A Novel Approach to Planar Mechanism Synthesis Using HEEDS

John Oliva and Erik Goodman

Michigan State University

Introduction

The problem of mechanism synthesis (or design) is deceptively complex and has been the subject of much attention since soon after the discovery of the wheel. In this paper, a novel approach to automated mechanism synthesis is described that uses a technique called "convertible agents" to simultaneously find the most appropriate mechanism *type* for a given problem, while also finding an optimum set of *dimensions* for that mechanism to realize a specified behavior.

The convertible agent technique has been developed in response to the unique design challenges encountered when synthesizing a mechanism for both type and dimensionality. This synthesis technique selects the best-suited mechanism type from a set of different planar single-degree-of-freedom mechanism types and optimizes its dimensions to meet the design objective at hand. The method is readily scalable to account for any number of different mechanism types and complexities.

The developed convertible agent approach is also well suited for design applications outside of mechanism synthesis in which there are distinct topological design possibilities, each with parametric variables to be optimized. The approach uses a parallel optimization strategy, as described below.

Parallel Optimization

In a parallel optimization, the search is carried out in a parallel fashion (on different processors or not). This method was inspired by Darwin's observations on the Galapagos Islands. Because the islands are geographically isolated, many endemic species were able to evolve independent of the evolution occurring in other parts of the world. Some of these species may have perished if they had been competing for the same resources as more powerful species on other continents. From an optimization point of view, the concept is to have multiple separate populations ("islands") of designs evolving independently, so that a very strong-performing design found early in one population does not immediately overpower the entire computational domain, which may still yield fruitful designs. This method allows the search process to overcome the tendency to prematurely converge to locally optimal, rather than globally optimal, solutions. The islands may also be allowed to pass good designs to each other ("migration") on a periodic basis.

Lin et al. [1] expanded upon this approach with their Injection Island Genetic Algorithm (iiGA). In this approach, the optimization scheme uses multiple parallel populations of candidate designs, but each island may search with a different representation of the problem, thereby increasing search efficiency.

In the current study, the HEEDS design optimization software package provides the backbone of the mechanism synthesis. HEEDS can be used in virtually any discipline. The user provides the function evaluation portion of the design analysis, while HEEDS takes care of the core optimization. Furthermore, the user defines how each design will be represented as it is passed between HEEDS and the function evaluation program, as well as how the performance of each design will be reported back to HEEDS.

HEEDS provides the user with a range of different optimization strategies from traditional optimization schemes, like quadratic programming, to evolutionary based methods, like genetic algorithms. HEEDS also offers a proprietary search method, SHERPA, that uses a combination of different search strategies and has demonstrated its effectiveness on parametric optimization problems [2]. All of the mechanism synthesis studies presented here used the SHERPA search strategy.

Similar to the iiGA model, HEEDS has the added power of being able to define multiple search "agents" to perform an optimization task. These agents are analogous to the parallel islands in the iiGA model. Likewise, as in the iiGA approach, HEEDS then provides the option of "linking" the defined agents together so that they can share design information on a periodic basis determined by HEEDS during the optimization run. Just as with an iiGA, the agents can use different representations of the problem definition, and the user merely needs to define how one representation "maps" into the other [2].

Mechanism Synthesis Using HEEDS

In the current study, HEEDS was used in conjunction with custom-written mechanism evaluation programs to synthesize planar single-degree-of-freedom mechanisms; however, any commercial or in-house analysis program could have been used to evaluate each proposed mechanism. Six different mechanism types were considered in this case study. The six types included a four-bar mechanism, Stephenson's six-bar-mechanisms (types I, II, and III), and Watt's six-bar-mechanisms (types I and II). These mechanism types will be referred to as "4B", "S1", "S2", "S3", "W1", and "W2", respectively. The six mechanism types are illustrated schematically in Figure 1.

The techniques used here are readily scalable to account for any number of different mechanism types; the six types in this study are very common and were chosen to demonstrate the effectiveness of the technique.

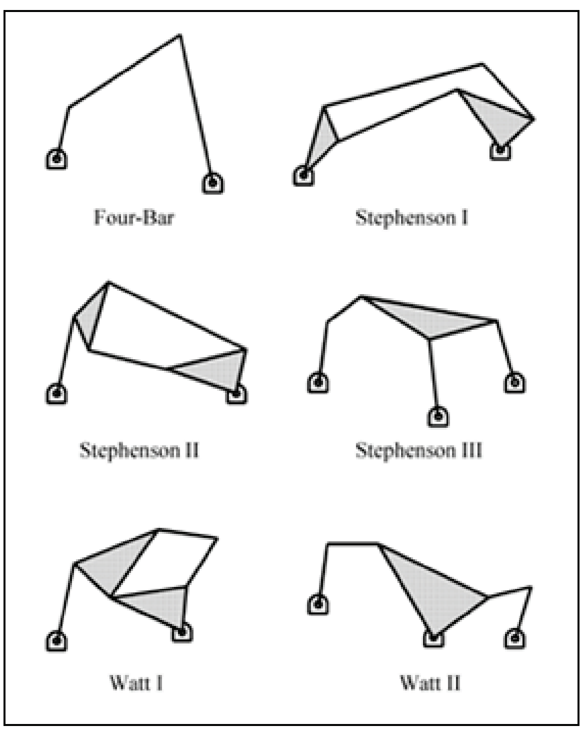

Figure 1. Mechanism types considered in this study.

Two different approaches were used when synthesizing the mechanisms using HEEDS. The first was to establish six independent search agents, one for each mechanism type. Although all six types were being evolved simultaneously within HEEDS, the agents had no interaction with each other, so the results of this first approach were no different than if six independent runs were conducted, each searching for a single mechanism type. The six search agents are illustrated in Figure 2.

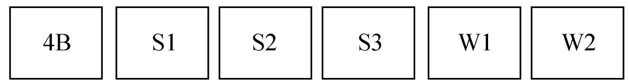

Figure 2. Schematic of six independent, parallel mechanism search agents.

A second approach was to link these same six agents together so that they could periodically exchange information regarding the best designs that each had found so far during the evolutionary process. This linking is shown in Figure 3. Notice that a link is created from every agent to every other agent to enable them to exchange information directly.

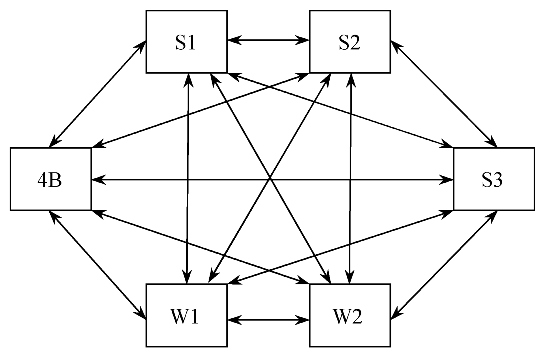

Figure 3. Schematic of six linked mechanism search agents.

Detailed results from this case study will be presented later to demonstrate the relative effectiveness of the different strategies discussed here. However, it is helpful to discuss the results in general terms now, because those results provide the motivation for the third method that was developed.

When comparing the results from the independent agents versus those from the linked agents, in general, there was no change in quality between the two result sets. Thus, the mechanism agents do not appear to gain any meaningful design information when exchanging data with each other. The authors speculate that this is analogous to phenomena witnessed in the natural world. For example, two species may share a lot of topological features (for example dogs and cats), yet the two may not be compatible enough to enable reproduction between the species.

In the case of mechanisms (Figure 1), S2 and W1 mechanisms share a lot of topological features; they both have two ground pivot points, they both have three binary links and two ternary links. Yet, the linked agent strategy results indicate that the parameters that typically yield a well performing S2 mechanism do not translate into a W1 mechanism that performs well.

Also, certain design problems tend to consistently converge to the same mechanism type as the optimum solution. Conversely, this same mechanism type may be the worst performing type for a different case study. This demonstrates the need to consider a range of possible solutions for any given problem, because the top-performing type is usually not obvious.

Convertible Agent Approach

A new strategy, termed “convertible agents,” has been devised to overcome the shortcomings of the existing strategies just described. In this approach, the search process begins just as it did when using the linked agents. Thus, there are six mechanism search agents, one for each mechanism type, each looking for a solution to the problem at hand.

The capabilities of HEEDS were enhanced, though, by developing a program that runs in parallel to the HEEDS internal optimization algorithm. This program essentially monitors the progress of the design process as it is happening. After a subset of optimization iterations has been performed by HEEDS, the parallel program compares the best mechanisms that have been found up to that point by each agent. The agent finding the worst-performing mechanism type is then converted into an agent searching for the best-performing type. In this way, the computing resources that were being spent on a mechanism type that was likely (though not guaranteed) to be underperforming for the entire optimization run, are reallocated to search for the type that has proven to be successful. This comparison and conversion process continues on a specified periodic basis through the duration of the design process. The general tendency is for all of the agents to be converted to just one or two different types by the conclusion of the process.

From the very beginning during the convertible agent strategy, the agents are always linked together as illustrated in Figure 3. When the agents are dissimilar, this linking does not provide much benefit, as demonstrated earlier. However, once the agent conversion process yields multiple agents searching for the same mechanism type, this linking has proven to make the agents' search efficiency become much greater than when each agent proceeds independently.

Mechanism Representation

To quantify the performance of each mechanism, the mechanism is stepped through its full range of motion. In the case of the mechanism shown in Figure 4, the crank link AB would be rotated through a full 360°, with a step size of 1°.

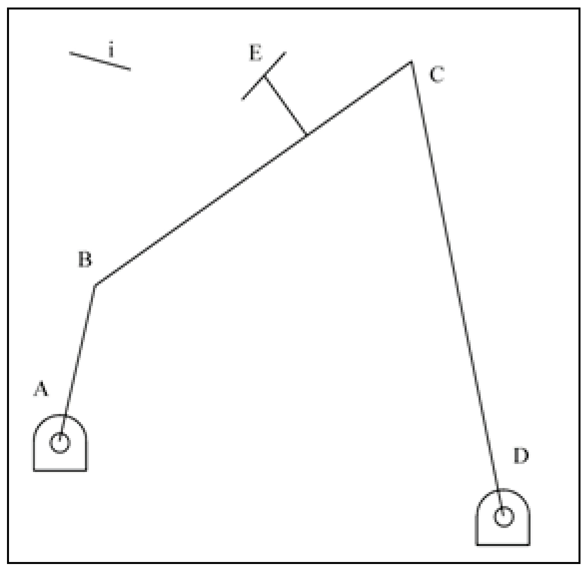

Figure 4. Representative four-bar mechanism with target.

For every crank angle position θ, the orientation of the entire mechanism is determined. Of paramount interest is the position of the target element at *E*. Once the position of *E* has been found, the distance *d* between it and each of the desired targets can be calculated as:

$$d_{i,\theta} = \sqrt{(E_x - i_x)^2 + (E_y - i_y)^2}$$

This is actually done for each side of the target and target element, respectively, and the sum of those two is determined. Throughout the full range of motion of the mechanism, the minimum value that is determined for *d* for each target *i* is maintained.

$$d_i = \min_{\theta=0°\to 359°}\left(d_{i,\theta}\right)$$

After the mechanism has been analyzed through its full range of motion, the sum of minimum distances for all of the targets is taken as the mechanism's objective function or performance value. Mathematically this is expressed as:

$$ObjectiveFunction = \sum_{i=1\to N} d_i$$

Note that the mechanism evaluation codes used here can accommodate any number *N* of targets. The codes also allow mechanisms that produce meaningful results through a range of motion that is less than 360°. Mechanisms that are fully constrained are avoided by assigning them arbitrarily large objective function values.

In summary, the complete mechanism synthesis implementation consists of HEEDS producing candidate designs, which it passes to the mechanism evaluation code. The evaluation code determines each mechanism's objective function according to the above equation, and then passes that information (a single value for each mechanism) back to HEEDS. HEEDS then uses this data to produce the next set of mechanism candidates. This is true for the three strategies employed: independent agents, linked agents, and convertible agents. The convertible agent method has the added component of the monitoring program tracking the process and converting agents as needed.

Case Study: Furniture Hinge Mechanism

This case study comes from the field of furniture/ cabinet design. The objective is to develop a hinge that provides a smooth range of motion while taking up as little space as possible.

A series of five target positions were selected to replicate the desired motion of a furniture hinge design as originally described by Chen [3]. Other details such as allowable link lengths, permissible pivot locations, and sizes in general were chosen here to be consistent with Chen's work. The geometry of this design space is shown in Figure 5.

In Figure 5, the origin is taken as the contact point between the cabinet door and the cabinet structure. The cabinet would extend up along the +Y axis, and the door would extend back along the -X axis, in its

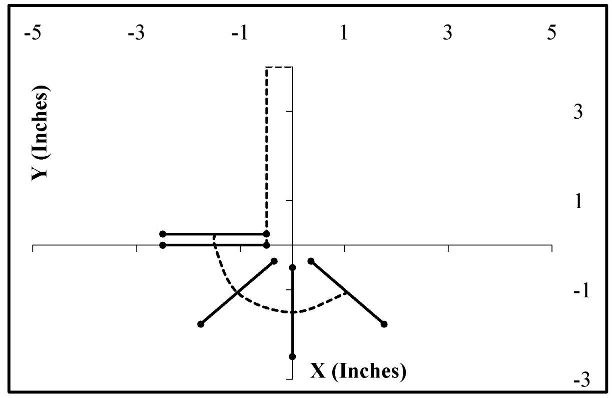

Figure 5. Design space and target locations for furniture hinge mechanism.

closed position. The five lines plotted in the figure are the five target positions for the hinge through its range of motion. They are connected with a dotted line to indicate the expected path between them. Notice how the two targets closest to the cabinet are exactly parallel with each other, yielding the opening motion. Also note that the first target is inset from the door when it is in its closed position. This is to meet the criteria that the hinge can be surface mounted. Finally, the box in the figure extending from the origin to the point (-0.5, 4.0) represents the allowable range that was specified for the location of the fixed ground points. An example of a mechanism designed to meet the specifications for this case study is shown in Figure 6.

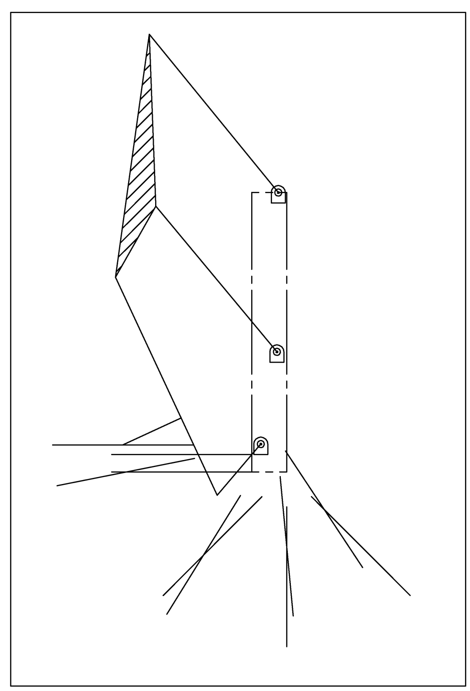

Figure 6. Example mechanism for furniture hinge case study.

The average mechanism synthesis results obtained for this case study are summarized in Table 1.

Table 1. Average objective function comparisons for furniture hinge mechanism.

Mech. Type	Ind. Agents	Linked Agents	Conv. Agents	Ind. vs. Linked	Ind. vs. Conv.
4B	1.40	1.71	1.21	-22.1%	13.6%
S1	2.58	1.66	0.99	35.7%	61.6%
S2	1.81	1.81	0.61	0.0%	66.3%
S3	2.54	2.10	0.99	17.3%	61.0%
W1	3.97	3.03	-	23.7%	-
W2	2.35	2.06	1.15	12.3%	51.1%

The first three columns show the average objective function results obtained when using independent agents, linked agents, and convertible agents, respectively. The final two columns compare the effectiveness of the three approaches using the independent agents as a baseline for comparison. Notice the sign convention adopted for this comparison. A mechanism that passes through the targets more exactly is indicated by a lower objective function value. However, when comparing the average objective function values in this paper, better results are indicated with a positive percentage comparison.

As shown in Table 1, four of the mechanism types saw respectable gains with the linked agent approach, while only the S2 mechanism type remained constant, and the 4B mechanism type was worse. The convertible agents found much better results for all of the mechanism types with the exception of W1. The W1 type performed very poorly as a furniture hinge mechanism using all of the synthesis methods attempted - so poorly, in fact, that the convertible agents never converged to a solution that used the W1 topology, hence its entry for the convertible agents is left blank in Table 1. Due to the probabilistic nature of the convertible agent approach, there is a chance that the agents will converge to any of the specified types during a given run. However, after a series of runs as were performed here, very good types (in this case the S2 type) and very poor types (here W1) tend to emerge.

It is also interesting to note once again that the W1 mechanism type was found to be the worst type for this particular synthesis case by all three evolutionary strategies. This is notable because in the original work, Chen concluded that the W1 type was the "most feasible" for the hinge design [3]. However, Chen approached the problem from a different perspective, using the Creative Mechanism Design Method to first select the mechanism type, and then optimizing the dimensions of that type. Here, by synthesizing the type and dimensionality of the mechanism simultaneously, a very different conclusion is drawn.

Conclusions

Synthesizing mechanisms is an engineering design problem that has both captivated and frustrated generations of engineers. Here, a fully automated synthesis strategy that simultaneously optimizes both the type and dimensionality of a mechanism has been devised. The convertible agent evolutionary approach developed in this paper has demonstrated itself to be a more robust and efficient evolutionary synthesis strategy than any of the methods that have come before it.

Furthermore, the convertible agent approach developed herein is readily scalable to consider any number of different mechanism types that go beyond those considered in this study. Mechanisms with different joint types, increased numbers of links, or non-planar behavior can be directly added with the specification of the respective search agents. With each additional type considered, the designer will gain confidence in knowing that they are using the mechanism type best suited for a particular application.

Acknowledgements

This effort has been supported at various stages through the support and resources provided by Red Cedar Technology, the National Superconducting Cyclotron Laboratory at Michigan State University, and Grand Valley State University.

References

1. Lin, S.-C., Punch, W., and Goodman, E. (1994). "Coarse-Grain Parallel Genetic Algorithms: Categorization and New Approach", *Proceedings of the Sixth IEEE Symposium on Parallel and Distributed Processing*. pp. 28–37.
2. Red Cedar Technology (2005). *HEEDS User's Manual – Version 5.0*. www.redcedartech.com
3. Chen, F.C. (2005). "Analysis and Verification of a Watt I Six-Bar Furniture Hinge Mechanism", *Proceedings of the I MECH E - Part C - Journal of Mechanical Engineering Science*, vol. 219, issue 10, pp. 1107-1117.