# Temporal Evolution of Design Principles in Engineering Systems: Analogies with Human Evolution

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**Abstract.** Optimization of an engineering system or component makes a series of changes in the initial random solution(s) iteratively to form the final optimal shape. When multiple conflicting objectives are considered, recent studies on *innovization* revealed the fact that the set of Pareto-optimal solutions portray certain common design principles. In this paper, we consider a 14-variable bi-objective design optimization of a MEMS device and identify a number of such common design principles through a recently proposed automated innovization procedure. Although these design principles are found to exist among near-Pareto-optimal solutions, the main crux of this paper lies in a demonstration of temporal evolution of these principles during the course of optimization. The results reveal that certain important design principles start to evolve early on, whereas some detailed design principles get constructed later during optimization. Interestingly, there exists a simile between evolution of design principles with that of human evolution. Such information about the hierarchy of key design principles should enable designers to have a deeper understanding of their problems.

**Keywords:** Multi-objective optimization, Automated innovization, MEMS design, Evolution, Design principles.

## 1 Introduction

Gathering better and richer knowledge about a problem always fascinated man. In the context of engineering design, this amounts to discovering and understanding a number of aspects related to the design problem at hand. First and foremost, the designer is interested in knowing what shape, parameters, materials etc. would make a solution *optimal* with respect to one or many objectives of design. Optimality is an important consideration, as the designers are aware that an optimal design is always competitive and can never be bettered by any other solution. With the classical mathematics-oriented [11] and non-traditional optimization tools, such as evolutionary algorithms, simulated annealing, etc.

that are available today, finding a near-optimal solution to a complex engineering problem involving non-linear objectives and constraints, mixed nature of variables, computationally expensive evaluation procedures, and stochasticities in evaluation process can all be achieved reasonably well.

Secondly, with the machine learning and data mining tools available today, designers can hope to know more beyond just finding the optimal solutions of a problem. They can provide a deeper understanding about the properties of optimal solutions and gather valuable knowledge for their future use. A recent study on *innovization* proposed the use of two or more conflicting objectives to find a set of trade-off near Pareto-optimal solutions and then an analysis of the solutions to unveil hidden design principles common to them [7]. The recent use of machine learning principles enabled an automated innovization task [1, 2] by which design principles of certain structure can be identified by a careful clustering-cum-classification study.

Optimization is an iterative process in which the task is started with one or more random solutions. Solutions are then modified by the algorithm's operators to hopefully find better solutions. The solution update procedure is continued iteratively till one or more satisfactory solutions are found. The process, if thought carefully, is an evolutionary process, in which a set of random naive solutions (most likely not resembling at all with the final optimal solutions) get changed to take shape of optimal solutions. This process can be viewed similar to the human evolution, a process that started from the creation of prokaryotes cells (around 4,000 million years ago (Ma)) to eukaryotes (around 2,100 Ma) to sponges (around 600 Ma) to vertebrates (around 500 Ma) to tetrapods (around 390 Ma) to synapsida (around 256 Ma) to reptiles (around 250 Ma) to placental mammal (around 160 Ma) to primates (around 75 Ma) to Hominidae (around 15 Ma) to Australopithecus Afarensis (around 3.6 Ma) to Homo erectus (around 1.8 Ma) to Homo Sapiens (160 thousand years ago) and to the ancestors of modern day Homo Sapiens (around 12,000 years ago) [9]. Several milestone developments along the way made the evolution of modern human possible and the information about these key developments are important for the evolutionists to have a better understanding of how we have come and where we may go from here. The development of back-bone (vertebrate) as early as around 500 Ma was the first major event in the human evolution. Thereafter, the development of legs around 390 Ma was another major breakthrough that allowed the creatures to leave water and come to land. Many other significant anthropological developments took place along the way, which eventually helped create high-performing living creatures like humans.

In this paper, we consider a specific engineering design task for our study and first find a set of trade-off, near-Pareto-optimal solutions using an EMO procedure. These high-performing solutions can be viewed similar to the human population of today who can be considered better and high-performing compared to all of their ancestors since the beginning of life formation about four billion years ago. Thereafter, we perform an automated innovization task to these high-performing design solutions to reveal a set of design principles that are common to them. These principles may be thought similar to the features that are common to the human race, such as having a backbone, legs, skulls etc. of certain type. As the human history of evolution reveals a chronology of developments (such as being a vertebrate first, then developing legs, and so on), in this paper, we are particularly interested in investigating the evolutionary history of the design principles. For this purpose, we suggest a computational procedure and reveal interesting time-line of formation of design ideas along an optimization process. Such information about a problem provides valuable insight about the importance of various design principles and should help designers to better understand their problems and eventually create better designs.

### 1.1 Multi-Objective Optimization and Automated Innovization

Multi-objective optimization considers multiple conflicting objectives and theoretically gives rise to a set of Pareto-optimal solutions, each of which is optimal corresponding to a trade-off among the objectives. Since the outcome are multiple solutions, multi-objective optimization is ideal for finding a set of alternate solutions either for finally choosing a single preferred solution or to launch a future analysis. Due to the population approach and ability to introduce artificial niches within a population, evolutionary algorithms (EAs) are ideal for solving multi-objective optimization problems, particularly for handling a maximum of three or four objectives.

For the purpose of future analysis of Pareto-optimal solutions, as mentioned above, recent studies have proposed an *innovization* task for discovering innovative solution principles through a multi-objective optimization procedure [7]. Since Pareto-optimal solutions are all optimal, they are likely to possess some common properties related to design variables, objectives and constraints that remain as 'signatures' to Pareto-optimal solutions. After the proof-of-principle results were demonstrated in a number of engineering design problems in the original study [7], a few recent studies have attempted to discover common design principles automatically using a sophisticated machine learning procedure [1, 2], which we discuss here in brief.

Automated innovization, proposed in 2010, uses a grid-based clustering technique to identify correlations in any multi-dimensional space whose dimensions are provided by the user. It thus also overcomes the limitation of SOM-based data-mining where the search for features is restricted to the objective space and the decision space. The procedure was later extended [2] so that design principles hidden in all possible Euclidean spaces formed by the variables and objectives (and any other user-defined functions) can be obtained simultaneously without any human interaction. This is achieved at the cost of restricting the mathematical structure of the design principles to a multiplicative form given by, $\prod_{j=1}^{N} \phi_j(\mathbf{x})^{a_j b_j} = c$, where $\phi_j$'s are the symbolic entities (variables, objectives functions etc.) called basis functions which can have a Boolean exponent $a_j$ and a real valued exponent $b_j$. It is argued that since many natural, physical, biological and man made processes are governed by formulae with the same structure (power laws [10]), most correlations are expected to be mathematically captured by it. By definition, the expression on the left hand side of above equation is a design principle if it evaluates to approximately the same value for a majority of the Pareto-optimal solutions. $c$ is thus a measure of commonality and the extent of this commonality is obtained by clustering the evaluated $c$ values. For further details readers are referred to [2].

## 2 MEMS Design Case Study

MEMS are tiny mechanical devices that are built upon semiconductor chips and are measured in micrometers. They usually integrate across different physical domains a number of functions, including fluidics, optics, mechanics and electronics and are used to make numerous devices such as pressure sensors, gyroscopes, engines and accelerometers. The present design problem concerns a comb-drive micro-resonator shown in Figure 1. There are 14 design variables as shown in Figure 1, $V$ is the voltage amplitude and $N_c$ is number of rotor comb fingers. The variable bounds are: $2\mu m \leq L_b, L_t, L_{sy}, L_{sa} \leq 400\mu m$, $2\mu m \leq w_b, w_t, w_c \leq 20\mu m$, $10\mu m \leq w_{sy}, w_{sa}, w_{cy} \leq 400\mu m$, $4\mu m \leq x_0 \leq 400\mu m$, 7 Volts $\leq V \leq$ 50 Volts and $3 \leq N_c \leq 66$. The design is subject to 10 linear

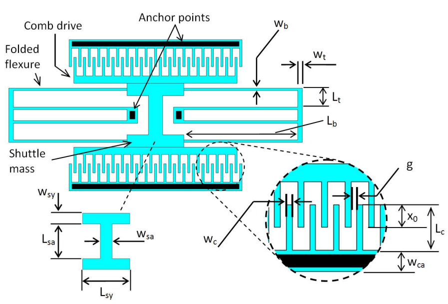


**Fig. 1.** MEMS model adapted from [8].

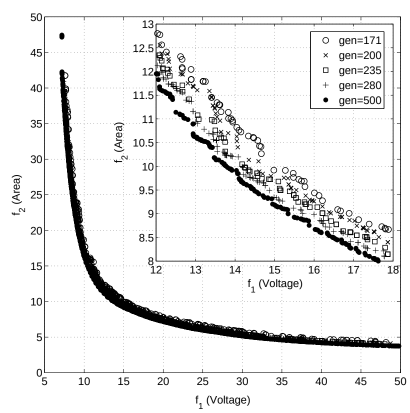


**Fig. 2.** Progress of EMO solutions towards Pareto-optimal front.

constraints and 14 non-linear constraints. The objectives of design are (i) minimization of the power consumption (applied voltage), and (ii) minimization of the total area of MEMS device. Further details about the problem can be found in [8].

### 2.1 Generation of Pareto-optimal Front

This highly non-linear design optimization problem was previously solved using NSGA-II [6] with an external archive for collecting the non-dominated solutions

[13, 12]. In this study, the original implementation of NSGA-II is used instead. To have statistical invariance, 10 different runs are performed each with $P = 500$ population members for $MAXGEN = 500$ generations. Each NSGA-II run uses the same parameters: SBX (Simulated Binary Crossover [5]) operator with $p_c = 0.9$ and $\eta_c = 15$, and polynomial mutation operator [4] with $p_m = 0.033$ and $\eta_m = 20$. All variables except $N_c$ are real-valued. A binary string of length 6 bits is used to represent $N_c$, for which $p_c$ and $p_m$ are 0.9 and 0.0125, respectively. The non-dominated solutions from each run are accumulated and sorted using the dominance criterion. This process gives rise to $1,198$ trade-off high-performing solutions.

To ensure a proper convergence, a local search procedure (the nonlinear gradient-based minimization algorithm `fmincon` from MATLAB) is applied to the $\epsilon$-constrained MEMS design problem [3] on each of $1,198$ solutions. However, since gradient-based algorithms cannot efficiently handle discrete variables, in order to improve any non-dominated solution along one of the objective axis, $N_c$ and the other objective are kept fixed. It is observed that the difference between NSGA-II solutions and the local-searched solutions are quite small. The improved non-dominated front is shown in Figure 2.

## 3 Results

The previous study [12] attempted to visually decipher design trends among these solutions. In the following section, we apply a recently-proposed automated innovization algorithm [1] to unveil design knowledge in a more quantitative way.

### 3.1 Design Principles using Automated Innovization

$1,198$ non-dominated solutions obtained above are used for the innovization study. All 14 design variables and the two objective functions are chosen as the basis functions needed for the automated innovization study. The optimization formulation of the automated innovization problem is solved using a single-objective NSGA-II which uses the following settings: (i) population Size = 500, (ii) number of generations = 500, (iii) niched tournament selection operator, (iv) single-point binary crossover with $p_c = 0.85$ and SBX with $p_c = 0.90$, and $\eta_c = 10$, (v) bitwise mutation with $p_m = 0.15$ and polynomial mutation with $p_m = 0.05$ and $\eta_m = 50$. Table 1 lists all 15 design principles found by the automated innovization study. The last column is a measure of the extent of commonality among the $1,198$ non-dominated solutions. It is referred to as the significance and is simply the percentage of the trade-off solutions whose $c$ values get clustered. Minimum allowable significance is a user parameter in innovization and has been set to 70% in this case. A few interesting aspects of the comb driven micro-resonator design problem obtained from the automated innovization study are as follows:

1. Six design principles, namely DP1, DP2, DP4, DP7, DP8 and DP9 are all more or less constant for at least 80% of the data. The third column shows

**Table 1.** Automated innovization results for the MEMS design problem.

| Notation | Design principle | Cluster average ($\mu_{largest}$) | Significance |
|---|---|---|---|
| DP1 | $w_c^{1.0000} = c$ | 2.000231E-06 | 98.50 % |
| DP2 | $w_{sy}^{1.0000} = c$ | 1.000441E-05 | 97.16 % |
| DP3 | $L_{sa}^{1.0000} = c$ | 1.169490E-05 | 88.23 % |
| DP4 | $w_t^{1.0000} = c$ | 2.001497E-06 | 87.65 % |
| DP5 | $L_t^{1.0000} = c$ | 6.873649E-06 | 87.40 % |
| DP6 | $L_{sy}^{1.0000} = c$ | 3.605399E-05 | 86.56 % |
| DP7 | $w_{sa}^{1.0000} = c$ | 1.000482E-05 | 86.06 % |
| DP8 | $w_b^{1.0000} = c$ | 2.000028E-06 | 84.72 % |
| DP9 | $w_{cy}^{1.0000} = c$ | 1.000088e-05 | 79.63 % |
| DP10 | $f_1^{1.0000} L_b^{0.6470} = c$ | 1.078929E-01 | 78.46 % |
| DP11 | $f_2^{1.0000} L_b^{-0.4888} = c$ | 3.671301E+02 | 74.12 % |
| DP12 | $f_1^{0.2546} f_2^{1.0000} L_b^{-0.3563} = c$ | 2.812855E+02 | 73.79 % |
| DP13 | $f_2^{1.0000} L_b^{-0.4800} L_c^{-0.1160} = c$ | 1.258088E+03 | 72.70 % |
| DP14 | $f_1^{1.0000} L_b^{0.6490} L_c^{0.1429} = c$ | 2.112050E-02 | 72.70 % |
| DP15 | $f_1^{0.7737} f_2^{1.0000} = c$ | 7.301285E+01 | 70.45 % |

that all these design principles tend to their lower bounds. It is interesting to note that all the associated variables are widths, indicating that for this MEMS component, the overall width should be as low as physically possible (provided they satisfy the constraints) for (near) Pareto-optimality.

2. Each of DP3, DP5 and DP6 are also approximately constant on the front. However they surprisingly take a value intermediate in their variable ranges. This indicate that the corresponding length variables are very important and will determine Pareto-optimality for this problem.
3. The flexure beam length $L_b$ is important in an indirect way. DP10 signifies that it is inversely proportional to the voltage $f_1$. The instantaneous voltage applied across the comb drive is associated with the force created to move the shuttle mass and the flexure beams are designed to compensate this movement. It is obvious that more the force (which in turn is due to higher voltage), the stiffer the structure should be and hence a shorter beam length ($L_b$) is required.

The design principles and their implications mentioned above are interesting and provide a designer interesting insights about the particular MEMS design. However, in the following section, we discuss a further post-optimality analysis procedure that is more revealing and also has a deeper connection to the timeline developments of human evolution.

### 3.2 Evolution of Design Principles

Consider the various anthropological features that homo sapiens acquired during the process of human evolution. There is sufficient documented evidence which tells us that these features evolved gradually over millions of years, rather than appearing out as a single event, driven by the natural mechanisms of reproduction, genetic mutation and natural selection. The design principles obtained in Table 1 can be thought of as analogous to these features since they are common to most of the solutions (at least 70% in this case), just like the anthropological features that distinguish humans from other living beings. We are interested here in investigating if there exist a gradual evolution of the above design principles over iterations just like the chronology of anthropological feature development over millions of years. If such a gradual development of key design features is observed, the information would be valuable to the designers for a better understanding and further their future use. Similarity between natural and artificial evolutions can help both fields with cross-breeding of their key concepts.

We propose the following procedure for recording the evolutionary time-line of design principles. The non-dominated solutions at each of the 10 runs at each generation $t$ is stored. Thereafter, each of the 13 identified design principles (DP$i$, $i = 1, \ldots, 13$) is checked for their appearance in the combined data in each generation. The significance of DP$i$ ($S_t^{\mathrm{DP}i}$) at generation $t$ is calculated as the proportion of points satisfying the DP to the total non-dominated points at that generation. Thereafter, a plot of the significance value of each DP with generation will reveal the relative appearance of the DP during the optimization process. Here, we provide the algorithm in step by step format with the following input: (i) design principles (DP$i$, $i = 1, 2, \ldots$) obtained after the automated innovization task, (ii) cluster information associated with each DP$i$, and (iii) generation-wise population members for each run:

**Step 0:** Set $t \leftarrow 0$.

**Step 1:** Collect non-dominated solution set $\mathbf{P}_t$ at generation $t$ from all runs. Thereafter, remove the dominated points and keep the non-dominated points in $\mathbf{P}_t$.

**Step 2:** Evaluate DP$i$ at all solutions in $\mathbf{P}_t$ to compute the $c$ values and collect them in set $\mathbf{C}_t$.

**Step 3:** Every element $c_j \in \mathbf{C}_t$ is checked for its existence in any of the $K$ clusters of DP$i$ using the criterion, $c_j \in$ cluster $k \Leftrightarrow \mu_k - d\,\sigma_k \leq c_j \leq \mu_k + d\,\sigma_k$, where $\mu_k$ and $\sigma_k$ are the mean and standard deviation of the $k$-th cluster, respectively. The number of elements $U$ in $\mathbf{C}_t$ that do not belong any of the $K$ clusters is recorded.

**Step 4:** Calculate the significance of DP$i$ in the current generation $t$ as follows: $S_t^{\mathrm{DP}i} = \frac{P-U}{P} \times 100\%$, where $P$ is the population size used to solve the original multi-objective problem.

**Step 5:** If $t = t_{\max}$ **Stop** else $t \leftarrow t + 1$ and **Goto Step 1**. Here $t_{\max}$ is the number of generations used for solving the original multi-objective problem.

We apply the above procedure to the MEMS design problem for the first 13 of the 15 design principles obtained by automated innovization. DP14 is a combination of DP10 and DP13. DP15 does not involve any decision variables. Hence, we do not consider them for the evolution analysis. Figure 3 shows $S_t^{\mathrm{DP}i}$ for each of the 13 DPs at various generations. The evolution history shown in the figure reveals the time at which each of DPs started to evolve during the

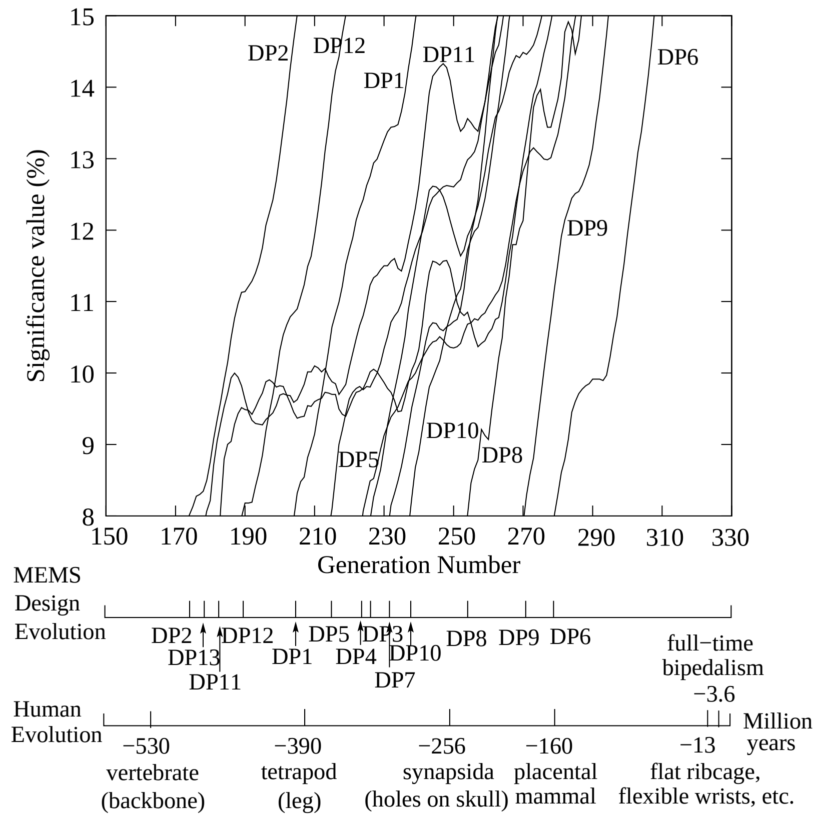


**Fig. 3.** Evolution of 13 design principles show a gradual development. Similarity with events in human evolution is also shown for a comparison.

optimization process. We show the evolution when there is around 10% existence of the particular DP in the combined population. Clearly, a gradual evolution pattern of DPs can be seen: (DP2, DP13, DP11, DP12, DP1, DP5, DP4, DP3, DP7, DP10, DP8, DP9, DP6). This information of some DPs being evolved earlier than others may provide valuable knowledge to the designers.

For the first 10 generations, no feasible solution was found. Thereafter, when some feasible solutions were created, it took another 160 generations for the first design principle DP2 to emerge among the non-dominated solutions. At around 171 generations, about 10% of the non-dominated points of all 10 runs have the DP2 property: $w_{sy}$ is constant. This variable denotes the thickness of the web of the I-shaped element. The fact that this property has started to evolve first means that this design principle is a fundamental requirement for any design to take shape of an optimal solution. This is equivalent to the development of backbones as early as around 530 million years ago for the eventual evolution of a human.

After the emergence of DP2, the next few generations created DP13 which is a relationship between the area of MEMS device, $L_b$ and $L_c$. The principle states that for a MEMS with smaller area, smaller values of $L_b$ and $L_c$ are needed. Third and fourth DPs (DP11, DP12) emerge after a while. These DPs enables a more direct relationship between the area and $L_b$ to be created in the form of DP11 and DP12. As an analogy, the emergence of DP11 and DP12 may be compared with further anthropological developments, such as formation of legs, that made a significant leap towards human evolution. In this sense, fixation of $w_{sy}$, $L_b$ and $L_c$ early on during the optimization process remain as fundamental developments towards becoming optimal.

Thereafter, after a gap of 15 generations, a new DP emerges. This is DP1 denoting that the variable $w_c$ must be constant. The variable $w_c$ is the thickness of the comb tooth. When the MEMS with a previously evolved feature (DP12) fixed a direct relationship between $L_b$ and the area, the thickness of each comb was the next parameter to get fixed. DP1 dictates that the optimal design requires a fixed tooth size, but the number of tooth directly proportional to the length of the flexure beam. From this generation onwards, detail design principles involving a few other variables ($L_t$ from DP5, $w_t$ from DP4, $L_{sa}$ from DP3, $w_{sa}$ from DP7, $w_b$ from DP8, $w_{cy}$ from DP9) evolved. As the solutions approach the Pareto-optimal front, DP15 relating two objective values starts to get formed and around 235 generation a direct relationship between the first objective (applied voltage) and $L_b$ forms.

Finally, DP6 that requires the variable $L_{sy}$ to be constant evolves at around 280 generations. This variable relates to the width of the web of the I-shaped element. When more characteristic variables get settled with evolution, this was the final fixation needed for the solutions to become close being Pareto-optimal.

It is interesting to note from Figure 2 that evolution of all DPs take place when the non-dominated points are close to the Pareto-optimal front. This observation is similar to the fact that most of the major anthropological developments in human evolution took place in a relatively short time span since the creation of life forms. The chronology of evolution of design principles discovered above from multiple EMO runs clearly puts forward a hierarchy of importance of them and highlights their inter-relationships. Such important information are difficult to obtain in any other ways.

## 4 Conclusions

In this paper, we have extended the use of automated innovization principles to make a deeper understanding of an engineering design problem. The key design principles found by the innovization procedure have been investigated for their chronological evolution during the optimization process. A computational procedure has been suggested for this purpose. It is observed that certain design principles get created early on during the optimization process, while some other detail design principles form later. We have argued that the evolution of design principles during the course of optimization has a remarkable similarity to the time-line history of significant anthropological developments for human evolution over many millions of years. The connection is interesting and puts natural and artificial design of systems on a similar platform, thereby allowing cross-breeding of ideas between two areas. The evolutionary information thus obtained may provide a clear hierarchy of important design features needed to constitute an optimal design. Such knowledge is vital for designers in having a clear understanding of key features and their inter-relationships and also to make use of them in their future design scenarios.

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