AC 2009-1120: TEACHING ENGINEERING AND TECHNOLOGY STUDENTS TO DEVELOP GENETIC ALGORITHMS FOR THE DESIGN OF ENERGY SYSTEMS

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Teaching Engineering and Technology Students to Develop Genetic Algorithms for the Design of Energy Systems

Introduction

Delivering the energy required by industry and the consumer at a reasonable price is a major problem facing the United States and the international community. The United States needs a comprehensive plan to meet its energy needs for the next 50 years. Popular goals are focused on limiting energy consumption, increasing renewable sources, promoting conservation, and making energy conversion more efficient. To muster political support, there has to be an emphasis on safety, ethics, and maximizing domestic resources. New energy technology is continually being introduced: e. g. ultracapacitors, efficient batteries, solar cells, fusion reactors.[1,2,3] Energy plans need to take countenance of these new technologies on the horizon.

In order to prepare engineering students to develop energy plans, they should be exposed to methods in their educational programs. How do you find the best solutions for complex energy systems? What kinds of algorithms are appropriate for this type of problem? These are the questions the author posed to his mechatronics class? Mechatronics[4] is a subject that joins electrical engineering with mechanical engineering. Energy systems are mechatronics systems in that they are part mechanical and part electrical and electronic. The students' challenge was to optimize an energy plan for the U. S. for the next 50 years. The class divided themselves into different factions. Since genetic algorithms lend themselves to systems that have indefinite factors, this was the category of algorithm that was chosen for this investigation.

A population of different energy resources was compiled. For each faction, a spreadsheet was created which contained a detailed summary of the energy plan components. Each faction then created and applied a genetic algorithm to their starting plans. Genetic algorithms are based on Darwin's Theory of Evolution.[5] An algorithm is a strategy for solving a problem. Using genetic algorithms, the solutions evolve by making a series of prescribed changes and then select those changes that allow the system to best adapt to the environment. Genetic algorithms were first proposed by John Holland.[6,7]

Current State of U. S. Energy

The components of the energy plan included wind power from wind mills, fossil fuels for transportation, solar energy including solar panels and thermal solar, nuclear reactors, nuclear fusion, steam power plants. At the time of the class, gasoline prices in the US were at an all time high so one of the goals was to make the U.S. less dependent on fossil fuels and in particular foreign sources of fossil fuels. The total energy expended by the United States for all purposes in 2006 was approximately 100 quadrillion BTUs or 105 exajoules.[8] This is the total energy that the U.S. population consumed and which was supplied from all sources. This included the energy derived from fossil fuels for power and transportation which was about 90%.[8] The rest of the energy came from nuclear, wind, solar, hydroelectric and hydrothermal sources.

Genetic Algorithms

Genetic algorithms lend themselves to complex adaptive systems (CAS) .[6,7] These are systems where the parts interact to create novel properties but evolve and create new rules as the conditions change. Energy systems are complex adaptive systems.

Building Blocks and Recombination

According to Holland,[6,7] the CAS system is divided into building blocks in order to apply genetic algorithms. The building blocks of the system correspond to the genes which are manipulated in nature to give diversity to species. The genes are the agents of change. Nature has provided several algorithms for manipulating genes. The most prominent ones are mutation and crossover. In mutations, the genes are physically changed. In crossover, the genes crossover from one chromosome to the other and there is a shuffling of the genes. Once the genetic algorithm is applied, there is a selection process to see if the new child system is improved over the previous adult system. In nature, Darwin calls this "natural selection."[5] The species that are better able to adapt as the environment changes are able to survive and procreate.

The students in the class were assigned to apply genetic algorithms[9] to adapt an energy plan. The students defined both the crossover and mutation operators based on this energy application. They developed the operators for crossover and mutation based on the process found in nature. The students chose the energy features to be modified, added, replaced, or deleted.

Method

The first step was to generate an initial population of energy systems (plans). The initial population of nine energy systems was created by the nine students in the class. Each student represented a different interest group (see Table 1 below). The second step was to apply a fitness function to the system and ascertain the fitness of each plan.

The students decided on the general form of the fitness function which was:

(1) limit the rate of increase in energy consumption, (2) limit the rate of decrease in energy production, (3) minimize the unit energy cost, (4) maximize the renewable sources, (5) maximize the domestic sources, (6) minimize the air/water/soil pollution including CO_2, and (7) maximize the efficiency. These fitnesses were incorporated into matrices and each normalized as a percentage of 1.

The third step was to apply the genetic operations. The students implemented the evolutionary change functions as:

Crossover[9,10]: Incorporate a better mix of current resources and current technologies

Mutation[9,11]: Incorporate new technologies.

After genetic operators were applied, a set of constraints were applied. Then the process was repeated. The process ran for a set number of cycles (generations) until it converged to a best fit. The rate of convergence had to stay within prescribed limits.

Flowchart of Method:

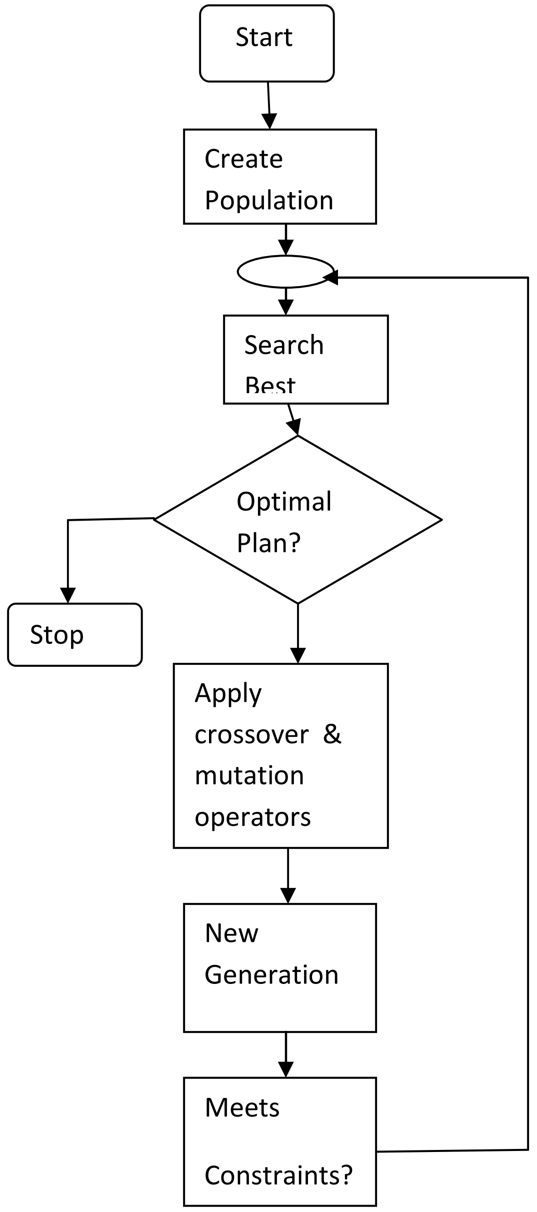

Table 1: Interest Groups

Representative of the Federal administration including the Dept. of Transportation and Energy
Representative of the U.S. Automobile Manufacturer's Association
Representative of the Oil and Gas Companies
Representative of the Power Utilities
Representative of the Nuclear Power Industries
Representative of the Wind Power Companies
Representative of the Solar Energy/Fuel Cell Groups
Representative of the Fusion Research Groups
Representative of the Environmental and Conservation Groups

Creating the Subunits

Schemata are templates for subunits that have similar characteristics. Schemata usually fit into categories (herein chromosomes). The chromosomes and the schemata used for the energy plan are as follows:

Table 2: Six Chromosomes

1. Raw sources:
a. Schemata: oil, natural gas, coal, biomass, geothermal, wind, sunlight, nuclear (radioactive) materials, tides, water, heavy water
2. Production:
a. Schemata: power plants, nuclear reactors, fusion devices, wind mills, fuel cells, dams (hydroelectric)
3. Transportation:
a. Schemata: trucks, trains, ships, pipelines, wires(grids), lasers (beams)
4. Storage:
a. Schemata: batteries, capacitors, tanks and tank towers
5. Consumption (efficiency):
a. Schemata: motors (appliances), compressors,

heaters, insulators
6. Conservation:
a.Schemata: mass transit, car pooling, walking, biking

Each schemata has the following parameters as one row of each chromosome matrix C_{ijk} where i=schemata (row), j = parameter (column), k = chromosome (1-6).

C_{i1} = Type, C_{i2} = % total output in joules, C_{i3} = % total cost in \$/joule,

C_{i4} = % pollution limit parts/liter/joule, C_{i5} = % domestic/joule, C_{i6} = % renewable/joule,

C_{i7}= efficiency= % C_{i2}/% total Input in joules

C_{i1} (type) refers to the type of schemata (e.g. oil)

C_{i3} through C_{i7} are dictated by type C_{i1}

Therefore, C_{i1} is manipulated by the mutation operator and C_{i2} is manipulated by the crossover operator.

Fitness of each chromosome $F(k) = \sum_j \sum_i C(i,j,k)$ for i = 1,n schemata and j = 1,7

Total Fitness = $\sum_k F(k)$

The top nine fit plans were chosen for the next generation.

The following constraints were placed on each new generation:

Constraint 1 – energy production not fall (e.g. below 105 exajoules)

Constraint 2 – average cost per joule not fall below that of the last generation

Constraint 3 – average efficiency not fall below that of the last generation

Any member of the new generation consisting of 6 chromosomes that did not meet the constraints was eliminated.

Search Best Fit

In order to search for the best plan, The Microsoft Excel Solver Add-in[9] was used to minimize the cost per joule and the amount of pollution and maximize the energy production, the domestic sources, the use of renewables and the efficiency.

Max(output + domestic sources + renewables + efficiency) + Min(cost + pollution)

Plan Completion (Convergent Criteria)[10]

The students devise their initial plan based on the literature and then applied the genetic algorithm to search for the best plan in 10 years, 20 years, and 42 years (2050). One of the convergent criteria was the number of generations. G number of generations was equilibrated to Y number of years.

Developing the crossover and mutation operators:

Crossover Operator

The students chose the shuffle crossover operator[11] as the best approach to generate new plans. In the version of the shuffle crossover, a diploid plan was formed from each set of parent plans:

Combin(9, 2) = 9! / ((9 - 2)! 2!) = 36 diploid plans, assuming 9 parent plans.

In the diploid plan, there are two schemata for each gene in the chromosome. The schemata are shuffled so at random one of each of two schemata per gene go to haploid child one or haploid child two. From each diploid plan, two haploid child plans are created. 72 haploid child plans are created in each generation.

Mutation Operator(new technologies)

A mutation operator[12] adds, changes, deletes or replaces schemata. As opposed to shuffling, it introduces something new. The students defined the mutation operator as introducing a new technology. A certain percentage of the energy output is replaced by a new technology and likewise the percentages of other schemata are reduced.

$$100\%\ \text{output} = \sum_i C(i,2,k) - \sum_i R_i * C(i,2,k) + C(n+1,2,k) \quad \text{for } i = 1, n+1 \text{ schemata}$$

where Ri is the percentage output reduction of existing schemata and C(n+1,2,k) is the output of the mutation.

A list of new technologies was compiled that could then be introduced as mutations. The list below indicates the chromosome where the mutation will be introduced and the type of mutation (new technology).

Table 3: Mutations

Production -100 new nuclear reactor plants within ten years
Conservation -Funding for research in new methods for nuclear waste disposal
Conservation -Store waste in Yucca Mt
Consumption -create nuclear cars
Conservation -Recycle nuclear fuel
Conservation -Promote usage of bicycle and walking
Conservation-Promote car pooling and public transportation
Production – increases solar homes and buildings
Production –increase funding for research into solar
Production-fusion plant
Consumption--appliances able to run directly off solar
Consumption-affordable solar vehicles
Storage-ultracapacitors
Storage-high capacity, fast charging batteries
Raw Sources - oil shell research
Transportation - industry: trucking, public transportation, airplanes, railway with fuel efficient alternatives
Conservation - tax cuts for households using eco friendly energy
Production - 15% increase in wind power in 20 years
Production - off shore wind plants
Production - Building plants in wind zones
Production - Increase funding for turbine research
Production - Tax credits for companies using wind turbines

Once the genetic operators were applied, a new generation of 72 children was complete. Each child plan was examined to see if it met the constraints. Any plan that was not within the limits of the constraints was cut from the generation. The cycle started over again and the fitness function was applied to the new generation.

Results

The students worked on the algorithms for 8 weeks. They met for 2 hours once a week. The first week was organizational. The last week was summary. So the generations cycled over 6 weeks. During that time, the algorithms consisting of the crossover and mutation operators were created, modified, and then applied to the plans. The constraints were clearly specified. Those plans which were not within the bounds of the constraints were eliminated. The remaining plans were optimized in order to search for the best fit? The resulting best plans were recorded and reviewed.

Generations

Since the plan was to encompass a time period starting at the current year and ending in 2050. The generations cycled 1, 2, 4, 4, 4, 6 generations respectively over the six weeks. Each generation became 2 years of plans. The generations cycled 21 times and were recorded at 5, 10, and 21 generations.

An optimal plan at 5, 10 and 21 generations is shown below in Table 4:

Table 4: An Optimal Plan

Plan					
2008				US $	US $
Energy Type	Megawatt-hrs	%	Exajoules	cost/kw-hr	Total Cost
Oil	11,816,654,100	0.3954885	42.50595	0.037	$437,216,201,700
Natural Gas	6,977,369,100	0.2335238	25.09845	0.043	$300,026,871,300
Coal	6,666,481,700	0.2231188	23.98015	0.051	$339,990,566,700
Nuclear	2,446,038,600	0.0818658	8.7987	0.09	$220,143,474,000
Fusion	0	0	0	n/a	n/a
Wind	146,645,000	0.004908	0.5275	0.05	$7,332,250,000
Solar	58,658,000	0.0019632	0.211	0.2	$11,731,600,000
Hydroelectric	791,883,000	0.0265033	2.8485	0.085	$67,310,055,000
Tidal	29,329,000	0.0009816	0.1055	0.035	$1,026,515,000
Geothermal	263,961,000	0.0088344	0.9495	0.1725	$45,533,272,500
Fuel Cells	29,329,000	0.0009816	0.1055	0.03	$879,870,000
Biomass	652,276,960	0.0218309	2.34632	0.0325	$21,199,001,200
Total	29,878,625,460	1	107.47707		$1,452,389,677,400
2018				US $	US $
Energy Type	Megawatt-hrs	%	Exajoules	cost/kw-hr	Total Cost
Oil	12,370,972,200	0.3784725	44.4999	0.057	$705,145,415,400
Natural Gas	7,129,879,900	0.2181286	25.64705	0.043	$306,584,835,700
Coal	7,411,438,300	0.2267425	26.65985	0.061	$452,097,736,300
Nuclear	2,534,025,600	0.0775249	9.1152	0.08	$202,722,048,000
Fusion	0	0	0	n/a	n/a
Wind	293,290,000	0.0089728	1.055	0.05	$14,664,500,000
Solar	117,316,000	0.0035891	0.422	0.15	$17,597,400,000
Hydroelectric	879,870,000	0.0269184	3.165	0.075	$65,990,250,000
Tidal	58,658,000	0.0017946	0.211	0.035	$2,053,030,000
Geothermal	527,922,000	0.016151	1.899	0.1445	$76,284,729,000
Fuel Cells	58,658,000	0.0017946	0.211	0.03	$1,759,740,000
Biomass	1,304,553,920	0.039911	4.69264	0.03	$39,136,617,600
Total	32,686,583,920	1	117.57764		$1,884,036,302,000
2028				US $	US $
Energy Type	Megawatt-hrs	%	Exajoules	cost/kw-hr	Total Cost
Oil	5,924,458,000	0.1518797	21.311	0.1	$592,445,800,000
Natural Gas	10,558,440,000	0.2706767	37.98	0.05	$527,922,000,000

Coal	7,332,250,000	0.1879699	26.375	0.08	$586,580,000,000
Nuclear	5,865,800,000	0.1503759	21.1	0.06	$351,948,000,000
Fusion	0	0	0	n/a	n/a
Wind	879,870,000	0.0225564	3.165	0.05	$43,993,500,000
Solar	351,948,000	0.0090226	1.266	0.1	$35,194,800,000
Hydroelectric	2,639,610,000	0.0676692	9.495	0.05	$131,980,500,000
Tidal	586,580,000	0.0150376	2.11	0.035	$20,530,300,000
Geothermal	1,055,844,000	0.0270677	3.798	0.1005	$106,112,322,000
Fuel Cells	1,466,450,000	0.037594	5.275	0.03	$43,993,500,000
Biomass	2,346,320,000	0.0601504	8.44	0.03	$70,389,600,000
Total	39,007,570,000	1	140.315		$2,511,090,322,000
2050				US $	US $
Energy Type	Megawatt-hrs	%	Exajoules	cost/kw-hr	Total Cost
Oil	1,466,450,000	0.0282486	5.275	0.1	$146,645,000,000
Natural Gas	2,932,900,000	0.0564972	10.55	0.05	$146,645,000,000
Coal	1,466,450,000	0.0282486	5.275	0.08	$117,316,000,000
Nuclear	2,932,900,000	0.0564972	10.55	0.06	$175,974,000,000
Fusion	9,385,280,000	0.180791	33.76	0.05	$469,264,000,000
Wind	7,742,856,000	0.1491525	27.852	0.05	$387,142,800,000
Solar	6,012,445,000	0.1158192	21.6275	0.08	$480,995,600,000
Hydroelectric	2,639,610,000	0.0508475	9.495	0.05	$131,980,500,000
Tidal	7,596,211,000	0.1463277	27.3245	0.035	$265,867,385,000
Geothermal	1,055,844,000	0.020339	3.798	0.1005	$106,112,322,000
Fuel Cells	7,508,224,000	0.1446328	27.008	0.03	$225,246,720,000
Biomass	1,173,160,000	0.0225989	4.22	0.03	$35,194,800,000
Total	51,912,330,000	1	186.735		$2,688,384,127,000

Conclusions

The research showed that engineering students can learn to generate a set of energy plans using genetic algorithms. The students demonstrated that they can learn to form and revise their own specialized genetic algorithms based on crossover and mutation operators and based on the particular application such as complex energy systems. They were able to formulate the energy plans in the form of spreadsheets using tools such as Microsoft Excel and then apply the genetic operators to the plan components and finally use the add-in solvers to optimize the plans. This method can be applied to other plans for complex systems

Planning and implementing cheaper, more abundant and more efficient energy systems will lead to solving many of the problems the world faces today. It was therefore important that these engineering and technology students be exposed to the types of energy systems that they could design and build in the future. Their future jobs may involve deciding which systems to build.

They will be making decisions about where funds, resources, and labor should be invested in the energy systems of the future and on what timetable.

Levers and Emergent Properties

Emergent properties are properties that come from combining components.[13] The emergent property is a property that is not evident from any one component but requires all the components to act together. The whole is greater than the sum of its parts. Levers as they apply to CAS are points of change that result in emergent properties. Change most often occurs from crossover but less often from mutation. For example in order to fly, an emergent property, you need wings and power and a tail working together.[14] The lever is the set of changes that produces a new emergent property (i.e. flying). It is important that engineering and technology students be familiar with CAS systems so that they will have the skills to find the levers and emergent properties of the advanced systems of the future.

References

1. Mierlo, J. V., Van den Bossche, P., & Maggetto, G. (2004). Models of Energy Sources fir EV and HEV: fuel cells, batteries, ultracapacitors, flywheels, and engine-generators. *J. of Power Sources. 128 (1)*, 76-89.
2. Shaheen, S. E., Brabec, C. J., Sariciftci, N. S., Padinger, F., Fromherz, T., & Hummelen, J. C. (2001). 2.5% Efficient Organic Plastic Solar Cells. *Appl. Phys. Lett. 78*, 841.
3. Petzoldt, R. W. (2002).Direct Drive Target Survival During Injection in an Inertia Fusion Energy Power Plant. *Nucl. Fusion. 42*, 1351-1356.
4. Bolton, W. (2008). *Mechatronics: a multidisciplinary approach*. New York, NY: Pearson Prentice Hall.
5. Darwin, Charles (1872). *The origin of species by means of natural selection, or the preservation of favoured races in the struggle for life*. London: John Murray.
6. Holland, J. H. (1975). *Adaptation in natural and artificial systems*. Ann Arbor, MI: University of Michigan Press.
7. Holland, J. H. (2008).Biology's Gift to a Complex World. *The Scientist. 22 No. 9*, 36-43.
8. U.S. Department of Energy. Retrieved January 10, 2009, from International energy annual 2006 Web site: http://www.eia.doe.gov/pub/international/iealf/tablee1c.xls
9. Fylstra, D., Lasdon, L., Watson, J., & Waren, A. (1998). Design and Use of the Microsoft Excel Solver. *Interfaces*, *28 (5)*, 29-55.
10. Sivanandam, S. N., & Deepa, S. N. (2008). *Introduction to genetic algorithms*. New York: Springer-Verlag.
11. Burkowski, F. J. (1999).Shuffle Crossover and Mutual Information. *Proc. 1999 Congress Evolutionary Computation. 1*, 1574-1580.
12. Hugosson, J., Hemberg, E., Brabazon, A., & O'Neill, M. (2007). An Investigation of the Mutation Operator using Different Representations in Grammatical Evolution. *Proc. Int. Multiconf. Comp. Sci. and Infor.*

    Tech., *1*, 409-419.
13. Checkland, P. (1999). Systems Thinking. In Currie, W. L. & Galliers, B. (eds), *Rethinking Management*

Infor. Sys .(45-57) Oxford: Oxford University Press.

14. Josephy, A., Gordon, A, & McFarland, M. W. (1962). *The american heritage history of flight*. New York: Simon and Schuster.