Multi-Competence Cybernetics: The Study of Multi-Objective Artificial Systems and Multi-Fitness Natural Systems

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"Scientists discover the world that exists; engineers create the world that never was"

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Abstract

This chapter provides a comparative discussion on natural and artificial systems. It focuses on multi-objective problems as related to the evolution of systems either naturally or artificially; yet, it should be viewed as relevant to other forms of adaptation. Research developments, in areas such as evolutionary design, plant biology, robotics, A-life, biotechnology, and game theory, are used to support the comparative discussion. A unified approach, namely Multi-Competence Cybernetics (MCC) is suggested. This is followed by a discussion on the relevance of a Pareto-approach to the study of nature. One outcome of the current MCC study is a suggested analogy between species and design concepts. Another resulting suggestion is that multi-fitness dynamic visualization of natural systems should be of a scientific value, and in particular for the pursuit of understanding of

natural evolution by way of *thought experiments.* It is hoped, at best, that MCC would direct thinking into fruitful new observations on the multi-fitness aspects of natural adaptation. Alternatively, it is expected that such studies would allow a better understanding of the similarities and dissimilarities between the creation of natural and artificial systems by adaptive processes.

1 Introduction

Comparing natural and artificial systems has been the focus and drive of the fathers of cybernetics. Such a comparative approach has also served as a major stimulator in the development of the field of Evolutionary Computation (EC). Observing the bio-inspired field of EC it is straightforward to realize the strong link with the field of Mathematical Programming (MP). Many developments in EC could be viewed as advancements in MP as related to both Single- and Multi- Objective Optimization (SOO and MOO, respectively). The similarity between SOO, as implemented in EC, and that of natural evolution is quite apparent.

Wondering about the similarities between natural evolution and optimality has been extensively discussed in the literature, and the comparison between optimality and adaptation has been a subject of an ongoing debate (e.g., [1]). As outlined in section 2.3, most of the available discussions on optimality as related to natural evolution can be viewed as referring to SOO rather than MOO. Considering the significance of MOO in the development of artificial systems, the above observation seems striking. Therefore, it is justified to explore the relations between MOO and natural evolution. This chapter provides a discussion on this topic using research developments in areas such as: evolutionary design, plant biology, robotics, A-life, biotechnology, and game theory. It should be noted that the focus of this chapter is on adaptation as related to evolution, yet some aspects of the discussion should be relevant to other forms of adaptation.

The following contains four sections. Section 2 provides the background needed for the suggested comparison. In section 3, several observations are made with respect to the suggested comparison. In addition, section 3 provides a definition of Multi-Competence Cybernetics (MCC) and it explains the notion of multi-fitness. Section 4 includes a short comparison between natural and artificial design, as well as a recently suggested comparison between design concepts and species as related to MCC. Section 5 provides a short list of MCC questions that might shed some light on future

MCC research topics. Finally, Section 6 summarizes and concludes this chapter.

2 Background

This section provides some overview of issues that are relevant to the comparative discussion and suggestions of this chapter.

2.1 Introduction to Cybernetics

Existing definitions and scope

The traditional definition of cybernetics, as *"the science of communication and control in the animal and the machine,"* is attributed to Norbert Wiener [40]. The fathers of cybernetics, such as Wiener, studied analogies and metaphors between animals and machines starting at the level of a neuron up to and including the level of societies. It should be pointed out that there are a host of different definitions of cybernetics as listed by the American Society for Cybernetics (see: www.asc-cybernetics.org/foundations/definitions.htm). Of a special interest to the current discussion are the non-traditional definitions such as: *"the art of securing efficient operation"* (by L. Couffignal), *"...[the] mathematical and constructive treatment of general structural relations, functions and systems"* (by F. von Cube), *"the art and science of manipulating defensible metaphors"* (by G. Pask), and *"the art and science of human understanding"* (by H. Maturana). It is clear from this collection that cybernetics can be viewed from different and much broader perspectives than that of the original one. Modern cybernetics involves three types of systems, as schematically depicted in figure 1.

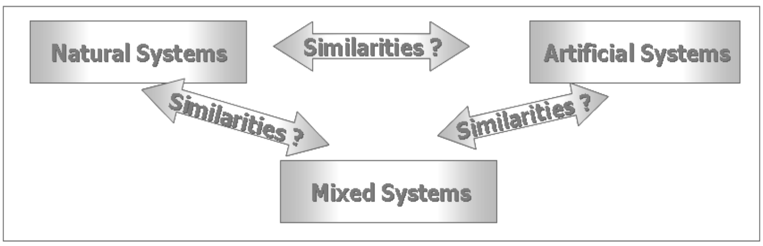

Figure 1: The scope of modern cybernetics

As suggested in figure 1, and in accordance with Pask's definition of cybernetics, the scope of cybernetics involves comparisons between the different systems. This issue is briefly described in the following.

The two view-points of cybernetics

Cybernetics includes two interesting viewpoints. In fact, Holland [18] implicitly refers to them in his discussion on the role of genetic algorithms, by stating that: *"It should be emphasized that the plans (algorithms) set forth have a dual role."* Referring to the upper part of figure 1, the first view of cybernetics is aimed at studying natural systems to support the development of better man-made systems (with arrow to the right), whereas the second view-point involves using new ideas, which are generated as a part of the development and the analysis of artificial systems, to possibly find new explanations to nature (left-pointing arrow). When considering the first viewpoint of cybernetics, it should be noted that the common engineering design process is substantially different from the way evolution creates its biological products. Yet, the desire to imitate or at least to be inspired by nature is strong and has been proven to be fruitful from engineering standpoint (e.g., soft computing methods, bio-inspired robotics).

Although most of the work in cybernetics could be viewed as focusing on the first viewpoint, the second view should not be ignored. Given the success of bio-inspiration some sort of similarity must exists, and a major question is whether the similarity is applicable to also support the second view of cybernetics. As an example of the second viewpoint consider the use of EC in explaining natural evolution as done in [11]. EC has made an extensive use of metaphors and analogies from its early days, and this has provided a rich vein for its continual development. Yet, there are several difficulties when considering the use of EC to study natural systems. In the more general sense, the difficulties of using the second view-point of cybernetics are related to: a. controversies concerning Artificial Life (A-life) studies in general, b. controversies concerning the association of adaptation with optimality, and c. difficulties in testing theories of evolution. In this chapter a forth issue is added and discussed, namely, difficulties in trying to relate the notion of multi-objectiveness to the common terminology of biology. In the next three sections (2.2, 2.3, 2.4) some aspects of the three types of difficulties are briefly discussed, whereas the forth issue is dealt with in section 3.

2.2 Cybernetics and A-life

The scientific exploration of nature and its evolution is an ongoing process that involves observations, theories, and occasionally some experiments. Acceptable theories, which are based on observations, are always subject to the possibility of being replaced or just extended. Darwinism has already been extended into neo-Darwinism as the scientific knowledge expanded. In spite of the fact that the basic ideas of Darwin still prevail, the pursuit for a better and more complete understanding of natural evolution is far from over. The study of evolution has inherent difficulties due to the time scale involved, the lack of complete information about the past, the complexity of natural systems, and the difficulties of performing experiments.

The second viewpoint of cybernetics might help to somewhat compensate for these inherent difficulties. A related approach is that of the Evolution of Artificial Creatures (EAC). EAC is a research topic of relevance to fields such as Robotics, Mechatronics, and Cybernetics. It is an experimental setup for research in A-Life; a field that attempts to investigate living systems through the simulation and synthesis of life-like processes in artificial media. In spite of its controversial nature A-life research approach has about two decades of recorded research achievements with a growing research community and related conferences. One way to view A-life studies is to consider it as *thought experiments* as suggested in [13]. This means, according to Di Paolo et al. [13], that: "*although simulations can never substitute for empirical data collection, they are valuable tools for re-organizing and probing the internal consistency of a theoretical position.*" Such a scientific justification to A-life helps to resolve, to some extent, the controversial aspect of this approach.

2.3 Cybernetics, Adaptation, and Single-objective Optimization

Securing efficient operation, as stated in the proposed definition of cybernetics by Couffignal (see section 2.1), suggests a close relation of cybernetics to optimization of systems. It also hints at a close relation with control and with adaptation of systems. Efficiency is usually associated with some measure with respect to a goal or an objective. Holland [18] lists three major components in the adaptation of a system, namely the environment, the adaptation plan to induce improvements, and a performance measure to be associated with the environment. When referring to artificial systems Holland [18] states: "*Here the plans serve as optimization procedures*...." In support of his uniform treatment of adaptation, Holland provides illustrations from different fields. In all of his illustrations, when referring to optimization, it appears that the reference is to SOO (including the weighted sum of performances). Holland's suggestion seems logic in view of the similarity between the notion of *fitness of an organic individual* and that of the notion of *performance of an artificial individual*. This fundamental aspect of evolving natural (artificial) systems, namely fitness (performance), serves to measure which organic (artificial) individual has a better chance to "survive" (selected as a candidate in an adaptation step for optimality).

It seems suitable to continue this review, on the resemblance between adaptation and optimality, with some historical aspects of the use of the famous and confusing term, namely, *survival of the fittest*. Fittest fuzzily implies optimization and optimum, and therefore it requires clarification. The notion of *survival of the fittest* has been in the center of on going debates, which are dated back to the time of Darwin. At the extreme it has been the focus of some theological discussions. In such debates it has been claimed to be a tautology; namely, that it means survival of those better at survival, hence it is meaningless. Gould [16] suggests that the rebuttal by Darwin is most compelling. According to Gould: "*Darwin insisted, in principle at least, that fitter organisms could be identified, before any environmental test, by features of presumed biomechanical or ecological advantage.*" The term *survival of the fittest* has also played a role in discussions on what is known as social Darwinism, and in particular with respect to the justification of controversial ideologies such as racialism. These kinds of debates may have caused certain resentment to the term, and probably contributed to the need to better express what adaptation is all about. In fact, although many researchers in the field of EC are still using the term *survival of the fittest*, most contemporary biologists almost exclusively use the alternative term of *natural selection*, and acknowledge its complex nature[1]. With this respect, biologists tend to agree that natural selection plays a role in the evolution of traits, as an adaptation process, but may fail to agree about the significance of its role with respect to other evolutionary forces (e.g., [30]).

Both fitness and performance are typically considered as scalars. Usually, performance, as applied to optimization, is understood as a value, which is measured with respect to some objective or to a weighted sum of objectives. With respect to the latter it should be noted that the weighted sum of objectives should be considered as a SOO approach. Fitness, is

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[1] Apparently, Spencer [37], and not Darwin, coined the term *survival of the fittest*. The interested reader is referred to Wikipedia where an historical trace of the origin of the term can be found.

aimed at describing the natural capability of an individual of a certain genotype to reproduce, namely to be able to transfer at least a part of its genetic material to the next generation. Fitness of a genotype, in biology, is commonly measured either in absolute or relative terms. In the former measuring method fitness is a ratio of the number of individuals after selection to those before, as related to a particular genotype. To measure absolute fitness is usually difficult, hence the idea of a relative fitness has emerged. In both methods, fitness is a scalar. Wright [41] suggested studying natural evolution by visualizing the distribution of fitness values as if it was a landscape. For this purpose a distance measure between genotypes is needed. The concept of a fitness landscape, or adaptive landscape, involves the set of all possible genotypes, their degree of similarity, and their related fitness values. A similar visualization is commonly used in SOO, where the values of the performance of all solution candidates are visualized as a landscape. In maximization problem the aim is to find the peak or peaks of the landscape. When taking an adaptationist viewpoint, and using the metaphor of landscape as described above, evolution might be viewed as a local optimization rather than a global one. For example, Orzack and Sober [30] defined adaptationizm as: *"the claim that natural selection is the only important cause of the evolution of most nonmolecular traits and that these traits are locally optimal."* Although their view of adaptationism is somewhat extreme, the general understanding is that natural selection is similar to local optimization. In fact, as pointed out by Parker and Maynard Smith [31], optimization and game theories have been widely used, particularly by field biologists, to analyze evolutionary adaptation. Yet, as it appears from the description of Parker and Maynard, in such studies *optimization criterion rather than criteria* is associated with fitness. One should not confuse between the notion of payoffs, which is used in such studies, and that of criteria, since that (as stated in [31]) *"payoffs are expressed in units of the criterion to be maximized."*

Taking all of the above arguments into account one should claim that there is a similarity between adaptation and optimality, and in particular with respect to SOO. When viewed closely, it appears that most discussions, which deal with adaptation versus optimization and do not explicitly refer to SOO and/or MOO, should be considered as implicitly referring to SOO. With this respect, as already pointed out in the introduction (section 1), it should be noted that this chapter deals primarily with adaptation in the sense of evolution.

So far the discussion has focused on the similarity between *fitness of an organic individual* and *performance of an artificial individual*, as related to adaptation and optimization. When focusing on shape and structure, in nature and the artificial, it appears valid to further discuss the similarity in terms of physical terms, such as energy, rather than in biological terms (such as the number of individuals after selection). Bejan [6] has investigated such a similarity with respect to tree-like structures, and has generalized his observations into a theory. According to his constructal theory: *"For a finite-size system to persist in time (to live), it must evolve in such a way that it provides easier access to the imposed currents that flow through it."* The constructal theory, which has emerged from the design of engineered systems, assumes that geometric forms that appear in nature are predictable through optimization under constraints. Furthermore, similar to studies on adaptation and optimization, the discussion in [6] refers to SOO. The only apparent exception is the citation from the work of Nottale [29] on fractals, which states: *"One of the possible ways to understand fractals would be to look at the fractal behavior as the result of an optimization process…Such a combination…may come from a process of optimization under constraint, or more generally of optimization of several quantities sometimes apparently contradictory…"* Interestingly, this citation is left, by Bejan [6], without a discussion on the possible role of MOO in the constructal theory. Recently [7], MOO approach to the design of heat exchangers has been discussed in conjunction with the constructal theory. Yet, no reference has been made with respect to heat exchangers in nature.

In summary, although of a controversial character, there are studies on the similarities between natural and artificial systems as related to optimization. Most of such studies, which use optimization theory to explain evolutionary adaptation, either explicitly or implicitly refer to SOO. There are, however, some exceptions, which are discussed in section 3.

2.4 Validation of Adaptation Theories

The second viewpoint of cybernetics, which has been described in section 2.1, may help producing new theories and explanations about nature. Yet, any borrowed idea, from engineering design or alike, needs validation. Recalling the idea of the role of A-life as *thought experiments*, as discussed in section 2.2, it is worthwhile to note that Parker and Maynard Smith [31] have used a similar argument. They have justified optimality theory in evolutionary biology by saying that: *"Optimization models help us test our insight into the biological constraints that influence the outcome of evolution. They serve to improve our understanding about adaptations, rather than to demonstrate that natural selection produces optimal solutions."* In some sense, the use of optimization models in the study of natural adaptation could be view as a part of A-life. In any case if model predictions match the actual observations then one may hope to have made the right assumptions about the natural process and its modeling. Clearly, models by themselves cannot validate a theory and empirical evidence is a must. Unfortunately, it is well known that empirical research on natural evolution has many limitations, and has not resulted with a well-accepted evolution theory, but rather with a variety of opinions and debates (e.g., [1, 30, 35]). While evolution theories and their extensions are difficult to substantiate by empirical evidence, it is noted that *thought experiments*, on ideas such as presented in this chapter, might lead to future planning of evolutionary experiments. As noted by Sarkar [35], with respect to empirical adaptationism, such tests might become increasingly plausible with the advent of large sets of complete genomic sequences.

2.5 Multi-objective Problems in Engineering Design

The following provides background on engineering design in the spirit of the second viewpoint of cybernetics. Namely, ideas from engineering design, which are presented here, are to be borrowed (in sections 4 and 5) for the pursuit of understanding nature.

General

Product development commonly involves tradeoffs among contradicting objectives (e.g., accuracy vs. cost). The significance of such tradeoffs to creative design has been highlighted in the TRIZ method, which resulted from a comprehensive study of patents by Altshuller, as described in [36]. Traditionally multi-objective problems (MOPs) have been treated by a SOO-like approach using either a weighted sum of the objectives or a goal attainment method. Such problem definitions and solution techniques could be viewed as range-dependent approaches. Modern processing technologies provide a means to consider parallel search methods which are suitable for range-independent MOPs that may involve a search towards a Pareto-front and the associated non-dominated solutions (see the introduction to this volume).

EC tools are known to be suitable for supporting engineering design (e.g., [8]). Their attractiveness for engineering design has been strengthened by the recent developments of reliable and generic Multi Objective Evolutionary Algorithms (MOEAs), and by the introduction of interactive EC methods for engineering design (See recent reviews by Coello [10], and by Parmee [32], respectively). Pareto-based search has also been implemented for engineering design and other applications by non-EC methods (e.g., [21]). Yet, evolutionary multi-objective search and optimization techniques are becoming the most popular methods to solve MOPs in general and in particular for engineering design [10]. The majority of such studies concerns the search of particular Pareto-optimal designs from the set of alternative designs. Recently a non-traditional MOP approach, involving set-based concepts, rather than particular designs, as the focus of the search and selection, has been developed at Tel-Aviv University aiming at the support of engineers. The brief description of the concept-based approach, which is given below, follows a recent review by Moshaiov and Avigad [25]. There are two main reasons for the outlining of the concept-based approach below. First, this background provides a typical spectrum of engineering considerations that are quite common to the use of multi-objective search and optimization in design. Second, as pointed out in Moshaiov [23, 24], species and design concepts might be similar, at least in some metaphorical sense. In fact, this observation served as a trigger for the work presented here, which summarizes and continues the suggestions of [23, 24].

An overview on the concept-based approach

The concept-based approach involves the search and selection of conceptual designs. The major motivation for the development of the concept-based approach is rooted in the significance of conceptual design to the survivability of companies (e.g., [38]). The concept-based approach is not restricted to MOPs. Yet, its development efforts have concentrated on MOPs due to the nature of engineering design, which commonly involves tradeoffs among contradicting objectives [25].

The concept-based approach deviates from the traditional representation in which each concept has a one-to-one relationship with a point in the objective space. In general a conceptual solution should be viewed as a category of solutions. Hence, in contrast to the traditional approach, in the concept-based approach a conceptual solution is represented by a set of particular solutions. This allows *performance variability*, which results from the particular solutions that are associated with a conceptual solution. The set-based concept representation provides a stage for a synergistic human-computer interaction. In the concept-based approach computers are utilized to extensively search the decision space at the level of particular solutions, whereas humans articulate their preferences at the level of conceptual solutions. Such preferences may be articulated not only at the level of concepts, but also at the level of sub-concepts (e.g., [4]). In addition to such inherent concept-related preferences, concept-based MOPs may involve range-related preferences. Both types of preferences could be implemented either a-priori, or interactively during the search. The recent review paper, by Moshaiov and Avigad [25], lists a variety of EC studies and contributions, which have been made at Tel-Aviv University on the concept-based approach. Among the studied concept-based topics are: a dynamic goal approach, a Pareto approach, a structured EC approach with sub-concepts, interactivity by preferences of concepts and sub-concepts, subjective-objective fronts, various concept robustness issues, concept selection by variability and optimality, extension to an epsilon-Pareto approach, generalization to path planning, application to simultaneous mechanics and control design, and various computational aspects.

It should be noted that in engineering design the selected solution might not necessarily be from the Pareto-optimal set (e.g., [4, 32]). Yet, an understanding of the concepts' relative performances along and in the vicinity of the front is significant to concept and solution selection (e.g., [26]). This is illustrated in figure 2a. Assume that the figure contains the performances of all solutions of two concepts. Both concepts (designated by stars and circles) play a role in the front. Yet, when a look beyond the front is taken, the "star concept" of figure 2a might be more robust than the circle one. This may happened when the solutions of the first two ranks are to be disregarded due to some uncertainties. Alternatively, human preferences might result in the excluding of one or both concepts and the selection of another concept (not shown) that is not on the concept-based front but rather on the subjective-objective front, as described in [4].

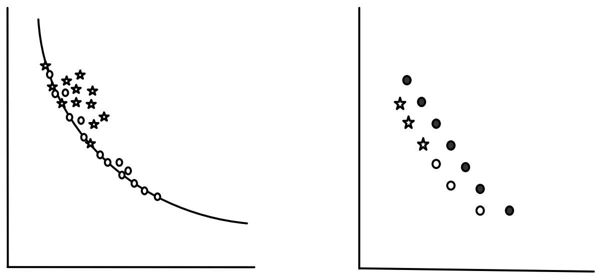

Figure 2a: Two concepts **Figure 2b:** Three concepts

Recently, Avigad and Moshaiov [3] argued that concept selection measures should not be dependent solely on the concept-based Pareto but rather be selected by an approach that takes into consideration variability and optimality of the concepts. This is illustrated in figure 2b. Here, the performances, in a bi-objective space, of three concepts are depicted as circles, stars, and black dots, respectively. In this min-min problem the concept-based Pareto-front consists of solutions from the first and second concepts (circles and stars), and yet one should not ignore the third concept since that in comparison with each of the other concepts it has a better variability with respect to the objectives. In engineering design, such variability might be important due to the variability of market demands (e.g., [5]). The variability and optimality issue adds up to the interactivity and concept robustness issues that motivated the use of an epsilon-Pareto approach for concept-based problems [24, 26].

In summary, the concept-based approach deals with the search and selection of conceptual designs by way of a set-based representation of each concept in a multi-objective space. In this chapter, the concept-based approach is used for a comparison between design concepts and species (see section 4.3). The comparative discussion of section 4.3 follows the cybernetic principles and ideas that are described below.

3 Introduction to Multi-competence Cybernetics

This section discusses the notion of Multi-Competence Cybernetics (MCC). It starts with general observations concerning MOO as related to nature (section 3.1). Next, in section 3.2 the term MCC is introduced and justified as a replacement for the term Multi-objective Cybernetics (MOC), which has been originated and used by the author in [24]. Finally, section 3.3 provides some insight to the notion of multi-fitness.

3.1 General Observations

Observing the main stream literature on natural evolution, as related to the comparison of adaptation with optimality, it is striking to note the lack of a consistent and extensive discussion on the similarities and dissimilarities with respect to MOO. The "astonishment" is due to the recognition that MOPs play a major role in engineering design (as described in section 2.5), and that nature has produced what can be considered as remarkable designs. An intriguing question has to be raised, namely, given that natural adaptation is possibly related to SOO could a similar relation exists with respect to MOO? Several related observations are made in the following:

- Pareto-related ideas were not available at the time of Darwin's *origin of species.* Yet the following point is quite surprising.
- There is no reference on a multi-objective evolutionary theory; optimality theory in evolutionary biology seems to involve the use of a criterion and not a mixture of criteria (e.g., [31]).
- The notion of objectives is controversial with respect to nature

- An equivalent notion to *tradeoffs of objectives* might be that of *tradeoffs of functions and forms*, or *tradeoffs in behavior*.
- There is no well-known general theory of evolution that relates fitness with *tradeoffs of functions and forms* (or alike).
- The term *tradeoffs* has been used with respect to optimal theory of natural evolution, however it has been referred to the counteracting costs and benefits of strategy changes with respect to a criterion and not in a multi-criterion case (e.g., [31]).
- There is, however, evidence for a suggestion to use MOO in studying biological systems, and of its practical results (e.g., [14, 27]).
- Adopting TRIZ, as suggested in [9], to a biological patents' database, might shed light on possible analogies as related to tradeoffs.
- There is an increasing evidence of studies that could be viewed as belonging to *multi-objective A-life*, and/or to the related topic of *multi-objective robotics* (e.g., [39] and [26] respectively)
- Studies on multi-objective robot path planning, such as that of [26], involve the contradicting objectives of *fast versus safe*. Such characteristics appear essential for survival in nature.
- Multi-objective optimization is used in bioinformatics and computational biology (see a recent review in [17]), yet much of this could be viewed as engineering-related activities.
- Studies on multi-objective machine learning, such as in [19] and in chap? of this volume, are strongly related to multi-objective aspects of neural networks. Hence might be important to an MCC discusion on learning and control aspects of adaptation.
- There is evidence of the use of multi-criteria decision making in ecological planning (e.g., [34]), and of the use of multi-objective optimization in bio-processing (e.g., [20]). Yet, such activities could be viewed as bio-engineering-related activities, and do not necessarily provide evidence to any human-independent natural process in the sense of Dawkin's *blind watchmaker.*
- MOEA is useful for control (as revealed in reviews such as that of Coello [10]). Yet, it could be viewed as engineering-related activities.
- There is evidence on the existence of multi-objective game theory (e.g., [15, 22, 28]). Although practiced primarily for operation research it could be viewed as relevant to biology.
- Multi-objective game theory has been implemented in games that have some metaphorical value with respect to biology (e.g., [22]).
- Human behavior clearly shows the significance of contradicting objectives and conflict resolution in natural systems (societies). This is apparent in studies on multi-objective game theory (e.g., [28]).

- MOEA is used for understanding nature (e.g., [33]). Yet, such studies do not tell much about natural evolution but rather on the human inference process in the process of understanding it.

The above list of observations includes a compilation of evidence as related to MOO and nature in the spirit of the second viewpoint of cybernetics. It provides some evidence that MOO might support understanding of nature at least in the form of *thought experiments* (see section 2.2). This falls within the idea expressed by Parker and Maynard [31], namely that: "*optimization models…serve to improve our understanding about adaptation.*" To support the extension from SOO to MOO one must try to understand the possible role of MOO in understanding nature. This is explained in the following.

3.2 Defining Cybernetics and Multi-competence Cybernetics

Modern cybernetics is viewed here as *the study of competence of natural and artificial systems within the scope of analogies and metaphors.* It follows the definitions of von Cube, and Pask, and constitutes a shift from the terminology of Couffignal (see section 2.1). Namely, *securing efficient operation* is replaced with the term *competence*. The former terminology appears to be adequate to only the first viewpoint of cybernetics that focuses on the design of the artificial, whereas the latter seems to be more appropriate to both points of view. Namely, the chosen terminology does not imply the involvement of a designer. *Competence* should be understood here, in the context of artificial systems, as the designer's objective that reflects the designer perception on what type of competence of the system is to be used when comparing design alternatives. On the other hand, in the case of natural systems, competence should be viewed as fitness in the sense that no purpose should be implied by the term. Yet, as pointed out by Parker and Maynard Smith [31], with respect to optimality theory in evolutionary biology, the optimization criterion is often an indirect measure of fitness. The suggested broad view on cybernetics refers to the study of the competence of systems, including natural and artificial ones. Hence, Holland's work [18] on adaptation in natural and artificial systems should be viewed as a study within the field of cybernetics.

The transformation from the traditional definition of cybernetics, as *the science of communication and control in the animal and the machine*, to the above one, appears to have a rationale. Understanding *communication and control* should not be separated from understanding *morphology and mechanics*, as pointed out by modern research on the evolution of artificial creatures (see sub-section 2.2). In fact, evolution appears to suggest a mixed view on the *how* and *what* is *governed* and *governing*.

Following the above definition of cybernetics it is suggested to define Multi-Competence Cybernetics (MCC) as ***the study of multi-competence of natural and artificial systems within the scope of analogies and metaphors***. Here, the focus is not on debates such as: optimality versus adaptation, and adaptationism versus pluralism. Rather, a unified view is suggested on adaptation in natural and artificial systems that extend ideas such as presented in [18] to incorporate the notions of multi-objective adaptation in artificial systems and multi-fitness adaptation in nature. In other words, the MCC suggestions made here do not aim at adding to any controversy but rather to provide a framework of thinking when comparing natural and artificial systems. The proposed unified view could be substantiated by empirical, logical, and simulation-based arguments, using the accumulation of evidence, which is presented in sub-section 3.1. The proposed MCC approach is further explained in the following.

3.3 Justifying the Notion of Multi-fitness and its Visualization

The proposed extension from cybernetics to MCC may look trivial but it requires a justification and clarifications. When artificial systems are concerned the notion of *multi-competence* seems clear as it translates to *multi-objective*. The natural counterpart of the notion of *multi-competence* as *multi-fitness* is however not as trivial to justify. In other words, in spite of the fact that comparing the notion of *fitness* with the notion of *performance,* or with that of *objective*, is not rare, the suggested notion of *multi-fitness* and the related notion of *Pareto-front* would appear strange, unfamiliar, and even unacceptable to most biologists (For an exception see [14]).

By its definition fitness is to be measured under the same survival condition. One could argue that there are different types of survival threats and that they can appear in nature either separately or together. In fact, some generic classical threats are well known. For example, shortage of food could be a survival threat and so is a predator. Certain traits or strategy may fit one type of a threat but not necessarily all types of threats. This means that the notion of fitness cannot be separated from the type of survival threat. In other words there could be different types of fitness as related to the different generic threats. To further illustrate the issue of multi-fitness it should be noted that threats on a particular individual might change from one type to the other during the individual's lifetime. The changes may also apply to different individuals of a population in a different order. The time scale of such changes may span over generations and not just over the lifetime of the individual. An individual or a species may also change the environment, which adds another dimension to the above discussion. This can be further illustrated and discussed using the terminology of game theory and winning criterion. The *game of survival* is not just one game, it is a series of games. The rules of wining are not fixed and they may vary with time and space. The criterion (type of threat) may change from one game to the other, and one could also perceive that even one game may have multi-criteria (e.g., [15, 22, 28]), namely different threats that are happening simultaneously.

One could therefore think of the multi-competence problem in nature as the study of the trajectories of individuals and species in a multi-fitness space. As pointed out by Parker and Maynard Smith [31] fitness can be expressed either directly or indirectly. Taking a *form and function approach* to the indirect expression of fitness, the above discussion could be compared with that of [14] and [27]. According to [14] the study of form-function relations of branched structures could be advanced by the use of multi-objective optimization. In [27], simulated adaptive walks are used to study the early evolution of the morphologies of ancient vascular plants, in a multi-fitness fashion, using multi-tasks and their related fitness landscapes. Clearly, both direct and indirect expressions of fitness suggest that a multi-fitness (multi-competence) dynamic visualization of natural systems should be of a scientific value, and in particular for the pursuit of understanding of natural evolution by way of thought experiments and A-life studies. It may also be significant for the analysis of empirical data. Such visualization is perceivable up to 3-D but its extension might pose a difficulty. This is similar to the visualization problem that occurs in multi-objective design (e.g., [21]). While saying all of this, one should realize that it is not so clear to what a degree the notion of Pareto-front is significant for the understanding of evolution. This issue is further discussed in section 4.2 following some further description of the general aspects of MCC.

4 Fundamentals of Multi-competence Cybernetics

As suggested in section 3, understanding analogies and metaphors between the natural and the artificial, as related to MOPs, seems important. Yet, such an attempt is inherently difficult and often speculative. The prime merit of the following is perhaps in raising some questions and pointing at potential approaches that have resulted from the research on the concept-based approach in engineering design. Speculation could be avoided by focusing on possible analogies as a means for possible inspiration and for the production of useful metaphors. This could trigger thought experiments that should not be understood as an attempt to necessarily pose any new theories on nature.

The common process of engineering design defers substantially from evolutionary design. Yet, here the interest is primarily on design by artificial evolution as compared with that of nature. In the following section 4.1 some general aspects of comparing these design processes are discussed. Next, section 4.2 provides an MCC discussion on the notion of Pareto-front. Finally in section 4.3, an MCC comparison is carried out with respect to the possible similarities of design concepts and species.

4.1 General Aspects

Many topics that have been mentioned in the background (section 2), and especially as related to the concept-based approach, reflect typical issues in engineering design. In particular they relate to evolutionary multi-objective design. Among such typical issues are:

1. The generic nature of design tools, and in particular EC-based ones
2. The closeness to A-life aspects
3. The structured nature of the representations of engineering solutions
4. The uncertain and subjective nature of design goals and objectives
5. The interest in the non-dominated set and the objective tradeoffs
6. The lack of sufficient modeling of performances
7. The subjectivity of concept-related preferences
8. The inherent variability of conceptual solutions
9. The interest in solutions that are robust and the different types of robustness
10. As above with respect to robust concepts
11. The need to extend the Pareto approach for the general concept selection problem
12. The need for an efficient search

The above issues are typical to engineering design; yet, one may claim some similarities with nature at least as related to the possibility of though experiments. The first three items do not pose any serious dissimilarity problem. Items 4-5 appear related to the dynamics and variability of the survival conditions in nature (see section 3.3 and also the discussion in the next paragraph). Items 6-7 are related to the difficulties of modeling that appears to be a common problem in both natural and artificial systems. Items 8-11 relate to the MCC comparison between concept and species, which is discussed in section 4.3. Finally item 12 demonstrates a major difference between natural and artificial evolution that is related to the purpose aspect of engineering, which does not exist in nature. Some of the above issues are further discussed below.

Engineering design is a purpose-directed process and not a result of the work of a blind watchmaker. It involves dynamic goals and the exact preference of objectives is uncertain and may vary during the design and among the designers. In nature, since that the environment changes with time, and threats are dynamic, evolution is a dynamic process and fitness and the multi-fitness problem is dynamic as well (see section 3.3). In the case of conceptual design the desire to obtain the full spectrum of non-dominated solutions is related to the issue of the uncertainty of objectives (e.g., due to variability of market demands [5]). This may resemble a desire to predict natural evolution under the uncertainty of the trajectories of evolution, or in environments with variable conditions. This issue is further discussed below.

4.2 Is Pareto Relevant to the Study of Nature?

Comparing individuals or species in a multi-competence space does not necessarily mean that the notion of a Pareto-front is relevant to the understanding of nature. Yet, as already pointed out some evidence exists that demonstrates the significance of a Pareto approach to the understanding of natural systems (e.g., [14, 27]). One should realize that the use of the idea of non-dominated solutions in engineering design is either a result of postponing the decision on the objective preferences or of trying to compare performances of different solutions under different situations without a preference on a particular situation. In such cases the efforts of obtaining the front allows a better understanding of the design tradeoffs. When dealing with nature one should be careful in making Pareto-related statements. It is arguable that a Pareto-front can be useful in the analysis of natural solutions, yet such an analysis should assume that there is no particular trajectory of scenarios. In spatio-temporal evolution scenarios a dynamic weighted sum approach, or a dynamic prioritization approach, might be more relevant than the Pareto approach. Such alternatives to the Pareto approach do not necessarily mean that the performances of individuals and species are not bounded in some sense by a global Pareto-front. Understanding the applicability of the notion of *non-dominated sets* in natural evolution might help to also shed some light on its possible contribution to natural diversity. Of a particular interest might be the use, in the MCC context, of fuzzy and multi-objective game theory (e.g., [28]). This may help incorporating the fact that the “assignment of fitness values in nature” by way of contradicting competences might be only fuzzily understood by humans.

4.3 Comparing Concepts and Species

Understanding that an analogy between design concepts and species might exist had an important impact on the development of different concept-based MOEAs (see [2]). The following provides some background to this observation. In biology the term species commonly refers to the most basic biological classification comprising of individuals that are able to breed with each other but not with others (except from rare cases). In nature, a niche can be viewed as a subspace in the environment with finite resources that must be shared among the population (society) of that niche, while competing to survive. In evolutionary algorithms the term speciation (or "niching") commonly refers to an automatic technique to overcome the tendency of the population to cluster around one optimal solution in a multi-modal function optimization. Speciation techniques help maintaining diversity to prevent premature convergence, while dealing with multi-modality. Speciation could be viewed as an automatic process, or an operator, that gradually divides the population into sub-populations (species). Each of these sub-populations deals with a separate part of the problem (*niche* of the search space). Commonly *niche* refers to an optimum of the domain and the fitness represents the resources of that niche. The common process of speciation is also a niching process as it finds the niches, while dividing the population into the niches.

Species that are either competing or cooperating are viewed as co-evolving. Competitive co-evolution has been computationally employed with single as well as with multi-populations. In contrast to niching, where species are automatically formatted, in co-evolution of competing species, the species are commonly predefined (although their populations' relative size may be subject to automatic changes). This situation resembles that of the concept-based approach, in which the association of sets of particular solutions with concepts is predefined. The last observation clearly indicates a possible analogy between concepts and species. Both are represented by sub-sets of the populations. Beyond the mathematical similarities, it seems intuitive to view different species as different *design concepts of nature*.

A crucial part of the algorithm, in [4] and in similar studies, is the penalty functions that are used for the fitness. These include a *front-based concept-sharing penalty* and an *in-concept front niching penalty*. The *front-based concept sharing* is applied to preserve *concept diversity*, and to prevent a good concept from hindering the evolution of other potential concepts within a front. The *in-concept front niching* preserves the *diversity of particular solutions* within each concept belonging to a particular non-dominated front (rank). In a recent investigation [2] the algorithm, such as in [4], has been modified to improve the analogy by eliminating crossover operations between concepts. In [2] a crowding approach has been implemented to penalize the fitness. In developing the penalties and the algorithms, the focus has been on engineering design and the wish to find a good representation of the optimal concepts. With the elimination of crossover operations between concepts in [2], it appears that the process of the simultaneous multi-objective concept-based evolution could be viewed as the evolution of species towards and along a Pareto front.

While supporting the development of computational mechanisms to simultaneously evolve species/concepts towards and along a Pareto front, by a metaphorical EC approach, a host of questions should be raised as to the applicability of such comparisons with respect to improving the understanding of nature. The main question from the second viewpoint of cybernetics is to what a degree it would be possible to advance the potential analogy between design concepts and species to obtain better understanding of evolution. Furthermore, it is still questionable if new metaphors might arise from taking a MOO view rather than a SOO view on nature. Clearly, the existing concept-based algorithms have been developed for engineering design applications and not as simulators of natural selection. Yet, as described in section 3, multi-competence situations in the sense of multi-fitness or multi-functionality do exist in nature. Very basic survival situations in nature could involve tradeoffs in behaviors such as fast (to obtain food) versus safe (to avoid dangers), which has been the subject of a concept-based robotic-related study in [26]. Incorporating spatio-temporal evolution scenarios into the concept-based approach might create a new way of studying natural evolution in the sense of the second viewpoint of cybernetics. The following is an open question for future research. Would it be possible to say that, regardless of different scenarios, nature evolve species towards optimality in a multi-objective sense, just as humans are trying to create conceptual designs that are satisfying in some Pareto sense?

Engineering design often involves satisfying solutions that are not necessarily Pareto-optimal. Similarly, it is expected that natural selection involves "design solutions" that could be viewed as advancing towards a Pareto-front, but are not optimal in the Pareto sense. With this respect it appears logical to try not only an epsilon-Pareto approach but also a fuzzy Pareto approach.

Of a particular interest for future research is to investigate potential analogies and metaphors as related to current studies on the robustness of concepts (e.g., [5]), which should not be confused with robustness of particular solutions (e.g., [12]). This topic encompasses different types of robustness with respect to different types of uncertainties, and requires the introduction of measures not only for multi-objective optimality of concepts, but also for their robustness. With this respect, methods of comparisons, in the multi-objective sense, of particular solutions and of concepts (sets), as well as their rationale, might also serve as an MCC research playground when such questions are asked with respect to species. A more questionable idea is to try and compare the interactivity aspects of the concept-based approach with evolutionary issues of mixed systems (see figure 1). Finally, it should be noted that, due to the fact that the concept-based approach is a set-based approach, analogies might be explored not only with respect to species but also with respect to other biological categories.

5 Hypothetical MCC Questions

The study of multi-objective optimality and robustness of conceptual solutions, which is motivated by engineering, could be carried out using a multi-objective concept-based EAC. In such design studies the EC approach allows evolution that is purpose-directed. Similarly EAC can be used as an A-life set-up to try and explore the role of MOO in the natural evolution of species with a *blind watchmaker approach*. Performing such independent studies might be complemented with related MCC questions. The above discussion in section 4 raises some interesting MCC questions. Among such speculative questions are:

1. Is Pareto-optimality relevant to natural selection in any sense?
2. As above with respect to local versus global front.
3. Given the dynamic aspects of the survival conditions in nature, could it be possible to compare it as similar to the varying market demands in engineering?

4. Does robustness of concepts have a biological counterpart of robustness of species?
5. As above in relation to descendents of a biological ancestor?
6. Could evolving Pareto-optimal/robust design concepts be related to game-based theories of evolution?
7. Would it be possible to use ecology and bio-technology multi-objective planning to support an MCC-based studies of natural evolution?
8. What are the consequences of a Pareto approach to natural evolution with respect to discussions on natural diversity?
9. What would be the implications of the use of fuzzy multi-objective game theory in MCC studies?

The above list of MCC questions could certainly be extended. Of a particular interest are related-questions about other forms of adaptation in nature as well as questions associated with evolutionary developmental biology. Such issues are left for future research.

6 Summary and Conclusions

This chapter introduces Multi-Competence Cybernetics (MCC). The current study focuses on a comparative discussion concerning the multi-competence evolution of systems in nature and the artificial. Research developments, in areas such as evolutionary design, plant biology, robotics, A-life, biotechnology, and game theory, are used to justify the proposed MCC approach. Several questions are raised, which are related to a long-standing controversy on adaptationism and optimality. Among such questions is that on the relevance of a Pareto approach to the study of nature. At the risk of a controversial discussion this chapter suggests a comparison between species and engineering design concepts and hints at possible analogies with respect to their multi-competence. Another resulting suggestion is that multi-fitness dynamic visualization of natural systems should be of a scientific value, and in particular for the pursuit of understanding of natural evolution by way of *thought experiments.* In addition, future MCC research directions are proposed. It is concluded that MCC is a justified framework of thinking that has a ground in past and present findings both in engineering design research and biology. Yet, its scope, as demonstrated here, is bound to be controversial, which makes it both an intriguing and exciting research area. It is hoped, at best, that MCC would direct thinking into fruitful new observations on the multi-fitness aspects of natural adaptation. Alternatively, it is expected that such studies would allow a better understanding of the similarities and dissimilarities between the creation of natural and artificial systems by adaptive processes.

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