International Journal of System Dynamics Applications
Volume 11 • Issue 6

Hybrid Computational Intelligence System for Fashion Design:

A Case of Genetic-Fuzzy Systems With Interactive Fitness Evaluation

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ABSTRACT

The domain of fashion design evolves continuously and is highly personalised, demanding intelligent and customised recommendation. The traditional artificial intelligence-based systems offer solutions based on stored knowledge; hence, they can be quickly obsolete and require high effort. To meet the fashion designers' needs and provide tailor-made recommendations effectively, a hybrid genetic-fuzzy system is proposed with interactive fitness functions. The system is based on generic hybrid architecture using fuzzy logic and genetic algorithm, which can be used to evolve various products in different domains and tested with interactive fuzzy fitness functions. The design of the generic architecture meets the research gap identified through an in-depth literature survey. To prove the utility of the architecture, an experiment is carried out showing encoding scheme, genetic operators, fuzzy membership functions, and fuzzy rules. The results are also discussed, along with the comparison, advantages, applications, and possible future enhancements.

KEYWORDS

Fashion Design, Genetic-Fuzzy Systems, Interactive Fuzzy Fitness Functions

1. INTRODUCTION

It is said that the dressing sense of a person conveys the person's character, mood, attitude, faith, and status. Garments are essential not only for safety and protection but also for the exhibition of personality and to show a specific aspect such as religious beliefs. People may choose from ready-made clothes or tailor-made depending on various factors such as design, price, fitting, etc. In the post-Covid-19 era, where people cannot afford to explore places like design studios and boutiques physically for a unique and customised product, it is difficult to quench the thirst for fashion. Further, a personal designer is also not an affordable solution for everybody. On the other hand, the designers also need to find innovative designs for the garment to get a competitive advantage on the global market and to lock in their loyal and valuable consumers. In this post-pandemic era, when the virtual has become a new standard, there is a need for an intelligent system that recommends the design of garments to consumers and fashion designers.

Many ideas and styles appear on the World Wide Web (Web), social media and catalogues. Finding an appropriate and customised design is a real difficulty in the domain. Traditionally, the creation of a garment is mainly based on designers' experience and users' choices. Sometimes, besides the

DOI: 10.4018/IJSDA.20221101.oa2

common people, the fashion designers also face a challenge to find innovative fashions in various cloth categories. Such decision making about fashion is more creative, artistic, and mundane in nature. As observed, the machines are not very good at such innovative and mundane tasks. Another challenge from the user's side is to decide on a purchase based on standard ratings and recommendations made by different categories of users. The authenticity of such a review is also needed to be taken into consideration.

Suggestions about fashion in the domain of ready-made garment are always challenging considering the involvement of many parameters and the diversity of the users. This is one of the significant reasons why such systems need customisation. Earlier, traditional artificial intelligence-based systems were used to provide customised and effective solutions through a recommendation system. As intelligence requires knowledge, such intelligent systems are primarily knowledge-based. The most popular knowledge-based systems experimented by professionals are the expert system. However, acquiring and representing knowledge are challenging and tedious tasks. Often, such expert systems are not adaptive enough and do not offer advantages such as self-learning and automatic knowledge update. Because of the stored knowledge in the knowledge base, which can not update itself, such systems also tend to be quickly obsolete. Here, a computational intelligence/machine learning-based system helps a lot. With the advancements of modern computational intelligence techniques, it is possible to meet these challenges. Techniques such as artificial neural network, evolutionary algorithms, and fuzzy logic are considered as the significant components of the modern machine learning consortium. The artificial neural networks learn in an automatic manner from big amount of data in supervised and unsupervised manners. The evolutionary algorithms help evolve better and optimised solution components according to the customised fitness functions. Fuzzy logic-based systems especially handle uncertainty and approximate reasoning. Each technique has its pros and cons. Artificial neural networks and genetic algorithms do not handle uncertainty and reasoning, as they do not explicitly store knowledge. A fuzzy logic-based system does not have the virtue of self-learning or evolutionary advantages. Hence, hybridisation of more than one technique is suggested in recommending fashion designs to the users in the most customised manner.

An intelligent system should know its users. Such a facility can be made available with the notion of the stored users' profiles and preferences. With the information provided in the users' profiles, the system can evolve customised designs in automatic and most user-friendly ways. The users' profile contains users' data and vague values about users' choices and preferences with the help of fuzzy linguistic variables. For the evolution of the design, a technique called genetic algorithm from the computational intelligence consortium is considered. The paper presents two major components. The first one is the standard genetic algorithm that is hybridised with fuzzy logic. The second component is the evolution of the design of fashion garments with the genetic algorithm that undergo fitness evaluation through various fuzzy membership functions in an interactive way. The basic motivation for the proposed research work is to design a generic genetic-fuzzy architecture, using which a customised recommendation about the garments can be made. This paper presents a generic, domain-independent algorithm for genetic-fuzzy hybridisation that can be used in several such applications to provide dual advantages of genetic evolution and computing with words and natural evolution.

The paper is organised as follows. Section 2 of the paper presents a literature review on the use of genetic algorithms, fuzzy logic, and genetic-fuzzy hybridisation in fashion design and other domains. The section also summarises the findings by identifying the research gap. Section 3 presents a generic architecture of the genetic-fuzzy hybrid computational intelligent system. Section 4 discusses an experiment to utilise the architecture presented in section 3. The experiment takes some garments in initial populations, encodes them, and calculates the fuzzy fitness. The achieved result is presented in the graphical format for comparison. Section 5 concludes the paper by giving applications, limitations, and further possible research work.

2. LITERATURE REVIEW

The literature review presented in this section is classified into three categories, namely (i) Solutions based on genetic algorithm-based techniques, (ii) Solutions based on fuzzy logic techniques, and (iii) Solutions based on other approaches, including hybrid machine learning techniques. At the end of the section, common observations and limitations are enlisted.

(i) **Solutions based on genetic algorithms:** A genetic algorithm is a computational intelligence technique inspired by the natural evolutional principle, also known as the survival of the fittest. Generally, where search space is too big and/or traditional models for solution are not available, genetic algorithms are used. In the genetic algorithm, the randomly (or naturally) selected and encoded candidates form an initial population that undergoes the testing. If some candidates are fit for the solution (by comparing with the ideal or expected solution), they are selected in the next population. On these selected and encoded candidates, various genetic operators such as selection, mutation, and crossover are applied to generate more offspring. These offspring are again tested and undergo further evolution. This process continues until one gets a satisfactory solution. Typically, the genetic algorithms are used for function optimisation and other search-based applications. The paper (Agarwal & Pal, 2021) demonstrates the use of the genetic algorithm in the domain of optimisation.

Genetic algorithms can also be used to evolve design components in different domains. Such applications are demonstrated in many designing processes, including fashion design (Hee-Su & Sung-Bae, 2000) and material design (Jennings, Lysgaard, & Hummelshøj, 2019). The latest documentation on state of the art on genetic algorithms is available at (Wang & Sobey, 2019).

It is to be noted that the creditability and quality of a genetic algorithm-based solution are dependent on its fitness functions. Well defined and strict fitness functions restrict loose and bad quality solutions from the evolution process. The fitness functions come in both the categories, general as well as application-specific. When personalised and customised solutions are required for real-time applications, interactive fitness functions are used. Such fitness functions can be seen in (Takagi, 2001), (Tsai, Hsiao, & Hung, 2006), and (Rodriguez, Diago, & Hagiwara, 2011) for evaluation of desired solutions in various domains. However, fuzzy logic is not applied to these solutions.

(ii) **Solutions based on fuzzy logic:** Fuzzy logic has been used for many recommender systems (Wang, Zeng, Koehl, & Chen, 2015) and (Ramadan & Altamimi, 2017). An IoT based approach is discussed in the work of (Chan, Lau, & Fan, 2018), which describes the use of fuzzy logic for the IoT based data gathering for fashion based retail application. A mathematical framework is also proposed in (Wang & Mendel, 2016) to manage fuzzy opinions about various products. Fuzzy logic is also used by (Chen, et al., 2019) and (Wang, Zeng, Koehl, & Chen, 2014) to handle uncertainty and to offer users some extent of ease of selection in the domain. In the work of (Yang, Jiang, & Zhang, 2020), fuzzy clustering techniques has been used to classify the garments based on their texture. The use of fuzzy logic is also seen in the work of (Zhang J., et al., 2020) for intelligent garment selection.

(iii) **Solution based on other machine learning approaches:** Other approaches, besides the categories mentioned above, are also used for the domain of fashion design and garment selection. An ontology-based garment recommendation is suggested in the work of (Ajmani, Ghosh, Mallik, & Chaudhury, 2013). Different researchers propose the use of advanced machine learning technologies in the context of developing countries (Omamo, Rodrigues, & Muliaro, 2020), modelling customer value generation (Herrera, Carvajal-Prieto, Uriona-Maldonado, & Ojeda, 2019), and supply chain risk management for products (Ray, 2021).

The traditional artificial intelligence-based system, called the knowledge-based system, is used by (Kyu Park, Hoon Lee, & Jin Kang, 1996). The paper (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012) talks about the big data in the garment industry and enlist the managerial problems associated with it. Interesting work is demonstrated for the use of a machine learning technique in the classification of pants according to the person's lower body shapes (Dong, et al., 2018). Another use of the neural network for the fashion recommendation is seen in (Jo, Jang, Cho, & Jeong, 2019), (Shin, Yeo, Sagong, Ji, & Ko, 2019), and (Sachdeva & Pandey, 2020). A collaborative fashion recommendation system is also mentioned in (Stefani, Stefanis, & Garofalakis, 2019). In the current scenario, social media is also contributing a lot towards research by providing a platform for sharing, discussion, business, and research. To feel the fashion-related objects more effectively, augmented reality-based systems are also developed and discussed on social media platforms in the work of (Adilah & Alamsyah, 2019). An analytical based method for cloths recommendation is experimented by (Zhang Y., et al., 2017), (Jain & Kumar, 2020) and (M'Hallah & Bouziri, 2016) using a hierarchical analysis method along with other techniques.

Fuzzy logic and artificial neural network are hybridised in the work of (Wang, et al., 2020) for garment pattern design. Genetic and fuzzy logic hybridisation is also used in a model for e-customisation for garment recommendation system. However, the system does not use interactive fitness functions. More details about the latest artificial intelligence and machine learning-based systems for garment recommendation is available in (Abd Jelil, 2018). Ensemble machine learning is used in the work of (Lukyamyzi, Ngubiri, & Okori, 2020) in the food industry domain.

In addition to the above-mentioned solutions, many eCommerce websites, blogs, and applications are available to guide and enhance fashion sense, such as Trendtation[1], Heartifb[2], Trendfriend[3], and Askmen[4].

The above-listed solutions and other solutions that are generally practised by the professionals and researchers in the domain have some limitations, as listed below.

- First of all, the traditional Artificial Intelligence (AI) models are not much helpful for the domain of fashion design as fashion evolves continuously and the domain is highly personalised. The acquisition and representation of knowledge along with other facilities such as explanation, reasoning, self-learning, and inference require lots of effort and obsolete very quickly. With traditional AI, fashion designing suggestions are always based on stored images and knowledge.
- Generalised solutions and recommendations might not be accepted by users with great zeal when it comes to fashion.
- Modern AI methods such as genetic algorithms with standard fitness functions and other components might not work here because of the nature of the domain and the requirement of personalised suggestions. It is easy to encode and evolve the design of fashion garments; however, it is challenging to evaluate to design with traditional and generic fitness functions.
- Further, such solutions are primarily applicable for a limited domain or a stand-alone non-hybrid type of system.
- As the standard genetic fitness functions might not work for such a domain, it is advised to use interactive fitness functions. This helps towards customised solutions to evolve, however, responses from the users always remain vague and uncertain. The generic algorithms, even with the help of the interactive fitness functions, might not help here.
- Domains such as garment design involve a considerable amount of big data, which cannot be handled by traditional methods, classical artificial intelligence and stand-alone machine learning system. Hybridisation is strongly needed. Techniques such as a genetic algorithm cannot provide effective fitness function without the help of fuzzy logic.
- As stated, the fashion design domain is constantly enriched with a lot of data from which new trends can quickly be learned with the virtue of artificial neural networks and deep learning mechanisms. However, the system using various types of the artificial neural network does not

provide advantages of evolution that come from genetic algorithms and advantages of approximate reasoning and handling uncertainty that come from fuzzy logic.

- None of the above-listed applications or research methodology uses user profiles to evolve a suitable design that is very specific and personalised as per the user's requirements.

To overcome the above mentioned limitations, a hybrid computational intelligence system for fashion design with interactive genetic fitness functions and fuzzy logic benefits is discussed in the next section.

3. THE ARCHITECTURE OF GENETIC-FUZZY SYSTEM

This section represents the design of a hybrid evolutionary system using a genetic algorithm and fuzzy logic to evolve customised garment designs.

The basic objective of the proposed research work is to design a domain-independent architecture that utilises the hybridisation of two techniques, namely (i) genetic algorithm and (ii) fuzzy logic. As discussed, there are two main objectives of the genetic-fuzzy architecture. The first objective is to evolve a suitable and customised design for garments as per the user's choice and preferences. For this, the genetic algorithm technique is used. Each individual garment is encoded into a binary genetic string, and with the selection, crossover and mutation genetic operators, the individual is evolved into a better generation. For the fitness test, domain-specific novel fuzzy interactive fitness functions are used. The second objective is to handle uncertainty and vagueness while interacting and operating with the system using a linguistic variable. This can be done with the help of fuzzy membership functions to understand the linguistic variables used in the user profiles and in the fitness functions. The design of the architecture is illustrated in Figure 1 followed by a discussion on the components of the architecture.

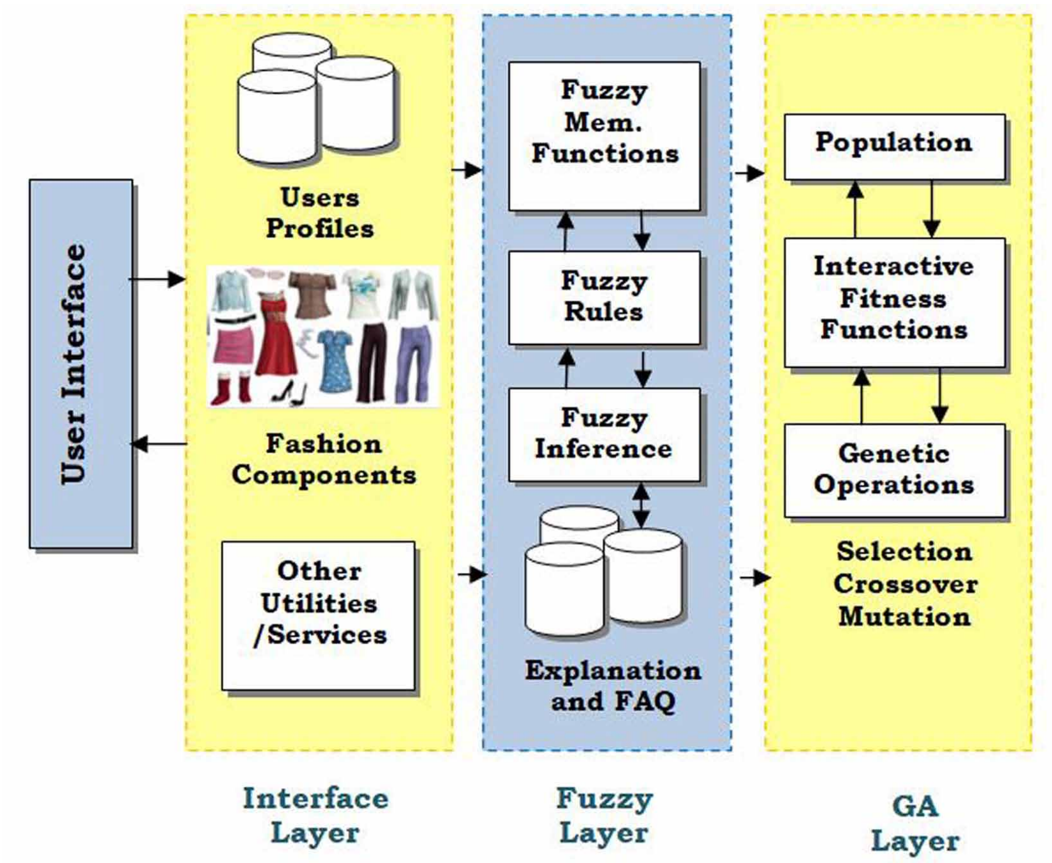
The architecture illustrated in Figure 1 works as follows. During the initial phase of the system, information related to users is collected and stored in the user profile repository. As the primary objective is to evolve a customised design, such knowledge of users becomes very important. User's information is collected in two main categories, namely (i) basic information and (ii) about garment and fashion choices. The first category involves the name, age, gender, weight, height, occupation, etc. The advanced category involves body type, interest, colour choices, preferable styles, quality of material, etc. The information is stored in user profiles and used for the selection of appropriate design. It is to be noted that some of these values are vague and can not be easily measured with crisp logic. To accommodate such linguistic fuzzy values in the system, the use of fuzzy logic is proposed. Variables such as age, quality, etc., fall under this category. As the system is designed as a web-based system to reach maximum users, some middleware services are also used here. This layer is called the **interface layer**. The fuzzy layer interprets the fuzzy variables used by the system, which contains fuzzy membership functions and fuzzy rules. Later, this layer can be used to modify the evolved design further and provides reasoning facility on demand.

The evolution of the design component is done by the third layer, called the **genetic algorithm layer.** Starting with the encoded initial population, the layer evolves necessary designs for a fashion garment. As per the standard genetic algorithm, the initial population starts with a few randomly selected designs. These individuals are encoded and undergo various genetic operations such as crossover, mutation and selection. Later they are evaluated for the fitness towards the required solution.

The genetic algorithm used in the research is given as follows.

The individuals are encoded using the binary encoding mechanism considering the basic components of a garment such as material, length, collar or neck shape, sleeves, embellishments, pockets, waistline, style, prints, colour, etc. Some of the components among these are suggested by in (Sajja, 2020). For each component, a group of 3 binary digits is selected, which represents a sufficient design. An example of encoding and genetic operations is shown in Figure 2.

Figure 1. Generic Architecture of a Genetic-Fuzzy System for Fashion Design



On the initial population having some random elements encompassing the above 10 values in the encoded format, the aforementioned genetic algorithm is applied to evolve strong individuals. For the fitness function, interactive user's feedback is considered in the absence of a particular quality measure for a good design. The interface layer does this task with fuzzy logic benefits. This process is carried out until users are interested in evolving the design, or no further improvement is seen in the feedback of users after a few generations.

The next section discusses the experiment and results in detail.

4. EXPERIMENT AND RESULTS

For this experiment, 3 digit binary encoding is selected for each of the 10 parameters selected. As stated, it is sufficient to represent a considerable number of designs. If the population size is significantly large, instead of 3 digits, more digits can be considered. For demonstration, 5 items are shown below with different shapes, styles, colours, materials, and patterns.

Item 1: { Round, Deep, Red, Sleeveless, No Pockets, Full Embellishment, Long, Chiffon, Party, Plain }
Item 2: { Straight, Collar, Black, Short, Simple Pockets, Low Embellishment, Midi, Silk, Party, Plain }
Item 3: { Fish Cut, Boat, White, Long, No Pockets, No Embellishment, Long, Crepe, Festive, Plain }

Algorithm: Genetic Algorithm

```
Parameters® P: Set of Parameters, Initial Strings in Population I
Output®: Strings of P, Modified Population I
1 Initialization: Initialize t¬true, Mut_Prob=p, Pool I
2 Evaluate_fitness(I); //Return if evaluation is ok
3 While (t)
4 Select Individual from I
5 Crossover Individuals
6 Mutation of Individual using Mut_Prob
7 I¬Modified I
8 Evaluate_fitness(I)
9 t=t+1
11 Return (I)
12 Go To Step 2.
13 Procedure Crossover()
14 Select mates
15 Obtain a crossover point C, length L
16 Interchange(Mate1, Mate 2, C, L)
17 Return(Mate 1, Mate 2)
18 Procedure Mutation(Mut_Prob)
19 Test Mut_Prob
20 Select individual
21 Bit¬Random()
22 Change (Bit)
23 Return(Individual)
```

Item 4: { A line, Square, Beige, Short, Side Pockets, No Embellishment, Short, Silk, Casual, Floral Print }
Item 5: { Wavy, Boat Neck, Blue, Elbow, Side Pockets, Low Embellishment, Midi, Rayon, Casual, Strips Print }

These items are encoded for generic operations for further evolution. See Table 1 for the demonstration of the encoding strategy with the selected examples.

Genetic operators such as selection, mutation, and crossover can be applied to individuals to generate a new population.

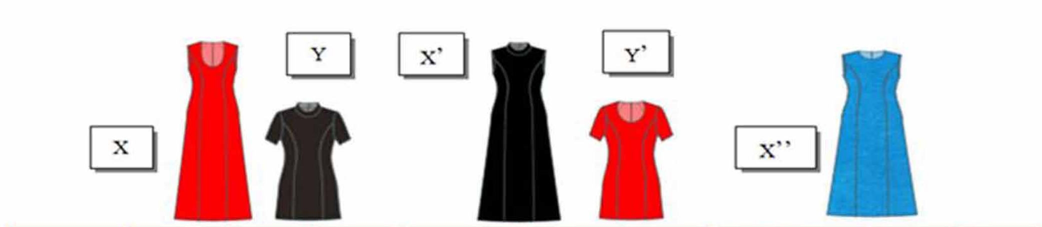
Table 2 shows the modified population after applying genetic operators to generate new individuals.

Operation 1: Mutation on Item 1 Component 4, Position 1;
Operation 2: Crossover between Item 2 and Item 3 for Components 2 and 3;
Operation 3: Crossover between Item 4 and Item 4 for Components 8, 9, and 10;
Operation 4: 2 Sites Mutations on Item 5 Component 3, Position 1 and Component 6, Position 1;

This modified population represents new elements, which undergoes fitness checking. Here fitness functions are fuzzy and interactive. Every newly evolved individual (an innovatively designed garment) is shown to users for their feedback. The feedback is collected from users on its various aspects. All the features or components of an individual design might not be considered equally important. Hence, all the features have got different weights. The weights of different parameters are taken as shown in Table 3.

For every individual, users are asked to provide fuzzy rank/values for the parameters. Weights of the parameters are pre-determined with the help of domain experts and professionals from the locations where the garments have to be supplied. The weighted sum is calculated using the weights

Figure 2. Encoding and Operations on Individuals



	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
X	Round	Deep	Red	Sleeveless	No Pockets	Full	Long	Chiffon	Party	Plain
Encoding	100	101	101	001	001	111	111	110	111	001
Y	Straight	Collar	Black	Short	Simple	Low	Midi	Silk	Party	Plain
Encoding	001	011	111	010	010	001	101	111	111	001
Crossover Between X and Y, Parameter 2 and 3 are exchanged										
X'	Round	Collar	Black	Sleeveless	No Pockets	Full	Long	Chiffon	Party	Plain
	100	011	111	001	001	111	111	110	111	001
Y'	Straight	Deep	Red	Short	Simple	Low	Midi	Silk	Party	Plain
	001	101	101	010	010	001	101	111	111	001
2 Site Mutations on X, Parameter 3, Position 2 and 3										
X''	Round	Deep	Blue	Sleeveless	No Pockets	Full	Long	Chiffon	Party	Plain
	100	101	110	001	001	111	111	110	111	001

Components: *C_1: Shape, C_2: Neck, C_3: Color, C_4: Sleeves, C_5: Pockets, C_6: Embellishment, C_7: Length /Waist, C_8: Material, C_9: Style, C_{10}: Print*

Table 1. Encoding of the initial Population

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Item 1	100	101	101	001	001	111	111	101	110	111
Item 2	101	100	111	010	100	010	110	110	110	111
Item 3	110	110	100	111	001	001	111	001	111	111
Item 4	101	101	110	010	010	001	101	110	101	110
Item 5	111	110	001	101	010	010	110	010	101	101

and the feedback from the user, based on which the fitness of the individual is decided. Table 4 and 5 show the fitness calculated for the initial population and modified population, respectively, by considering the fuzzy feedback given by a user. Here, the user might have given the fuzzy value as the fitness of various parameters. To evaluate the fitness, besides the weights of the parameters, the fuzzy membership functions are also needed. Some membership functions are illustrated in Figure 3.

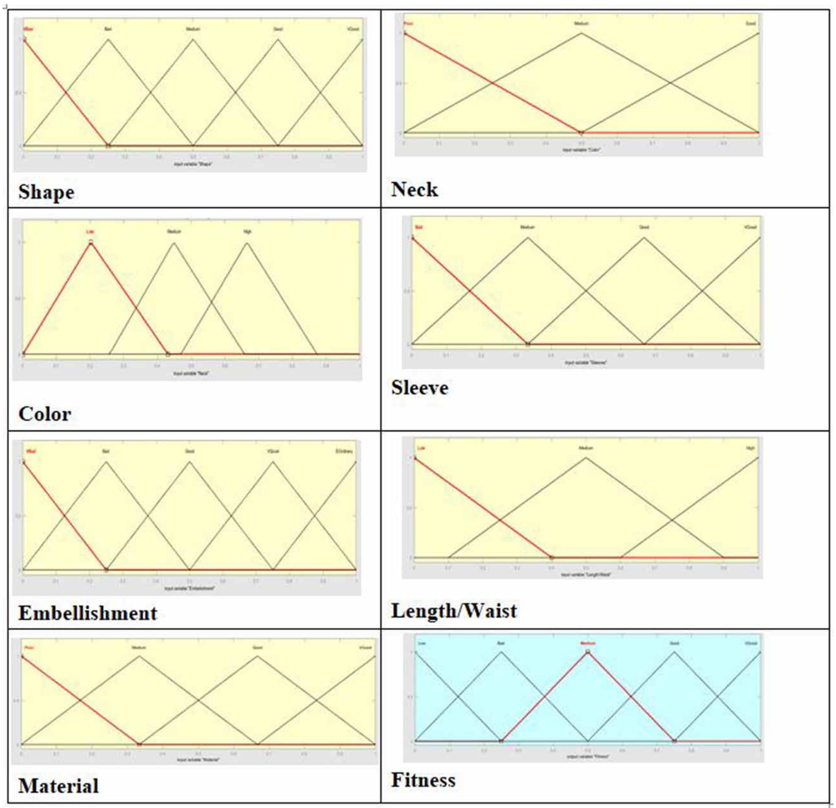
Table 2. Modified Population

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Item 1	100	101	101	101	001	111	111	101	110	111
Item 2	101	**110**	**100**	010	100	010	110	110	110	111
Item 3	110	**100**	**111**	111	001	001	111	001	111	111
Item 4	101	101	110	010	010	001	101	**010**	**101**	**101**
Item 5	111	110	101	101	010	110	110	**110**	**101**	**110**

Table 3. Weights for Different Components

Components	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Weight	0.1	0.1	0.05	0.05	0.05	0.15	0.1	0.15	0.15	0.1

Figure 3. Fuzzy Membership Functions



The user given fuzzy feedback is converted into the equivalent crisp values, and with pre-determined weights, fitness for every item is calculated. Table 4 and Table 5 also show these values besides the fuzzy feedback.

It can be observed that from Table 4 and Table 5, the average fitness, as well as the maximum fitness of design, has improved. Figure 4 illustrates the progress in fitness considering a few generations. This process can be continued for a fixed number of iteration, or a satisfactory design has evolved.

Table 4. Fitness of the Initial Population for Fashion Designing

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	Fitness
Item 1	VG	P	VG	G	M	H	M	G	L	H	
	0.8	0.2	0.8	0.5	0.5	0.7	0.4	0.5	0.2	0.8	0.52
Item 2	VG	P	VG	VG	H	M	H	VG	L	H	
	0.8	0.2	0.8	0.7	0.6	0.4	0.75	0.8	0.2	0.6	0.55
Item 3	G	M	VG	M	M	P	G	P	H	H	
	0.6	0.4	0.8	0.4	0.5	0.3	0.5	0.2	0.65	0.6	0.46
Item 4	M	G	L	VG	H	P	L	VG	M	L	
	0.4	0.6	0.2	0.8	0.6	0.2	0.2	0.8	0.5	0.2	0.44
Item 5	G	M	L	G	H	M	H	P	M	M	
	0.6	0.4	0.2	0.5	0.6	0.4	0.75	0.15	0.5	0.5	0.45

Table 5. Fitness of the Modified Population

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	Fitness
Item 1	VG	P	VG	**VG**	M	H	M	G	L	H	
	0.8	0.2	0.8	**0.8**	0.5	0.7	0.4	0.5	0.2	0.8	0.54
Item 2	VG	**P**	**VG**	VG	H	M	H	VG	L	H	
	0.8	**0.4**	**0.8**	0.7	0.6	0.4	0.75	0.8	0.2	0.6	0.57
Item 3	G	**M**	**VG**	M	M	P	G	P	H	H	
	0.6	**0.2**	**0.8**	0.4	0.5	0.3	0.5	0.2	0.65	0.6	0.45
Item 4	M	G	L	VG	H	P	L	**VG**	**M**	**L**	
	0.4	0.6	0.2	0.8	0.6	0.2	0.2	**0.15**	**0.5**	**0.5**	0.36
Item 5	G	M	**VG**	G	H	**H**	H	**P**	**M**	**M**	
	0.6	0.4	**0.8**	0.5	0.6	**0.7**	0.75	**0.8**	**0.5**	**0.2**	0.59

Sample fuzzy rules used in the system for evaluation of the feedback are illustrated in Figure 5 and Figure 6.

For the experiment, feedback of approximately 100 users is taken through a fuzzy input interface. With the initial population of the 40 different fashion garments from (http://www.st.ewi.tudelft.nl/~bozzon/fashion10000dataset/) for every user, an appropriate and acceptable design is evolved in a few generations. Also, for approximately 94% of the cases, the acceptable design has evolved in less than 15 generations. It is to be noted that the mutation probability is kept between 1 and 2 to introduce necessary diversity in the population, and crossover probability is kept at 75%. The performance,

Figure 4. Progress in the Fitness

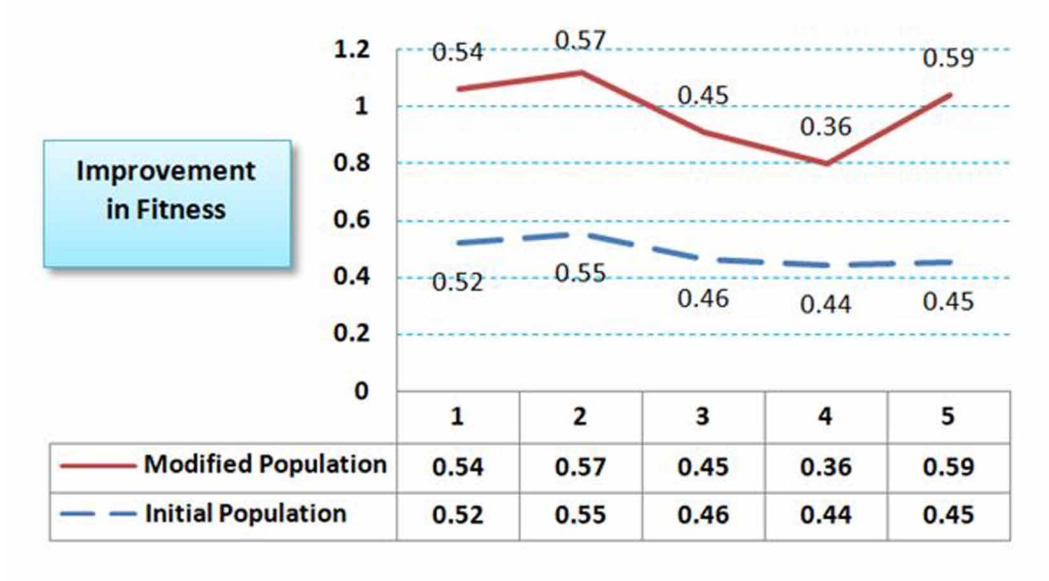


Figure 5. Sample Rules for Fuzzy Feedback Evaluation

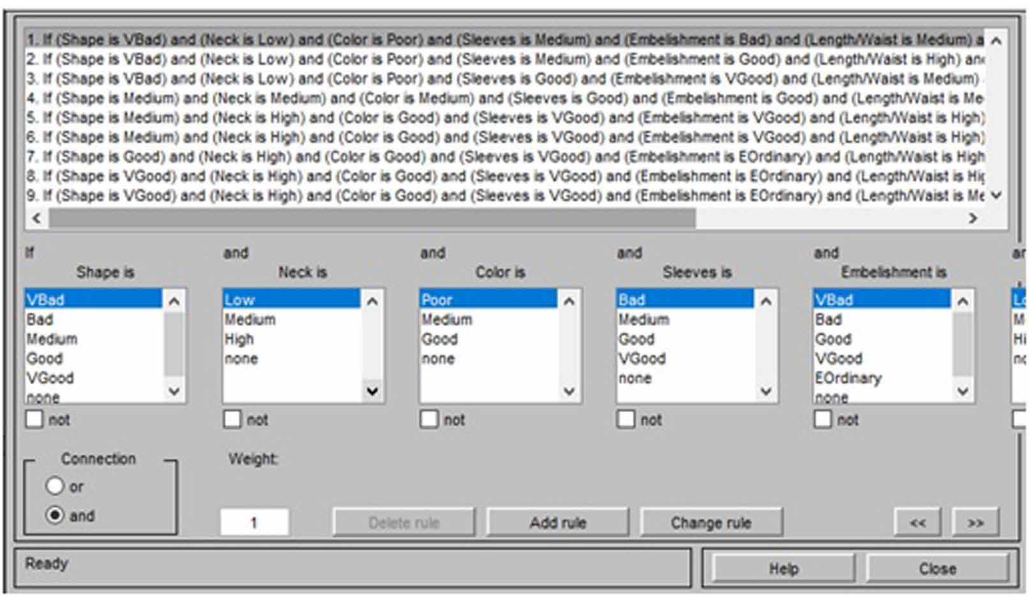
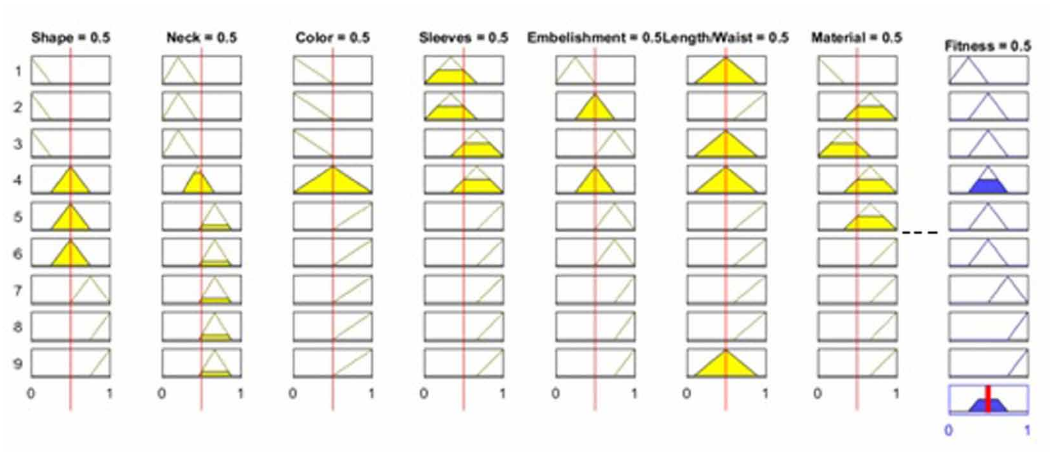


Figure 6. Graphical View of Rules



as far as accuracy and F-score are concerned, the proposed approach gives approximately accuracy as 0.86 and F-Score as 0.86 too. The other machine learning algorithms, as mentioned in the work of (Jain & Kumar, 2020), provide accuracy as well as F-score ranging from 0.75 to 0.84, whereas the proposed approach gives us a value of 0.86 for both accuracy as well as F-score. See Table 6 for the comparison of the accuracy as well as F-score. This degree of improvement in the small datasets seems insignificant; however, where it comes to a large amount of datasets, such a small improvement also brings considerable improvement in the efficiency, besides advantages based on intelligent recommendations.

Table 6. Performance Comparison

	Accuracy	F-Score
Decision Tree	0.81	0.81
Random Forest	0.84	0.84
Naieve Bays	0.75	0.75
Genetic – Fuzzy	0.86	0.86

5. CONCLUSION

The fashion industry handles a huge amount of data related to product designs. The use of modern and hybrid machine learning techniques such as a genetic-fuzzy system helps a lot in effective and customised garment recommendations. In this cut-throat competition in the post-pandemic era, where so many options are available online, such a tailor-made and intelligent system is one of the better solutions. As observed, the old fashion used to repeat themselves with some change. They might undergo several mutation and crossover operations. In this scenario, the genetic algorithm might be useful, which searches for a suitable design for its user and evolves the better and customised design. Further, the hybridisation of the genetic algorithm with fuzzy logic offers dual benefits of natural evolution and fuzzy logic approximate reasoning and dealing with vague inputs. Besides the hybridisation, the fuzzy interactive functions which are capable of dealing with linguistic variables add value to the system.

The architecture designed here is very generic and can be used to evolve designs of various products such as interiors of home, furniture, various consumer products, ornaments, software and big to small machines. For the development of the trust-based system or recommendation systems based on modern machine learning techniques in various domains, the architecture is useful.

There are few enhancements possible to the research work demonstrated in this paper. The experimental system presents all the designs deals in 2D, which can be further improved to the 3D. Parameters such as upper and lower body type, skin colour, eye colour, patterns liked by the user such as strips, floral, geometrical, solid, etc.; the previous history of purchase, link to the pictures on social media of the person, if available, can be added for improved customised design evolution.

Further, to handle the advanced level of the uncertainty involved in the domain, type-2 fuzzy membership functions can be used. A proper and complete graphical user interface can also be designed for commercial products based on the proposed architecture. One can think of a mobile application also.

REFERENCES

Abd Jelil, R. (2018). Review of Artificial Intelligence Applications in Garment Manufacturing. In S. Thomassey & X. Zeng (Eds.), *Artificial Intelligence for Fashion Industry in the Big Data Era* (pp. 97–123). Springer Singapore. doi:10.1007/978-981-13-0080-6_6

Adilah, D., & Alamsyah, A. (2019). An Augmented Method of Selecting Fashion Talent by Adding Social Media Characteristic. In *2019 International Conference on ICT for Smart Society (ICISS)*, (pp. 1-5). doi:10.1109/ICISS48059.2019.8969834

Agarwal, A., & Pal, K. (2021). Optimization of Unit Commitment Problem Using Genetic Algorithm. *International Journal of System Dynamics Applications*, *10*(3), 21–37. doi:10.4018/IJSDA.2021070102

Ajmani, S., Ghosh, H., Mallik, A., & Chaudhury, S. (2013). An ontology based personalized garment recommendation system. In *Proceedings of the 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, (pp. 17-20). IEEE Computer Society. doi:10.1109/WI-IAT.2013.143

Chan, C. O., & Lau, H. C., & Fan, Y. (2018). IoT data acquisition in fashion retail application: Fuzzy logic approach. In *2018 International Conference on Artificial Intelligence and Big Data (ICAIBD)*, (pp. 52-56). doi:10.1109/ICAIBD.2018.8396166

Chen, X., Chen, H., Xu, H., Zhang, Y., & Cao, Y. (2019). Personalized fashion recommendation with visual explanations based on multimodal attention network: Towards visually explainable recommendation. In *42nd International ACM SIGIR Conference on Research and Development in Information Retrieva*. ACM. doi:10.1145/3331184.3331254

Dong, M., Hong, Y., Zhang, J., Liu, K., Wagner, M., & Jiang, H. (2018). A body measurements and sensory evaluation-based classification of lower body shapes for developing customized pants design. *Industria textilă, 69*.

Hee-Su, K. (2000). Application of interactive genetic algorithm to fashion design. *Engineering Applications of Artificial Intelligence*, *13*(6), 635–644. doi:10.1016/S0952-1976(00)00045-2

Herrera, M. M., Carvajal-Prieto, L. A., Uriona-Maldonado, M., & Ojeda, F. (2019). Modeling the Customer Value Generation in the Industry's Supply Chain. *International Journal of System Dynamics Applications*, *8*(4), 1–13. doi:10.4018/IJSDA.2019100101

Jain, S., & Kumar, V. (2020). Garment Categorization Using Data Mining Techniques. *Symmetry*, *12*(6), 984. doi:10.3390/sym12060984

Jennings, P. C., Lysgaard, S., & Hummelshøj, J. S. (2019). Genetic algorithms for computational materials discovery accelerated by machine learning. *NPJ Computational Materials, 46*(5).

Jo, S., Jang, H., Cho, H., & Jeong, J. (2019). Scenery Based Fashion Recommendation with Cross Domain Geneartive Adverserial Networks. In *2019 IEEE International Conference on Big Data and Smart Computing*, (pp. 1-4). doi:10.1109/BIGCOMP.2019.8679117

Kyu Park, C., Hoon Lee, D., & Jin Kang, T. (1996). Knowledge-base construction of a garment manufacturing expert system. *Journal of Clothing Science and Technology*, *8*(5), 11–28. doi:10.1108/09556229610151099

Lukyamyzi, A., Ngubiri, J., & Okori, W. (2020). Towards Ensemble Learning for Tracking Food Insecurity From News Articles. *International Journal of System Dynamics Applications*, *9*(4), 129–142. doi:10.4018/IJSDA.2020100107

M'Hallah, R., & Bouziri, A. (2016). Heuristics for the combined cut order planning two-dimensional layout problem in the apparel industry. *International Transactions in Operational Research*, *23*(1-2), 321–353. doi:10.1111/itor.12104

McAfee, A., Brynjolfsson, E., Davenport, T., Patil, D., & Barton, D. (2012). Big data. The management revolution. *Harvard Business Review*, *90*(10), 61–70. PMID:23074865

Omamo, A. O., Rodrigues, A. J., & Muliaro, W. J. (2020). A System Dynamics Model of Technology and Society: In the Context of a Developing Nation. *International Journal of System Dynamics Applications*, *9*(2), 42–63. doi:10.4018/IJSDA.2020040103

Ramadan, R. A., & Altamimi, A. B. (2017). Hierarchal Fuzzy Logic Controller and Internet of Things (IoT) Information: Disease Spreading as a Test Case. *International Journal of System Dynamics Applications*, *6*(3), 1–28. doi:10.4018/IJSDA.2017070104

Ray, P. (2021). Agricultural Supply Chain Risk Management Under Price and Demand Uncertainty. *International Journal of System Dynamics Applications*, *10*(2), 17–32. doi:10.4018/IJSDA.2021040102

Rodriguez, L., Diago, L., & Hagiwara, I. (2011). Interactive Genetic Algorithm with fitness modeling for the development of a color simulation system based on customer's preference. *Japan Journal of Industrial and Applied Mathematics*, *28*(1), 27–42. doi:10.1007/s13160-011-0032-2

Sachdeva, H., & Pandey, S. (2020). Interactive Systems for Fashion Clothing Recommendation. *Interactive Systems for Emerging Technology in Modelling and Graphics*, 287-294.

Sajja, P. S. (2020). *Illustrated Computational Intelligence: Examples and Applications*. Springer.

Shin, Y., Yeo, Y., Sagong, M., Ji, S., & Ko, S. (2019). Deep Fashion Recommendation System with Style Feature Decomposition. *2019 IEEE 9th International Conference on Consumer Electronics*.

Stefani, M., Stefanis, V., & Garofalakis, J. (2019). CFRS:ATrends-Driven Collaborative Fashion Recommendation System. In *2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA)*, (pp. 1-4). Patras, Greece: Academic Press.

Takagi, H. (2001). Interactive evolutionary computation: Fusion of the capabilities of EC optimization and human evaluation. *Proceedings of the IEEE*, *89*(9), 1275–1296. doi:10.1109/5.949485

Tsai, H. C., Hsiao, S. W., & Hung, F. K. (2006). An image evaluation approach for parameter-based product form and color design. *Computer Aided Design*, *38*(2), 157–162. doi:10.1016/j.cad.2005.10.001

Wang, L., & Mendel, J. M. (2016). Fuzzy opinion networks: A mathematical framework for the evolution of opinions and their uncertainties across social networks. *CoRR, abs/1602.06508*.

Wang, L., Zeng, X., Koehl, L., & Chen, Y. (2014). Intelligent fashion recommender system: Fuzzy logic in personalized garment design. *IEEE Transactions on Human-Machine Systems*, *45*(1), 95–109. doi:10.1109/THMS.2014.2364398

Wang, L., Zeng, X., Koehl, L., & Chen, Y. (2015). Intelligent Fashion Recommender System: Fuzzy Logic in Personalized Garment Design. *IEEE Transactions on Human-Machine Systems*, *45*(1), 95–109. doi:10.1109/THMS.2014.2364398

Wang, Z., & Sobey, A. (2019). A comparative review between Genetic Algorithm use in composite optimisation and the state-of-the-art in evolutionary computation. *Composite Structures*, 233.

Wang, Z., Xing, Y., Wang, J., Zeng, X., Yang, Y., & Xu, S. (2020). A knowledge supported approach for garment pattern design using fuzzy logic and artificial neural networks. *Multimedia Tools and Applications*, 1–21. doi:10.1007/s11042-020-10090-6

Yang, J., Jiang, Y., & Zhang, Y. (2020). Edge Fuzzy Clustering by Eliminating Undesirable Features in Garment Texture Image Segmentation. *IEEE Access: Practical Innovations, Open Solutions*, *8*, 45368–45377. doi:10.1109/ACCESS.2020.2976793

Zhang, J., Liu, K., Dong, M., Yuan, H., Zhu, C., & Zeng, X. (2020). An intelligent garment recommendation system based on fuzzy techniques. *Journal of the Textile Institute*, *111*(9), 1324–1330. doi:10.1080/00405000.2019.1694351

Zhang, Y., Liu, X., Shi, Y., Guo, Y., Xu, C., Zhang, E., Tang, J., & Fang, Z. (2017). Fashion Evaluation Method for Clothing Recommendation Based on Weak Appearance Feature. *Scientific Programming*, *2017*, 1–12. doi:10.1155/2017/8093057

ENDNOTES

1 https://www.trendtation.com
2 https://www.heartifb.com
3 https://www.trendfriend.io
4 https://www.askmen.com

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