How to Cite:
Marjan, M. K., & Aljilawi, A. S. (2022). Dynamic optimization technique with differential equations. *International Journal of Health Sciences*, *6*(S2), 2205–2213.
https://doi.org/10.53730/ijhs.v6nS2.5482

Dynamic optimization technique with differential equations

Mazin Kareem Marjan
Ministry of Education, General Directorate of Education in Babylon
Email: mazen.marjan22@gmail.com

Ahmed Sabah Aljilawi
Department of Mathematics, University of Babylon
Email: aljelawy2000@yahoo.com

***Abstract*---**One of the primary objectives of the problem is to reduce the cost of fuel consumed by generator units, and in recent years, we have developed new models to accomplish this goal. The first model problem represents a load following scenario, which is a common occurrence in power grids. The optimizer's objective is to balance demand and supply in response to fluctuating demand dynamics. At two different stages of the production process, a single producer tries to satisfy two constrained objectives in this model problem 2. By replacing a cogeneration system with n = 2 generators that generate (1) electricity and (2) heat in response to variations in demand, Model II improves on Model I. Using a n = 3 system with two products, three products, and three distinct order profiles, the third model issue builds on the prior two. The primary product remains unchanged from the preceding standard, and the slope rate is limited to the production of the two primary products (for example, electricity and heat). To create a third product (for example, a solid oxide electrolysis cell), the first two products are combined (for example, hydrogen).

***Keywords*---**energy systems, design optimization, dynamic control objectives, python algorithms.

Introduction

Grid design and operation optimization are required, as modern society is reliant on massive amounts of electrical energy. Due to the complexity of the electric grid, tough control issues necessitate the use of powerful solvers and efficient formulations in order to achieve tractable solutions. We develop and evaluate an approximate dynamic programming approach for designing near-optimal control rules for time-dependent, nonlinear systems. Energy efficiency improvements are

Manuscript submitted: 27 Jan 2022, Manuscript revised: 18 Feb 2022, Accepted for publication: 09 March 2022

frequently quite rewarding investments.[6,7,11] They are, however, implemented gradually. One of the primary impediments is the considerable work required to identify possible cost savings in businesses. It is particularly challenging for small and medium-sized businesses (SMEs) to identify energy inefficiencies in systems and buildings. Benchmark values are required to determine the energy efficiency of facilities or entire organizations. Businesses must do peer comparisons to see whether their economic activities are energy efficient in contrast to others.

Individual case studies contain design characteristics a few examples are limiting the ramp rate, generating electricity, and using energy storage. [9,10,12,16] The variables utilized in the benchmark tasks are detailed in the following sections. An objective function, (d) stands for demand, (g) stands for generation, (r) stands for ramp rate and storage inventory, (e) stands for product i's storage capacity.

What is known as a mathematical model

Model I

A common occurrence in grid systems is a condition known as "load following." The optimizer tries to balance supply and demand in response to changing demand dynamics. When ramping constraints are imposed on a single generator, a perfect foresight attempt is made to respond to a single load. To avoid overproduction, a generator must ramp up production to keep supply and demand in sync at first.

$$Min_r \ \mathbf{K} = \int_{i=0}^{2} [1000\, max(0, d-g) + max(0, g-d)]\, dt$$
$$S.\ t. \frac{dg}{dt} = r$$
$$d = cos(2\pi t) + 3$$
$$-1 \le r \le 1$$
$$g(0) = d(0) = 4$$

Model II

Attempting to attain two restricted goals at the same time is the second model issue. With the addition of a cogeneration system (n=2) that generates (1) electricity and (2) heat based on changes in demand and a new heat demand profile, Model II outperforms Benchmark I in terms of efficiency.

$$Min_r \ \mathbf{K} = \sum_{i=1}^{n} \int_{i=0}^{2} [1000\, max(0, d_i - g_i) + max(0, g_i - d_i)]\, dt$$
$$S.\ t. \frac{dg_1}{dt} = r, \ \ g_2 = 2g_1$$
$$d_1 = \cos(2\pi t) + 3$$
$$d_2 = 1.5 \sin(2\pi t) + 7$$
$$-1 \le r \le 1$$
$$g_1(0) = d_1(0) = 4$$
$$g_2(0) = 8, \ d_2(0) = 7$$

Model III

Incorporating a trigenerational system, the third model problem improves on the previous two by introducing two producers, three items and three demand profiles. An identical primary producer is used to make the two fundamental products, with a limited ramp rate (e.g., electricity and heat). One more manufacturer can use the first two goods to make hydrogen and increase production capacity while avoiding supply shortages for the first two products using a solid oxide electrolysis cell. Foresight is a given for the optimizer, as was previously stated.

$$Min_r \;\; \mathbf{K} = \sum_{i=1}^{n} \int_{i=0}^{2} [1000\, max(0, d_i - g_i) + max(0, g_i - d_i)]\, dt$$
$$-0.1 \int_{i=1}^{2} g_3 dt$$
$$S.\ t. \frac{dg_1}{dt} = r_1, \quad \frac{dg_3}{dt} = r_3, \quad g_2 = 2g_1$$
$$d_1 = cos(2\pi t) + 3 + 2g_3$$
$$d_2 = 1.5\, sin(2\pi t) + 7 + 3g_3$$
$$d_3 = max[0, -0.2\sin(2\pi t)]$$
$$-1 \le r_1 \le 1, \quad -1 \le r_3 \le 1$$
$$g_1(0) = d_1(0) = 4$$
$$g_2(0) = 8, \; d_2(0) = 7$$
$$g_3(0) = d_3(0) = 0$$

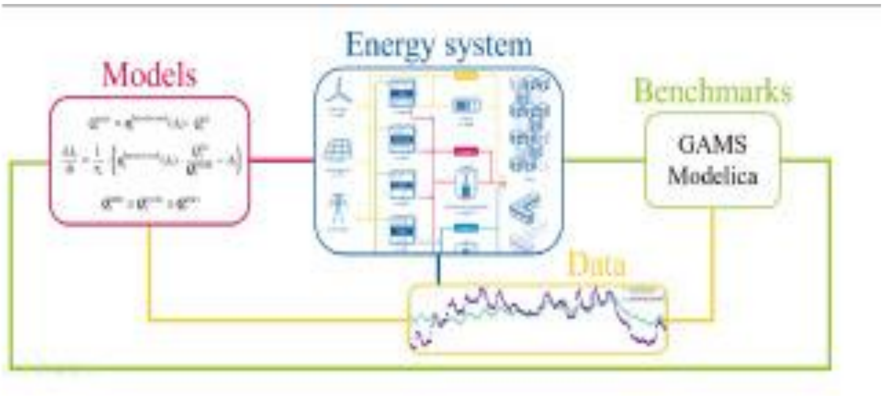


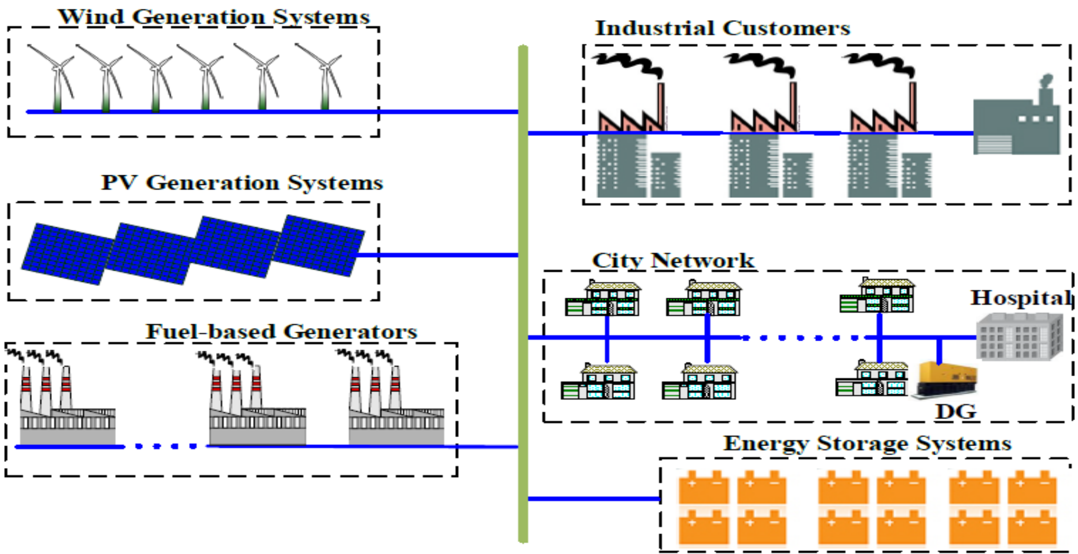
Figure (1) Graphical abstract

Energy Systems

Energy supply systems can be designed, operated, and controlled more efficiently using quasi-stationary, dynamic and linear and nonlinear models are all consistent. [8,13] To achieve quasi-stationary models, all temporal derivatives in the dynamic models must be zeroed out. linear models also become nonlinear when the distance between two support points is zero. It is thus possible to investigate the impact of linearization and the assumption of quasi-stationary behavior on energy supply system optimization without incurring distortions due to divergent modeling assumptions, as the assembled component models do. Note that the models shown here are solely reliant on the pace at which energy is pumped through them. For models with minute-scale thermal inertia, we suggest dynamic extensions. Electricity models on the other hand, because of the speed of electrical operations, are presumed to be (quasi)stationary models.

Design optimization

Due to the combination of combinatorial decisions and operational optimization, design optimization must deal with large-scale optimization difficulties. have even demonstrated that designing (distributed) energy supply systems is an NP-hard task. We include both minimum costs and minimum global warming impact in this case study,[5,6] which adds to the complexity of the design optimization challenge.



Figure(2) An overview of the structure of sustainable power systems

Dynamic control objective

The dynamic control objective function is a mathematical expression that is minimized or maximized in order to determine the optimal answer for a controller among all conceivable possibilities. The shape of this goal function is crucial in order to provide appropriate solutions for guiding a system to a desired state or trajectory.[2,3,14,15] The most frequently used objective statements refer to economic, safety, operability, or environmental objectives.

Python Algorithms

Students are forced to deal with the specifics of data structures and supporting procedures rather than constructing an algorithm when they utilize traditional programming languages. Python is an algorithmic programming language that has grown in popularity in education.[1,4] Python's features include its textbook-like structure and experimentation-friendly interaction. More crucially, we describe our novel use of the Python programming language to express aggregate data structures such as graphs and flow networks in a succinct textual format, which not only motivates students to experiment with algorithms but also greatly lowers development time.

Application of New model

Numerous applications of electricity and heat exist throughout the life cycle, including. Due to the heating action of electricity, a light bulb or the filament of a lamp emits light. The lamp filament is often constructed of tungsten metal, which melts around 3380 degrees Celsius. And electric iron is composed of alloys with a high melting point. Both the electric heater and the heater operate on the same principle. And an electric fuse, which is used to protect electrical devices from excessive voltage, if it exists. Electric fuses are typically constructed of metal or a metal alloy, such as aluminum, copper, iron, or lead. If the voltage exceeds the limiter, the fuse wire melts, protecting the electrical appliances.

Numerical Results

We obtain the optimal time to solve the problem by applying the new model from the previous objective function, as seen in Figure (3,4,5) and Table (1,2,3):

	scaled	unscaled
Objective	7.6186676198350831e+000	7.6186676198350824e+001
Dual infeasibility	1.4210854715202004e-014	1.4210854715202004e-013
Constraint violation	4.1958624075189022e-016	4.1958624075189022e-016
Complementarity	1.2278478753572035e-011	1.2278478753572034e-010
Overall NLP error	1.2278478753572035e-011	1.2278478753572034e-010

Table (1) model I

The solution was found.
Solution time : 0.43870000000000003 sec
Objective : 76.18767624693196

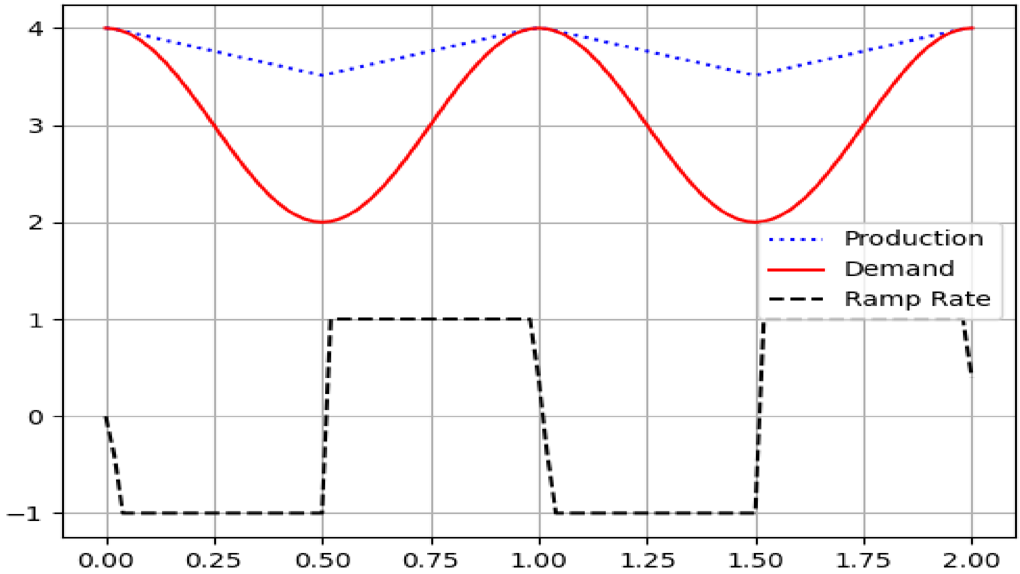


Figure (3) model I

	scaled	unscaled
Objective	2.8125484463777340e+001	2.8125484463777337e+002
Dual infeasibility	2.3386243534068152e-007	2.3386243534068152e-006
Constraint violation	9.0594198809412774e-014	9.0594198809412774e-014
Complementarity	3.6237809079003073e-008	3.6237809079003070e-007
Overall NLP error	2.3386243534068152e-007	2.3386243534068152e-006

Table (2) model II

The solution was found.
Solution time : 0.938 sec
Objective : 281.25677873795695

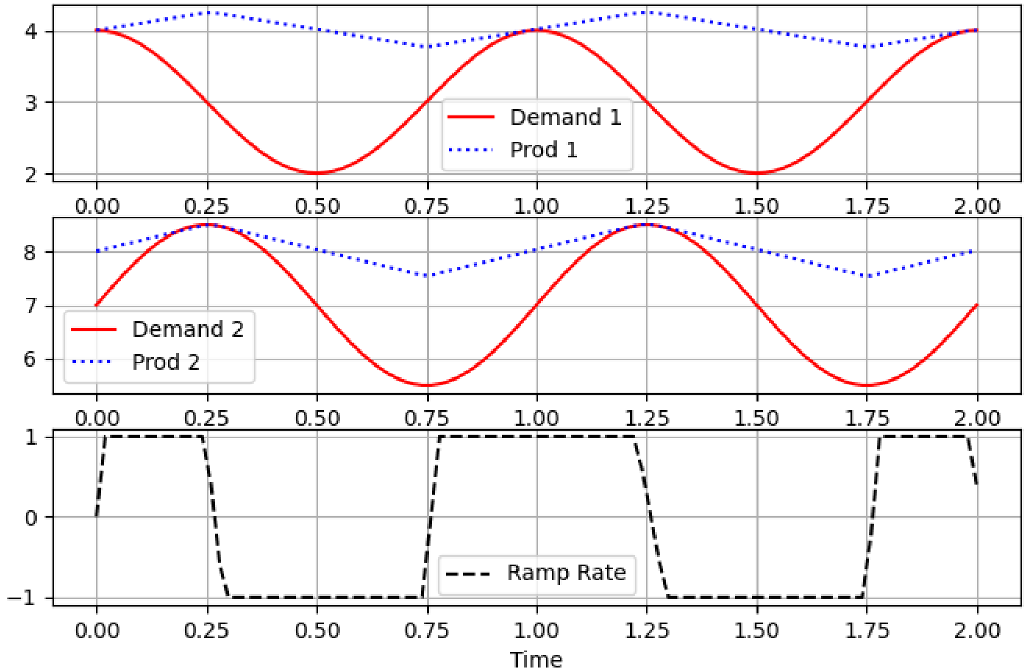


Figure (4) model II

iter	objective	convergence
0	5.47405E+02	1.00000E+00
1	2.19430E+02	2.71523E-03
2	2.18870E+02	1.00962E+00
3	2.18844E+02	1.20000E-09
4	2.18844E+02	3.49977E-10
5	2.18844E+02	2.57572E-14
6	2.18844E+02	2.57572E-14

Table (3) model III

Successful solution
Solution time : 4.3582 sec
Objective : 218.8442245711001

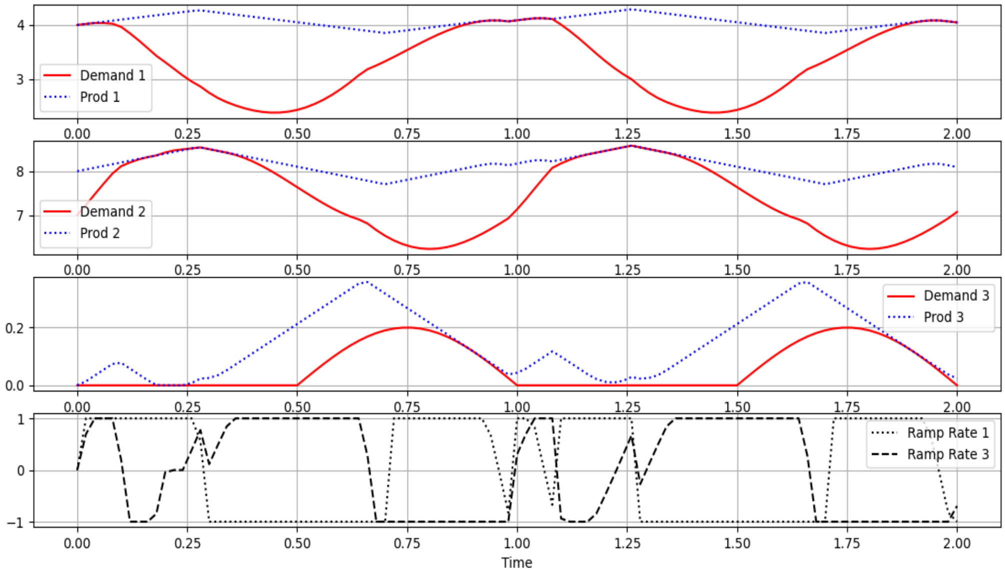


Figure (5) model III

The Description

In the first and second tables we stop when we get the least error, but in the third table we stop when the repetition becomes a value that does not change no matter how much more iteration of the objective function occurs .We note in the third, fourth and fifth figures that the blue color represents energy production, the red color represents energy demand, and the black color represents the regression rate in relation to production and demand.

Conclusion

Energy systems in the world have changed dramatically as a result of the widespread adoption of electrical energy, the importance of linking the concept of rationalizing electrical energy consumption with the progress of the world, and simple application methods that can be used by the public. Emphasis was also placed on solving the problem of producing electrical and thermal energy and benefiting from it in dissolving and oxidizing solid materials in a new way, solving the problems of future energy systems and contributing to the development of energy systems.

References

1. Beal, L., GEKKO for Dynamic Optimization, 2018.
2. Drake, J.H.; Kheiri, A.; Özcan, E.; Burke, E.K. Recent advances in selection hyper-heuristics. European Journal of Operational Research, 2020;285(2):405-428.
3. Kopei, V.B., Onysko, O.R. and Panchuk, V.G., 2019. Component-oriented acausal modeling of the dynamical systems in Python language on the

example of the model of the sucker rod string. PeerJ PrePrints, 7, p.e27612v1.
4. Liu, Q.; Gehrlein, W.V.; Wang, L.; Yan, Y.; Cao, Y.; Chen, W.; Li, Y. Paradoxes in Numerical Comparison of Optimization Algorithms. IEEE Transactions on Evolutionary Computation, 2020, in press.
5. Lopion, P.; Markewitz, P.; Robinius, M.; Stolten, D. (2018): A review of current challenges and trends in energy systems modeling. *Renewable and Sustainable Energy Reviews* 96, pp. 156–166.
6. Mitsos, A.; Najman, J.; Kevrekidis, I.G. Optimal deterministic algorithm generation. J. Glob. Optim. 2018, 71, 891–913.
7. Ni Y, Sandal LK. Seasonality matters: A multi-season, multi-state dynamic optimization in fisheries. European Journal of Operational Research. 2019; 275(2): 648–658.
8. Robinius, M.; Otto, A.; Syranidis, K.; Ryberg, D.; Heuser, P.; Stolten, D. (2017): Linking the Power and Transport Sectors—Part 2. Modelling a Sector Coupling Scenario for Germany. Energies 10 (7).
9. Simmons, C., Arment, J., Powell, K.M., Hedengren, J.D., Proactive Energy Optimization in Residential Buildings with Weather and Market Forecasts, Processes, MDPI, 7 (12), 929, doi: 10.3390/pr7120929, 2019.
10. Yaqoob, M., Loo, K.H., Chan, Y.P. and Jatskevich, J., 2019. Optimal Modulation for a Fifth-Order Dual-Active-Bridge Resonant Immittance DC–DC Converter. IEEE Transactions on Power Electronics, 35(1), pp.70-82.
11. Al-Jilawi, A. S., & Abd Alsharify, F. H. (2022). Review of Mathematical Modelling Techniques with Applications in Biosciences. Iraqi Journal For Computer Science and Mathematics, 3(1), 135-144.
12. Alridha, A., Wahbi, F. A., & Kadhim, M. K. (2021). Training analysis of optimization models in machine learning. International Journal of Nonlinear Analysis and Applications, 12(2), 1453-1461.
13. Kadhim, M. K., Wahbi, F. A., & Hasan Alridha, A. (2022). Mathematical optimization modeling for estimating the incidence of clinical diseases. International Journal of Nonlinear Analysis and Applications, 13(1), 185-195.
14. Alridha, A., Salman, A. M., & Al-Jilawi, A. S. (2021, March). The Applications of NP-hardness optimizations problem. In Journal of Physics: Conference Series (Vol. 1818, No. 1, p. 012179). IOP Publishing.
15. Salman, A. M., Alridha, A., & Hussain, A. H. (2021, March). Some Topics on Convex Optimization. In Journal of Physics: Conference Series (Vol. 1818, No. 1, p. 012171). IOP Publishing.
16. Alridha, A., & Al-Jilawi, A. S. (2021, March). Mathematical Programming Computational for Solving NP-Hardness Problem. In Journal of Physics: Conference Series (Vol. 1818, No. 1, p. 012137). IOP Publishing.
17. Shubham Sharma & Ahmed J. Obaid (2020) Mathematical modelling, analysis and design of fuzzy logic controller for the control of ventilation systems using MATLAB fuzzy logic toolbox, Journal of Interdisciplinary Mathematics, 23:4, 843-849, DOI: 10.1080/09720502.2020.1727611