Supporting mechatronic design via a distributed network of intelligent agents

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1. Overview

Product development is often performed by functionally and geographically distributed groups of people. In such an environment, there are many concerns that must be traded off against one another before a product can be brought to market. An example of this tradeoff is high performance versus low cost; a product with high performance generally costs more than a product with low performance. When such competing objectives arise, as they usually do in any product, then a solution must be negotiated among competing objectives.

Concurrent engineering (CE) is an approach to product development that integrates the overall knowledge, resources and experience of a company as early as possible in the design cycle. The goal of CE is to incorporate downstream objectives, such as manufacturing and sales, at the same time that traditional concerns, such as power consumption, volume, and dollar cost, are considered, thereby creating products with high quality and low cost, while meeting overall customer expectations. The most important contribution of applying CE principles to the design cycle is transforming a *serial* process to a *parallel* one. Such parallelism identifies design conflicts early on, avoiding problems that arise in the serial approach. This, in turn, speeds product development, while significantly reducing development costs.

National manufacturing networks (Pan, Tenenbaum 1991) have the potential to provide a tremendous improvement in the design and manufacturing process. In particular, these networks will enable designers to quickly access information sources and design services. Rather than being *passive* (Bowen, Bahler 1992a; Bowen, Bahler 1992b), we envision networks with embedded intelligence, where agents on the network can coordinate actions to actually create designs: this includes making design decisions, or advising human decision makers.

The traditional design process can be characterized as *point-by-point*; a single design is created in the space of all possible designs and is passed, in turn, to other groups (agents) for modification. Each agent, in turn, changes the design to meet its objective creating another *point*. The weakness of this approach is that the design process may never converge, as the changes introduced by one agent may be undone by another, which cause the first agent to change the design once again, and so forth, *ad nauseam*. It is the reduction of design time that drives our current research. Current design processes, even though they may use concurrent-engineering notions for improved communication, remain primarily serial. We illustrate this point with an example.

In Figure 1, two sets of agents are collaborating on a simple design: a product-development agent (PDA) and a reliability-assessment agent (RAA); the design for this example is shown in Figure 2. In this figure, a simple circuit that implements the functions processor and memory is to be designed by selecting parts from a processor and memory catalog. The agents are geographically and functionally distributed, and communicate through a *blackboard* where changes made by one agent are immediately visible to other agents. A design is developed first by the PDA satisfying some set of constraints, and, when complete, is *posted* to the blackboard where the RAA can evaluate it.

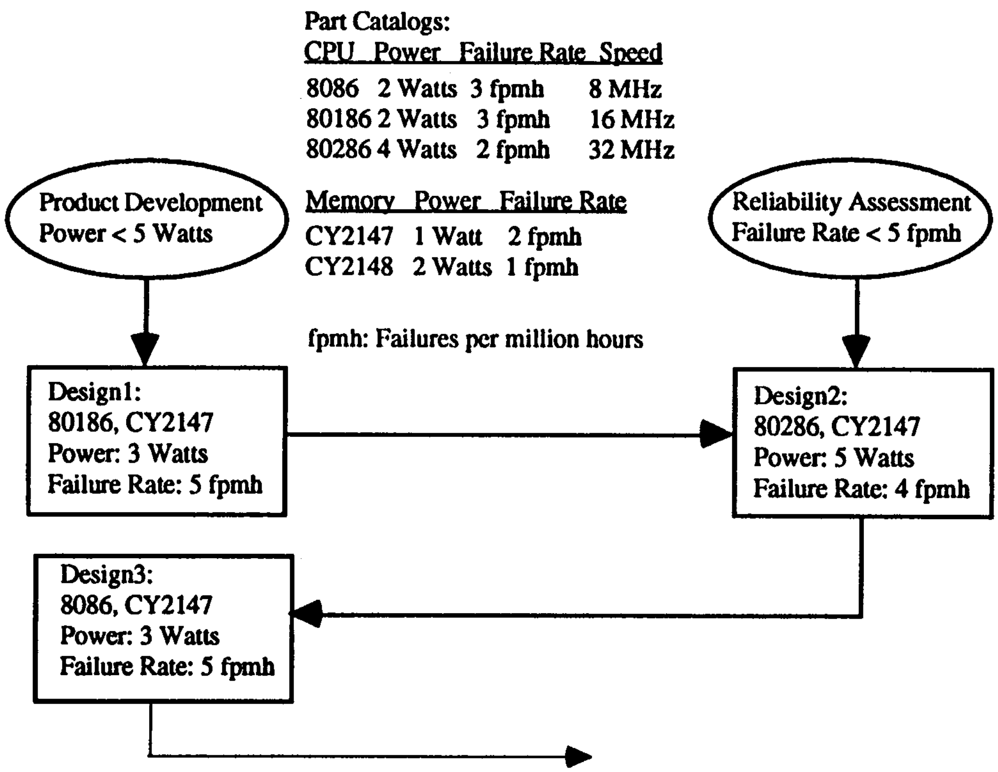


Figure 1: Sequential, Point by Point Design

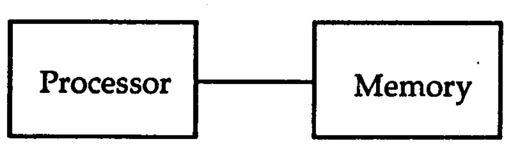
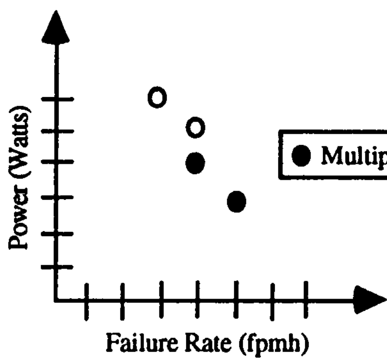


Figure 2: Processor/Memory Design

The PDA's goal is to develop a design that consumes less than five watts of power. This agent prefers designs with low power consumption and high processor speed. The initial design is labeled Design1 in Figure 1, and consists of the parts 80186 and CY2147. This is the design that consumes the least amount of power, and since the 8086 and the 80186 consume equal amounts of power, the 80186 is chosen because it is a faster processor than the 8086. The PDA then posts the design to the blackboard.

The RAA notices that the failure rate of the design is unacceptably high. This agent changes the design by replacing the 80186 with the 80286, since the 80286 has a lower failure rate, and then posts the design. When the PDA sees the modified design, it notices that the power consumption is too high, and so replaces the 80286 with the 8086, which consumes less power, and posts the design. The RAA rejects the new design for the same reason that the previous design was rejected. Passing the design back and forth in this manner will continue until there are no more parts to try, or outside intervention of a higher authority, such as a project leader, forces resolution.

The problem illustrated in this example is that each agent makes changes to the design that satisfy the constraints and preferences from its perspective, without regard to the impact that its decision will have on other agents. This results in needless iterations where a design with the same characteristics is repeatedly generated. In this example, a design characterized by power equal to three watts and failure rate of five failures per million hours that was developed by the product-development agent is instantiated multiple times with different parts. With hundreds of components, hundreds of constraints and many interested agents (marketing, finance, etc.), the problem is compounded and results in substantial wasted effort. Figure 3 shows the space of all possible designs for the example shown in Figure 1. In this figure, there are two designs having the characteristics power = 3 watts and failure rate = 5 fpmh, two designs having the characteristics power = 4 watts and failure rate = 4 fpmh, one design having the characteristics power = 5 watts and failure rate = 4 fpmh, and one design having the characteristics power = 6 watts and failure rate = 3 fpmh. This representation is not very concise, as it requires a point for each possible design. We have developed a much more abstract representation, which will be introduced later.



Representation: {(3, 6), (4, 5), (4, 4), (4, 4), (5, 3), (5, 3)}

Figure 3: Space of All Possible Designs

As a first step towards developing an intelligent design network, we have proposed an automated-configuration design service (ACDS) (Darr, Birmingham 1992) to support the construction and use of automated catalogs that can actively and concurrently assist in *configuration* design, a common type of design. Configuration design is a good starting point, because the task is well defined and of significant economic import, as a large number of artifacts are developed from catalogs of components (Mittal, Frayman 1987). Catalogs may be based on current paper catalogs, or on parameterized models of currently uncataloged part families. In time, we will include geometric features of custom parts, with their associated functions and manufacturing processes.

In this paper, we present two methods for implementing ACDS. The first uses negotiation among network agents to develop the design. This negotiation is based on eliminating constraint violations. The second approach, called Walras (Wellman 1992), uses microeconomic principles of market action to create a design. Both approaches provide similar services, however, the Walrus has been only recently implemented. Thus, detailed comparison between approaches is not yet possible because Walras has not yet been applied to concurrent design (or implemented in the ACDS framework).

2. The Service

ACDS is a collection of loosely-coupled, autonomous agents that self-organize based on design specifications. The agents coordinate their activities through a bidding process, eventually choosing a final (set of) design(s). This section overviews the organization and operation of ACDS.

ACDS will provide the following services to users:

1. A language allowing users (or service companies acting for the users) to construct precise, standardized descriptions of their products' full range of characteristics. With this capability, site-specific catalogs can be developed that represent the particular components used by an individual company or engineering group within a company. To protect proprietary information, access to agents can be controlled.

2. An associated language allowing system designers to precisely and quickly specify the mechatronic systems they desire.

3. Algorithms operating on these descriptions to select near-optimal parts from the catalogs, and to efficiently propagate selection decisions and constraints among catalog agents.

2.1 Inputs and Outputs

Design specifications comprise the following:

<u>Functions and interconnection:</u> The designer defines functions through a schematic with generic parts, and their logical and/or physical interconnections. In Figure 4 the functions are motor and controller. Ports, defined in a data dictionary, establish relationships among selected part attributes.

<u>Feasibility statements:</u> These describe the set of values associated with design attributes (*e.g.*, power, volume, *etc.*).

<u>Preference statements:</u> These describe characteristics the user would like the system to have. An example is "pay $1 for every pound of weight saved", and prefer lower weight designs to more reliable ones.

2.2 The Agents

Initially, there will three types of computation agents in ACDS: *catalog, constraint* and *system.* The system agents interface the user to the network, translating the specifications and broadcasting them to catalog agents. The system agents are also responsible for identifying a complete design. A design is complete when all the functions are covered by a nearly optimal selection of catalog parts. Some parts may cover more than one function, while other functions require more than one part, and ACDS may therefore change the design "configuration." Each catalog agent represents a catalog of parts, and includes descriptions of the value sets for a part's attributes, as well as constraints relating the attribute values. A constraint agent is associated with a particular constraint, such as design cost must be less than a user-specified bound, and is used to monitor the evolving design.

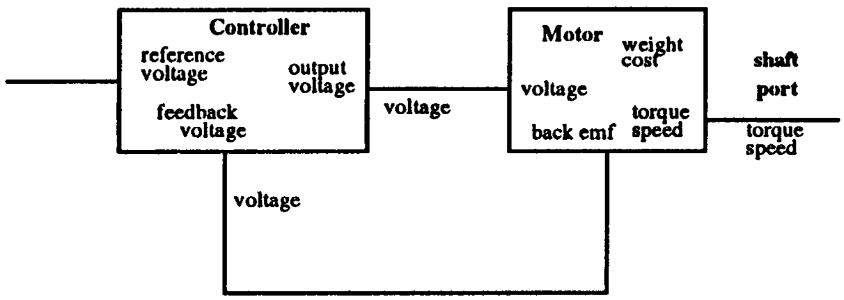


Figure 4: The functional input to ACDS.

2.3 Catalog and Part Models

ACDS catalog agents represent sets of physical parts. Catalogs are composed of part models, plus information abstracted from the part models to describe the catalog as a whole. A part model includes a set of attributes (e.g., access time), and statements about the set of values associated with the attribute, for example, that a memory's access time is somewhere in the interval [100 120] nS. Each part is characterized by the function(s) that it implements and the values that it has for some set of attributes. Figure 5 shows an example part catalog. In this catalog, the cost of CPU1 can vary from \$3 to \$8, depending on the quantity sold. Similar intervals are defined for the other attributes and parts.

Part	Cost ($)	Power (Watts)
CPU1	[3 8]	[12 30]
CPU2	[5 7]	[10 14]

Figure 5: Example Part Catalog

A utility value is assigned to each part in a catalog. This value is calculated using a weighted utility (or cost function) provided by the designer. These values specify a total ordering on the parts in a catalog. The part with the highest utility (or lowest cost function) value is the best part. Figure 6 shows an example part catalog with utility values.

Catalog agents receive specifications from the system agent. They then identify "partial solutions," subsets of their parts that may be desirable in the final design. They form abstract descriptions of these sets, and supply them to constraint agents. These descriptions are used to eliminate additional infeasible solutions in a form of network-consistency enforcement (Davis 1987; Mackworth 1977). When feasibility pruning is no longer effective, catalog agents *bid* a new solution subspace. A bid is formed by selecting a subset of the parts in a catalog, and making this subset the catalog agent's "current catalog". By forming bids based on preferences and information received from constraint agents, ACDS agents *narrow* the design space, while allowing all agents to process messages concurrently. This process continues until a final design results. An example of this narrowing process is given later.

Utility Function = 2/Cost + 1/Power

Part	Cost ($)	Power (Watts)	Utility
CPU1	[3 8]	[12 30]	[0.283 0.750]
CPU2	[5 7]	[10 14]	[0.357 0.500]

Figure 6: Example Part Catalog With Utilities

ACDS is intended to eventually support thousands of catalog agents distributed throughout the world, where each agent will represent the product line of a manufacturer. As such, catalog agents have the freedom to choose whether to participate in a design, so the catalog agents will change from design to design.

2.4 Constraints

ACDS constraint agents maintain consistency throughout the network by enforcing design constraints. The constraints are formed over part attributes (e.g., the sum of power consumption of all parts $\leq$ 15 W). Each constraint agent ensures that the evolving design space conforms to the constraint it represents. A constraint agent *monitors* the bids produced by each catalog agent, and provides information to the catalog agent regarding the violation status of the constraint. This information is used by the catalog agents to form new bids.

An important element of concurrent engineering is considering *downstream* concerns (*e.g.*, dependability, testability, manufacturability, and so forth) during the design process. Constraint agents can represent such concerns, and thus impact the design process as it occurs. For example, a constraint agent can monitor the failure rate (one measure of dependability), and cause designs with unacceptable rates to be eliminated.

ACDS constraints are linear, additive, non-directional, and can be of any arity. Non-directionality means that if a constraint is defined over n variables $C(x_1, ..., x_n)$, then given n-1 variables, the ith variable can be inferred: $x_i = C^{-1}(x_1, ..., x_{i-1}, x_{i+1}, ..., x_n)$.

Constraints originate from two sources. Non-part specific constraints, which are static, come from the system agent. An example of this type of constraint is total power consumption: $\sum \text{power consumed} \leq 6$ Watts. Part-specific constraints, which are dynamic (Mittal, Falkenhainer 1987), come from catalog agents, since the system agent does not know which catalog agents will participate in the design. An example of this type of constraint is the access time for some CPU: access time = 2*clock speed - memory-access time.

A dynamic constraint has a predicate indicating when it is active. The value of the predicate for a static constraint is always true. Dynamic constraints can be made active or inactive during the design process, depending on the parts that are currently being considered. When inactive, a constraint is not evaluated. This is useful when parts have different properties. For example, different types of CPUs have different constraints for memory-access time. Only those parts that are used to form a bid have their dynamic constraints activated.

In ACDS, all static constraints are created by the system agent when the network is established. Dynamic constraints are created by the catalog agents that contain them. When a catalog agent accepts an invitation to participate in a design it creates separate processes for each of its dynamic constraints, thereby distributing the computational load.

2.5 Set-based Descriptions

We are interested in creating mechatronic (highly integrated mechanical and electrical systems). Because these systems are composed of radically different types of components, representation is a major concern. We have developed a representation scheme, called Labeled-Interval Calculus or LIC (Ward, Lozano-Perez, Seering 1990), that captures the operating characteristics of both mechanical and electrical devices. The LIC distinguishes between the statement that a motor is restricted to speeds ONLY between 0 to 1800 RPM, and the statement that it will under normal operating conditions take EVERY speed in that interval. With this representation we can apply the same design algorithms regardless of the components involved.

Instead of reasoning over single points in the set of all possible designs, ACDS reasons over design spaces, which are *sets* of points in the space of all possible designs. The ACDS design space is represented as a set of intervals, where each interval corresponds to a design attribute (Davis 1987; Ward, Lozano-Perez, Seering 1990). Each interval specifies the possible range of values for some attribute for all designs in the design space. Each catalog agent defines its design space as a set of intervals for each attribute in its catalog. Each constraint agent defines its design space as the set of intervals provided by catalogs having attributes that appear in its constraint. Figure 7 shows the design space representation for the example in Figure 1. In this representation, the set of all possible designs has been replaced by a set of intervals that represents the *region* within which all possible designs must lie.

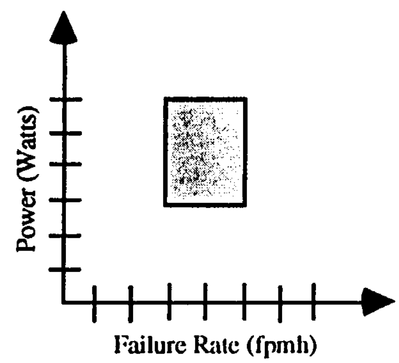


Figure 7: Design-Space Representation

The design space representation provides three advantages over current schemes:

1) Precise descriptions of a broad range of mechanical and electronic components, providing the basis for a degree of standardization not now possible.

2) Concurrent execution of the design process by many different agents.

3) Rapid exploration of vast design spaces by simultaneous reasoning about sets of design possibilities.

2.6 Communication Issues

Because participating agents will be distant from each other, and might number in the thousands, communication resources will be held at a premium. A fundamental challenge in ACDS is to balance the benefits and costs of concurrent participation by many agents in the design process. Concurrency has the potential for speeding the process, discovering novel designs, and being resilient to partial failures in the network. It does, however, strain both communication channels and computation resources as agents sift through massive amounts of message traffic to find useful pieces of information. In fact, it could be argued that the traditional point-by-point design approach has evolved not so much due to organizational barriers among designers as to problems of information overload.

Our communication model is that agents should avoid information overload through judicious message exchanges, and should expend computational resources in favor of communication resources. As the network changes due to component choices, new communication paths must be established to maintain network consistency. Problems, such as potential circularities in constraints and synchronizing component bids to search the design space systematically, will require new protocols that ensure progress toward a design while still promoting substantial concurrency.

Scaling up to larger networks covering wider areas will pose research challenges ranging from low-level encoding schemes that minimize numbers of bits transmitted, to high-level heuristic knowledge that guides decisions about which agents to include in the design process and what to demand of them. For example, given that different catalog agents might have common components (the brands of components they carry might intersect, for example), heuristic methods might prune the set of agents needed to ensure coverage of all relevant components. While such heuristics may miss the best designs, they may lead to a better balance between the cost of creating a design and that design's end-use utility or performance. As an example, to reduce message traffic and computation, a network might exclude a catalog agent which has a poorer collection of parts than other catalog agents (its parts are subsumed by another), but has better prices on the parts it does contain. If finding the best price is worth the additional effort, then ACDS should not exclude this catalog, or should work initially with catalogs with the best selection, and then after deciding on a design should open the bidding for each part to all applicable catalogs (much like a person might go to a large car dealership to investigate the range of models, and after deciding on a model will call other dealerships to find the best price).

3. Example

This section illustrates the operation of ACDS using a simple example. After the user has entered the design, ACDS sends an invitation, containing the functions to implement and the design specifications, to all of the catalogs currently on the network. Once all catalog agents have accepted or declined the invitation to participate in the current design, the catalog agents send their design spaces to the constraint agents so that infeasible parts can be removed.

After infeasible parts have been identified and removed, the catalog agents send their design spaces to the constraint agents (this is called a bid) and the constraint agents evaluate the intervals to determine if violations are present. If a constraint is violated, then the constraint agent sends the amount of violation to each catalog agent. If a constraint is not violated, then the constraint agent sends the amount that the constraint is satisfied by (called slack), to each of its participating catalog agents.

When the catalog agents receive the amount of violation or slack from each of the constraint agents, then the catalog agents create new design spaces that reduce the amount of violation on the intervals for the violated constraints, without exceeding the slack on the intervals for the satisfied constraints. The catalog agents bid their new design spaces and the process continues until all constraints are satisfied, at which point each catalog agent sends its the highest rated part as a solution, or until a determination is made that no solution exists. No solution exists if none of the catalog agents can create a new design space.

For this example, the user specifies that the design should implement the functions CPU, memory and serial port, that the cost of the final design be less than or equal to $11.00[1], and that the failure rate be less than or equal to 10 failures per million hours (fpmh). The cost function for this example is a simple weighted sum of the attributes, where the weight of the cost attribute is 10 and the weight of the failure-rate attribute is 1. Using a cost function of this form, a part with a low value for cost function is preferable to a part with a high value for cost function. The catalog agents CPU, memory and serial port respond, indicating that they are willing to participate in the design. The system agent creates the constraint agents cost and failure rate. If there were any dynamic constraints, then the catalog agents would create these constraints at this time. At this point, the network consists of the catalog agents {CPU, memory, serial port} and the constraint agents {cost, failure rate}. Each catalog agent creates a design space by forming an interval over each of the design attributes. The initial ACDS network, including the design spaces for each catalog, is shown in Figure 8.

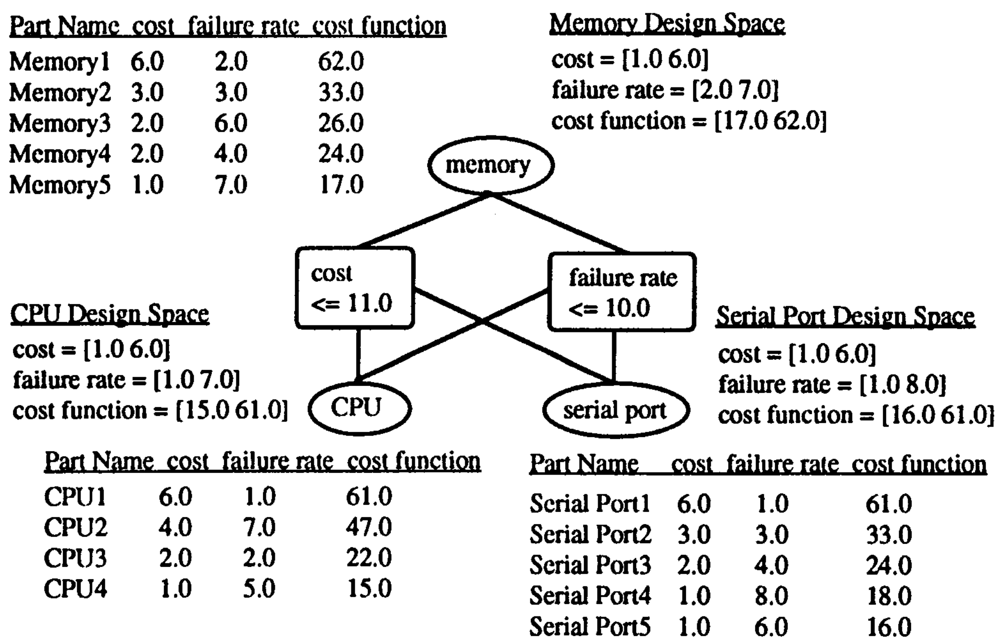


Figure 8: Initial ACDS Network

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[1] If the lower bound on an attribute is omitted, then it is assumed to be 0. Similarly, if the upper bound on an attribute is omitted, then it is assumed to be $+\infty$.

The system agent next notifies each catalog agent of the appropriate constraint agents and vice versa. The system agent does this by sending the address and the name of each constraint agent to each catalog agent. If a catalog agent contains parts that have values for attributes appearing in the constraint represented by a constraint agent, then the address of the constraint agent is recorded in the local address table of the catalog agent, who then sends a message to the system agent indicating that the constraint agent needs to know the address of the catalog agent. The system agent then sends the address of the catalog agent to the constraint agent. In this way, the catalog agents know only the addresses of constraint agents that it must communicate with, and vice versa.

3.1 Pruning Infeasibles

After the design spaces are created, the CPU, memory and serial port catalog agents send the intervals to the cost and failure-rate constraint agents.

The cost and failure-rate constraint agents collect the intervals from the catalog agents, forming the design spaces cost = {[1.0 6.0] (from CPU), [1.0, 6.0] (from memory), [1.0 6.0] (from serial port)} and failure rate = {[1.0 7.0] (from CPU), [2.0 7.0] (from memory), [1.0 8.0] (from serial port)}. These design spaces are used to form arc-consistent intervals. The arc-consistent intervals for the failure-rate constraint agent is calculated as shown in Figure 9.

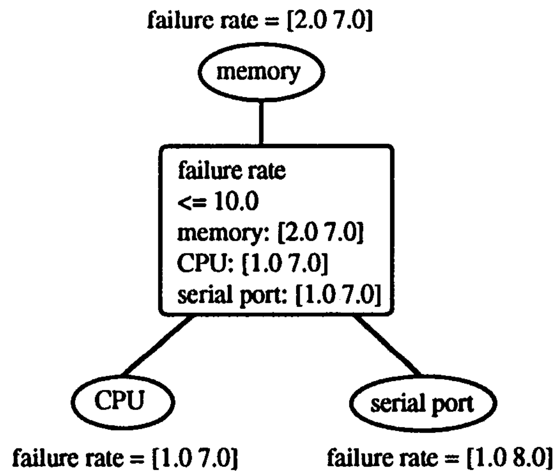


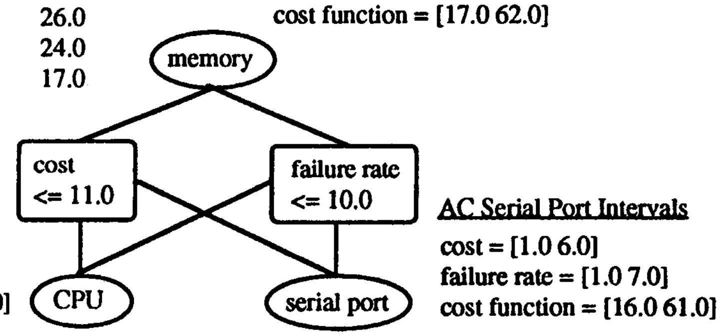
Figure 9: Arc-Consistent Design Spaces

The interval [1.0 7.0] for the failure-rate attribute of the serial port catalog agent is calculated as follows: the minimum value for the failure-rate attribute that can be achieved by the memory and CPU catalog agents are 2.0 and 1.0 fpmh, respectively. In order for the constraint to be satisfied, the maximum value possible for the serial port catalog agent must be no greater than 10.0 - (2.0 + 1.0) = 7.0. This value becomes the upper bound for the serial port catalog agent for the failure rate interval.

The constraint agents send these arc-consistent intervals to each catalog agent, who remove any infeasible parts (i.e., parts that lie outside the arc-consistent intervals), forming new design spaces. Figure 10 shows the new catalogs. This operation can be used to eliminate the 80286 in the example at the beginning of the paper. This would eliminate many of the iterations described, at virtually no cost.

3.2 Design-Space Bidding

Once all infeasible parts have been removed, each catalog bids its design space to the constraint agents for evaluation. The constraint agents collect the intervals from all the catalog agents, and determine whether or not a constraint has been violated.



Part Name	cost	failure rate	cost function
Memory1	6.0	2.0	62.0
Memory2	3.0	3.0	33.0
Memory3	2.0	6.0	26.0
Memory4	2.0	4.0	24.0
Memory5	1.0	7.0	17.0

Part Name	cost	failure rate	cost function
CPU1	6.0	1.0	61.0
CPU2	4.0	7.0	47.0
CPU3	2.0	2.0	22.0
CPU4	1.0	5.0	15.0

Part Name	cost	failure rate	cost function
Serial Port1	6.0	1.0	61.0
Serial Port2	3.0	3.0	33.0
Serial Port3	2.0	4.0	24.0
~~Serial Port4~~	~~1.0~~	~~8.0~~	~~18.0~~
Serial Port5	1.0	6.0	16.0

Figure 10: Arc Consistent Catalogs.

In this example, the constraint agents create a design space of the form:

$$[\sum_{\text{catalog agents}} \text{catalog agent interval lower bound} \quad \sum_{\text{catalog agents}} \text{catalog agent interval upper bound}]$$

A constraint agent is satisfied if every value contained in the interval satisfies the constraint. Once the violations are determined, a message is sent to each catalog agent, containing the amount of violation if the constraint is violated, or the amount of slack if the constraint is satisfied. This step is illustrated in Figure 11. For example, if the maximum values of each intervals contributing to cost are added, the upper bound is violated (the sum is 18.0). Thus the cost interval for some catalog agent must be reduced.

3.3 Design-Space Pruning

Since there are constraint violations, each catalog agent must modify its catalog in such a way as to satisfy the violated constraints. A new design space is formed by removing parts or re-introducing parts that were previously removed.

Since each constraint agent is violated, each catalog simply removes the part with the highest value for each of the attributes, as is shown in Figure 12. This results in the catalogs consisting of the set of parts surrounded by boxes. The old and new design spaces are shown alongside the corresponding catalog agents.

If it had been the case that there were only two parts in some catalog, and one of those parts had the highest value for one of the attributes and the other part had the highest value for the other attribute, then if both parts were removed, the catalog agent would be left with a null catalog. This means that there is no solution, which may or may not be the case. In such a case, the part with the highest value for the cost function is removed. If there were any dynamic constraint agents, then those constraint agents that depended on parts just removed would be deactivated.

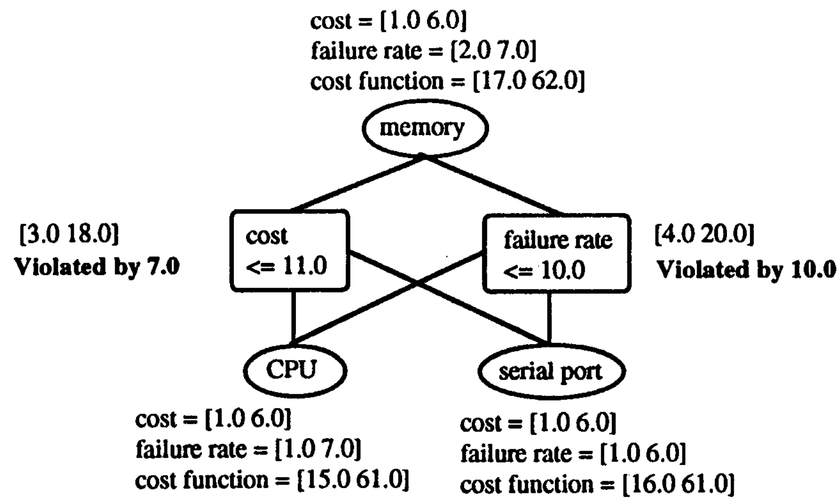
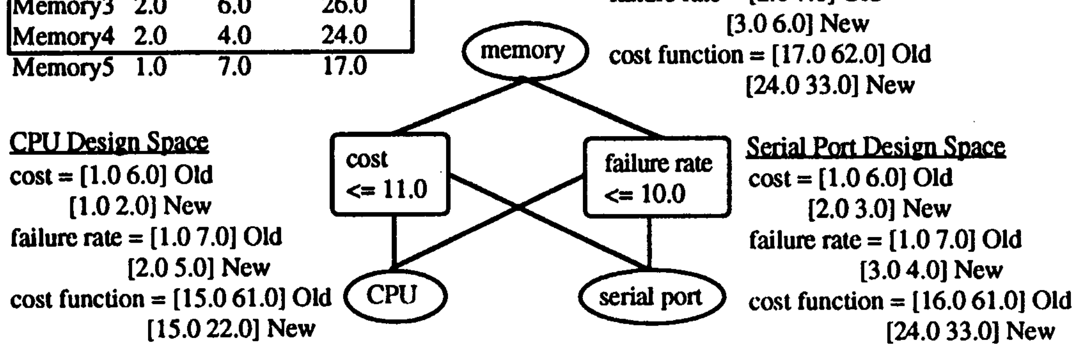


Figure 11: Bid #1

Part Name	cost	failure rate	cost function
Memory1	6.0	2.0	62.0
Memory2	3.0	3.0	33.0
Memory3	2.0	6.0	26.0
Memory4	2.0	4.0	24.0
Memory5	1.0	7.0	17.0



Part Name	cost	failure rate	cost function
CPU1	6.0	1.0	61.0
CPU2	4.0	7.0	47.0
CPU3	2.0	2.0	22.0
CPU4	1.0	5.0	15.0

Part Name	cost	failure rate	cost function
Serial Port1	6.0	1.0	61.0
Serial Port2	3.0	3.0	33.0
Serial Port3	2.0	4.0	24.0
Serial Port5	1.0	6.0	16.0

Figure 12: Design Space #1

The new design spaces are bid to the constraint agents as shown in Figure 13. Note that the cost constraint is now satisfied and has slack of $3.00, while the failure-rate constraint is still violated.

Since there is now some slack in the cost constraint agent, each catalog agent has the option of reintroducing parts that were removed during previous iterations. The catalog agents begin by removing the remaining part with the highest value for the failure-rate attribute, since the failure-rate constraint agent is still violated. Consider the memory catalog agent; we notice that there are three parts currently in the catalog: Memory2, Memory3 and Memory4. Of these three parts, Memory3 has the highest value for the failure-rate attribute and is thrown out. The catalog at this point consists of Memory2 and Memory4. The memory catalog agent next considers reintroducing parts that were previously thrown out, namely Memory1 and Memory5.

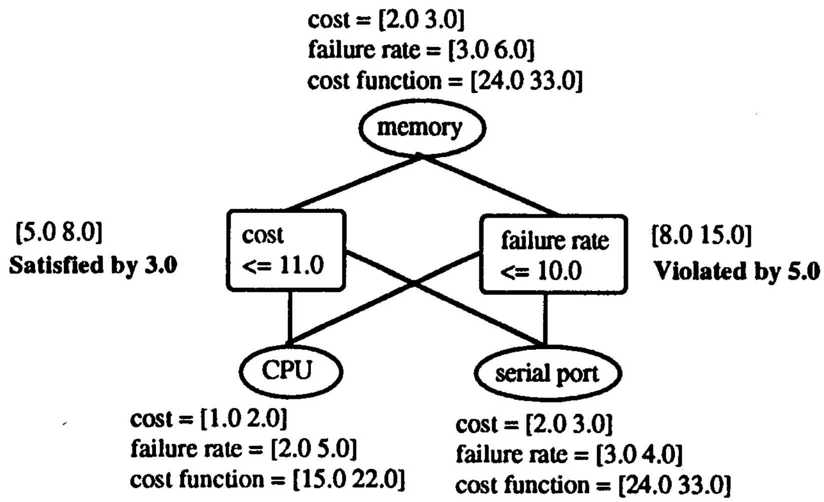


Figure 13: Bid #2

In reintroducing new parts, there are two criteria that must be taken into account. The first is that the value of the attribute of a part under consideration cannot increase the upper bound on any violated constraint agent. The second is that the value of a part under consideration cannot increase the upper bound on any satisfied constraint, relative to the previous design space, by more than the slack amount from that constraint agent. The current memory catalog agent, consisting of the parts Memory2 and Memory4, has an upper bound on the failure-rate attribute of 4.0 fpmh. The previous catalog (Memory2, Memory3, Memory4) had an upper bound on the cost attribute of 3.0, and the slack for the cost constraint was 3.0. Using this information, we can reintroduce any part whose value for the cost attribute is less than or equal to $6.00, and whose value for the failure-rate attribute is less than or equal to 4.0 fpmh. The only part in the memory catalog that falls within these bounds is the part Memory1, so this part is re-introduced and the bid is made. If there were any dynamic constraint agents that were de-activated when this part was originally thrown out, they would now be re-activated.

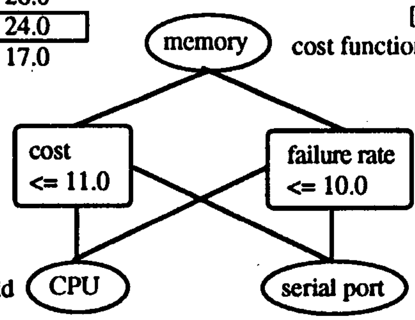
Each catalog agent performs the same reasoning, and the resulting catalogs are shown in Figure 14. These design spaces are bid and evaluated as shown in Figure 15.

After this most recent bid, the cost constraint is now violated and the failure-rate constraint is now satisfied by a slack amount of 1.0 fpmh. Each catalog agent uses this information to create another set of catalogs as is shown in Figure 16.

In Figure 16 the CPU catalog agent was unable to create a new design space. The previous catalog (shown in Figure 14) consisted of the part CPU3. The information received from the last round of bids was that the cost constraint was violated by $3.00 and the failure-rate constraint was satisfied by 1.0 fpmh. The CPU catalog agent cannot do anything to help to satisfy the cost violation, since there is only one part in the catalog. It cannot re-introduce any parts because the slack on the failure-rate constraint is too small. If each catalog agent were in the same position of not being able to create a new design space, then no solution exists. These new design spaces are bid and evaluated as shown in Figure 17.

Part Name	cost	failure rate	cost function
Memory1	6.0	2.0	62.0
Memory2	3.0	3.0	33.0
Memory3	2.0	6.0	26.0
Memory4	2.0	4.0	24.0
Memory5	1.0	7.0	17.0

Memory Design Space
cost = [2.0 3.0] Old
[2.0 6.0] New
failure rate = [3.0 6.0] Old
[2.0 4.0] New
cost function = [24.0 33.0] Old
[24.0 62.0] New



CPU Design Space
cost = [1.0 2.0] Old
[2.0 2.0] New
failure rate = [2.0 5.0] Old
[2.0 2.0] New
cost function = [15.0 22.0] Old
[22.0 22.0] New

Serial Port Design Space
cost = [2.0 3.0] Old
[3.0 6.0] New
failure rate = [3.0 4.0] Old
[1.0 3.0] New
cost function = [24.0 33.0] Old
[33.0 61.0] New

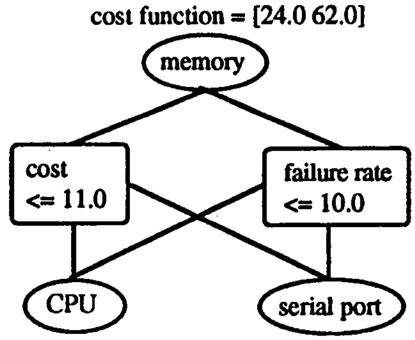
Part Name	cost	failure rate	cost function
CPU1	6.0	1.0	61.0
CPU2	4.0	7.0	47.0
CPU3	2.0	2.0	22.0
CPU4	1.0	5.0	15.0

Part Name	cost	failure rate	cost function
Serial Port1	6.0	1.0	61.0
Serial Port2	3.0	3.0	33.0
Serial Port3	2.0	4.0	24.0
Serial Port5	1.0	6.0	16.0

Figure 14: Design Space #2

cost = [2.0 6.0]
failure rate = [2.0 4.0]
cost function = [24.0 62.0]

[7.0 14.0]
Violated by 3.0



[5.0 9.0]
Satisfied by 1.0

cost = [2.0 2.0]
failure rate = [2.0 2.0]
cost function = [22.0 22.0]

cost = [3.0 6.0]
failure rate = [1.0 3.0]
cost function = [33.0 61.0]

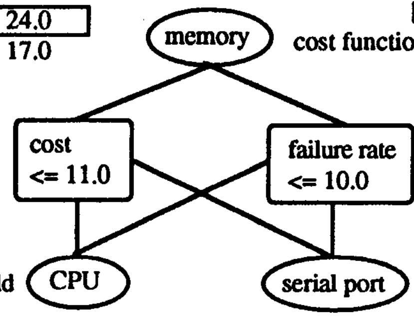
Figure 15: Bid #3

3.4 Solution

Once all the constraints are satisfied, as they are in Figure 17, the catalog agents select the remaining part with the lowest value for the cost function to form a solution. Because all constraints are satisfied, the combination of these parts is guaranteed to be a valid solution. In this example, the CPU catalog agent selects the part CPU3, the memory catalog agent selects the part Memory4 and the serial port catalog agent selects the part Serial Port3. The design consisting of these parts satisfy all constraints and is sent to the system agent as the solution. The system agent verifies that all functions have been covered and displays the solution. This is shown in Figure 18.

Part Name	cost	failure rate	cost function
Memory1	6.0	2.0	62.0
Memory2	3.0	3.0	33.0
Memory3	2.0	6.0	26.0
Memory4	2.0	4.0	24.0
Memory5	1.0	7.0	17.0

Memory Design Space
cost = [2.0 6.0] Old
[2.0 3.0] New
failure rate = [2.0 4.0] Old
[3.0 4.0] New
cost function = [24.0 62.0] Old
[24.0 33.0] New



CPU Design Space
cost = [1.0 2.0] Old
[2.0 2.0] New
failure rate = [2.0 5.0] Old
[2.0 2.0] New
cost function = [15.0 22.0] Old
[22.0 22.0] New

Serial Port Design Space
cost = [3.0 6.0] Old
[2.0 3.0] New
failure rate = [1.0 3.0] Old
[3.0 4.0] New
cost function = [33.0 61.0] Old
[24.0 33.0] New

Part Name	cost	failure rate	cost function
CPU1	6.0	1.0	61.0
CPU2	4.0	7.0	47.0
CPU3	2.0	2.0	22.0
CPU4	1.0	5.0	15.0

Part Name	cost	failure rate	cost function
Serial Port1	6.0	1.0	61.0
Serial Port2	3.0	3.0	33.0
Serial Port3	2.0	4.0	24.0
Serial Port5	1.0	6.0	16.0

Figure 16: Design Space #3

4. A Market-Oriented Programming Approach

Another approach to distributed design that we are concurrently exploring is the potential use of market price mechanisms to allocate resources among collaborating design teams. The rationale for this approach is that in some circumstances, the market can efficiently allocate resources toward their most productive use with minimal communication or coordination overhead. All interaction among agents occurs via exchange of goods, according to terms dictated by a set of standard prices.

We have implemented a general system for "market-oriented programming" based on concepts from the microeconomic theory of general equilibrium. In the general-equilibrium framework, there are two types of agents: those that simply exchange goods (consumers), and those that can transform some goods into other goods (producers). In our computational version of a market price system, we implement consumer and producer agents and direct them to bid so as to maximize utility or profits, subject to their own feasibility constraints. Under certain technical assumptions, the equilibria of this system correspond to desirable or optimal resource allocations.

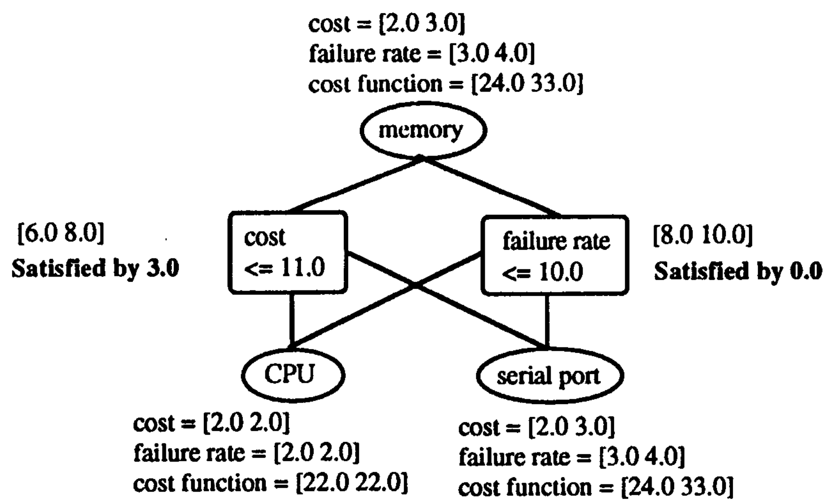
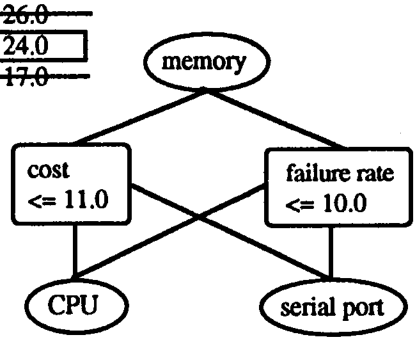


Figure 17: Bid #4

Part Name	cost	failure rate	cost function
~~Memory1~~	~~6.0~~	~~2.0~~	~~62.0~~
Memory2	3.0	3.0	33.0
~~Memory3~~	~~2.0~~	~~6.0~~	~~26.0~~
Memory4	2.0	4.0	24.0
~~Memory5~~	~~1.0~~	~~7.0~~	~~17.0~~



Part Name	cost	failure rate	cost function
~~CPU1~~	~~6.0~~	~~1.0~~	~~61.0~~
~~CPU2~~	~~4.0~~	~~7.0~~	~~47.0~~
CPU3	2.0	2.0	22.0
~~CPU4~~	~~1.0~~	~~5.0~~	~~15.0~~

Part Name	cost	failure rate	cost function
~~Serial Port1~~	~~6.0~~	~~1.0~~	~~61.0~~
Serial Port2	3.0	3.0	33.0
Serial Port3	2.0	4.0	24.0
~~Serial Port5~~	~~1.0~~	~~6.0~~	~~16.0~~

Figure 18: Final Solution

To cast a distributed resource-allocation problem in terms of a computational market, one needs to identify

- the goods (commodities) traded,
- the consumer agents trading and ultimately deriving value from the goods,
- the producer agents, with their associated technologies for transforming some goods into other goods, and
- the agents' bidding behavior.

Our implemented system, called Walras, provides an environment for specifying these features of a computational market.

Given the specification, Walras "runs" the economy to derive its competitive equilibrium, that is, a set of prices for the goods where (1) consumers bid so to maximize utility, subject to their budget constraints, (2) producers bid so to maximize profits, subject to their technological possibilities, and (3) net demand is zero for all goods. Details of Walras's bidding process and underlying assumptions are provided elsewhere (Wellman 1992).

Distributed configuration design is one of the tasks to which we have applied Walras. In a multiagent design problem, each agent has responsibility for choosing a component to serve a given function in a device, and the overall design consists of the combination of component choices. Decentralizing the problem can be difficult, due to dependencies in the component choices for each function, as well as interactions among the components in determining device performance attributes, or preferences for those attributes.

For example, consider a simple two-component device consisting of a motor and a speed controller. We are interested in a device with the best performance (highest torque with finest tolerance on the speed range) but that minimizes some other attributes (weight, power consumption, and dollar cost). There may be several choices for each component, which combine via cross product to define the overall design space. Choices for the components interact, because the horsepower ratings for the motor and speed controller must be compatible, and because both components contribute to weight and dollar cost.

The market perspective on this kind of problem would view the performance and resource attributes as commodities traded and transformed across the components. In some approaches to distributed design (including human design organizations), some aggregate attributes are budgeted in a hierarchical manner, so that the part implementing a given function may be allocated some fixed fraction of the weight or dollar cost. This kind of scheme is too rigid, because we do not know what the appropriate fractions should be until we make some progress in the design. This is where the market approach should help. If attributes such as weight are tradable commodities, then the components can buy and sell rights to take up weight according to which can make the most effective use (i.e., get the most relative performance improvement) from each incremental unit of weight.

To cast one of these problems in Walras, we first define a consumer agent to represent the end-user of the device we are designing. We specify for this consumer a utility function defined over possible combinations of all of the attributes. The consumer also has an endowment of the basic resources (weight, dollar cost, power) corresponding to the maximum feasible that can be allocated to the device. This endowment limit performs the same function as the constraint agent in ACDS.

For each component (ACDS catalog agent), we define a producer agent. The producer agent transforms the basic resources into performance attributes (torque, voltage) according to the specifications of each possible choice for the component. In other words, the catalog describes the technology available to the corresponding producer.

The consumer's problem is to set demands maximizing utility, subject to the budget constraint (i.e., it cannot spend more than the value of its endowment), at the going prices. The producers face a discrete choice among the possible component instances, each providing a series of values for resource and performance attributes. The producer bids according to which choice would be most profitable at the given set of prices. If none offers positive profits, the producer bids zero.

When run on some simple design problems, Walras produces a set of component choices. However, due to the discreteness (and other non-convexities) of the problem, the overall design is not guaranteed to be optimal. At best, we can hope for *local* optima. In current work, we are attempting to characterize the performance of the scheme for special cases. In addition, we are looking into hybrid schemes that use the market to bound the optimal value by computing the global optimum for a smooth and convex relaxation of the original problem. This is analogous to branch-and-bound schemes that make use of regular linear-programming algorithms for integer-programming problems.

5. Discussion

We have chosen a distributed architecture for several reasons. Design expertise for a complex artifact is usually distributed across different groups and may be geographically dispersed within a single company or in multiple companies. Centrally locating all relevant expertise, in most cases, is awkward at best. A distributed architecture naturally models the real-world distribution of expertise. This distribution of knowledge also speeds computation, subject to communication costs, by sharing the computation load across many different computers. With the advent of high-speed communication networks, communication cost will constantly fall.

A distributed architecture provides the user of ACDS with easy access to a wide variety of part catalogs from many different vendors, without being aware of who or where those vendors are. The only concern of the designer should be that the parts selected satisfy the specifications. By considering parts from a variety of sources, ACDS has the opportunity to generate the best possible design.

A distributed architecture also allows each vendor to maintain its catalog agent at its site. Changes or additions to the part catalogs can be made locally and be immediately available to all users over the network. ACDS allows vendors to join the network without knowing who or where the designers using the network are located. This allows a new vendor to become known to a large population of designers, and be on an equal competitive footing with more established vendors.

ACDS will allow designers to realize their designs in significantly shorter time than is currently possible using today's concurrent design processes. Furthermore, designs will be less costly and of higher quality since ACDS can consider a much greater variety of designs than any human could effectively create.

ACDS will allow descriptions of many part characteristics, such as the behavior of mechanical devices, that cannot properly be described using current languages. This will allow automation of many manual design processes.

ACDS will provide a uniform representation for a wide range of types of data important to the design process, including marketing and finance information, as well as engineering data. This will make agent inter-operability an inherent property of the service, and will significantly contribute to enterprise integration.

ACDS relies on several concepts from the distributed artificial intelligence literature. ACDS draws from multistage negotiation (Conry, Kuwabara, Lesser, Meyer 1991), distributed constraint-satisfaction problems (Yokoo, Durfee, Ishida, Kuwabara 1991), and negotiated search (Lander, Lesser 1992). Negotiated search is a cooperative search and conflict resolution paradigm realized by TEAM, a system for performing parametric design of steam condensers. Each TEAM agent possesses knowledge about a single steam condenser component. These agents are independent, except for parameters that are shared among components. TEAM agents communicate via shared memory. In this system, an initial design is generated and placed in shared memory so that all agents can evaluate it. Each agent examines the design and proposes extensions to the design that solve some sub-problem. The catalog and constraint agents of ACDS are collapsed into one agent in TEAM. Like ACDS, agents in TEAM share a global utility (or cost) function to help guide decision-making.

Other systems that operate in the domain of concurrent engineering and are similar to ACDS include the Design-Fabricator Interpreter (DFI) system (Werkman 1992), and the Galileo2 system (Bowen, Bahler 1992b). The DFI system is an example of the point-by-point approach to concurrent engineering in the domain of structural engineering. In this system, agents that represent human experts in the areas of design, manufacturing and assembly evaluate and comment on a design from their particular perspective. Much like ACDS, this system supports concurrent engineering by incorporating downstream concerns early in the design process, using agents to represent multiple perspectives. The DFI system is more of a design evaluation tool used to critique a preliminary design to identify possible downstream problems. The DFI system can be thought of as automating the stage at which a higher authority is required to resolve a conflict, where each agent proposes an acceptable design, and an arbitrator makes a decision.

The Galileo2 system is a constraint programming language that facilitates concurrent engineering. This system allows constraint networks to be divided into different, possibly overlapping fields of view that correspond to the perspectives of engineering teams. By assigning fields of view to manufacturability, testability, maintainability, and others, this system supports concurrent engineering. Galileo2 is an interactive system which allows a user to specify constraints on the final design from a given perspective. Galileo2 is not a synthesis tool like ACDS, but is rather a design evaluation tool. Galileo2 makes it easier for designers to communicate, but the process of resolving conflicts still requires manual intervention. Both ACDS and Galileo2 use constraints to represent various design perspectives, but differ in the way these constraints are used. In Galileo2, constraints are used to form a constraint network, where constraints are propagated throughout the network to notify users that a constraint has been violated. In ACDS, constraints are used to rule out parts that are provably infeasible.

6. Current Status

A prototype version of ACDS has been developed that contains core ACDS functionality in a rudimentary form. This version was used to create the example in Section 3, and allows system agents to establish contact with catalog agents distributed anywhere in the nation. Currently, ACDS has agents operating in Ann Arbor, Michigan (The University of Michigan), Pittsburgh, Pennsylvania (Carnegie Mellon University), and Palo Alto, CA (Stanford University). Similarly, constraint agents can be distributed throughout a network.

We are beginning to expand the capabilities of ACDS. A mechanical-drawing system and several analysis packages (e.g., thermal and reliability) are being integrated into ACDS. This will allow designers to create custom designs that are synthesized from catalog components, and to analyze these designs from a variety of perspectives that are not easily captured in constraints. This will be a major step in moving ACDS towards the goal of supporting all aspects of design.

ACDS has been developed to be fully compatible with KQML (Finin et al. 1992), a language for knowledge exchange among intelligent agents. (KQML is being supported by DARPA's Knowledge-Sharing Effort.) This compatibility means that ACDS can conveniently exchange knowledge with agents developed by other parties, and can easily integrate into existing engineering networks.

Walras is being integrated into the full ACDS environment. We expect to report soon on comparisons between the approaches.

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