Chapter 30
Mechatronic Design Automation: A Short Review

Zhun Fan, Guijie Zhu and Wenji Li

Abstract This paper gives a short review on mechatronic design automation (MDA) whose optimization method is mainly based on evolutionary computation techniques. The recent progress and research results of MDA are summarized systematically, and the challenges and future research directions in MDA are also discussed. The concept of MDA is introduced first, research results and potential challenges of MDA are analyzed. Then future research directions, focusing on constrained multi-objective optimization, surrogate-assisted constrained multi-objective optimization, and design automation by integrating constrained multi-objective evolutionary computation and knowledge extraction, are discussed. Finally, we suggest that MDA has great potential, and may be the next big technology wave after electronic design automation (EDA).

Key words: Mechatronic Systems, Design Automation, Evolutionary Design, Bond Graph (BG)/ Genetic Programming (GP), Evolutionary Optimization.

30.1 Introduction

Mechatronics is a type of hybrid system that consists of mechanical, electrical, pneumatic, hydraulic and control subsystems. Therefore, the design of mechatronics is different from the design of traditional mechanical, electronic and hydraulic systems.

In the design process of mechatronic systems, several types of energy conversion need to be fused [10]. In addition, the design of continuous and/or discrete controllers may also need to be considered in mechatronic systems. As a result, MDA

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needs to consider the automatic concurrent design of controllers and controlled objects. Since a mechatronic system is usually very complicated, it is so far difficult to achieve a good strategy for automatically designing and optimizing such a complex system.

The design of mechatronic systems usually relies on the long-term experience of engineers, which entails long design cycles and frequent modifications. In addition, the result of the design is not guaranteed to be optimal. Thus, the research on MDA is important to help designers improve design performance and efficiency.

The remainder of the paper is organized as follows. Section 30.2 overviews recent work on MDA, including a discussion on issues and challenges in MDA. Section 30.3 gives future research directions on MDA. Finally, conclusions are drawn in Section 30.4.

30.2 Mechatronic Design Automation (MDA)

Mechatronic systems with the properties of intelligence, flexibility and multi-functionalities are becoming important and have received broad attention in recent years. As a special type of mechanical system, mechatronics is a full-featured and powerful system composed of electronic devices and mechanical components. Fig. 30.1 shows the different characteristics between electronic systems and pro-mechanical systems (including micro-electro-mechanical system, mechatronic system and pure mechanical system). The properties of coupling and modularity of the above-mentioned systems are also illustrated in Fig. 30.1.

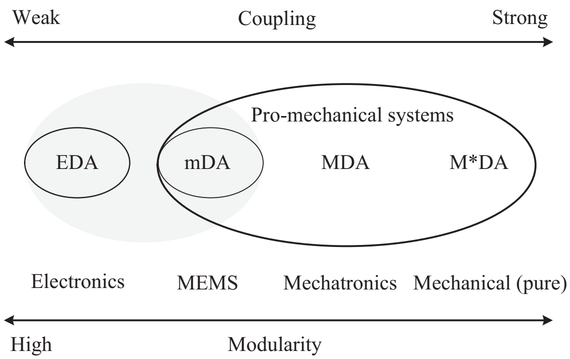


Fig. 30.1: The relationships of design automation of different systems

In Fig. 30.1, EDA, mDA, MDA and M*DA represent the design automation of electronic system, micro-electro-mechanical system(MEMS), mechatronic system and pure mechanical system, respectively. EDA is easy to be realized due to the high modularity and low coupling of digital electronic systems. The pure mechanical system has the lowest modularity and the strongest coupling. Thus, the implementation of M*DA is much more difficult than that of EDA, mDA and MDA. At present, EDA and mDA have already made great progress. The methods and experiences from EDA and mDA can be transferred to help to optimize the design of mechatronic systems.

The most significant difference between MDA and EDA is that the former contains a multi-domain physical system integrated with control systems [51]. Mechatronics is an essential stage for the evolution of modern products, which contains many components from different engineering fields, such as mechanical, electrical, hydraulic and control engineering. Chakrabarti [8] proposed a kind of MDA framework which can generate a series of conceptual designs that meet pre-set requirements. However, the dynamic behavior of the designed mechatronic system has not been studied. Campbell [7] studied and developed an agent-based MDA framework, which has the capability to adapt to dynamic environments. However, it lacks a detailed analysis of the dynamic behavior of the designed system. Behbahani [5] proposed a concept of mechatronic design quotient (MDQ), which can integrate multiple design objectives into one single objective. Then, the formulated optimization problem is solved by using single objective optimization algorithms. However, when the multiple design objectives are conflicting with each other, the performance of this method can not be guaranteed. In fact, when the geometry of the Pareto front of the formulated problem is convex, this method can only find two endpoints, a fact that can be proved theoretically [33]. Thus, multi-objective optimization algorithms are more commonly used methods to solve the mechatronic design optimization problems with more than one objective.

Bond graphs (BGs) are an unified modeling method for multi-domain systems [55]. BGs have already been widely used in modeling various of real-world physical systems such as robots [32], hybrid electric vehicles [21] and wind turbine systems [35], etc. Fig. 30.2 shows an example of a single BG model that can uniformly represent resonator units in three different fields, including mechanical, electrical, and micro-electro-mechanical systems. Since BGs can clearly represent topologies of a system, it becomes an excellent candidate tool in searching open-ended design spaces. Tay et al. [42] utilized BG to automatically generate the design of a mechatronic system that meets the pre-defined design specifications, in which a genetic algorithm (GA) is used to search in the design space. Finger and Rinderle [22] proposed to apply the BG method to conduct the generation process from pre-defined design specifications to physical implementations that meet these design specifications. Seo et al. [39] proposed an automatic design methodology called BG/GP for mechatronic systems, which combines BG and genetic programming (GP). Compared with other methods, the proposed BG/GP method has obvious advantages which are shown in Table 30.1.

From Table 30.1, it can be observed that BG, GA and GP have different properties. BG can be used for the modeling and effective evaluation of multi-domain systems. GP and GA can both search the design space for optimizing the design. However, compared with GA, GP has more advantages due to its strong capability of searching open-ended design spaces. Therefore, GP can optimize the topology

Table 30.1: Comparisons of various design methods [14]

Properties	Design Methods				
	BG	GA	GP	BG/GA	BG/GP
Multi-domain	✓			✓	✓
Topological Variation			✓		✓
Developmental Process		✓	✓	✓	✓
Automated Synthesis		✓	✓	✓	✓
Design Optimization		✓	✓	✓	✓
Efficient Evaluation	✓			✓	✓

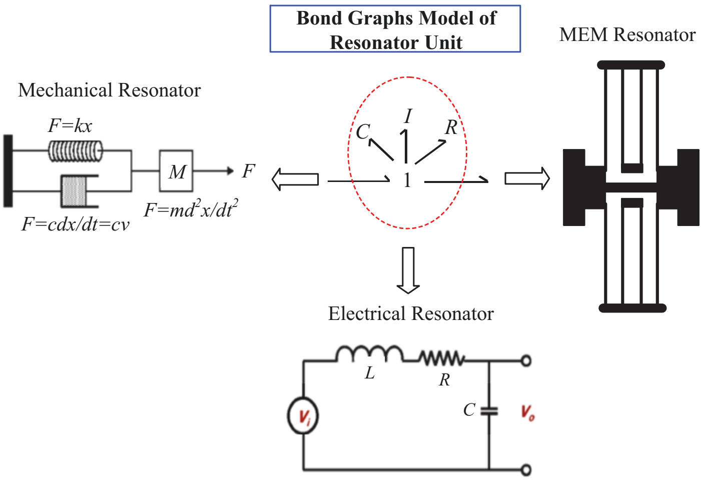


Fig. 30.2: One bond graph represents resonators in different application domains

and parameters of a mechatronic system simultaneously. BG/GA integrates BG and GA, and BG/GP integrates BG and GP, which has the capability to deal with topological variation that is not included in BG/GA.

In BG/GP, the BG is used for the modeling of multi-domain systems, while GP is used for the automatic exploration of the open-ended design spaces. Fig. 30.3 shows the mapping from genotype to phenotype in BG/GP method. The BG serves as an intermediate medium from the GP tree to the final physical realization, which is analogy to the mapping from genotype to phenotype. BG/GP not only can automatically perform open-ended topological search, but also optimize parameters of a system at the same time.

The BG/GP proposed by Fan et al. has already been applied to the design of electrical and mechatronic systems, such as analog filters [39], electric filters [19] and the driver system of a printer [20]. At the same time, Wang et al. [45] pro-

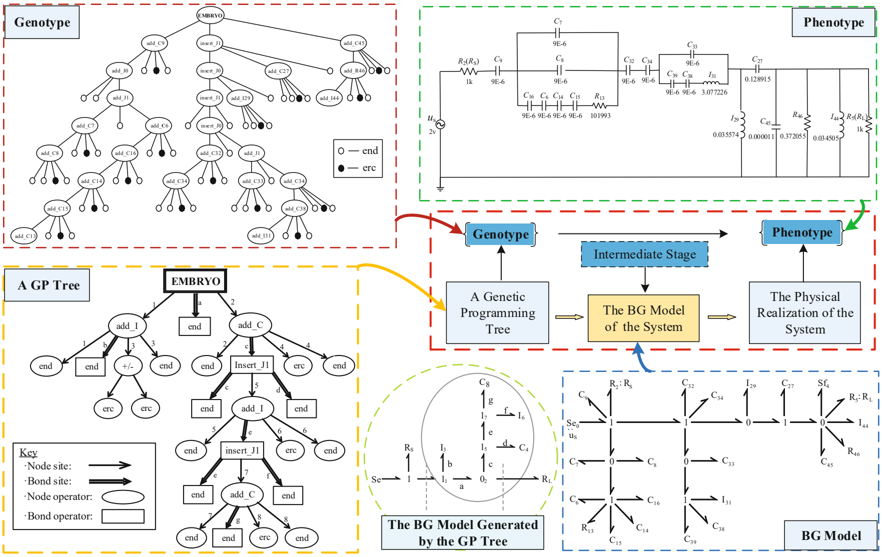


Fig. 30.3: An example of genotype-phenotype mapping

posed a knowledge-based evolutionary design framework for mechatronic systems by combining the BG/GP method with human knowledge, as shown in Fig. 30.4. This framework is demonstrated by a quarter-car suspension control system synthesis and a MEMS bandpass filter design application. Through the above-mentioned cases, the automated design method based on BG/GP provides new ideas for designing of mechatronic systems, which has potential to improve the performance of existing design schemes.

The traditional design methods for mechatronic systems often have long design cycles. Therefore, improving the search efficiency of automated design algorithms is important. Hu et al. [26] proposed a hierarchical hair competition (HFC) model which has the ability to avoid local premature convergence. Oduguwa et al. [36] proposed an intelligent design framework which can integrate the human knowledge and judgement. Zhang et al. [54] proposed a competitive mechanism based on a multi-objective particle swarm optimizer. Wang [43] proposed a hierarchical surrogate-assisted evolutionary algorithm for optimizing the airfoil of a flying wing configuration whose fitness evaluation is time-consuming and computationally expensive. The proposed hierarchical surrogate model is embedded in the covariance matrix adaptation evolution strategy (CMA-ES) to solve the RAE2822 airfoil optimization problem. The search efficiency of the algorithm can be improved by using these mechanisms.

As we all know, mechatronic systems usually consist of multiple sub-systems which come from different domains. Inspired by the study of symbiosis in nature, Potter et al. [38] proposed a general coevolution framework. They designed a rule-based control system for autonomous robots by using this co-evolution framework.

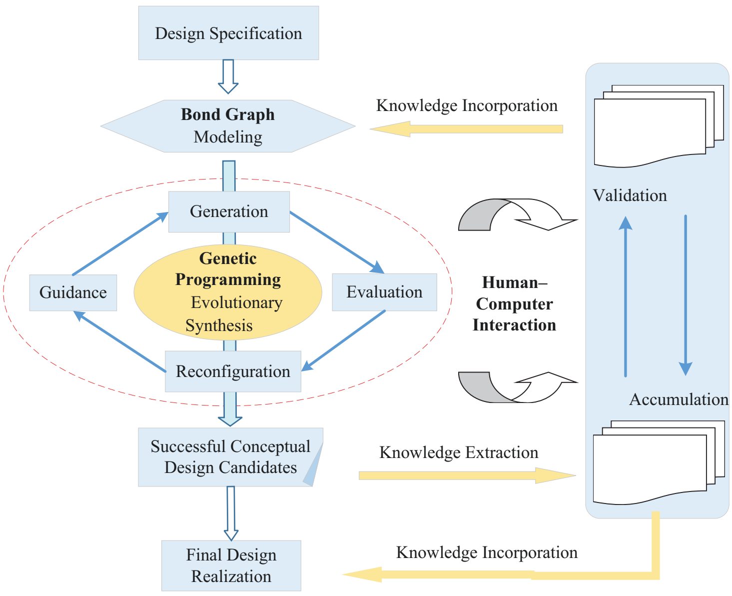
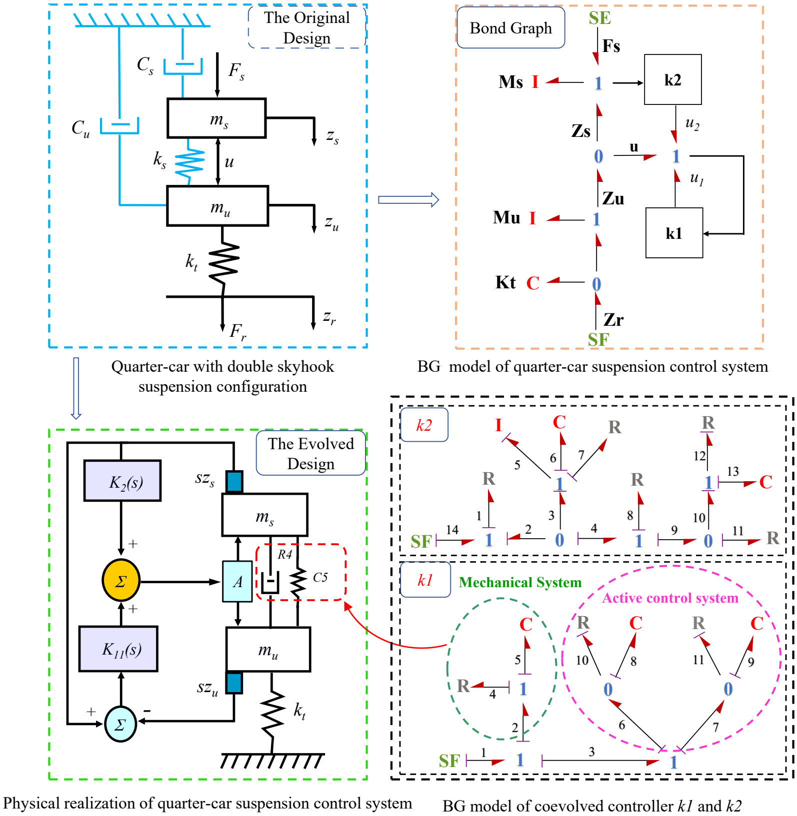


Fig. 30.4: The framework of evolutionary synthesis of mechatronic systems

Although a general architecture of co-evolution has been proposed, the problem of modeling dynamic systems and the selection of different specific species was not well solved. Wiegand et al. [47] provided experimental validation analysis of various collaboration mechanisms and presented some basic recommendations on how to choose a mechanism for a particular problem.

Wang et al. [46] proposed a unified mechatronics modeling and brain-limb collaborative evolution design method. An automobile suspension system was designed as shown in Fig. 30.5. Compared with the traditional method, this method integrated the features of unified modeling of multi-domain systems and an open topological search. It can help designers get a set of more advanced and optimal designs. Burmester et al. [6] presented a model driven development approach called MechatronicUML [4, 23] for the design of self-optimizing mechatronic syetems. They used the proposed MechatronicUML approach to design discrete and continuous control syetems. Fan and Dupuis studied the evolutionary design of hybrid mechatronic systems with continuous and discrete properties [12, 13]. They combined the lookahead controller, hybrid BG, and GP to design the DC-DC converter [13] and used a Finite State Machine (FSM), hybrid BG, and GP to design multiple-tank system [12] automatically.

Robot systems, as a sort of complex mechatronic systems, have received great attention from the industry and academy. For example, Asea Brown Boveri Ltd (ABB), a well-known robot company, has established a long-term cooperative relationship with the team of Professor Peter Krus from Linköping University.



Quarter-car with double skyhook suspension configuration

BG model of quarter-car suspension control system

Physical realization of quarter-car suspension control system

BG model of coevolved controller *k1* and *k2*

Fig. 30.5: Cooperative coevolutionary synthesis of quarter-car suspension control systems

They have conducted in-depth research on design automation for robot systems. Tarkian [41] clearly defined the concept of "design automation" and used a multi-objective evolutionary algorithm to optimize the design of robotic manipulators. In 2000, Lipson [31] designed computer-generated robotic systems by using evolutionary computation and employing a 3D-printer to prototype them. In [25], a design automation method for a soft robot was proposed, which combined the evolutionary algorithm and the Gaussian mixture model to perform an open topological search. Jamwal et al. [27] proposed a fuzzy sorting selection method based on multi-objective evolutionary algorithms to optimize a three-degree-of-freedom wearable ankle rehabilitation robot. In terms of lightweight design of manipulators, Zhou and Bai [56] designed a service manipulator by using an integrated design optimization approach, where manipulator kinematics, dynamics, drive-train design and strength analysis by means of finite element analysis (FEA) were generally considered. Yin et al. [50] proposed a method for designing a lightweight manipulator, in which the quadratic Lagrange algorithm was used to optimize the structure and the drive trains of the manipulator.

30.3 Future Research Directions

In the 21st century, mechatronic systems have received growing attention as an emerging discipline. The above-mentioned research is devoted to solving some challenging problems in MDA, which stimulates the future development of this discipline. Some issues and directions that deserve further study are listed as follows.

30.3.1 Constrained Multi-Objective Optimization

Generally, in real-world design problems, a designer considers not only one single design objective, but multiple conflicting objectives with a set of constraints, simultaneously. Therefore, the design of mechatronic systems can be formulated as a constrained multi-objective optimization problem (CMOP).

Constrained multi-objective evolutionary algorithms (CMOEAs) are commonly used methods to solve CMOPs, because they can achieve a set of feasible and non-dominated solutions in a single run. Currently, CMOEAs can be generally classified into two categories according to their selection mechanisms. One is the dominance-based CMOEAs, and the other is the decomposition-based CMOEAs.

In dominance-based CMOEAs, solutions are selected the next generation based on non-dominated ranks. Typical examples include NSGA-II-CDP [11] and SP [48]. In decomposition-based CMOEAs, a CMOP is decomposed into a set of constrained single objective optimization subproblems, and each subproblem is solved in a collaborative way. Representative examples include MOEA/D-CDP [28], C-MOEA/D [1], MOEA/D-Epsilon [49], and MOEA/D-SR [28].

Recently, two decomposition-based CMOEAs, MOEA/D-IEpsilon [16] and MOEA/D-ACDP [15], have been proposed for solving CMOPs with large infeasible regions. In MOEA/D-IEpsilon [16], the epsilon level, which is used to relax constraints, is set dynamically according to the ratio of feasible to total solutions in the current population. Experimental results indicate that MOEA/D-IEpsilon is significantly better than four other decomposition-based CMOEAs, including MOEA/D-Epsilon [49], MOEA/D-SR [28], MOEA/D-CDP [28] and C-MOEA/D [1]. In MOEA/D-ACDP [15], the proposed angle-based constrained dominance principle (ACDP) is embedded in MOEA/D to solve CMOPs. Experimental results demonstrate that the proposed MOEA/D-ACDP [15] is significantly better than the state-of-the-art CMOEAs, including C-MOEA/D [1], MOEA/D-CDP [28], MOEA/D-Epsilon [49], MOEA/D-SR [28], NSGA-II [11] and SP [48].

To get across infeasible regions more efficiently, Zhun et al. [17] proposed a push and pull search (PPS) framework. In the push stage, a multi-objective evolutionary algorithm (MOEA) is used to explore the search space without considering any constraints, which can help to get across infeasible regions very quickly. In the pull stage, a CMOEA with improved epsilon constraint-handling is applied to pull the population to the feasible and non-dominated regions. Experimental results indicate that the proposed PPS method is very effective and efficient in solving CMOPs.

To promote research on constrained multi-objective optimization, Zhun et al. [18] proposed a difficulty-adjustable and scalable (DAS) test suite with three primary types of difficulty, which reflect various types of challenges presented by real-world optimization problems, in order to characterize the constraint functions in CMOPs. Nine CMOPs and nine constrained many-objective optimization problems (CMaOPs), called DAS-CMOP1-9 and DAS-CMaOP1-9, were proposed to evaluate the performance of two popular CMOEAs, MOEA/D-CDP and NSGA-II-CDP and two popular constrained many-objective evolutionary algorithms (CMaOEAs), CMOEA/DD and CNSGA-III, respectively. Experimental results indicate that these methods can not solve these problems efficiently, which stimulates researchers to continue to develop new CMOEAs and CMaOEAs to solve the suggested DAS-CMOPs and DAS-CMaOPs.

In general, to solve CMOPs efficiently, a single constraint-handling mechanism is not enough. A future research direction is to dynamically invoke appropriate constraint-handling mechanisms to search according to the state of the evolving population of a CMOEA.

30.3.2 Surrogate-Assisted Constrained Multi-objective Optimization

In most engineering design problems, the evaluation of objectives and constraints is expensive. Some objectives and/or constraints can only be calculated by doing physical experiments or calling simulation software, such as aerodynamic shape design, structural design, large scale circuit design, pharmaceutical design, etc. Thus, the evaluation process is time- and money-consuming. Optimization problems with the above-mentioned characteristics are also called expensive optimization problems. At present, the most representative work for solving expensive optimization problems is the surrogate-assisted evolutionary algorithm. By using surrogate models in the evolutionary process, the number of fitness evaluation can be reduced significantly.

In recent years, research on surrogate-assisted evolutionary algorithms has attracted increasing attention [9, 29, 34, 37]. For example, Jin et al. [30] proposed an evolutionary algorithm that can effectively solve nonlinear constrained optimization problems. An approximate model was built for each constraint function with increasing accuracy. Experimental results suggest that the proposed method is competitive compared to state-of-the-art methods for solving nonlinear constrained optimization problems. Chugh et al. [9] proposed a surrogate-assisted reference vector guided evolutionary algorithm for computationally expensive many-objective optimization problems. It adopted the Kriging model to approximate each objective function to reduce computational costs. Sun et al. [40] proposed a surrogate-assisted cooperative swarm optimization method for solving high-dimensional expensive problems. In the proposed method, a surrogate-assisted particle swarm optimization (PSO) algorithm and a surrogate-assisted social learning-based algorithm cooperatively search for the global optimum.

Mechatronic systems are a kind of complex and multi-energy domain coupled system which consists of components from different engineering fields. The design process of mechatronic systems is also complex, time-consuming and computationally expensive. Therefore, the research on surrogate-assisted CMOEAs to solve optimization problems of mechatronic systems efficiently is a direction worthy of further study.

30.3.3 Design Automation by Integrating Constrained Multi-Objective Evolutionary Computation and Knowledge Extraction

In the evolutionary process of CMOEAs, a large amount of data is generated, which contains a lot of knowledge related to the optimization problem. However, in traditional CMOEAs, these data are not mined, which results in a huge waste of resources.

As we all know, machine learning methods can assist MOEAs to improve search efficiency in selection and recombination processes [44, 52, 53]. Moreover, machine learning methods [2, 3] have the capability to acquire knowledge automatically and to refine knowledge bases, such as discovering new concepts and new models, finding errors in the knowledge bases, and optimizing and simplifying knowledge, etc. The fusion of machine learning methods with evolutionary algorithms not only improves the performance of the algorithms, but also acquires some design knowledge. The obtained knowledge can be transformed to other related scenarios, and generate some innovative designs [24]. Therefore, knowledge-driven optimization, by fusing CMOEAs and machine learning methods, is a very promising research direction for design automation of mechatronic systems.

30.4 Conclusion

We provide a preliminary overview of research work in MDA. With the growing amount and size of mechatronic systems being developed, the need for design automation for mechatronic systems is paramount. In MDA, evolutionary optimization, such as the surrogate-assisted CMOEA, has been shown to be successful at exploring large search spaces of optimization problems of mechatronic systems with expensive fitness evaluation, which has great potential for solving the design optimization problems of mechatronic systems. In the future, MDA integrating knowledge extraction and surrogate-assisted CMOEAs will further improve the performance of design automation algorithms and generate more innovative designs.

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