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A Comprehensive Design for a Manufacturing System using Predictive Fuzzy Models

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Abstract

Today, the design factors of manufacturing systems are still an active research topic and the predictive models are highly interested by the scholars. Design and manufacturing costs are some of the key issues for determining the competitive product in the global market. During current research a guideline to estimate mechanical cost of developing and manufacturing processes presented. The anticipated equation embeds both engineering factors and cost management contributors that could be applied to estimate, predict, control, and reduce costs. Applicable cost factors have been determined by designers using any suitable method for weighing and ranking in the related industries. The cost design model has been established by comparing the target cost of design and design real cost. The target cost of design should be experimentally nominated based on the product's cost and profit in the context. The manufacturing cost-based design cost forecasting model then validated using an effective fuzzy statistical method. The proposed model creates economical manufacturing of an affordable design in line with the design capability for manufacturing in terms of cost & price.

Keywords:

Design; Cost, Criteria; Model; Mechanical; Estimation; Function; Manufacturing; Fuzzy; linear; DFM

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Abbreviations:

ANFIS	Adaptive neuro fuzzy interface system	MFG	Manufacturing
		MPP	Market product price
ANN	Artificial neural network	MRA	Multiple regression analysis
CFs	Cost factors	MSE	Mean squared error
DFM	Design for manufacturing		
DRC	Design real cost	NNs	Neural networks
FCM	Fuzzy clustering means	PDP	Profit designed product
FMEA	Failure mode and effects analysis	QC	Quality control
MAE	Mean absolute error	RMSE	Root mean squared error

1. Introduction

In a competitive environment, it is necessary that the design process and cost engineering are combined for calculating the cost of design with the definition and selection of cost-effective factors. Cost estimation in the early stages of design projects involves a great deal of uncertainty. Therefore, there is a great demand for an effective way to reduce uncertainty in the product's cost estimation. An effective-cost prediction method can be the process of identifying and measuring cost-effective factors in design for manufacturing (DFM). Optimization and cost reduction in the manufacturing process must begin with the design process and the prerequisite of this is to identify all the aspects of the design cost.

These factors must be general, functional, flexible and integrated to be able to illuminate all the design cost perspectives regardless of product type and scope for the designer and manufacturer. The design cost factors should also cover all stages of the design, and the more these criteria are in the early stages of design, the more efficient it will be to control and optimize them. Our method can be used to predict manufacturing costs based on the cost of mechanical design.

Before 1980, the cost estimation and determination of design and manufacturing projects has been accomplished by two methods: (1) feasibility study and (2) use of cost data in similar projects. Since artificial intelligence became popular in the 1980s, a new approach to estimating design costs has been introduced, while several studies have used different methods to estimate costs across a wide range of industrial applications. Later, in the 1990s, neural networks (NNs) were introduced as a branch of artificial intelligence as an alternative method of estimating manufacturing costs. (Anderson, 2017) presented a report on the design and engineering cost analysis of minerals processing. The use of neural networks for cost product packaging modeling was developed by (Zhang et al. 1996; Shtub and Versano, 1999) compared to neural network performance and regression analysis when estimating the cost of constructing a steel pipe bending process. (Cavalieri, et al. 2004) compared parametric models and neural networks to estimate production costs and concluded that the neural network performs better and is more reliable. (Verlinden, et al. 2008) developed MRA and ANN-based models to estimate the cost of a sheet metal production. (Bo LI, et al. 2017) Researched on Design Innovation Approaches: product form, decoration materials, brand image building cost control& product promotion for Enhancing Product Value Based on Cost Control. (Arabzadeh and Niaki, 2018) estimated the cost of spherical storage tanks by artificial neural networks and hybrid regression. (Chan , 2002) introduced an expert system for manufacturability and cost evaluation. (Izadi et al. 2020) presented a review and cost structure models and cost factors of road freight transportation.

The early stages of product development have uncertainties and factors such as the design time and the manufacturing process, and this directly affects the cost estimation of the product and design project (Xu et al. 2012). (Kolbachev, 2017) suggested that the cost of manufacturing a machine early in the engineering process can be estimated. Such an estimate is based on its parametric information integration index. Design processes are a structural index entropy-based approach.

The most important reason for doing this research is the need to have a flexible way of accurately calculating the design cost to predict the manufacturing cost with actual cost data in the design process regardless of the type, shape and raw material used in making the product. It provides an applied flexible method for identifying & selecting design cost factors based on a mechanical designed product. Determination and calculation of design costs are existed by these factors for providing in a competitive market. The monitoring of cost-effective factors helps to optimize the price of the designed products. Calculated design costs as outputs can be used to predict manufacturing costs as a criterion of design for manufacturing and cost feasibility study. In the following, you will find out how to design cost factors, how to choose the most effective factors, and the design cost model and its application environment. The manufacturing cost forecasting function is also presented using the design cost in two linear-numerical and fuzzy-regression methods using real data.

The rest of this paper is followed by four sections. Section 2 addresses the materials and methods of this paper to study the background as well as the comprehensive method. Section 3 is the results of the analyses on the proposed method. Section 4 performs the validation, comparison and sensitivity of the method. Finally, the conclusion and future works are drawn in Section 5.

2. Materials and methods

This model offers a comprehensive, flexible, and proactive approach that is based on the collection of frequently used operational data on the cost of designing or estimating them and makes it possible to predict and estimate the cost of manufacturing based on a fuzzy regression method for a product or set designed and it will develop the DFM method. Figure 1 illustrates a comprehensive view to the proposed method.

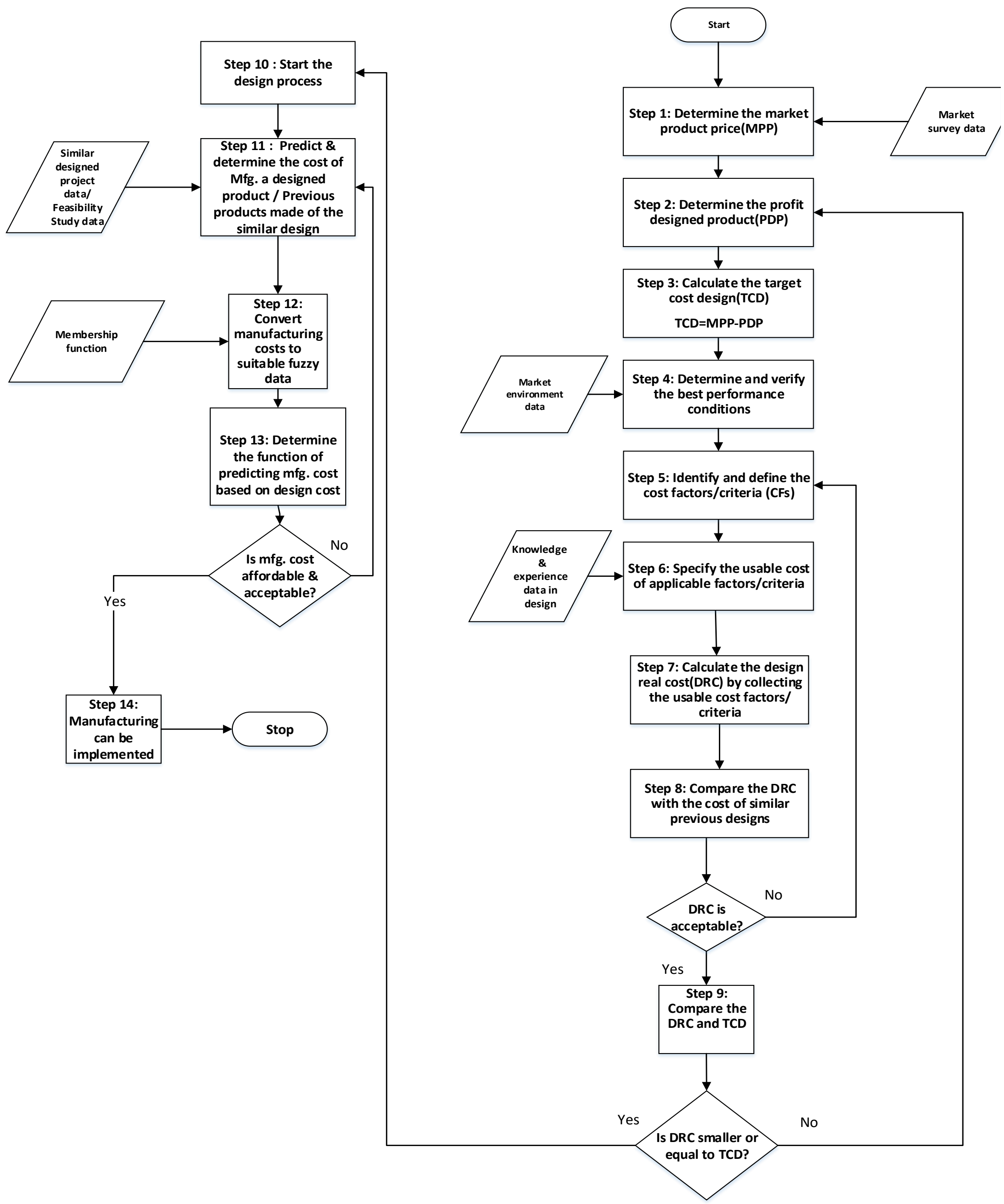

Fig. 1. A graphical view of our comprehensive method

According to the flowchart the following steps must be taken:

Step 1 & 2: Determination of market product price (MPP) & profit designed product (PDP):

Designer organizations can consider the designed product as a marketable product and determine the selling price based on the information related to the market and also consider the amount of profit from this sale based on their market strategies.

The MPP and PDP should be determined by reliable data through the systematic market surveys and feasibility study.

Step 3: Calculation of target cost of design (TCD):

This model has two inputs from the internal environment (Design Real Cost) and external environment (Target Cost of Design). This step delivers the target cost of design (TCD) so it is needed to analyze all of the stages in the product design process and the cost is calculated by determining effective factors. The TCD is predicted by the PMP and PDP. The DRC should be calculated before starting the design process as proactive action. So a database for recording the DRC's results is required to compare this information with the TCD. Analyzed information must have a target, trend, comparison, cause, and scope.

At the beginning, this process in designer companies documented procedure is recommended.

Step 4: Determining and verification the best performance conditions:

Based on their strategic plans, design and manufacturing organizations should determine the conditions of the product presentation environment in terms of product price and the desired profit margin.

For identifying the best condition, the following issues should be considered:

The market price of product (MPP) should be presented as higher than average in the desired market.

The design real cost (DRC) could be occurred in the low and medium level.

Profit designed product (PDP) could be had two levels between medium and high.

Step 5: Identification and definition of cost factors (CFs):

This step gives the design real cost (DRC) that helps for determining the affordable product's manufacturing volumes and it is used for estimating the returned capital of the product design.

The new contributive method is based on researches, studies, technical interviews and audit results of several companies so this general practical model is applicable for determining cost in engineering design for economic manufacturing.

The DRC formula has been generated by the effective design cost factors with a general application for all of the design & manufacturing organizations.

The following set of factors is used to calculate the DRC by applicable factors with notification to the rate of usability. The data related to the factors have been recorded by designers during the suitable stages of design activities.

The following factors are used in the stages of mechanical design process regardless of product type, product application, and product complexity but the applicability level of these factors should be determined based on the scoring method through the knowledge of designers and designer's qualifications.

CF_1: Cost of the design feasibility study

This mechanical feasibility study will address the current mechanical system and suggest an alternative approach for mechanical system design. The design feasibility study is proactive teamwork that is providing evidence of capability for designing of the desired product as needed design inputs. This cost covers all of the dimensions of the feasibility study to product's definition, written of engineering performance, tolerances review, adequate capacity, required tools and equipment, such as FMEA, risk analysis, life cycle analysis. (Nonami et al. 2005)

CF_2: Human cost (Designers)

The human cost could be defined as salary, bonus, gifts and it is applicable for full time/ part-time personals which are in a design team. (Li et al. 2018)

CF_3: Software cost (General, Technical & Special)

All of the costs related to software and applications that used in the design process for creating design outputs, design reviews, calculations and re-calculations, simulation and solving methods and operational testing could be specified. (Sánchez et al. 2017)

CF_4: Cost of customer's verification/ user's validation

Sometimes designers need to get verification or validation for more confidence and the cost of these activities should be calculated for adding to design cost. (Maropoulos et al. 2010)

CF_5: Cost of design's references

Designers need to use books, standards, journals, technologies, knowledge, seminars, training workshops, specialized exhibitions, technical consulting. (Silva et al. 2019)

CF_6: Cost of documented researches

Collection of data and creation information related to design and development of products could be a contented descriptive model of a design process, a respective model of design, computer-based models, languages, representations, and environments of design, analysis of design such as DFM, reliability, & serviceability. (Finger et al. 1989)

CF_7: Cost of design's benchmarking

Cost of activities for comparing a product in current and past such: similar designs, idea, sketch, technologies, patents. (Nick et al. 2010)

CF_8: Cost of design review between inputs & outputs

A structured approach is described to analyze the design of mechanical systems and equipment which includes the design specification, and system, functional unit & component levels of design. The design review considers maintainability, reliability and all other factors which contribute to the total performance of a plant. Specific analysis techniques are described with respect to their applicability to different stages in a design review exercise. It covers all of the activities which be included comparison reports, structured meetings, and completion of review checklists, force analysis, DFM's reports, and client's review. (Thompson et al. 2007)

CF_9: Cost of prototype building/Product Modeling

One of the tangible costs in the design process is prototype building and this cost should be determined in operational condition for more effectiveness. (Jones et al. 1996; Otto et al. 2000)

CF_{10}: Cost of necessary tools, gages & equipment for verifying/validating

If designers use some tools for measuring, control and verification, these costs will be added to the cost of design projects. (Ertas et al. 1992)

CF_{11}: Cost of time-consuming for design

Design is one of the operations that is based on time planning / duration and could be affected by cost of design. This factor shall be measured by the monetary unit. (Xu et al. 2006; Holliman et al. 2019)

CF_{12}: Cost of design changes

Each change in design stages shall be passed through review, verification and validation steps and all of these activities can increase the cost. It could change the design outputs in conjunction with design inputs so. (Ullah et al. 2016)

CF_{13}: Cost of specific environmental condition as applicable

This is the cost of design for an environment such as material purification, less material variety, avoidance of toxins, use of recycled materials and includes eco-design, raw materials selection and use, manufacturing, material handling, installation and maintenance, use and end of life. (Sahiti et al. 2016)

CF_{14}: Cost of re-calculations/testing /inspections

Includes the cost of calculations with other design methods such as design verification, cost of laboratory tests, operational testing, durability testing, design of experiments calibration & measurement system analysis. (Hwang et al. 2004)

Applicability of the cost factors for mechanical design stages are shown in Table 1. This table shows the importance of CFs with a number of applications for measuring and monitoring. After the definition and measurement of CFs, as it can be seen CF_2, CF_3 & CF_{10} must be measured and monitored continuously. The CF_{12} & CF_{13} should be controlled in planned intervals. Other CFs is used for increasing cost-effectiveness.

Engineering design process is a specialized process that after achieving design costs, a decision-making process and team action formation must be done.

Table (1): Contribution of cost factors on design's stages

Tasks / cost factors	CF_1	CF_2	CF_3	CF_4	CF_5	CF_6	CF_7	CF_8	CF_9	CF_{10}	CF_{11}	CF_{12}	CF_{13}	CF_{14}
Design Planning	●	●	●							●				
Generate, Develop & Verification	●	●	●	●	●	●	●	●	●	●		●	●	
Manufacturing & test of prototypes		●	●					●	●	●		●	●	●
Changes & Improvement Improvement		●	●							●	●	●	●	●

Step 6: Specification of cost applicable factors:

The applicability coefficients of cost factor could be determined based on recognition and experience competent designers by surveys, interviews or Focus on group studies. At this point, design experts are scoring each of the cost factors with a scoring method based on product recognition. This stage can be done individually or in the form of a scoring team. It helps the designers who collect the most applicable cost factors for fast calculation of the real design cost.

Step 7: Calculation of design real cost (DRC) by collecting cost factors:

Based on the available factors, the design team will be able to anticipate and determine each of the cost factors that have been selected as the applicable factor in the previous step and calculate the DRC by summing all the factors. Also, if the organization has already had experience in the previous similar design project, it can use its cost data at this stage.

Step 8: Comparison of the DRC & the cost of similar previous designs (Where appropriate):

If possible, the organization has had successful design projects in the past and its cost records are available, these results can be used to confirm the results of the new design costs.

Step 9: Relating the DRC and TCD:

Comparison of the DRC and TCD for making an optimum decision for conducting design process:

(1) TCD-DRC ≥ 0 $\rightarrow$ Design Operation could be done.

TCD-DRC < 0 $\rightarrow$ Design process will be reviewed according to the cost management approach. It may be replaced with another option such as: outsourced design, change of design inputs, use of cheaper technology, elimination of unnecessary product specifications, and Customer agreement on reducing additional expectations.

Also, the analyzed data from this model for each designed product could be used as benchmarked information for designing of other similar products. Comparing these results in designed products/projects could help managers/leaders for getting factual decision making for increasing the design effectiveness.

Step 10: Implementing the design process:

The design process should be realized in conjunction with to design plan within any focus to eliminate non-value-added costs through design stages.

Step 11: Predicting & determining the cost of manufacturing of a designed product/ previous products made of the similar design:

Cost of design data and cost of manufacturing data is collected through the design and manufacturing processes. The cost of raw material could be excluded of these data because the Cost of materials is very different for different products. Accurate recording of design and manufacturing cost data is very effective in subsequent analyzes, and this data may be generated from an operational design and manufacturing process or a process of predicting and feasibility design and manufacturing.

Step 12: Converting manufacturing costs to suitable fuzzy data:

Since manufacturing costs are not always accurate during the design process, manufacturing cost data is converted to fuzzy data by mentioned fuzzy sets and suitable membership functions.

Step 13: Determining the function of predicting manufacturing cost based on design cost:

When numerical design data and fuzzy manufacturing data are generated into an appropriate number and acceptable accuracy in a product or collection, with known statistical method, the function of predicting manufacturing cost based on design cost or estimated design cost could be found by using the regression equation method. The value of the dependent variable for different values of the independent variable is estimated by the regression line. In order to estimate the appropriate factors for the model, an attempt is made to select the model that has the least error based on the available data.

This manufacturing prediction function can be considered as basic criteria in design methodology for manufacturing, which is the concern of most organizations.

Step 14: Manufacturing:

After estimating the manufacturing cost based on the function obtained from the previous stage and being acceptable, the manufacturing implementation can be started.

3. Results

In this section, to illustrate the performance of the design cost estimation to determine or predict the manufacturing cost, an attempt is made to use tangible numerical examples or illustrative examples and the results of these steps are analyzed and discussed Without any emphasis on the type of methods used such as Shannon entropy, Taguchi, etc.

For the determination of the MPP and PDP, Table 2 shows an illustrative example of steps 1 and 2 data with a simple calculation for three types of manufacturing i.e. Refrigerators, Hydraulic Cylinder and Waste Containers (sample industry). The target cost of the design (TCD) is calculated according to step 3.

Table (2): MPP and PDP cost data by market survey & total costs by feasibility study

Product No.	($)MPP	($)PDP	($)MPP-PDP	($) Total Cost of mfg., material & overhead material	($)TCD
Stationary & hyd. cylinder 2 tone	20	2	18	17	18-17=1
Stationary & hyd. cylinder 5	28	3	25	24	25-24=1
Stationary & hyd. cylinder	32	3	29	27	29-27=2
Stationary & hyd. cylinder	37	4	33	31	33-31=2
Stationary & hyd. cylinder	40	4	36	34	36-34=2

At the stage 4, the best performance conditions could be validated by using Taguchi method (Zhang et al. 2009; Parameshwaranpillai et al. 2011). In this situation for example, it will get 2 factors (DRC&

PDP) with two levels, it will be 4 experiments and the Taguchi's method introduces L4. Recording of trial conditions for the above definition are shown in Table 3.

Table (3): Description of the trial Condition (Taguchi L4)

Trial Condition	Factors	Level Description: 0<Low≪0.3 0.3<Medium≪0.7 0.7<High≪1	Level #
1	PDP	Medium	1
	DRC	Low	1
2	PDP	High	2
	DRC	Medium	2
3	PDP	Medium	1
	DRC	Medium	2
4	PDP	High	2
	DRC	Low	1

In order to better illustrate, we have defined the low, medium and high operating ranges in the range of zero and one as follows: Low (0, 0.3], Medium (0.3, 0.7], High (0.7, 1]

Results of Taguchi's method (Table 4) shows the best S/N ratio is in nominal QC type for trial#3. Which means The Profit designed product (PDP) & Design real cost (DRC) should be in high range or the more cost-effective the design is, the more successful the product is in sales and profit.

Table (4): Results of the analyzed QC Types

QC Type	Conditions	Sample#1	Sample#2	Sample#3	S/N Ratio	Average
	Trial #1:	0.7	0.7	0.1	-15.403	
Bigger	Trial #2:	0.8	1	0.8	-1.384	-6.7405
	Trial #3:	1	0.9	0.9	-0.632	
	Trial #4:	1	1	0.2	-9.543	
	Trial #1:	0.7	0.7	0.1	4.814	
	Trial #2:	0.8	1	0.8	1.191	
Smaller	Trial #3:	1	0.9	0.9	0.588	2.06675
	Trial #4:	1	1	0.2	1.674	

	Trial #1:	0.7	0.7	0.1	9.208	
nominal	Trial #2:	0.8	1	0.8	18.75	
	Trial #3:	1	0.9	0.9	24.771	14.8595
	Trial #4:	1	1	0.2	6.709	

In step 5, all the effective factors of the design cost were defined, and in order to introduce an illustrative numerical example, we first present the factors that can be used according to step 6, using the average score of the three independent design groups (Table 5), and then return to step 5. These data are based on a simple scoring method between 1 to 10, which means that the score moves from point one to point ten, the usability decreases.

Table (5): Average score on the gathered data from 7 independent designer groups

Inputs	CF_1	CF_2	CF_3	CF_4	CF_5	CF_6	CF_7	CF_8	CF_9	CF_{10}	CF_{11}	CF_{12}	CF_{13}	CF_{14}
1	6	2	8	3	5	6	7	3	4	2	3	5	5	3
2	7	2	5	4	4	4	5	2	3	2	2	6	4	3
3	7	1	6	2	3	4	4	2	4	1	2	4	6	4
4	8	2	8	3	5	6	7	3	5	2	3	5	5	5
5	6	3	6	3	4	6	6	3	4	3	2	4	4	5
6	5	1	5	4	5	7	7	4	3	2	3	5	4	3
7	7	1	6	3	4	6	6	2	2	1	2	7	5	4

It is needed to specify the usability factor for each factor by using a matrix with (m) rows (number of options) and (n) columns (number of indicators/factors). Each element of this matrix; x_{ij} is called as decision-making matrix data and the data matrix values have been normalized using equation 1 and the entropy of the probability distribution; E_{ij} has been calculated. After calculating the degree of deviation dj, the weight rate has been specified. The level of the construct's approximating to the optimum condition may be presented as a level of the construct's entropy which is evaluated by using Shannon's methodology (Ghasemzadeh et al. 2018) Lowering the entropy level gets the construct's conditions closer to the optimum and formulated by equation.

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \; ; j = 1,2, \dots , n \tag{1}$$

$$Ej = -\left[\frac{1}{Ln\,(m)}\right] * \sum_{i}^{m} (Pij \times Ln\; Pij) \; ; i = 1,2, \dots , m \tag{2}$$

$$dj = 1 - Ej \tag{3}$$

$$Wj = \frac{dj}{\sum_{j=1}^{n} dj} \tag{4}$$

Table(6): Calculations of the usability of CFs by Shannon's entropy

Cost Factors	CF_1	CF_2	CF_3	CF_4	CF_5	CF_6	CF_7	CF_8	CF_9	CF_{10}	CF_{11}	CF_{12}	CF_{13}	CF_{14}
SUM	46	12	44	22	30	39	42	19	25	13	17	36	33	27
P_{1j}	0.13	0.16	0.18	0.13	0.167	0.15	0.16	0.15	0.16	0.15	0.17	0.13	0.15	0.11
P_{2j}	0.15	0.16	0.11	0.18	0.133	0.10	0.11	0.10	0.12	0.15	0.11	0.16	0.12	0.11
P_{3j}	0.15	0.08	0.13	0.09	0.1	0.10	0.09	0.10	0.16	0.07	0.11	0.11	0.18	0.14
P_{4j}	0.17	0.16	0.18	0.13	0.167	0.15	0.16	0.15	0.2	0.15	0.17	0.13	0.15	0.18
P_{5j}	0.13	0.25	0.13	0.13	0.133	0.15	0.14	0.15	0.16	0.23	0.11	0.11	0.12	0.18
P_{6j}	0.10	0.08	0.11	0.18	0.167	0.17	0.16	0.21	0.12	0.15	0.17	0.13	0.12	0.11
P_{7j}	0.15	0.08	0.13	0.13	0.133	0.15	0.14	0.10	0.08	0.07	0.11	0.19	0.15	0.14
E_j	0.99	0.95	0.99	0.98	0.993	0.99	0.99	0.98	0.983	0.96	0.98	0.99	0.99	0.98
d_j	0.00	0.04	0.00	0.01	0.007	0.01	0.00	0.01	0.017	0.03	0.01	0.00	0.00	0.01
W_j	0.02	0.21	0.04	0.05	0.036	0.04	0.04	0.08	0.088	0.16	0.05	0.04	0.02	0.06

The last row of Table 6 (W_j) is shown as percentage in Table 7 and used for ranking of cost factors, in which shows that the cost factors 2, 8, 9&10 have the most impact or importance in comparison with other factors. This means that approximately 20% of the cost factors estimate 80% of the design cost.

Table (7): Ranking of Cost factors based on usability

Cost	CF_1	CF_2	CF_3	CF_4	CF_5	CF_6	CF_7	CF_8	CF_9	CF_{10}	CF_{11}	CF_{12}	CF_{13}	CF_{14}
%W	2	22	4	6	4	5	4	9	9	16	5	5	3	6
Rank	14	1	11	6	12	8	10	4	3	2	5	9	13	5

In step 7, the design cost of a stationary hydraulic cylinder (Jack) at different tonnages is provided in Table 8 by illustrative example.

Table (8): The CF's data of the Stationary & Hydraulic Cylinder in different capacities

Cost Factors ($)	CF_1	CF_2	CF_3	CF_4	CF_5	CF_6	CF_7	CF_8	CF_9	CF_{10}	CF_{11}	CF_{12}	CF_{13}	CF_{14}
2 Ton	196	3920	539	1392	343	882	578	2450	2548	2871	902	735	270	1568
5 Ton	196	3920	539	1392	343	882	578	2450	2548	2871	902	735	270	1568
10 Ton	200	4000	550	1420	350	900	590	2500	2600	2930	920	750	275	1600
15 Ton	218	4360	600	1548	382	981	843	2725	2834	3194	1003	818	300	1744
20 Ton	228	4560	627	1620	399	1026	673	2850	2964	3340	1049	855	314	1824

The data of Table 8 should be specified for each part of hydraulic cylinders exactly as following Table 9.

Table (9): The DRC's data of the Stationary & Hydraulic Cylinder in different capacities

Parts DRC ($)	Jack Base	Filler Cylinder	External Shell	Nut	Valve	Drainer	Keeper	Pod	Inside Cylinder	Brass	Lever	Filler Piston	Piston's Screw	Piston	Handle
2 Ton	222	1302	1508	161	1851	116	960	925	994	89	13	960	1337	126	823
5 Ton	222	1302	1508	161	1851	116	960	925	994	89	13	960	1337	126	823
10	229	1441	1574	146	1921	120	987	961	961	93	13	1014	1307	133	854
15	243	1539	1642	153	2052	128	105	102	1026	10	14	1180	1411	174	112
20	243	1550	1651	155	2032	132	106	106	1042	10	14	1194	1423	172	172

Table 10 has been formed by TCD (the last column of Table 2) and DRC (the sum of rounded values of Table 9 in accordance to steps 8 and 9 in which the difference of these amounts are positive showing the design implementation could be done according to step 10; since the design process is affordable.

Table (10): TCD & DRC data for comparison and decision making to start the design process

Product type	($) Target cost of design (TCD)*20000	($) Design real cost (DRC)	($) TCD-DRC
2 Ton	20000	19000	1000
5 Ton	20000	19000	1000
10 Ton	40000	20000	20000
15 Ton	40000	22000	18000
20 Ton	40000	23000	17000

When the amount of the 4^{th} column of the Table 10 is positive, the implementation of design will be affordable and the design process could be started. The results are shown that implementation of design will be more economic when the capacity of the hydraulic jack is high.

As mentioned in step 11, at this stage, the numerical data related to the manufacturing (mfg.) cost are determined or predicted in the same structure as the design cost in Table 11.

Table (11): The Mfg. cost's data for Stationary & Hydraulic Cylinder in different capacities

Parts / Mfg. ($)	Jack Base	Filler Cylinder	External Shell	Supporting Nut	Valve	Drainer	Keeper	Pod	Inside Cylinder	Brass bushing	Lever	Filler Piston	Piston's Screw	Piston	Handle
2 Ton	3.3	0.27	0.25	1.1	0.15	0.11	0.14	0.5	0.3	0.2	0.17	0.12	0.5	0.65	0.15
5 Ton	3.6	0.30	0.26	1.2	0.17	0.12	0.15	0.5	0.4	0.23	0.2	0.13	0.5	0.75	0.17
10 Ton	4.4	0.33	0.33	1.3	0.21	0.14	0.18	0.6	0.5	0.27	0.2	0.15	0.6	0.88	0.19
15 Ton	4.9	0.37	0.35	1.5	0.25	0.15	0.2	0.9	0.55	0.32	0.25	0.19	1	1.2	0.25
20 Ton	5	0.38	0.36	1.5	0.25	0.16	0.2	1	0.6	0.35	0.3	0.19	1	1.2	1.2

Since manufacturing costs are not always accurate during the design process, manufacturing cost data is converted to fuzzy data by triangle membership functions. The Fuzzy set and membership functions are shown in Table 12.

Table (12): Fuzzy sets and membership functions

Triangle (Min, Mode, Max)	**Scope**	**Membership Function**	**Fuzzy Set**
$(\mathbf{3.75, 5, 5})$	$3.75 \leq x \leq 5$	$U(x) = (x - 3.75)/\ (5 - 3.75)$	Very High
$(\mathbf{2.5, 3.75, 5})$	$2.5 \leq x \leq 3.75$ $3.75 \leq x \leq 5$	$U(x) = (x - 2.5)/\ (3.75 - 2.5)$ $U(x) = (5 - x)/\ (5 - 3.75)$	High
$(\mathbf{1.25, 2.5, 3.75})$	$1.25 \leq x \leq 2.5$ $2.5 \leq x \leq 3.75$	$U(x) = (x - 1.25)/(2.5 - 1.25)$ $U(x) = (3.75 - x)/(3.75 - 2.5)$	Medium
$(\mathbf{0, 1.25, 2.5})$	$0 \leq x \leq 1.25$ $1.25 \leq x \leq 2.5$	$U(x) = (x - 0)/(1.25 - 0)$ $U(x) = (2.5 - x)/(2.5 - 1.25)$	Low
$(\mathbf{0, 0, 1.25})$	$0 \leq x \leq 1.25$	$U(x) = (1.25 - x)/(1.25 - 0)$	Very Low

In this part, the data on manufacturing costs have been converted to fuzzy data and fuzzy data have been specified in Table 13 as illustrative fuzzy example. In the following, with the help of this example, we will analyze fuzzy regression and validate the results for further transparency.

Table (13): Lingual terms and equal fuzzy sets for manufacturing cost for stationary and hydraulic cylinder

Part Number	Design cost	Fuzzy set Mfg.	Triangle Fuzzy Mfg.	Part Number	Design cost	Fuzzy set Mfg.	Triangle Fuzzy Mfg.
1	2228	High	(2.5,3.75,5)	39	1026	Very Low	(0,0,1.25)
2	2228	High	(2.5,3.75,5)	40	1067	Low	(0,1.25,2.5)

3	2295	Very High	(3.75,5,5)	41	994	Very Low	(0,0,1.25)
4	2437	Very High	(3.75,5,5)	42	994	Very Low	(0,0,1.25)
5	2439	Very High	(3.75,5,5)	43	961	Very Low	(0,0,1.25)
6	1302	Very Low	(2.5,3.75,5)	44	1026	Very Low	(0,0,1.25)
7	1302	Very Low	(0,0,1.25)	45	1042	Very Low	(0,0,1.25)
8	1441	Very Low	(0,0,1.25)	46	891	Very Low	(0,0,1.25)
9	1539	Very Low	(0,0,1.25)	47	891	Very Low	(0,0,1.25)
10	1550	Very Low	(0,0,1.25)	48	934	Very Low	(0,0,1.25)
11	1508	Very Low	(0,0,1.25)	49	1052	Very Low	(0,0,1.25)
12	1508	Very Low	(0,0,1.25)	50	1092	Very Low	(0,0,1.25)
13	1574	Very Low	(0,0,1.25)	51	1371	Very Low	(0,0,1.25)
14	1642	Very Low	(0,0,1.25)	52	1371	Very Low	(0,0,1.25)
15	1651	Very Low	(0,0,1.25)	53	1334	Very Low	(0,0,1.25)
16	1611	Low	(0,1.25,2.5)	54	1437	Very Low	(0,0,1.25)
17	1611	Low	(0,1.25,2.5)	55	1448	Very Low	(0,0,1.25)
18	1468	Low	(0,1.25,2.5)	56	960	Very Low	(0,0,1.25)
19	1539	Low	(0,1.25,2.5)	57	960	Very Low	(0,0,1.25)
20	1550	Low	(0,1.25,2.5)	58	1014	Very Low	(0,0,1.25)
21	1851	Very Low	(0,0,1.25)	59	1180	Very Low	(0,0,1.25)
22	1851	Very Low	(0,0,1.25)	60	1194	Very Low	(0,0,1.25)
23	1921	Very Low	(0,0,1.25)	61	1337	Very Low	(0,0,1.25)
24	2052	Very Low	(0,0,1.25)	62	1337	Very Low	(0,0,1.25)
25	2032	Very Low	(0,0,1.25)	63	1307	Very Low	(0,0,1.25)
26	1165	Very Low	(0,0,1.25)	64	1411	Low	(0,1.25,2.5)
27	1165	Very Low	(0,0,1.25)	65	1423	Low	(0,1.25,2.5)
28	1201	Very Low	(0,0,1.25)	66	1268	Very Low	(0,0,1.25)
29	1283	Very Low	(0,0,1.25)	67	1268	Very Low	(0,0,1.25)
30	1321	Very Low	(0,0,1.25)	68	1334	Very Low	(0,0,1.25)
31	960	Very Low	(0,0,1.25)	69	1745	Low	(0,1.25,2.5)
32	960	Very Low	(0,0,1.25)	70	1727	Low	(0,1.25,2.5)
33	987	Very Low	(0,0,1.25)	71	823	Very Low	(0,0,1.25)
34	1052	Very Low	(0,0,1.25)	72	823	Very Low	(0,0,1.25)
35	1067	Very Low	(0,0,1.25)	73	854	Very Low	(0,0,1.25)
36	925	Very Low	(0,0,1.25)	74	1129	Very Low	(0,0,1.25)
37	925	Very Low	(0,0,1.25)	85	1727	Low	(0,1.25,2.5)
38	961	Very Low	(0,0,1.25)	-	-	-	-

4. Comparison, Validation & Accuracy Analysis

After normalizing the design cost and mfg. cost of base part of hydraulic cylinder 2 ton in the 1st column of the Tables 9 & 11, Fig. 2 is depic

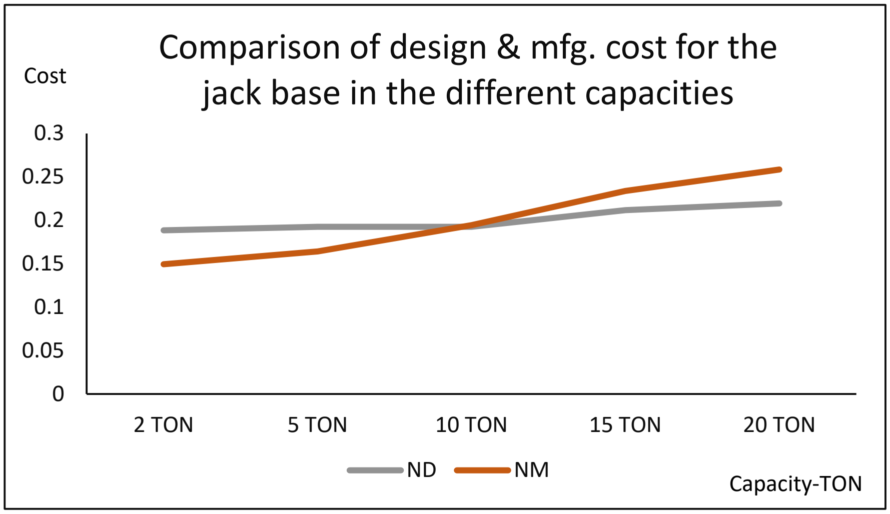

Fig.2. Trend cost of the design and mfg. for the base part in different capacities.

After studying the cost of design for hydraulic cylinders in a variety of capacities in Table 9, Fig. 3 could be considered.

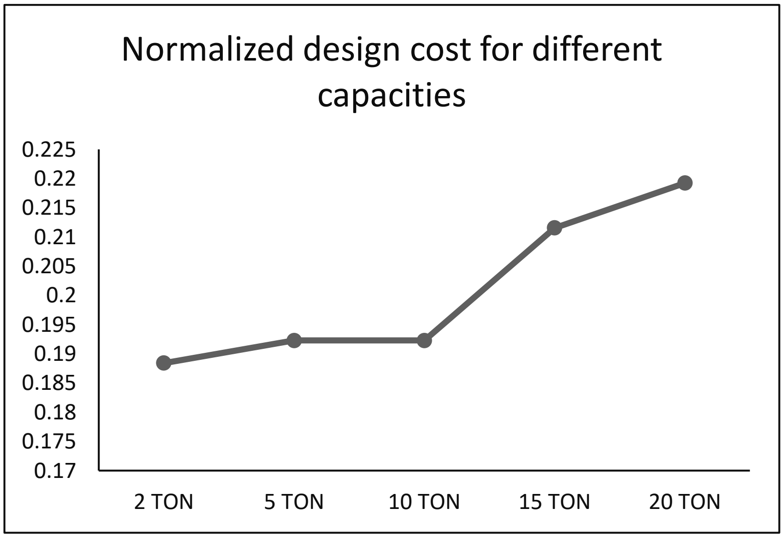

Fig.3. Design cost of the hyd. cylinders with different capacities.

The cost of manufacturing for hydraulic cylinders in a variety of capacities as given in Table 11, could be shown in Fig. 4.

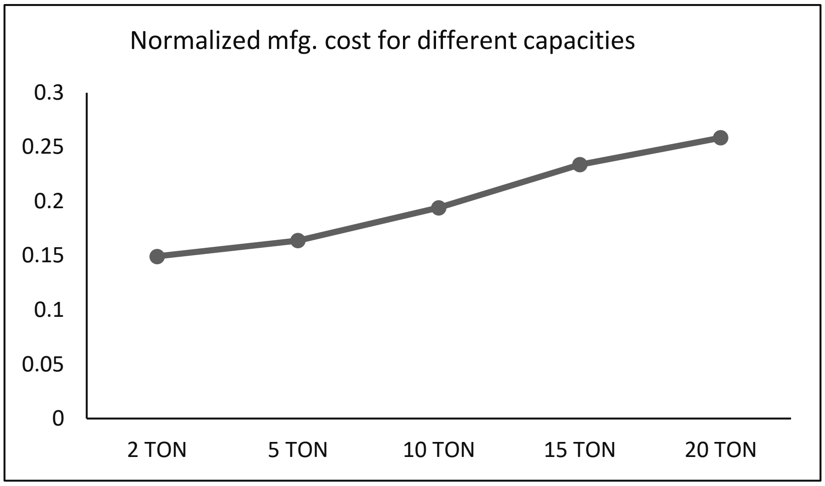

Fig.4. Cost of manufacturing the hyd. cylinders with different capacities.

The next figure shows the linear regression function of the manufacturing cost based on design cost for different capacities between 2-20 ton & it helps to facilitate of estimation the cost of manufacturing by design cost for higher capacities of hydraulic cylinders such as 25,30.

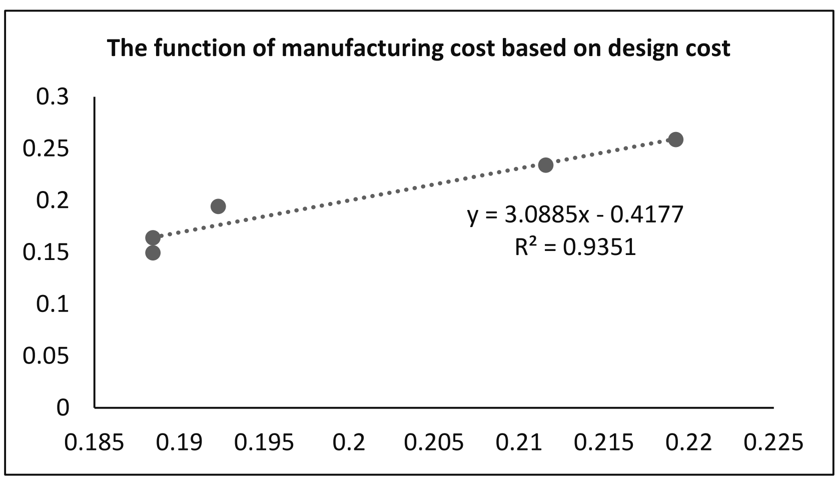

Fig.5. Regression function of the mfg. cost based on design cost for different ton.

The neuro-fuzzy hybrid system is a learning mechanism that utilizes the training and learning neural networks to find parameters of a fuzzy system based on the symptoms created by the mathematical model. Adaptive learning is an important characteristic of neural networks. Adaptive Neuro-Fuzzy Inference System (ANFIS) is used for system identification based on the available data (Loganathan et al. 2013), this modeling approach is based on data classification and then applying activation functions or so-called membership functions.

The purpose of this is to move data from scalar space to a higher dimension so that data can be easily processed. One of the most important functions used in this field is the Gaussian activation function which gives good accuracy in modeling. In summary, the data is first given to the network and based on input and output it generates an elementary model by membership and clustering functions using the fuzzy clustering means (FCM). In the following, this basic model is optimized by a hybrid or error propagation algorithm, and we present the fuzzy and final learning model. The data presented after sorting and removing the additional columns have 4 columns (see the Table13, 1 of the columns is that design and another 3 columns are fuzzy mfg.) As such, the first column being the input and the next three columns the output of the fuzzy model. The method is such that the data is first divided into two subsets by a random separator function.

The first subset contains 85% of the data used to train fuzzy networks. The second subset contains 15% of the data used for fuzzy model validation and testing. The fuzzy converter is therefore trained by 85% of the data and then tested with the remaining 15% to ensure the correct model performance. It is necessary to explain that the modeling process is performed 3 times to model all three outputs with the input of the first column. Inputs are the design's costs and outputs are manufacturing's cost.

Results of analysis have been drawn for 3 variable outputs such as coefficient of determination(R), R squared (R^2), mean squared error (MSE), root mean squared error (RMSE) and mean absolute error (MAE) in Table 14.

Table (14): ANFIS Parameters for three variable parameters

ANFIS Parameters	Variable 1	Variable 2	Variable 3
R^2	0.6987	0.8781	0.491
R	0.836	0.937	0.701
MSE	8.2	1.2	2273.5
RMSE	2.86	1.09	47.7
MAE	0.33	0.13	5.51

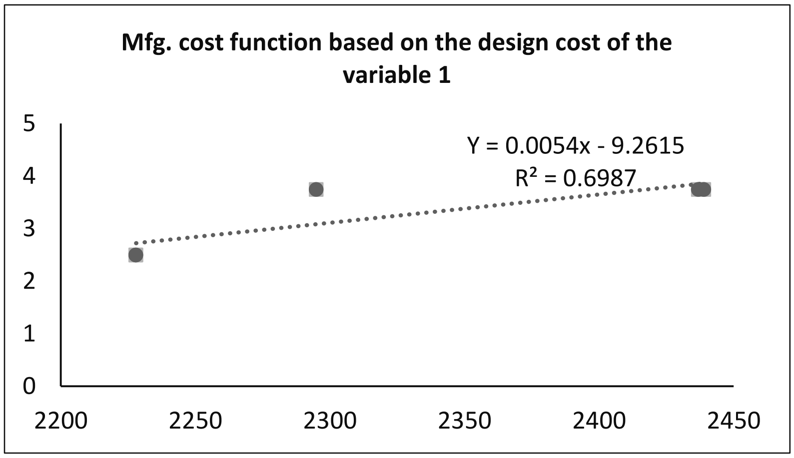

Fig.6. Mfg. regression function variable output 1

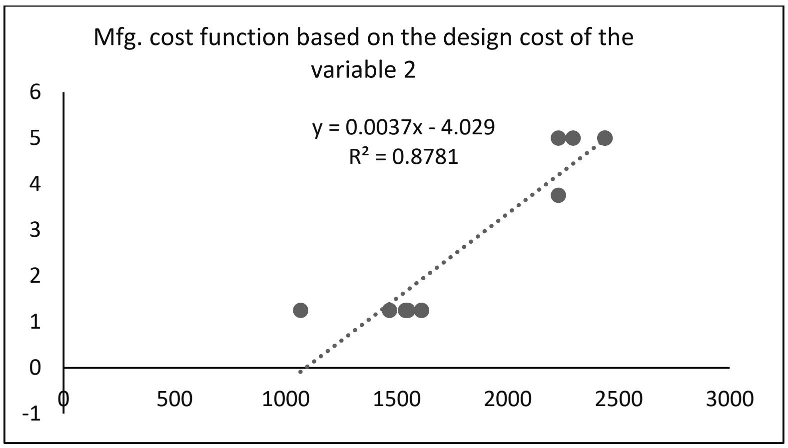

Fig. 7. Mfg. cost regression function Variable output 2

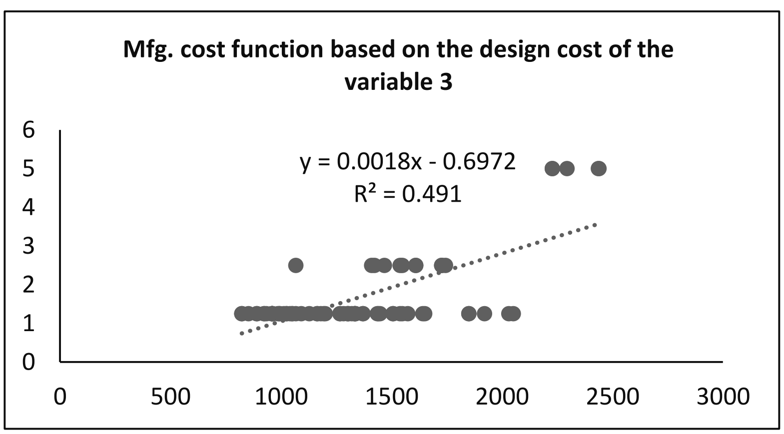

Fig. 8. Mfg. cost regression function Variable output 3

The coefficient R^2 indicates the dominance of the model in estimating the output data .Therefore, by studying the coefficient of R^2, in Table 14, it is specified that variables 2 is acceptable because it has a lower error rate so.

5. Conclusion

The proposed model presented is a scientific and practical one that has high applicability in designing and manufacturing organizations also it is applicable for making a factual decision in a design for the manufacturing process and it provides monitoring applied dashboard for managing, controlling and improving desired results of the design process.

We have developed a comprehensive method for determining cost- effective factors during the design and development process to predict and realize the real cost of design (DRC) in the framework of the target cost of design (TCD) and have evolved it with the suitable method for ranking and selecting effective applicable factors. These cost factors can help improve the integrity of the design and improve the performance of the designers as criteria for the design process.

The real cost of design also enables companies to evaluate the future of the designed product form (features, types, complexities, characteristics, and limitations). Design cost is a key feature of determining the final product's selling price and achieving profit in a competitive market. One of the most important things to pay attention to is that in this way the designed product can be considered as a final product to be delivered, meaning that this method will be applied to solely designer companies. Another benefit of this approach is that to reduce the cost of manufacturing, which is one of the most important issues of an organization today, it is necessary to rely on the design cost, and by focusing on design cost centers, organizations can achieve an effective design to reduce manufacturing costs. This achievement can enable design and manufacturing organizations to consider the cost of design and manufacturing as one of the key criteria in DFM's evaluation method for their products. This method allows designers to choose the best design at affordable costs from the proposed designs and it can be a mechanism for deciding cost-based design.it is a novel fuzzy approach to predict manufacturing cost based on optimal design cost that is adaptable to the nature of different design and manufacturing organizations. Also, studying the cost and value of the design for the manufacturing process based on measuring cost efficiency can be considered in further researches as its productivity indicator.

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