is low, a longer revision time is needed in the design process; when the increasing factor of satisfaction is also low, more revision rounds are needed, and the TMID system is observed to be especially useful under this condition. In particular, when the increasing factor of satisfaction is higher, which means that "the case when the individual designers can meet the chief designers demand with just one revision" appears more often (it is a rare case though), the TMID system may only bring marginal improvement to the design process.

Fig. 9 & Fig. 10 show similar results when I' follows *Normal*(30%, 0.1). Fig. 9 is similar to Fig. 7 in shape, but the time costs of TMID are significantly reduced and we observe in more than half of the combination of *S* and *I* that the time costs of the TMID process are better than that of the traditional process. Fig. 10 also shows that the average number of rounds is improved for the process with the TMID where for all cases the TMID process outperforms the traditional process.

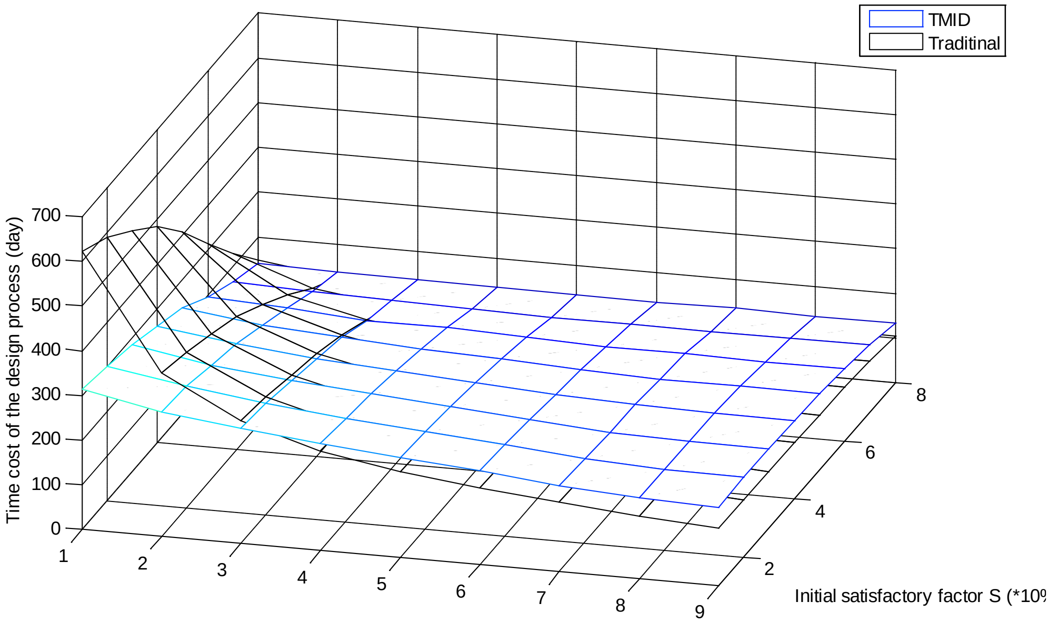


Fig. 7. Comparison of time cost with different *S* and *I* in simulations of the traditional design process and the TMID design process when $I' \sim$ *Normal*(10%, 0.1).

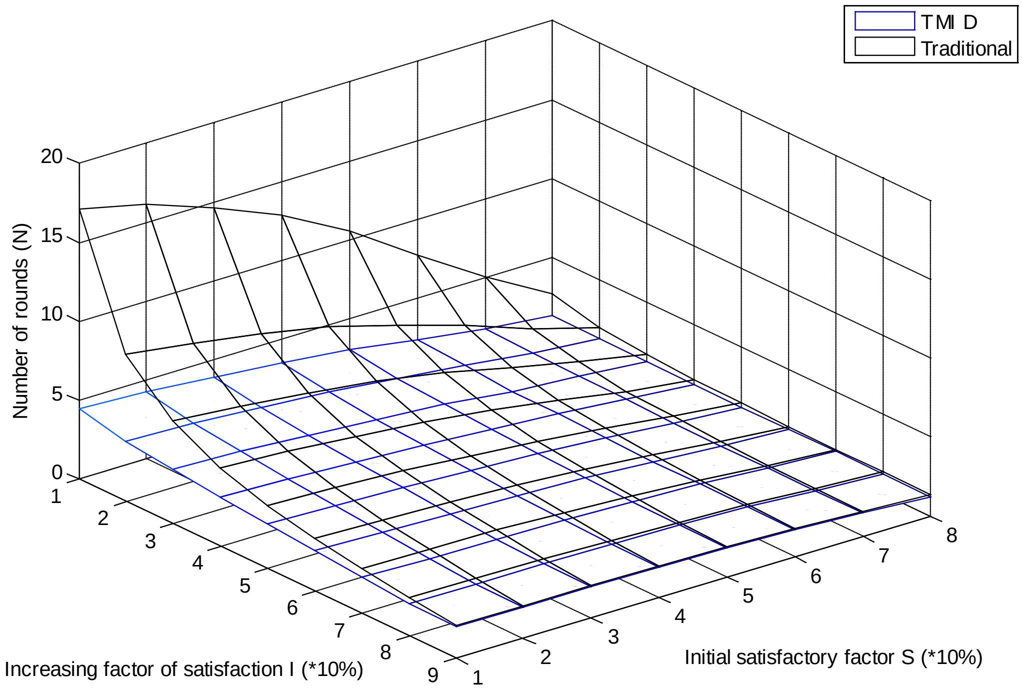


Fig. 8. Comparison of number of rounds with different *S* and *I* in simulations of the traditional design process and the TMID design process when $I' \sim Normal(10\%, 0.1)$.

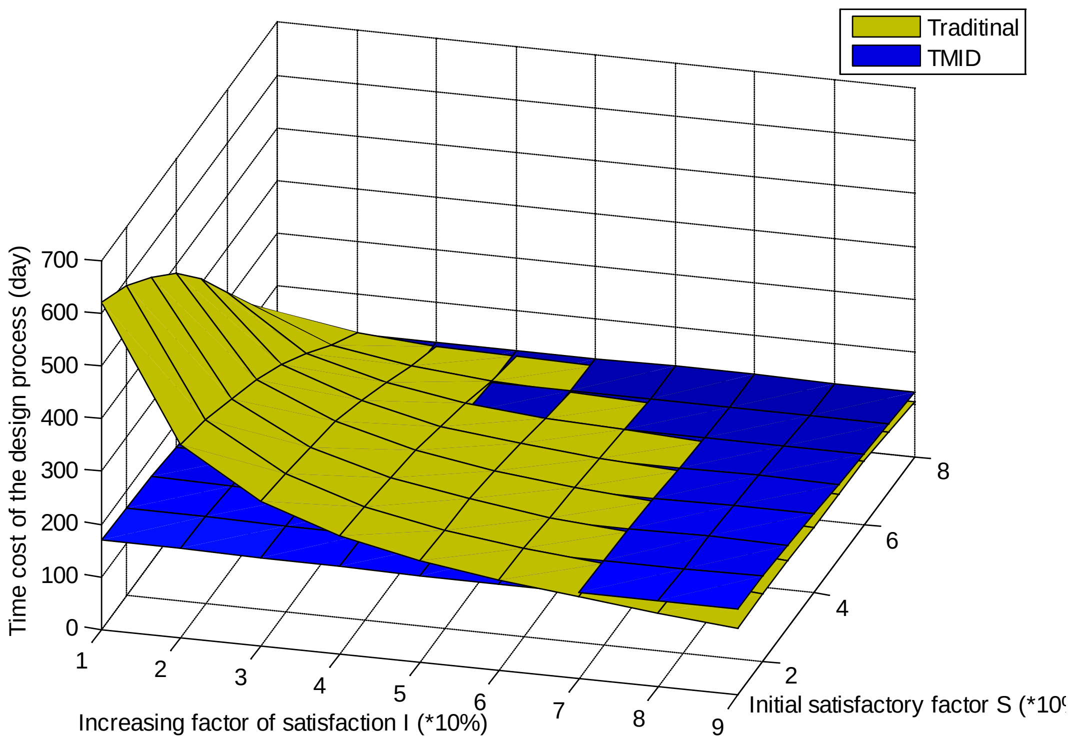


Fig. 9. Comparison of time cost with different *S* and *I* in simulations of the traditional design process and the TMID design process when $I' \sim Normal(30\%, 0.1)$.

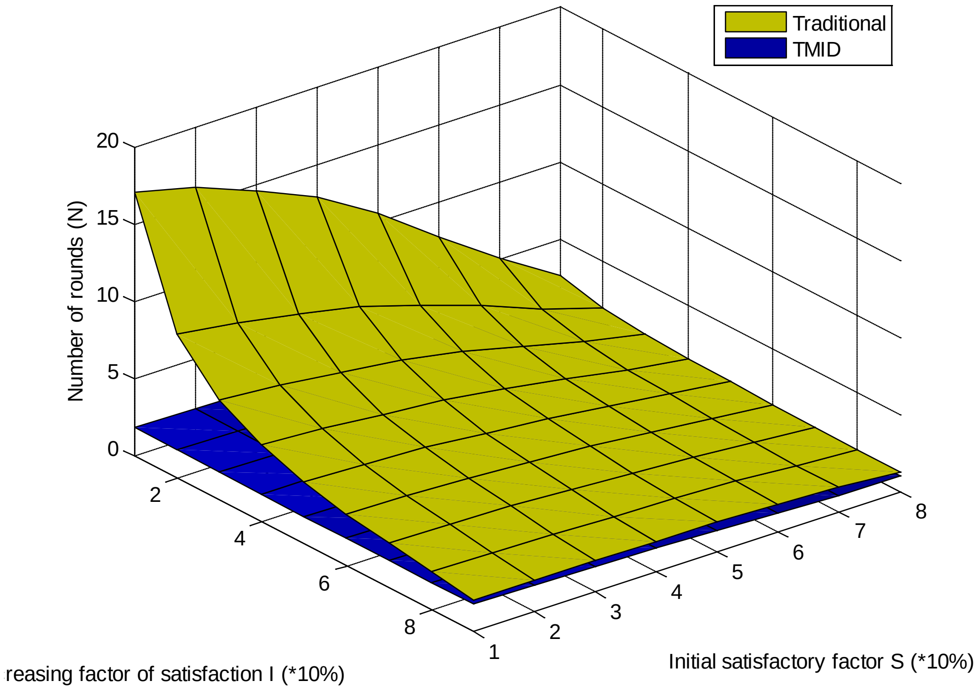


Fig. 10. Comparison of number of rounds with different *S* and *I* in simulations of the traditional design process and the TMID design process when $I' \sim Normal(30\%, 0.1)$.

B. Simulation with Real Data

From an interview with the knitwear company PC, we have collected the following data sets on the revision time t_r, the number of revision round $\overline{N}$, the time for initial design t_{id}, and the time for transportation t_{cd} in the total design time under the traditional process as shown in (5), and the average time for each procedure is given in Fig. 1. Each of the sample data sets has a size of 50 data points. These practical data sets reveal some facts of the traditional fashion design process. The degree of satisfaction *S* is modeled by $S' = S + (1 - S)I$, and the result for the number of revision rounds is given by Table VII. The real $\overline{N}$ has an average value of 1.38, the nearest values to it in Table VII are highlighted. By using the data from Table VII, we can tell that the initial *S* is around 80%, and *I* is around 60%. This reveals that both *S* and *I* are fairly high in practice, and this is in fact the real situation. We use *S* = 80% and *I* = 60% in the following simulation analysis.

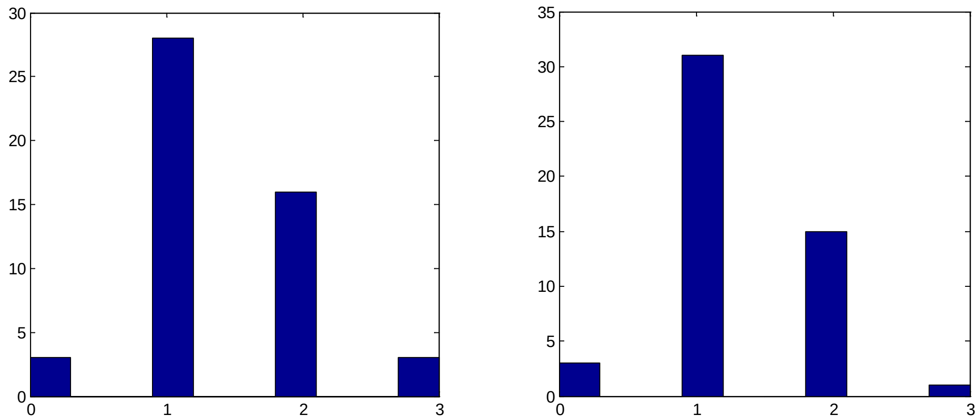
Table VII

SIMULATION RESULT OF TRADITIONAL PROCESS ON AVERAGE REVISION ROUNDS VS. VARIOUS INITIAL SATISFACTORY S AND INCREASE FACTOR I

I / Initial S	10%	20%	30%	40%	50%	60%	70%	**80%**	**90%**
10%	17.235	9.37	6.532	4.986	4.069	3.415	2.881	2.477	2.088
20%	16.241	8.762	6.151	4.722	3.887	3.231	2.832	2.384	2.064
30%	14.708	8.114	5.663	4.439	3.693	3.065	2.705	2.282	2.02
40%	12.908	7.181	5.075	4.022	3.356	2.861	2.543	2.169	1.993
50%	10.499	6.103	4.379	3.525	3.015	2.619	2.3	2.033	1.924
60%	8.02	4.555	3.425	2.87	2.528	2.252	1.971	1.829	1.809
70%	5.099	3.122	2.503	2.187	1.913	1.808	1.648	**1.595**	**1.566**
80%	2.861	1.913	1.675	1.518	1.452	**1.401**	**1.332**	**1.339**	**1.347**

In Fig. 11(a), the distribution of the real number of revision N is given by a histogram. Observing from Fig. 11(a), we find the shape of the histogram is similar to a lognormal distribution. A simple calculation from the lognormal cumulative density function with $\mu = 0.2, \sigma = 0.3$ have the data points fall within [0, 3] with probability of $p(0 \le t \le 3) = 95.0\%$, and Fig. 11(b) depicts a 50 sample data generated in one simulation run, which resembles the shape in Fig. 11(a). A Lillilifors test [49] is conducted on $ln(\overline{N})$ which verifies that N does follow the lognormal distribution. As a result, this lognormal distribution is used to model the number of self-revision rounds in the simulation experiment.

For the revision time t_r, the Lillilifors test proves that the sample comes from a distribution in the normal family and we therefore use a normal distribution with parameters of $\mu = 0.2, \sigma = 0.3$. The time for transportation t_{cd} is quite short (around the 2 days) comparing to the time for the whole process (usually more than 100 days), we just simply use its mean value in the simulation (since its variance does not significantly affect the result).



(a) Histogram of revision rounds N (b) Histogram of lognormal distribution

Fig. 11. The distribution of revision rounds.

Table VIII

THE PERCENTAGE SAVING OF TIME COST: TMID COMPARED TO THE TRADITIONAL PROCESS, WITH DIFFERENT I'

	I'	Time
TMID	0.1	-5.7%
	0.2	-8.6%
	0.3	-9.9%
	0.4	-11.6%
	0.5	-13.8%
	0.6	-14.5%
	0.7	-15.3%
	0.8	-15.6%
	0.9	-15.5%

The new simulation result of the traditional process (at S = 80% and I = 60%) gives a total time of design = 121.76 and number of revision = 1.002. While with the new setup of the simulation of TMID, the total time of design = 109.73 and the number of revision = 1.191, with I'=0.3. Comparing to the results on hypothetical data, the total time is reduced quite significantly but the revision rounds (of major revision) increases, this is because the number of self-revision rounds is reduced, which apparently affects the total time, but the satisfactory factor increases slowly and causes the total number of revision rounds to rise. Detailed results with various I' exhibiting similar property as the ones in the theoretical data are not shown here. The percentage time difference of the process with the TMID system compared to the traditional one is given in Table VIII. As a remark, the percentage time difference is given by $a = 100\% \times (t_{cdss} - t_{traditional}) / t_{traditional}$, where t_{cdss} is the time cost for the TMID process, and $t_{traditional}$ is the time cost for the traditional process. From Table VIII, we observe one prominent trend that when I' is larger, the significance of time cost reduction seems to be increasing and it gets to a steady state at around 0.8-0.9.

V. CONCLUSION, COMPANY INTERVIEW & INSIGHTS

In this paper, motivated by real world industrial practices, we have studied a new technology-mediated intelligent decision (TMID) scheme for the fashion design process. This TMID system is based on the team work spirit under the existing fashion design practices, and employs the fuzzy ANN approach in the analysis of the design qualities, where no discipline specific knowledge is required. Our experiments in using both real data sets and hypothetical data sets have indicated that with the help of fuzzy ANN models, the proposed TMID system exhibits significant improvement in enhancing the required time for the fashion design process while achieving a high design quality. Some specific insights are discussed below:

1. The simulation studies conducted in this paper have revealed that the time cost reduction via the TMID system is especially prominent when the initial design's degree of satisfaction (*S*), and the factor of quality improvement (*I*) are both high. Only for the case when *S* is low and *I* is very high (i.e. when the designer fails to understand the chief designer's initial brief, produces a very poor initial design while makes a very good improved revision), the fashion design process with the TMID system is not so helpful. From the analysis with real data sets on the design process from a knitwear company PC, we have found that the *S* and *I* in practice are high which provides a good support that the potential improvement by using our proposed TMID system is relatively high.

2. For the factor I', our experiments have shown that its increase can enhance the TMID system's performance but the magnitude of improvement is small, especially when I' is high. As a remark, our analysis also illustrates that the TMID process can shorten the design time even if the I' is as low as 10%. Since with the fuzzy ANN approximation of the MAUF, our TMID system is capable of "learning" human preferences and can get acceptable results even with very few historical data, this means it is very likely that we can have an I' which is large enough to guarantee a time improvement of the design process.
3. There exist some special and extreme cases in which our proposed TMID system may not yield any real benefits. For example, when there are too many self-revision rounds (just like when the individual designer tends to misunderstand or even disagree with the chief designer's advice), the TMID process may perform worse than the traditional one.
4. In order to further verify the significance of our proposed fashion design process with the TMID system, we conducted an interview with the knitwear company PC. The key comments include: (a) In the traditional fashion design process, owing to time constraint, the chief designer could only select 1-2 major design works for production. Thus, if the proposed new process/system could improve the number of outputs for selection (e.g., the chief designer could be given 3-4 design works for selection and hence production), the proposed system is very useful. (b) In practice, for many new designs, the company has to proceed with at most two revisions even if the quality of design is far from perfect because there is insufficient time for marketing a new fashion design. Thus, under our proposed TMID scheme, we can reduce the time required for creating a fashion design with respect to a given quality level. Thus, within the same given time frame, we can generate more designs for the chief designer to choose. This is known to be very important. Plus, since the company currently has to sacrifice the quality of design for many new designs because of the long lead time to market which means the company has to rush up a few designs with few revisions, with our proposed new design process, the company can actually enhance quality by creating more high quality choices for the chief designer to select. We are hence very pleased to notice that our proposed new fashion design process with the TMID system can address the crucial concerns of the company in practice.

To conclude, we believe that this paper has provided a new TMID system for enhancing the fashion design process. This system's performance has been tested with extensive experiments and it is known to be effective. Its features are also found to be useful in addressing many practical problems faced in the real world by knitwear companies. We hence believe that the proposed TMID system is applicable and significant in real world. Further explorations can be conducted by, for example, including more fuzzy preferences, introducing self-adaptive membership functions and employing the fuzzy reasoning. Moreover, a risk analysis [16], [44] on the level of risk (on the stochastic quality and time) associated with the TMID system in fashion design can be explored.

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Appendix: Company Background of the Collaborating Company

Established in 1984, Pearls & Cashmere (PC) has been associated with high quality cashmere products with stores in 5 stars hotels such as the Peninsula, Mandarin Oriental and Intercontinental. Pearls & Cashmere company designs, manufactures, markets and sells knit and woven products in the luxury goods industry. As a small pearl attached onto the Pearl of Orient that is Hong Kong, Pearls & Cashmere is a locally developed brand that is distinctive and unique. In 2005, it founded a new brand BYPAC (by Pearls and Cashmere), which employs professional international designers knowledgeable in fabrics, tailoring and design, to come up with new concept that qualify as a designer brand, truly international in standing. Today BYPAC boasts of a full range fashion items: sweater, pant, skirt, gloves, socks, scarf and shawl. The brand concept is to provide contemporary style with timeless elegance in luxurious fabrics and yarns. The core brand values focus on quality and value, with astonishing variety of colors and styles, from cashmere to cotton, sweaters to pants, accessories and gift items. BYPAC is committed to give customers with refined finishes and innovation in product development, from the design functionality to the fit and color choices. Being a vertical retailer, BYPAC controls every stage of the products; from yarn spinning to quality control at the factory and finally to the visual merchandising at the store. BYPAC also provides after sales customer service and ensure the product satisfaction at any time. The annual turnover of the Pearls and Cashmere company is in a range of US$50M and US$100M. The major export market includes Australia, China, Hong Kong, Japan, Korea, Taiwan and S.E. Asia. The offices are located at Hong Kong and at Shanghai respectively.

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