The connection between ADT and evolutionary methods in product development

László Soltész\textsuperscript{1,2} and Szilárd Nagy\textsuperscript{1,3}

\textsuperscript{1} PhD student, University of Miskolc, Miskolc, Hungary
\textsuperscript{2} Director of Center Of Competence Actuators EMEA, Emerson Automation Solutions, Eger, Hungary
\textsuperscript{3} Product Development Engineer, Emerson Automation Solutions, Eger, Hungary

e-mail: solteszlaszlo1977@gmail.com

Abstract. This paper presents similarities and connection points of Autogenetic Design Theory (ADT) and evolutionary methods. During a short historical overview, ADT is positioned in a timeline. The authors show where common issue points between the two approaches are. Then demonstrate how to use these methods, to avoid a long progress of iteration and tests of several versions and directions. Via an example study of truck floor design, benefits of evolutionary methods are highlighted and made understandable for readers.

1. Introduction
The historical evolution of product development processes shows a clear direction for improvement. These directions are giving some possible continuous ways, for further directions of the development of processes. Effective, usable, and clear product development process is more and more important today for companies in every industry, if they want to be competitive. One of the main reasons to use Product Development Processes is to reduce development time, manage the risk of bringing a new product to market, and to create better products [1]. An innovative and rapid product development process, can provide special, competitive advantages to firms, against their contenders [2]. Several product development methods were worked out and are available today; but no single version is perfect for all industries. That is why companies have to choose the best one for their expectations; though there remains a need to further tailor these methodologies, to precisely suit their needs. This improvement process cannot happen in one step. Feedback meetings and regular reviews of a product development project’s effectiveness, will shed light on bottlenecks and needs for improvement.

2. Autogenetic Design Theory
ADT – Autogenetic Design Theory, by Bercsey and Vajna, will be an inexorable methodology to use [5,6], if improvement of product development processes, show the evolution of processes step by step; while clearly concentrating on product design and evolution-related solutions of design-related works. The Autogenetic Design Method uses biological evolution, parallel with product development. New solutions are coming step by step during design research. Designers generate additional, possible design solutions, in every working stage. These solutions compete against each other. In every phase, the best solution will remain as the final design for that function [6]. In evolution,
the creation of individuals, is determined by evolutionary operators. Selection, recombination, mutation, and replication are these operators. Mutation drives this system to new insights, ideas, and non-expected solutions [5].

In ADT, at the start of product development, there is no exact, detailed, specification. Only some type of framework specification is established. This framework helps predict that the project’s development process scope will probably change, due to the status of design, new solutions, dynamically changing customer, or market requirements. That is why the definition and description of target functions happen at the start of the project [7].

![Figure 1. Development of integrated product development processes [3,4]](image)

During product development, project team members are focusing on operative tasks to deliver necessary results. Lessons from previous projects, can help to improve performance, by avoiding repeated mistakes [8]. During the analysis of the product development method from an evolutionary perspective, there are the following conclusions to highlight:

- Several, various alternatives are designed, matched, and compared in all phases of the product development process. These alternatives are competitors of each other, and the best one will be selected for further process.
- These searching, selecting, evaluating, and combining processes are also similar to the progress of natural evolution, in real biological life.
- To generate new solutions during the design process, always use the same or similar pattern of activities, independently from product complexity. These stages or patterns follow each other step by step when a phase is ready and accepted. It is mainly comparable with the TOTE scheme described by Miller and Ehrleinspiel [9,10]. It describes operations and cycles of tests, until the product can fulfill criteria, requirements, and no further development related tasks are necessary.
According to chaos theory, any small change or disruption in a system, can cause new, unpredictable system behaviors [11]. The result of product development usually goes unforeseen in time, because the creativity of design engineers predicts; that the product development process also contains several elements of a chaotic system or shows similarity to it from different aspects.

3. Product design with evolutionary methods

During the complex process of product design, the designer should create a product that satisfies customer requirements and hits company targets. These boundary conditions could be divided into two main parts – design targets and different constraints. Together they define a set of feasible solutions. Ranking the possible solutions and selecting the best one, is essential to create a marketable product. In many cases, this process can be mathematically modeled, as a nonlinear optimization problem.

\[
\begin{align*}
\min & \quad f(\bar{x}) \\
\text{subject} & \quad g_i(\bar{x}) \leq 0 \quad i \in \mathbb{N} \\
& \quad h_j(\bar{x}) = 0 \quad j \in \mathbb{N} \\
\bar{x} & = (x_1, x_2, \ldots, x_D)
\end{align*}
\]

In the equations, \(\bar{x}\) is a vector constructed from chosen design variables, that characterize the product. \(\mathcal{F}\) is a set of feasible solutions. \(S\) is searching for space without any restriction. \(f(\bar{x})\) is a design target (e.g., customer requirements, company targets, economic targets, different key performance indicators), or it is a deviation function from design goals. \(g_i(\bar{x})\) and \(h_j(\bar{x})\) are equality and inequality constraints (including mechanical constraints, economic constraints).

It is easy to see that solving the task is not easy, in many cases. It is difficult or impossible to solve with traditional deterministic methods. Good alternatives are genetic and evolutionary methods. Using selection, mutation, and recombination operations, they reach the final result with a series of iterative steps. Among the advantages of the methods, without the need for completeness; the most important ones are the following:

- multi-dimensional problems are easy to deal with
- complex nonlinear problems can be solved
- the task to be optimized is treated as a black box; no information about it is needed. A response to the input data is enough.

Disadvantages include, but are not limited to the following:

- require high computing capacity
- there is no specific information on the quality of the result. (e.g.: is the result the best solution, or by continuing the iteration could we get better quality; could we get better results from other starting points; etc?)

Over the past years, evolutionary methods have grown into a widely researched field of artificial intelligence. Initially, genetic algorithms dominated, which could only perform its evolutionary operations at the bit level. Later, evolutionary algorithms capable of performing operations with real values appeared. The first of these was differential evolution (DE) [12], followed by particle swarm optimization (PSO) [13]. Today, dozens of such algorithms appear every year. Some of these are effective methods: firefly algorithm (FA), dragonfly algorithm (DFA), flower pollination algorithm (FPO), bat algorithm (BA), and culture algorithm (CA). In terms of their internal structure, they are very different and can be useful in solving different tasks. It can be said that they consist of the following simple steps:

1. **determination of initial population**: random selection of \(n\) individuals from the \(S^D\) searching space
Table 1. Optimization results

|       | Original RHS section | I-section optima |
|-------|----------------------|------------------|
| $n_c$ | 14 12 10             | 16 14 12 10 8    |
| $b$ [mm] | 55,0 115,0 120,0 | 73,9 66,1 80,8 78,1 74,3 |
| $t_1$ [mm] | 5,4 3,0 3,4 | 4,6 5,9 5,6 7,0 9,4 |
| $A_1$ [mm$^2$] | 1274 1370 1496 | 1019,88 1116,36 1246,57 1437,52 1738,32 |
| Mass [kg] | 117,50 108,31 98,56 | 107,50 102,96 98,55 94,70 91,62 |
| Material cost [$] | 202,10 186,28 169,51 | 184,90 177,09 169,50 162,89 157,58 |

2. **selection**: $m \leq n$ selection of individuals from the population. It can happen randomly or according to the logic defined by the algorithm used.

3. **mutation, crossover**: creating new individuals using the individuals selected in point 2.

4. **recombination, reintroduction**: ranking new individuals and returning them to the original population so that the size of the population does not change. There will be individuals, both among the new ones and among the existing ones, who will die. There will be those who survive the selection.

6. repeating 2. – 4. points until a predetermined goal is reached

There are algorithms different from the classical steps described earlier. Such a discrepancy may be multiple selections and/or mutations within an iteration step, or the population size may vary continuously within boundaries.

The classical structure can be well illustrated through differential evolution. During the selection step, the entire population is selected as parent individuals ($m = n$). Depending on the type of task or the user’s discretion, new individuals may be created during the mutation in one of the following contexts:

- **DE/rand/1**
  \[
  \vec{v}_i^{(G)} = \vec{x}_{r_1}^{(G)} + F \left( \vec{x}_{r_2}^{(G)} - \vec{x}_{r_3}^{(G)} \right)
  \] (2)

- **DE/best/1**
  \[
  \vec{v}_i^{(G)} = \vec{x}_{best}^{(G)} + F \left( \vec{x}_{r_1}^{(G)} - \vec{x}_{r_2}^{(G)} \right)
  \] (3)

- **DE/current to best/1**
  \[
  \vec{v}_i^{(G)} = \vec{x}_i^{(G)} + F \left( \vec{x}_{best}^{(G)} - \vec{x}_i^{(G)} \right) + F \left( \vec{x}_{r_1}^{(G)} - \vec{x}_{r_2}^{(G)} \right)
  \] (4)

- **DE/best/2**
  \[
  \vec{v}_i^{(G)} = \vec{x}_{best}^{(G)} + F \left( \vec{x}_{r_1}^{(G)} - \vec{x}_{r_2}^{(G)} \right) + F \left( \vec{x}_{r_3}^{(G)} - \vec{x}_{r_2}^{(G)} \right)
  \] (5)

- **DE/rand/2**
  \[
  \vec{v}_i^{(G)} = \vec{x}_{r_1}^{(G)} + F \left( \vec{x}_{r_2}^{(G)} - \vec{x}_{r_3}^{(G)} \right) + F \left( \vec{x}_{r_4}^{(G)} - \vec{x}_{r_5}^{(G)} \right)
  \] (6)

where $r_1 \neq r_2 \neq r_3 \neq r_4 \neq r_5 \in [1, m]$ are random integers, $F \in [0, 1]$ is scaling factor, and $G$ is index of current generation.

After the mutation, the crossover comes:

\[
\psi_{i,j}^{(G)} = \begin{cases} 
\psi_{i,j}^{(G)} & \text{if } (rand_{j}[0,1] \leq C_R) \text{ or } (j = f_{rand}) \\
\chi_{i,j}^{(G)} & \text{otherwise}
\end{cases}
\] (7)

where $C_R = [0,1)$ is probability of crossover, $f_{rand} \in [1, D]$ is random integer.

During the recombination, if the new individual is better than the old one, it will be put into the population, and the old one will die:
\[ x_i^{(G+1)} = \begin{cases} \bar{u}_i^{(G)} & \text{if } f \left( \bar{u}_i^{(G)} \right) \leq f \left( \bar{x}_i^{(G)} \right) \\ \bar{x}_i^{(G)} & \text{otherwise} \end{cases} \] (8)

In [14] the authors contrast the traditional product design method with the evolutionary method. This approach’s effectiveness is well recognized, as they have managed to create a better product with this method.

A cross member of a truck floor was redesigned with a flower pollination algorithm. The results could be seen in Table 1. As you can see, the optimized I section cross members are lighter than the original rectangle hollow section members.

4. Conclusion

Autogenetic Design Theory and Evolutionary Method are both useful methodologies for special product development, design related tasks. Nowadays, especially in high-tech product cases, requirements form the market, and customers highly demand quick product changes, facelifts, and new products. Companies must react to this type of request; otherwise, they fall out of the market, or at least they definitely lose market share. There are several tools and methods to reduce the time of product development during the process; but for reducing lengthy and costly iteration projects, both ADT and evolutionary methods are a right choice. In this study, we found that these are really similar in basic working logic. Both are a perfect way of challenging product design in several areas of product development; not only in mechanical design, but also in telecommunications technology or product safety. The truck floor case study shows an example, of how the evolutionary method provides solutions for design-related questions in a short time, but with appreciated output. This approach’s effectiveness is well recognized as it has managed to create a better product.

5. Acknowledgment

The research work described in this paper is carried out with the support of the Ministry of Innovation and Technology, as part of the “Cooperative Doctoral Program” KDP-2020, with the support of the National Research, Development and Innovation Fund.

References

[1] Unger D W and Eppinger S D 2009 Comparing product development processes and managing risk Int. J. Prod. Dev. 8 382

[2] Jachimowicz F 2000 Industrial/academic partnership in research Chem. Innov. 17–20

[3] Ottosson S 2004 Dynamic product development — DPD Technovation 24 207–17

[4] Meerkamm H 1994 Integrierte Produktentwicklung im Spannungsfeld von Kosten-, Zeit- und Qualitätsmanagement VDI-Ber. 1136 Hrsg Entwickl.-Konstr.-Vertrieb

[5] Beresey T and Vajna S 1994 Ein Autogenetischer Ansatz für die Konstruktionstheorie 2;3 66-71;98-105

[6] Vajna S 2020 Berlin Integrated Design Engineering: Interdisciplinary and Holistic Product Development Springer International Publishing

[7] Kittel K, Fritzche M and Vajna S 2011 The autogenetic design theory and its practical application Int J Des. Eng. 4 91–113
[8] Soltész L, Berényi L 2021 Utilization of Lessons Learned in Product Development In: Jármái K., Voith K. (eds) Vehicle and Automotive Engineering 3. VAE 2020. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-15-9529-5_25

[9] Ehrlenspiel K 1991 Integrierte Produkterstellung Organisation — Methoden — Hilfsmittel Wettbewerbsfaktor Zeit in Produktionsunternehmen iwB Münchener Kolloquium ’91 ed J Milberg Berlin, Heidelberg: Springer pp 113–31

[10] Miller G A, Galanter E and Pribram K H 1991 Strategien des Handelns Stuttgart: Klett-Cotta

[11] De Meyer A, Loch C and Pich M 2002 Managing project uncertainty: from variation to chaos

[12] Storn, R., Price, K. Differential Evolution 1997 A Simple and Efficient Heuristic for global Optimization over Continuous Spaces Journal of Global Optimization 11, 341–359 https://doi.org/10.1023/A:1008202821328

[13] J. Kennedy and R. Eberhart 1995 "Particle swarm optimization," Proceedings of ICNN95 - International Conference on Neural Networks, Perth, WA, Australia, 1942-1948 vol.4, doi: 10.1109/ICNN.1995.488968.

[14] Sz. Nagy, K. Jármái 2020 Teherautó plató keresztartójának optimálása evolúciós módszerrel GÉP 16 86-90