Caroline C. Hayes
Department of Mechanical Engineering,
University of Minnesota,
Minneapolis, MN

Ashok K. Goel
Department of Computer and Cognitive Science,
Georgia Institute of Technology,
Atlanta, GA

Irem Y. Tumer
Department of Mechanical, Industrial and
Manufacturing Engineering,
Oregon State University,
Corvallis, OR

Alice M. Agogino
University of California Berkeley,
Berkeley, CA

William C. Regli
Drexel University,
Department of Computer Science,
Philadelphia, PA

Intelligent Support for Product Design: Looking Backward, Looking Forward

In celebration of the 10th anniversary of the Journal of Computing and Information Science in Engineering this article will provide a retrospective of past research on intelligent systems in engineering design research, and new perspectives. Intelligent systems and expert design knowledge have become important and integral parts of systems that support product design; they are embedded in many CAD tools, design knowledge repositories, design assistants, and design critics. Such tools have become common place for assisting designers in creating new designs, modifying old ones, or storing expert design knowledge for later use by oneself, other designers or future generations. Intelligent systems are becoming increasingly important as computer technologies have matured, and global competition has demanded increasingly better products, faster. As these trends continue, intelligent systems will be increasingly necessary for competitiveness. This retrospective will present past advances in a range of areas from model-based and case-based reasoning, machine learning, biologically inspired design, creative design, and virtual design. The work described has roots in many disciplines including engineering, artificial intelligence, psychology, human factors and management science. We present this work with an aim to identify directions in which the field is moving, and more importantly, to gain insights into future directions and critical areas for future research investments. [DOI: 10.1115/1.3593410]

1 Introduction

Computing and intelligent systems have become integral and critical parts of the engineering tools on which organizations that design products have come to depend. Such tools include intelligent computer-aided design (CAD) systems, design knowledge repositories, design assistants, and design critics, all of which aim to reduce designers' work and/or capture design knowledge while improving accuracy, safety, and quality. The goals of this paper are to provide a retrospective of research on intelligent systems in design research, to identify the directions in which the field is moving and to use those insights to suggest important areas for future research investments.

Intelligent systems in design research have resulted from rich cross fertilizations between engineering, artificial intelligence (AI), knowledge-based systems, human-computer interaction, human factors, and psychology. Such work has lead to important advances in the use, development, and theory of intelligent systems in product design, as well as vibrant new ways of thinking about design and other forms of complex problems solving. Because of their importance as design tools, smart investments in intelligent systems for design are critical for ensuring effectiveness in rapidly producing new, high quality products, the ability to compete in a rapidly moving global market, and a strong economic future.

We make no attempt to be comprehensive; the field is far too broad and rich to capture in a single article. Instead, we have selected specific topics that highlight particular issues that we view as important, particularly to inform thinking about future needs and directions. Other surveys on intelligent systems in design can be found in Refs. [1–6].

Product design is used to refer to any and all facets of the process by which a product specification is created. In practice, there is no clear dividing line between design, manufacturing, and other life-cycle issues; for example, a designer may need to work out part or all of the manufacturing plan and logistics in order to make cost-effective design decisions. However, for the purposes of this review, we focus on design, primarily computer-aided conceptual design. Designed products are not necessarily physical artifacts, nor are they all created by engineers. Products may be devices, such as the latest mobile phones, laptops, or music players; complex, distributed systems, such as healthcare information networks; or services, such as repair and maintenance contracts. Designing products and systems typically involves many people with wide ranging areas of expertise, who must often collaborate over long distances through virtual technologies.

Intelligent systems refer broadly to computer systems that perform some degree of intelligent reasoning. They range from those that are highly automated and perform their logic without much assistance from people, such as expert systems or genetic algorithms, to those that simply provide structure or access to critical knowledge, such as ontologies and design repositories, which people draw on when they do their *own* reasoning. In particular, intelligent systems that augment or amplify human reasoning, in contrast to those automate and replace human reasoning, are growing in importance for complex, knowledge, and judgment intensive tasks such as design. After early experiments in automated, knowledge-intensive systems it rapidly became apparent that designers do not necessarily want computers to create designs or make judgments for them. Designers prefer to remain in control, with intelligent computer assistants to help them with particular parts of the process. Thus, we include intelligent assistants and knowledge lean systems as important parts of modern day intelligent systems.

Researchers and product developers have long looked for new and better ways to use intelligent systems to assist in product design because it is a process that is very work intensive, complex, and error prone. Intelligent systems have the potential to shoulder some of the workload managed by experienced designers and manufacturing engineers, reduce errors, as well as help them to manage, organize design, and manufacturing data and knowledge, capture it for later reuse, and coordinate with others across distance. However, intelligent systems can also introduce new challenges and difficulties such as complexity, knowledge maintenance, and human-computer interaction issues.

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2 Historical Roots

Ever since computational machines with the capability of performing intelligent reasoning were realized in the 20th century, researchers and product designers have looked for ways in which to use intelligent systems to make product design more effective and to improve the quality, safety, and appeal of the resulting products [7].

Researchers started exploring the uses of computers and intelligent systems in design, and, more generally, product development shortly after the first "intelligent system" was developed. In 1956, Newell and Simon [8,9] created the first intelligent system, Logic Theorist; the very next year (1957) Hanratty developed PRONTO, an early CNC programming tool [10]. The first computer-aided design tools, such as Sketchpad [11] were developed a few years later. Although PRONTO and Sketchpad were not artificially intelligent tools, researchers had begun to think about the possibility of intelligent systems in tools to support product design.

In 1969, in "The Sciences of the Artificial" Herbert Simon proposed that in addition to the natural sciences, which characterize naturally occurring phenomena, we need a "science of the artificial" to characterize man-made phenomena [12]. A science of the artificial is a science of the design and synthesis of artifacts, in other words, the "realm of engineering." In this work, Simon viewed design as a psychological, social, and economic process in which the nature of human designers, organizations in which they exist, and economic constraints must jointly be considered. The topics that he covered foretold most of the concepts which have become recurring themes in intelligent systems for product design research:

(1) representation of design problems including design knowledge, spatial representations, and functional representations;
(2) problem solving structure and design organization;
(3) the nature of the design process, and
(4) a theory of design.

These themes are equally relevant today, as when Simon first proposed them over 40 years ago.

Over the years, intelligent systems have been used to enrich many facets of product design. Intelligent systems have become so pervasive that many are unaware of the role they have played in the development of today's search engines, data mining algorithms, operating systems, embedded computing, computer gaming, social computing, robotics, etc. There have been impressive and economically important successes, yet many challenges have persisted even after many years of research.

Intelligent systems are even more necessary than ever as global competition has become fiercer, products and product systems have become more complex and time-to-market shorter. They have become essential tools for competition in the global market place, and appropriate innovations and investments in this area will be critical for continued future participation in those markets.

3 Intelligent Systems Research in Product Design

Intelligent systems research in product design pertains to several closely related issues, which we will classify into seven categories [13]:

(1) uses of knowledge,
(2) content and representation of knowledge,
(3) organization and access of knowledge in memory,
(4) acquisition and learning of knowledge,
(5) human-computer interaction in tools to support product designers,
(6) support for collaboration across distance in product design tasks, and
(7) methodologies for studying product design.

Briefly, *uses of knowledge* pertain to design methods and tasks, such as the method of case-based reasoning to support the task of proposing a conceptual design or the method of model-based reasoning (MBR) for the task of adapting a proposed design to meet specific design requirements. *Content of knowledge* refers to the types and ontologies of knowledge, for example, knowledge of specific kinds of objects, variables, concepts, relations, processes, etc. *Representation of knowledge* refers to forms of knowledge such as logical predicates and production rules (e.g., if-then rules [9]), frames and schemas, drawings and diagrams, etc. The uses, contents, and representations of knowledge are the focus of much research on knowledge-based product design.

However, knowledge, in general, is useful only insofar as it can be acquired when feasible and accessed when needed. It is critical to knowledge-based product design. Topics in organization of memory and access of knowledge cover a wide range, including use of conceptual graphs and discrimination trees to organize design cases and use of functions as indices to the structural components and causal behaviors of a design. Topics in learning and acquisition of knowledge also cover a vast landscape, including issues such as learning of functional indices to design cases, learning of design patterns and principles from design cases, and learning functional models of designs from their drawings.

While the challenge of collaborating over distance is not specific to design, it has become a major issue in design practice [14,15]. Research in design and intelligent design tools must now consider the fact that design is now commonly carried out in the context of distance and virtual collaboration [16]. Intelligent design tools will be used in distance and virtual collaboration whether their designers intend for them to be used in this way or not. Therefore, such tools must be designed to be compatible with distance collaboration or miss their mark. Similarly, research on design methods and practice must take these practical realities into consideration, as they greatly impact the ways in which designers use tools, carry out design, and share knowledge. For example, studies indicate that explicit articulation of design goals and knowledge becomes more important in virtual distance collaborations, increasing the need for tools and schema for sharing design rationale, knowledge, and data [17].

Finally, research on knowledge-based design addresses methodological issues such as the empirical basis and epistemological foundations of design theories as well as measures and metrics for evaluating design techniques and decisions. Methodological topics in knowledge-based design include set- and graph-theoretic characterization of classes of design problems, axiomatization of design knowledge, protocol and in situ descriptive studies of designers, and construction of standardized datasets for evaluating the efficacy of design methods.

Table 1 expands on the intelligent product development themes above and describes their roots in artificial intelligence and related disciplines.

However, this table is not meant to imply that there is a one-to-one correspondence between problems and intelligent systems techniques; instead, it is intended to show examples of problems in which specific techniques have been used. Generally, any given intelligent system technique has been employed in many aspects of product design and vice versa. Nor should the reader infer that existing intelligent systems techniques could be taken directly and simply "applied" to a given product design problem. Quite the contrary, an intelligent systems technique may serve as an initial inspiration for how to approach a given design task, but most such techniques had to be changed, enriched, and refined in actually applying them to real problems. Thus, the process of combining intelligent systems and product design has advanced the scientific understanding of both areas.

4 Examples of Intelligent Systems in Product Design

The literature on intelligent systems design is very broad and we will not attempt to survey all of it here. Finger and Dixon [18,19] provide useful summaries of early work on knowledge-based design. Tong and Sriram's [2–4] three-volume anthology

Table 1 Artificial intelligence and product development

Product development topic	Roots in artificial intelligence (and related areas where noted)
Model-based reasoning	Qualitative reasoning, functional models
Model-based diagnosis	Qualitative physics, functional models
	Bayesian networks, reasoning about uncertainty
Knowledge-based design	Knowledge-based reasoning
	Production rules
	Problem decomposition
	Knowledge-based representation, abstraction, organization
	Ontologies, frames, schemas
	Knowledge acquisition and machine learning
	Causal reasoning
Design rationale capture & use	Intent inferencing
	Design archival systems
Design reuse and adaptation	Recommender systems
	Case-based reasoning
Generative designs	Shape grammars
	Evolutionary computing & genetic algorithms
	Multiagent systems
Manufacturing planning	Means-ends analysis
	Planning, constraint-based reasoning
Feature recognition and extraction	Image recognition and extraction
Design theory	Protocol analysis (from Psychology)
	Ethnographic studies (from Work Anthropology and Human Factors)
	"Sciences of the Artificial" Herbert Simon
Virtual design teams	Virtual and augmented reality
	Social computing and CSCW: computer supported cooperative work
System development methods	Human-centered systems (from Human Factors and HCI)
	Geometries and constraint propagation
	Product data models and ontologies
	Collaborative design tools
	Enterprise-wide data integration

describes many early knowledge-based systems. Dym and Levitt [20] and Dym [21] textbooks provide a view of engineering design from the perspective of AI in design, and several special issues provide many examples of AI in design, including IEEE Expert's special issues on AI in design (volume 12, numbers 2 & 3, 1997) and JCISE's special issue on AI in Design (volume 10, number 3, 2010). Below, we briefly review developments in intelligent systems in design and identify the main issues they raised and the questions that remain open today.

4.1 Knowledge-Based Design. Design tasks were among the early successful applications of artificial intelligence and knowledge-based systems research. Examples of design applications addressed by these early systems included Eastman's General Space Planner (GSP), which automatically designed two dimensional spatial arrangements [22], circuit and VLSI design [23,24], design of mechanical assemblies [25,26], and computer configuration design [27].

John McDermott's R1 [27] used hundreds of if-then production rules to capture knowledge about how to connect a computer's central processing unit with the peripheral units through buses and ports, etc. Later, the Digital Equipment Corporation deployed XCON [28], a revised and expanded version of R1, for several years to actually address computer system configuration problems in practice. Both R1 and XCON were considered to be major successes in their day.

Like R1, many other early knowledge-based design systems such as AIR_CYL [29,30], PRIDE [31], VEXED [32], VT [33], and ADIS [34] focused mainly on configuration design. In configuration design, all components and connections in the design are known and the task is to select specific instances of components and connections and assign specific values to variables characterizing them [35]. However, starting with AIR_CYL, research on AI in design branched into many directions, exploring abstraction in design analysis, forms of knowledge representation such as production rules, design methods such as plan refinement and constraint propagation, and use of domain knowledge.

Early work in knowledge-based design identified many issues that are important today. These questions include:

(i) What are useful taxonomies of design tasks and methods?
(ii) What are the various types of design knowledge?
(iii) How should design knowledge be organized so it can be accessed when needed?
(iv) How may design knowledge be acquired interactively from experts?
(v) How can machine learning (ML) be used to automatically acquire, categorize, and organize design knowledge?
(vi) How can the consistency of the knowledge base be maintained as new knowledge is added to it?
(vii) How should a design system explain its reasoning to a human?

4.2 Design Critics: Designer and Computer as Partners. Some of the drawbacks of knowledge intensive systems included brittleness, and the high cost of system development and maintenance [36]. Because of these drawbacks, there has been a shift over time from knowledge intensive automated design tools intended to replicate and replace human skills, to less knowledge-intensive design critics and assistants intended to augment human expertise, help human designers to structure and organize their own thinking, or support their interactions with other designers [28,29,37,40–43]. Some of the advantages of design critics and assistants over more highly automated design tools are that critics and assistants are typically less expensive to design and maintain. They are less knowledge intensive [44], and designers often prefer tools which allow them to remain "in the driver's seat" while still easing their workload.

Tools that support and partner with humans require an increased emphasis on human-computer interaction, human factors, and an understanding of cognitive processes. Consequently, the development of such tools also benefits from methods borrowed from these fields [45].

4.3 Model-Based Reasoning in Design. With its roots in qualitative reasoning (e.g., Refs. [46,47]) and functional reasoning in the AI community (e.g., Ref. [48]), MBR has received much attention in engineering design, and in particular, in assuring the reliability and performance of the resulting products. MBR methods draw inferences from models of the physical world, including the way in which physical objects may behave.

Specifically, as the necessity of identifying and understanding failures as early as possible has become more accepted in the design community, a significant body of work has emerged that uses function-based approaches to bridge the gap between failure analysis and conceptual design. The emphasis of this body of work has been on the use of *functional* descriptions to describe early concepts, moving away from the need for detailed models of system architectures used for traditional failure analysis methods such as failure modes and effects analysis (FMEA) (MIL-STD-1629 A), fault tree analysis (FTA) [49], and probabilistic risk assessment (PRA) [50–52]. *Functional design* or *function-based modeling* is used as a convenient way to express designs at the early stages by describing what they will do and how they will do it [53–60]. Abstract risk analyses can be applied in conceptual design to these function-based descriptions to provide insights on the risk of various possible functional failures. Failure analysis is then mapped to functional representations in order to improve diagnosability and reliability at the early functional and conceptual design stages [61–65].

MBR based on qualitative reasoning (as opposed to quantitative reasoning: Ref. [66]) provides a unique advantage during the early design stages where design information is primarily qualitative. Many authors have approached early design-stage analysis using model-based reasoning, with varying levels of success. The key challenge in these approaches is the ability to represent the qualitative aspects of the design effectively, enabling the designers to move away from the need to work with more detailed design information. Most of the approaches, presented here briefly, have in common their use of different abstractions of the design, but differ in the way they generate a mapping between these abstractions. They have all demonstrated successful applications of their approaches to large-scale complex systems.

Early examples using function-based representations to reason about failures in design include the work of Refs. [55,56,58,59,67–69]. Specifically, Goel and Chandrasekaran [55] used the functional representation scheme for redesign problem solving in which the design agent first used the functional representation for failure-driven diagnosis faults of faults and then repair of the faults. Umeda et al. [58] initially developed a functional redundancy designer to identify functional redundancies in design by analyzing structural architecture of a system to identify physical features of a design that are capable of performing identical functions. They later developed a model-based reasoner for diagnosis and reactive control [59].

In engineering, Pahl and Beitz [70] extensively discussed design functions and function decompositions. Early work on function in engineering includes Refs. [71,72]. Hubka and Eder's theory of technical systems, for example, describe function-means hierarchies that are similar in many ways to behaviors that achieve functions in the work of Refs. [56,69]. Recent work on functions in this tradition includes Refs. [60,73]. The functional basis scheme of Hirtz et al., for example, describes the use of an ontology of functions for enabling functional decomposition.

In addition, function-behavior-structure (FBS) paths were developed by Qian and Gero [67] in which relations among function, behavior, structure, and processes are utilized to define FBS paths. These are then used to retrieve design information to conduct analogy-based design. In parallel, Bhatta and Goel [74,75] developed structure-behavior-function (SBF) models for analogy-based design based on abstraction and transfer of design patterns. Another example is found in the Function Behavior Representation Language (FBRL) [68], which is a language developed for representing function and behavior with predefined tasks. It was later used as a basis for computer-aided support of FMEA type of analysis [76].

More recently, the Function-Failure Identification and Propagation (FFIP) analysis framework was introduced by Kurtoglu and Tumer [77] to help the process of identifying functional failures during the system design stage by combining failure identification with model-based reasoning approaches. FFIP is presented as a design tool that aims to eliminate or reduce the likelihood of reaching certain possible futures by formal analysis of risk of failures early in the design process and proper guidance of decisions before the design becomes solidified [77–80].

4.4 Case-Based Reasoning In Design. Case-based reasoning (CBR) enables the use of past design solutions to "redesign" solutions to meet new complex problems. CBR usually follows these steps: identification and retrieval of relevant cases, reuse and revision of the case to meet the new need, and archiving of relevant new cases. Much case-based reasoning research has been incorporated into product design work. AI theories of case-based reasoning [81,82] provide a framework for developing computational architectures and languages both for understanding design processes and for building interactive tools for supporting the design processes.

Early examples of development of CBR in design include CYCLOPS [83,84], STRUPLES [85,86], ARGO [87], and KRITIK [88,89]. That these systems were so different from each other indicates that CBR is not a technique that can be applied to any design problem, but a framework that needs to be adapted for specific classes of design problems. For example, ARGO used rule-based reasoning to transform design plans for designing VLSI circuits to meet functional specifications of new circuits. In contrast, KRITIK integrated case-based and model-based reasoning to produce conceptual designs for engineering devices such as heat exchange devices and electric circuits. If a designer specified a function, F, KRITIK generated a qualitative specification of a structure S, which could accomplish that function. To do so, it stored an inverse mapping (from structure S, to behavior B, to function F) in the form a structure–behavior–function (SBF) model for each past case. Thus, SBF model provided a functional vocabulary for indexing past design cases so that they could be stored and later retrieved, adapted, or verified. Maher and Gomez [90] provide a survey of some of the early case-based design systems; Maher and Pu [91] provide a more detailed treatment.

The last two decades saw an explosion of interest in CBR in product design. We identify four major trends in this period. The first trend was to develop interactive CBR design systems that provided access to libraries of design cases but left the task of design adaptation to the user [92–96]. A second trend was to integrate CBR with a wide variety of reasoning methods such as rule-based reasoning and model-based reasoning [97,98], constraint satisfaction [99,100], and genetic algorithms [90,101,102] in order to create or evolve emergent new designs from the original case base. A third trend was the development of hierarchical case-based reasoning in which design cases were decomposed into subcases at storage time and recomposed at problem-solving time [103]. A fourth major trend in research on CBR in 1990s was to develop CBR for a variety of design tasks, such as assembly planning [104], in a wide variety of design domains such as software design [105,106], and design of human-machine interfaces [107].

Currently, CBR, integrated with database-driven configuration design systems, has become so pervasive that we are not always aware when they are embedded in the systems we use. For example, much of the work in web-based commerce for mass customization has its roots in this earlier work.

More recently, diagrammatic CBR has been at the forefront of research. Gross and Do's [108] Electronic Napkin took queries in the form of simple design sketches and retrieved matching design drawings from a design case library. Geminus is a system that took design drawings generated by vector graphics programs as input and retrieved matching vector graphics design drawings from a diagrammatic case library [109]. Galatea uses diagrammatic knowledge to transfer design plans from a known design case to a new design problem [110].

4.5 Knowledge Representation and Standards. Representing knowledge for product design is one challenge; however as representation approaches mature, it is equally important to develop and adopt standards for representations to facilitate knowledge sharing, broad adoption, and interoperability between tools to support product design. Supporting these needs, the development of information exchange standards and interoperability techniques have begun to emerge from the knowledge representation community. In particular, RDF, OWL, etc. all have their roots in the high performance knowledge bases (HPKBs) and other DARPA AI programs in the late 1980s and early 1990s. These representations have had a great influence of data standards (XML, STEP, etc.) and now software interoperability standards (service based computing).

4.6 Machine Learning In Design. ML, another branch of AI, has intersected with product design in several ways [111,113]. Four main threads are identified in this article, which we will elaborate below.

Learning design domain knowledge. Examples include efforts by Maher and Li [114] and Reich [115]. Reich's BRIDGER system used knowledge-based classification learning techniques to learn design concepts in structural design.

Learning design rules from design examples include efforts by Arciszewski et al. [116] and Stahovich [117]. Stahovich's LearnIT system learned new parametric design rules for simple mechanical systems by observing a designer's sequence of decisions in a carefully selected set of training examples.

Learning case indices and design patterns include the IDEAL system, which uses model-based learning to learn indices for organizing and storing new design cases for later use [75] as well as to learn design principles and patterns from design cases [74]. Design patterns were proposed by Alexander as abstractions to capture the similarities between architectural designs [118,119].

Design adaptation and optimization through evolutionary computing make use of evolutionary computing algorithms that create progressively better solutions by iteratively creating many variants on existing solutions and keeping only the best. For example, genetic algorithms are one commonly used form of evolutionary computing that has been successfully used for design adaptation [90,101,120–124]. Below, in Sec. 4.7, we will describe how evolutionary computing can be used to create completely new solutions, not just modifications of existing solutions.

4.7 Creative Design. Augmenting and amplifying human creativity in design has long been a goal of AI research in design. As with intelligence, it is hard to define creativity or distinguish it from related notions such as innovation and invention. However, like intelligence, it may not be necessary to precisely define creativity to make progress in developing AI theories, techniques, and tools for aiding human creativity in design. Four of the common and sustained research threads in creative design include: generative design, analogical design, visual reasoning in design, and measurement of creativity in design.

Generative design allows an expansion of the design space beyond parameterization, with the ability to create new design concepts not related to those in the original case base. Generative designs can be created through a variety of methods including rule and constraint based approaches, in which the rules and constraints describe the characteristics of feasible and high quality solutions [42] and evolutionary computing approaches, which additionally use stochastic processes, such as genetic algorithms or simulated annealing, to optimize designs. Evolutionary computing algorithms start by creating a set of randomly constructed but feasible solutions and then iteratively improve those solutions. They do so by identifying the "best" solutions from the current set, according to specified criteria for what constitutes "best," generate many variants on good solutions, and keep only the best. Those best solutions become the "seeds" for the next generation of solution variants. This "hill climbing" process is repeated many times until acceptable solutions are reached. Genetic algorithms are one commonly used form of evolutionary computing that has been successfully used for design optimization [125,126] .

1stPRINCE [127] was an early effort at generative design from first principles. This program assumed knowledge only about physical constraints, basic relations, and fundamental equations to design mechanical structures such as beams, rods, and tubes to design more complex mechanical structures. Shape grammars use geometric features and associated rules to permit one shape to be part of another, creating new metashapes; these grammars can include rules based on first principles [128–131].

Analogical design is closely related to case-based design. In case-based design, the new design problem is very similar in its features to a known design case, for example, the design of a new pocket flashlight given the design of a similar household flashlight. In analogical design, the new design problem is quite different from known design cases in many of its features and yet is similar in terms of some abstract relationship [132]. For example, the design of a mechanism for controlling fluctuations in the angular momentum of a gyroscope by transferring knowledge about closed-loop feedback from the design of an operational amplifier circuit: while the designs of the gyroscope and the operational amplifier circuits are different in most features, they are similar in the use of feedback control. References [67,74,75,133] provide examples of analogical design systems. Cobb et al. [134] combine biologically inspired analogical design with case-based reasoning to create MEMS sensor design. Hey et al. [135] explore the relationship between use of analogies and metaphors to inspire creative solutions at different stages of the design process, and Kolb et al. [136] build on this work to develop an intelligent system called *Meta4acle* to inspire humans to think creatively.

TRIZ [137] is a theory of creative design based on analogies. In TRIZ, when addressing a design problem leads to a contradiction between two design goals, one strategy for solving the contradiction is to abstract the design problem and use the problem abstraction to identify a relevant "inventive" principle. TRIZ provides a taxonomy of 40 such inventive principles culled from a corpus of design inventions.

Visual reasoning in design was described earlier for some design systems that perform visual reasoning systems under diagrammatic case-based reasoning. In addition, Joskowicz et al. [138] developed algorithms based on configuration spaces for analysis of tolerance in kinematic pairs on a plane such as wheel and its driver. Stahovich et al. [139] have developed techniques for extracting behavioral models from design sketches. Yaner and Goel [140] describe an alternative, analogical method for building models from design drawings.

5 Future Research Challenges and Opportunities

Nothing happens in isolation. The specific directions that intelligent systems research in product design has taken over the years have been shaped by technological, social/organizational, economic, and methodological developments in many disciplines. Examples of technological developments in the last decade include the growing availability of powerful low-cost computers, ubiquitous and mobile computing and sensing, wireless platforms for sensing, computing and actuating, standards pertaining to design and manufacturing data, and social networking tools. With ever accelerating technological advancements, consumers are demanding more features and personalization in products, while market pressures are shrinking the "time to market" for new products and upgrades.

The move of many manufacturing industries to countries with low-cost labor is another challenge for product design in the future, as is the globalization of product design teams composed of specialists situated in multiple locations or countries. These technological advances and socioeconomic drivers provide challenges to product design and opportunities for intelligent systems solutions.

In response to these needs, CAD systems and design tools have become "smarter" and incorporate many forms of design knowledge, representations, and intelligent systems. Knowledge, databased, and constraint propagation have become standard parts of many modern CAD tools. Plug-ins with specialized knowledge bases have become readily available, and many intelligent assistants, such as design advisors, are incorporated in design tools [37,42,44]. However, we have only begun to realize the power of intelligent systems in product design; there are many new directions for the future which hold great promise for enhancing the effectiveness and ease with which people and intelligent systems may jointly create designs.

5.1 New Directions: Social, Virtual, and Global Design. Globally distributed design team members that carry out much of their joint design work in a virtual cyberspace [16]. However, they have found that some of their traditional tools and approaches that work well in face-to-face design teams need adaption or augmentation when applied to virtual teams.

While participation in virtual design teams has now become quite common [14], virtual design tends to be more difficult than design in more traditional face-to-face teams for numerous reasons [17]. For example, the loss of the rich contextual information from virtual settings, which is inherent in face-to-face settings [141], makes it more difficult to clearly articulate design goals, ideas, design descriptions, and project coordination information in a virtual team [15]. Consequently, relationships and trust between design team members in virtual teams may develop more slowly [142], and misunderstandings, miscommunications, and failed coordination are more common [143]. However, whether or not they are difficult, virtual teams have become an economic necessity because it is prohibitively expensive to bring all relevant talent to the same location for the duration of a design project.

To be as successful and effective as possible, virtual design teams benefit from more structured management and goal setting [17], and greater articulation of design goals, knowledge, and data—which makes the design representation and ontology research cited above all the more relevant and important. Social computing and networking tools, such as net meeting, twitter, and face book have already become quite common additions to the set of tools used by virtual design teams.

However, much remains to be done. Our understanding of how to manage global design teams has not kept pace with their increasing use [15]. We need to develop new management and incentive techniques that are tailored to the special needs and challenges of virtual design teams. We need better shared 2-d and 3-d virtual workspaces that can work with practical bandwidth limitations. Additionally, the heavily spatial nature of design tasks may impose its own special challenges which current social networking tools may not adequately address, such as the need to convey spatial concepts and kinematics quickly and effectively through gestures [144–147].

The economics of production changes as well with globally distributed supply chains. The embedded knowledge used in intelligent CAD must be adaptable to consider local manufacturing conditions, while at the same time promoting desired practices in design for assembly and manufacture and, increasingly so, the environment. There are many opportunities for intelligent systems research to support virtual and distributed product design, as well as customized knowledge bases for combinations of locations in the supply chain. This, in turn, puts increasing demands on the representation of design knowledge and data to facilitate information exchange and understanding in virtual design spaces and on tools that support virtual collaboration.

5.2 New Directions: Mass Customization, Smart Grids, and Information-Dense Products. Another driving force of the past decade is the consumer demand for the latest technologies that are tailored to personal needs. What role can embedded intelligence and miniature sensing play in advancing mass customization and personalization in designed products? Designers need tools that can handle increasingly networked, "information dense" products. Designers will need tools and approaches to help them manage the sheer volume of product information, so they may represent, organize, and navigate this vast space of information. Social computing and embedded sensing in new products add to the overwhelming wealth of data available to both designers and consumers. Interesting research questions relate to how personal devices can be part of a world-wide smart grid and how ubiquitous user data be mined in the design process.

5.3 New Directions: Cognitive Design Tools. As human interactions and processes change with technological advances, there will continue to be a need to understand the evolving cognitive processes associated with modern product design, both from the individual and the team perspectives. A better understanding of a design team's cognitive processes, group dynamics, and communication needs in today's global work environment is needed to create tools to support both co-located and virtual design teams.

Building on this descriptive research, there is an opportunity to fully integrate design tools and cognitive design processes to effectively augment human designers' capabilities as assisted cognition systems. Exciting research areas include intelligent sketching, tangible computing, and virtual design and decision teams. Developers of design tools will need to expand their repertoire of methods to include work borrowed from psychology, work anthropology, and human factors so that they may effectively study cognitive processes, the impact of work situated in a context, group dynamics, and the impact of tools on human performance.

Enabling creativity and innovation has become an important societal goal for intelligent engineering systems. Innovation will be the key to any country's ability to succeed financially in the future. Research in this area ranges from autonomous computational designers with emergent behavior to creative IT,[1] in which the computer stimulates and enhances human creativity. Finally, if we are to design tools that can support creative design, then we need some operational measures of creativity for human/computer-generated designs. Shah et al. [148] have provided an excellent set of metrics in novelty, variety, quality, and quantity of design ideas.

5.4 New Directions: Sustainable Design. Over the last decade, sustainable design, sometimes also known as environmental design or "design for environment," has emerged as an important design problem. Sustainable design refers to design of materials, products, processes, and services in accordance with the principles of biological diversity, ecological integrity, and environmental responsibility. Design for recycling and design for reuse has long been a part of Product Lifecycle Management (PLM), and their importance in PLM is likely to increase with time.

[1]http://www.nsf.gov/pubs/2009/nsf09572/nsf09572.htm

Sustainable design, however, goes much further than design for PLM. Sustainable design engages a new set of economic, social, and cultural values such as water conservation, energy efficiency, and minimal carbon emissions. By bringing in new design requirements and constraints into the design problem statement, sustainable design changes the design problem space itself. Many researchers in the design community have turned their attention to the challenges of sustainable design. The latest examples have been published in the ASME Journal of Mechanical Design's September 2010 special issue on Sustainable Design (Vol. 132, Issue 9.) Additionally, the AI community has started to focus on the issues of sustainable design, as is evidenced by the 2011 AAAI Symposium on AI in Sustainable Design at Stanford, CA.

Biologically inspired design, sometimes also called biomimicry or bionics, offers a large space of potential design solutions for addressing many problems in sustainable design [149–151]. While evolutionary computing techniques such as genetic algorithms are inspired by the processes of biological evolution [152], biologically inspired design makes use of the *results* of evolution. Although biological "designs" are not necessarily optimal relative to their "functions," functions and designs of biological systems typically have been finely honed by the evolutionary processes. As a result, biological designs often are not only multifunctional but also robust and efficient. Biologically inspired design seeks to make use of this robustness and efficiency of biological systems to address technological problems. The Biomimicry Institute's webportal, AskNature,[2] provides many examples of biologically inspired sustainable design.

Although neither sustainable design nor biologically inspired design is new, it is only in the last decade that they have become fields of systematic study. It is here—in the systemization of knowledge, problem solving, and learning for sustainable design—that AI can be most helpful. As we indicated in Sec. 3, AI has been successful at identifying types of knowledge and building schemes of knowledge representation and organization. Further, as Sec. 4 illustrates, AI is also successful at building computational methods for the use, access, acquisition, and communication of different kinds of knowledge. As an example, biologically inspired design by definition entails analogies from biology to design disciplines such as engineering, architecture, and computing. How then, might AI theories of case-based and analogical reasoning inform development of biologically inspired design methods? As another example, a need when scaling biologically inspired design from case studies into a design methodology is representation of biological knowledge in a language that is useful for engineering designers. How might AI theories of ontologies inform the development of a knowledge representation language that can bridge engineering and biology? The excitement surrounding AI and sustainable design can be gauged from the upcoming symposia organized by the Association for Advancement of Artificial Intelligence [153].

6 Conclusions

This paper has presented an overview of both the history and prospectus for intelligent systems in engineering design. It is the hope of the authors that this paper will serve as a useful guide for new students of the field, experienced practitioners, and researchers. While the breadth of the field makes any such effort impossibly incomplete, we hope that readers will find the path we have charted through this interdisciplinary area useful for organizing intelligent design research. Over the past decades, we have witnessed researchers and practitioner continuing to find new ways to marry intelligent systems techniques with complex engineering problems to produce work that expands and deepens our understanding of intelligent systems and has inspired much of the basic science surveyed here. It is a testament to the role ASME's JCISE, on this its 10th Anniversary, that many of these works have appeared on its pages in the past decade. It has created a home for these interdisciplinary problems and provides a gathering place for collecting the new advances in the application of intelligent systems to engineering problems.

[2]http://www.asknature.org/

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