RESEARCH ARTICLE OPEN ACCESS

RENEWABLE ENERGY INTEGRATION USING FDO

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Abstract:

This project, which focuses on integrating renewable energy, possesses the ability to enhance system performance and promote smoother interactions together with the electrical grid. This report suggests that adding renewable energy to the grid entails creating microgrids in distant locations using solar, wind, and storage systems or for islanded operations during grid disruptions. This includes developing new standards and codes for connecting distributed energy systems and designing a future that improves energy resilience without requiring significant infrastructure upgrades. The project conceives of a comprehensive energy system for parks that utilizes wind, solar, and geothermal energy, complemented by electricity, heat, and cold energy storage are the three categories.

Keywords **—**: Feedback Directed Optimization, System profiling.

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I. INTRODUCTION

Environmental contamination and the energy crises are critical challenges faced globally. Building energy use constitutes over a accounts for one-third of society's overall energy use. projected to reach 50% by 2060 due to ongoing development and economic growth. Thus, it is crucial to develop robust strategies for energy conservation and emission reduction. While an efficient building energy system is essential for reducing overall energy consumption, the current fragmentation between planning, construction, and operation in building energy systems results in suboptimal energy conversion efficiency. The park-level integrated energy system (PLIES) addresses this by utilizing the complementary aspects of various energy sources to overcome barriers in energy networks and provide a coordinated and efficient supply of cooling, heating, and electricity. This approach is a key topic in contemporary energy system research. As the concept of carbon neutrality evolves and renewable energy sources expand, the integration of PLIES with renewable energy and multi-energy systems is particularly significant for energy conservation and emission reduction. Effective planning and design are crucial to integrated energy systems, impacting the economy, environment, and system reliability. The planning and design phase must account for the variable, flexible, and evolving nature of renewable energy sources and system operation strategies. Traditional deterministic optimization methods are inadequate for capacity planning in this dynamic context.

II.LITERATURE SURVEY

In order to integrate modern solar energy utilization technology with hybrid energy storage—that is, heat, ice, and electricity storage—an innovative DES is presented. Moreover, a fresh operating plan is proposed.[1]. An approach to system optimization that leverages cooperative games to save energy costs and carbon emissions while promoting diverse participation in the system's overall coordinated and efficient functioning[2]. When it comes to demand response that impacts end-user comfort, economic methods to flexible modeling fail to acknowledge the significant impact of consumer biases and preferences.[3]. The price-based demand response is taken into account while optimizing the PLIES's configuration designs and operating strategy using a multi-objective optimization model.[4]. A regional integrated energy system planner whose goal is to reduce energy and environmental costs is represented by the first stage of the proposed model's optimization, while an operation issue whose main goal is to attain the system's optimal operation scheme is represented by the second stage.[5]. In order to find the best hybrid system configuration with the lowest energy cost and the lowest annualized system cost, this paper created an artificial bee colony (ABC) method.[6].

III.PROPOSED SYSTEM

The optimization procedure must adhere to the energy storage equipment restrictions listed in Section III as well as the primary equipment capacity limits set during the first optimization stage in order to provide the best possible results.

Electrical balance constraint

$$\begin{aligned} &N_{PV} \times P_{PV}(t) + N_{WT} \times P_{WT}(t) \\ &\quad + P_{battery,in}(t)\,\eta_c \Delta t + E_{grid-buy}(t) \\ &= (1+\beta) \times W_{HP}(t) + E_{user}(t) \\ &\quad + E_{grid-waster}(t) + P_{battery,out}(t)\, {}^{\Delta t}/_{\eta_d} \end{aligned}$$

Thermal balance constraints

$$N_{HP} \times Q_{HP-SH}(t) \times PLR + P_{tank,out}(t) = Q_{h-user}(t) + P_{tank,in}(t)$$

Cold balance constraint

$$N_{HP} \times Q_{HP-SC}(t) \times PLR + P_{tank,out}(t) = Q_{c-user}(t) + P_{tank,in}(t)$$

A widely used method for enhancing performance is Feedback Directed Optimization (FDO), which leverages runtime behavior data to guide the optimization process. This technique typically yields performance improvements in the range of 10-15%, and occasionally exceeding 30%. Since that even small-scale installations might include thousands of CPUs, the benefits of using FDO to datacenter applications are very noteworthy. The lengthy and complicated release procedure for FDO prevented it from being embraced by more than a dozen of Google's biggest CPU users, despite its benefits.

The three steps of traditional FDO are as follows:

1. Put together using equipment
2. Execute a benchmark in order to produce a representative profile.
3. Use the profile to recompile.

Line Offset Distance Origin: Binary
#0 # 1 foo() #2 #1 if (cond) { foo() 0x670:
if_stmt.binary; #2 #3 foo_stmt; 0x675:
foo_stmt.binary; #4 #3 >
#5, #6, and #0 bar()
bar(): 7 #1 bar_stmt; 0x690: bar_stmt.binary; 8 #2
foo(); 0x69d: if_stmt.binary; 9 #3 }
foo_stmt.binary, 0x6a2;

A basic program and its binary-level description D1 D2 D3 is the discriminator. Source: A = (foo()? bar() : baz());

Each tree in the forest that makes up the source-level profile is a ProfileNode node. For a single independent function inside the profiled binary, each tree represents the sampled profile data. In these trees, the inner nodes reflect instances of function inlining, while the leaf nodes represent

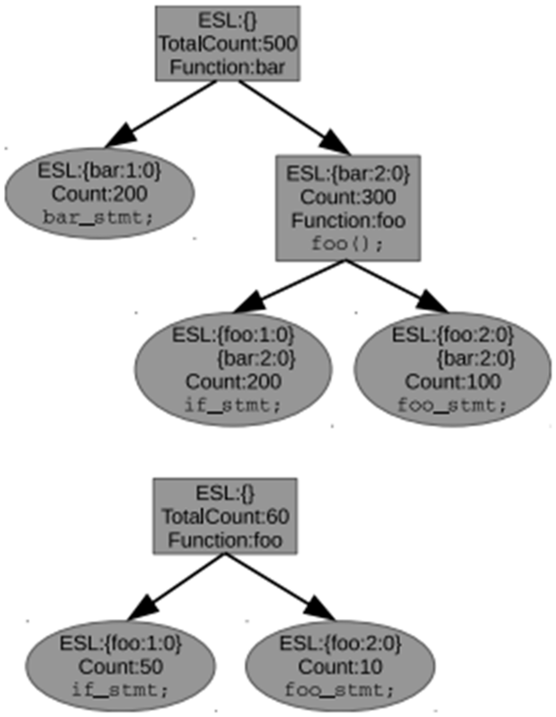

Fig 1: Flowchart of binary level profile source.

In comparing AutoFDO with traditional instrumentation-based FDO, it's important to note that instrumented profiles cannot be collected from production environments. Therefore, FDO as well as autoFDO on profiles gathered from benchmark tests. As shown in Table 1, AutoFDO often achieves over 90% of the speedup provided by FDO for most benchmarks. The main reason for the remaining gap is the use of imprecise debug information in order to embody the AutoFDO profile. AutoFDO is generally less effective in scenarios with complex and tightly nested loops due to:

• Highly accurate profile data (e.g., exact loop trip counts) are often required for feedback-directed loop optimization.

• Aggressive loop optimization typically compromises debug data.

Application	FDO	AutoFDO	Ratio
server	17.61%	15.89%	90.23%
graph1	14.68%	14.04%	95.65%
graph2	7.16%	6.27%	87.50%
machine learning1	8.92%	8.46%	94.85%
machine learning2	7.09%	6.60%	93.06%
encoder	8.63%	3.31%	38.37%
protobuf	16.96%	14.40%	84.94%
artificial intelligence1	10.12%	10.12%	100.00%
artificial intelligence2	13.24%	11.33%	85.61%
data mining	20.48%	15.54%	75.86%
mean	12.40%	10.52%	84.84%

Table 1: Performance comparison between AutoFDO with FDO on Google internal apps

Application	FDO	AutoFDO	Ratio
400.perlbench	15.27%	14.99%	98.17%
401.bzip	1.35%	1.00%	74.07%
403.gcc	7.73%	7.52%	97.28%
429.mcf	0.04%	2.75%	100.00%
445.gobmk	3.67%	3.23%	88.01%
456.hmmer	-0.73%	1.90%	100.00%
458.sjeng	6.19%	6.03%	97.42%
462.libquantum	-10.41%	-0.61%	100.00%
464.h264ref	1.61%	-1.75%	0.00%
471.omnetpp	4.03%	1.31%	32.51%
473.astar	8.86%	10.12%	114.20%
483.xalancbmk	14.44%	11.98%	82.96%
mean	4.40%	4.87%	112.33%

Table 2: Comparison between AutoFDO vs FDO performance using integer benchmarks from SPECCPU 2006

III. RESULTS AND DISSCUSSION

Later iterations' FDO performance even outperforms instrumentation-based FDO

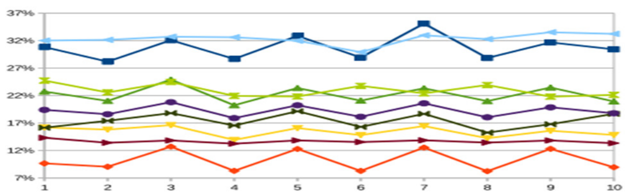

Fig 2: FDO speedup for many applications when compared to nonFDO binary

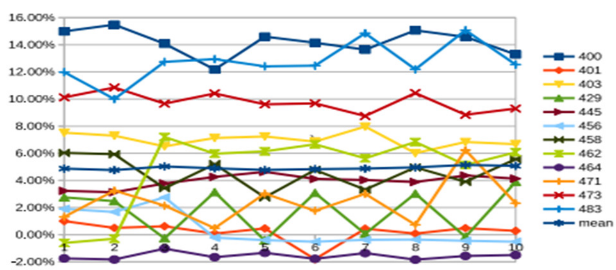

Fig 3: FDO speedup comparing with non-FDO

binary for SPECCPU 2006 integer benchmarks.

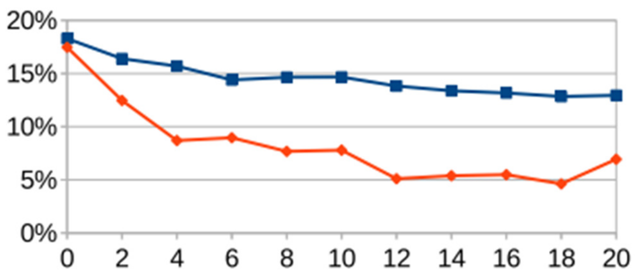

Fig 4: When compared to non-FDO binary over staleness, AutoFDO speedup

IV. CONCLUSION

AutoFDO has simplified the deployment of FDO in our datacenters by integrating production automation and scalability; only a few compiler settings are now needed. The number of cycles covered by FDO has doubled and client adoption has increased eightfold as a result of these changes.

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REFERENCES

[1]Z.Liu,G.Fan,D.Sun,D.Wu,J.Guo,S.Zhang,X.Yang ,X.Lin,andL.Ai, ''A noveldistributed energy system combining hybrid energy storage and a multi-objective optimization method for nearly zero-energy communities and buildings,'' Energy, vol. 239, Jan. 2022, Art. no. 122577.

[2]Y. Wang, ''A study on the optimization method for integrated energy systemoperation with multi-objective game theory,'' Energy, vol. 245, 2022.

[3]N. Good, ''Using behavioural economic theory in modelling of demand response,'' Appl. Energy, vol. 239, pp. 107–116, Apr. 2019.

[4]M. Wang, J. H. Zheng, Z. Li, and Q. H. Wu, ''Multi-attribute decisionanalysis for optimal design of park-level integrated energy systems based on load characteristics,'' Energy, vol. 254, Sep. 2022, Art. no. 124379.

[5]Y.Wang, ''A planning and operation method for regional integrated energy systems that considers both economic and environmental factors,'' Energy, vol.171, pp. 731–750, Mar. 2019.

[6]S. Singh and S. C. Kaushik, ''Optimal sizing of grid integrated hybrid PV biomass energy system using artificial bee colony algorithm,'' IET Renew. Power Gener., vol. 10, no. 5, pp. 642–650, May 2016.

[7]A. L. Bukar, C. W. Tan, and K. Y. Lau, ''Optimal sizing of an autonomous photovoltaic/wind/battery/diesel generator microgrid using grasshopper optimization algorithm,'' Sol. Energy, vol. 188, pp. 685–696, Aug. 2019.

[8]S. Sharma, S. Bhattacharjee, and A. Bhattacharya, ''Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost ofmicrogrid,'' IET Gener., Transmiss ., Distrib., vol. 10, no. 3, pp. 625–637, Feb. 2016.

[9]T. E. Gümüş, S. Emiroglu, and M. A. Yalcin, ''Optimal DG allocation and sizing in distribution systems with Thevenin based impedance stability index,''Int. J. Electr. Power Energy Syst., vol. 144, Jan. 2023, Art. no. 108555.

[10] M.Shivaie, M. Mokhayeri, M. Kiani-Moghaddam, and A. Ashouri-Zadeh,''A reliability-constrained cost-effective model for optimal sizing of an autonomous hybrid solar/wind/diesel/battery energy system by a modi f ied discrete bat search algorithm,'' Sol. Energy, vol. 189, pp. 344–356, Sep. 2019.

[11] A. Kaabeche, S. Diaf, and R. Ibtiouen, ''Firefly-inspired algorithm for optimal sizing of renewable hybrid system considering reliability criteria,'' Sol.Energy, vol. 155, pp. 727–738, Oct. 2017. 66412

[12] A. S. O. Ogunjuyigbe, T. R. Ayodele, and O. A. Akinola, ''Optimal allocation and sizing of PV/wind/split-diesel/battery hybrid energy sys tem forminimizing life cycle cost, carbon emission and dump energy of remote residential building,'' Appl. Energy, vol. 171, pp. 153–171, Jun. 2016.

[13] A. Abdelkader, A. Rabeh, D. Mohamed Ali, and J. Mohamed, ''Multiobjective genetic algorithm based sizing optimization of a stand-alone wind/PV power supply system with enhanced battery/supercapacitor hybrid energy Nov. 2018. storage,'' Energy, vol. 163, pp. 351–363,

[14] A. Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, ''Multi-objectivedesign under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming,'' Int. J. Electr. Power Energy Syst., vol.74, pp. 187–194, Jan. 2016.

[15]N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, and A. Maghami, ''Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO forreducing cost and increasing reliability,'' Energy, vol. 154, pp. 581–591, Jul. 2018.

[16] Y. Zhang, H. Sun,J. Tan, Z. Li, W. Hou, and Y. Guo, ''Capacityconfiguration optimization of multi energy system integrating wind turbine/photovoltaic/hydrogen/battery,'' Energy, vol. 252, Aug. 2022, Art. no.124046.

[17] J. D. Fonseca, J.-M. Commenge, M. Camargo, L. Falk, and I. D. Gil, ''Sustainability analysis for the design of distributed energy systems: A multi-objective optimization approach,''Appl. Energy, vol.290, May2021, Art. no. 116746.

[18] S. Chalil Madathil, E. Yamangil, H. Nagarajan, A. Barnes, R. Bent, S.Backhaus, S. J. Mason, S. Mashayekh, and M. Stadler, ''Resilient off gridmicrogrids: Capacity planning and N-1 security,'' IEEE Trans. Smart Grid, vol.9, no. 6, pp. 6511–6521, Nov. 2018.

[19] X. Li, L. Zhang, R. Wang, B. Sun, and W. Xie, ''Two-stage robust optimization model for capacity configuration of biogas-solar-wind integrated energy system,'' IEEE Trans. Ind. Appl., vol. 59, no. 1, pp. 662–675, Jan. 2023.

[20]M. Rahmani, S. H. Hosseinian, and M. Abedi, ''Stochastic two stage reliability-based security constrained unit commitment in smart grid environment,'' Sustain. Energy, Grids Netw., vol. 22, Jun. 2020, Art. no.100348.

