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PERSPECTIVE

Three Decades of Low Power: From Watts to Wisdom

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ABSTRACT Low power technologies have been critical to the advancement of many fields of research including computer architecture, analog, digital, and mixed signal circuit design, semiconductor technologies, wireless technologies, networks-on-chip, distributed computing, Internet-of-Things, and machine learning on mobile devices. Many of the research advancements in each of these low power fields seem independent of the other fields, but are actually inter-related through the flow of ideas between fields of research. Many ideas used in research seem novel within one field, but in actuality they are often borrowed from other fields showing the interdisciplinary nature of research with ideas transferring from applied physics and chemistry to areas in semiconductor technologies and computer engineering. In this paper, we first examine a few significant research ideas in the area of low power technologies and then explore the interdisciplinary nature, growth, and impact of low power technologies through a network science based analysis of research publications over the past 30 years.

INDEX TERMS Graph convolutional networks, graph machine learning, Internet of Things, low power technologies, network science, semiconductor technologies, wireless technologies.

I. INTRODUCTION

Throughout the years, the importance of low power technologies has continued to grow, driven by the proliferation of mobile devices, IoT devices, and the need for energy-efficient computing systems. As technology advanced, so did the sophistication of low power design techniques, leading to the energy-efficient devices used today. Over the past three decades low power technology has shifted from a focus on embedded systems to cyber-physical systems to intelligent systems (IOT devices and Efficient Machine Learning), which are continuing to grow in the 2020s.

These advancements in low power technologies are often viewed as singular breakthroughs in the media with a lone genius ushering in a new era of technology through an unexpected discovery, but this narrative is misconstrued as the data shows the growth of fields does not come from singular researchers or papers, but instead through many research efforts working to push the needle of innovation forward [1]. Several challenges and gaps persist in our understanding of low-power technologies as well. For applications in domains like IoT and wearable devices, achieving optimal performance while minimizing trade-offs on power efficiency remains a significant challenge [2]. The task of implementing robust security measures in resource-constrained settings also merits attention from the broader research community [3]. Given that software plays a crucial role in the utility of low-power applications, optimizing software to work efficiently with low-power hardware is an imminent concern [4]. Analyzing the historical growth of this field in the context of interdisciplinary interactions can motivate directions for future growth.

Past studies have examined the growth of fields such as physics [1] and computer architecture [5] by examining key

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trends in bibliometric data to discover which areas have contributed most to shaping the fields as they are today. However, there has been no significant study on the growth of low power technologies and their impacts on various adjacent fields over the past three decades. Moreover, past studies, like [5] do not examine the network-based nature of research and how innovations proliferate across and within research communities. While there have been past works creating citation networks of research papers, such as Cora [6] and CiteSeer [7], these works propose such citation networks as benchmark datasets for graph convolutional networks (GCN), not to analyze a field of research. In this analysis of low power research, we hope to shed light on how various topics have developed over the past 30 years using a network-based analysis. We create a citation network of low power research papers and use a GCN to determine the research topics of unlabeled research papers and the connections within a network of papers. While prior efforts to characterize the historic development of a field of research often rely on qualitative analyses like literature analysis and survey papers, our network-based methodology offers a novel quantitative framework for the analysis of the growth of a field and its interactions with adjacent fields over time.

Some of the early works on low power design can be traced back to the early days of integrated circuits and the development of electronic devices [8]. However, the term ''low power design'', as we understand it today, gained significance with the rise of battery-operated devices and portable electronics. Some notable work on low power design includes:

- CMOS Transistor Technology: The development of complementary metal-oxide-semiconductor (CMOS) technology laid the foundation for low power design. CMOS uses very little power when no current is flowing through the transistors, making it inherently energy-efficient compared to other technologies of the time [9].
- Power Management Circuits: The development of power management circuits allowed devices to enter low power modes during idle periods. This included advancements in voltage regulators and power gating techniques [10].
- Energy-Efficient Communication Protocols: As wireless communication technologies advanced, researchers worked on developing low power communication protocols, such as Bluetooth Low Energy (BLE), Zigbee, and other IoT communication standards [11].

However, given the overlapping and evolving nature of low power research, it is hard to define the boundaries of what low power research encompasses and excludes. For example, is a paper focused on efficient semiconductor technologies low power? Is a paper working on superconducting electronics (SCE) to develop efficient replacements for complementary metal oxide semiconductor (CMOS) technologies a low power paper? Is a paper developing a machine learning model for edge devices low power? We classify such interdisciplinary areas as low power research and extend beyond pure low power computer architecture papers.

For our analysis we start from a pool of over 68,000 low power papers published between 1990 to 2020 indexed in Web of Science (WoS). We classify these low power papers into the topic areas of: Analog and Mixed-Signal Circuits (AMSC), Semiconductor Technologies (SEMI), Computer Architecture and In-Memory Computing (CAIM), Distributed Computing and Real Time Computing (DCRT), Wireless and Internet-of-Things Technologies (WIOT), Networks-on-Chip (NOCS), Machine Learning and Artificial Intelligence (MLAI), Security (SECU), and Systems, Software, and Controls (SSCO). We also create a citation network of 5,161 low power papers using WoS, including low power papers from conferences and journals targeting low power technologies, as well as those not targeting low power technologies. Overall we used papers from 47 conferences and journals to construct our network. In the network, papers represent nodes and the citations of those papers represent edges. Once removing the disconnected nodes, we get a network of 3,294 nodes and 5,547 edges.

In this analysis of low power research we hope to shed light on how each topic area has developed over the past 30 years and predict how these areas, as well as low power research as a whole, will continue to develop in the near future. We summarize our contributions as follows:

1) We perform a coarse grained analysis of 68,000 low power papers and examine areas of growth and impact.
2) We construct a citation network using 5,161 low power papers for a more fine grained network based analysis.
3) We use a graph convolutional network (GCN) to perform node classification and link prediction on our proposed network in order to predict some possible future trends in low power technologies.

The remainder of this paper is organized as follows: in Section II we provide a historical perspective on some areas of growth in low power, in Section III we discuss the overall growth of low power research, in Section IV we discuss different low power research communities as well as their interactions, in Section V we perform a network based analysis on our low power citation network, in Section VI we discuss how we use graph machine learning for node classification and link prediction, as well as provide our experimental results, finally in Section VII we discuss the future of low power technologies.

II. HISTORICAL PERSPECTIVE

Low power research has seen tremendous growth over the last three decades. Low-power technologies have revolutionized the landscape of computer engineering and semiconductor technologies. The advent of low-power technologies has promoted a shift from a focus on raw performance to one that emphasizes energy and resource efficiency. This has pushed semiconductor manufacturers to develop smaller, more efficient chips, driving the industry towards smaller process nodes, higher transistor density, and overall improved performance per watt [2]. Innovations in this field have also supported the proliferation of portable devices like smartphones, tablets, and wearables, all of which are practical for everyday use because of the longer battery life enabled by resource-efficient technology [12]. Growth in the field of low-power design has and continues to support an ever-expanding range of computing applications, facilitating the integration of technology into various sectors, from healthcare and agriculture to smart infrastructure and beyond [13].

In the areas of AMSC and SEMI, growth has long been driven by technological advancements and transistor size scaling through Dennard's Scaling and Moore's Law [14], [15]. Growth within these fields has also been driven by the need to decrease power consumption and thermal effects of very large scale integration (VLSI) circuits [16]. More recently, with the end of Moore's Law, there has been growth in beyond-CMOS technologies that offer low power and high speed such as, single flux quantum technologies, adiabatic quantum flux parametron technologies [17], [18], and spintronics [15]. There has also been growth in the research for automating the design verification process in such SCE technologies [18], [19] and automating circuit sizing optimization in AMSC [20]. Another growing research area is the exploration of neuromorphic computing, which is defined as an approach to computing where the structure and function of the computer are inspired by emulation of the human brain [21]. Oxide-based resistive random-access memories (RRAMs) and memristive threshold logic (MTL) circuits have both been used for designing low power neuromorphic architectures [22], [23].

In the area of CAIM we have seen optimizations in hardware and software [24] ranging from advancements in parallel processing and cache design to advancements allowing for modern Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) [5], [25]. CAIM has seen notable progress in leakage reduction techniques, which have a significant impact on CPU, GPU, and memory hierarchy design [26]. Approximate computing and energy recovery techniques have also emerged as methods to achieve energy-efficiency and high-performance [27], [28]. Adiabatic switching is another important low power technique that has emerged enabling the signal energies stored on circuit capacitances to be recycled instead of dissipated as heat [29].

The domains of WIOT, DCRT, and NOCS encompass a wide range of innovations, spanning from the implementation of wireless sensors in low power biological settings to solutions dedicated to providing cost-effective connectivity for low power devices distributed over large geographical areas [30], [31]. For instance, Long Range Wide Area Network (LoRaWAN) enables long-range communication between devices with low power consumption, facilitating applications in a variety of fields such as agriculture [32], transportation [33], retail [34], intelligent cities [35], medical devices [36], and consumer devices [13], [37]. Along with the variety of applications of WIOT there are also a variety

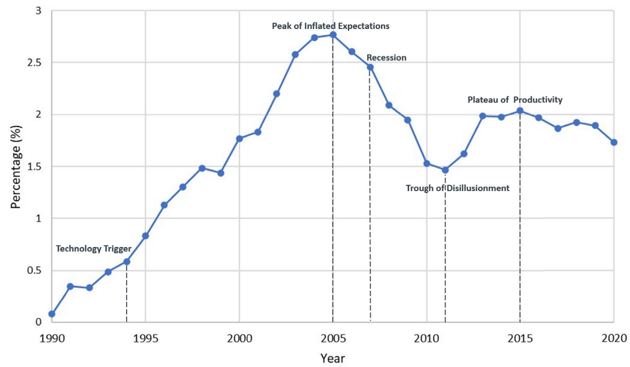

FIGURE 1. Percentage of low power papers indexed in WoS as a part of total engineering papers indexed in WoS from 1990 to 2020.

of requirements such as low data transfer rate, low power consumption, and cost-effectiveness [38]. Wireless communication protocols like Zigbee and Z-Wave are designed for low-data-rate, low-power applications and are often used in home automation systems [39]. Bluetooth Low Energy (BLE) is a wireless personal area network technology designed for short-range communications with significantly reduced power consumption compared to traditional Bluetooth, and it is also often found in home automation systems as well as wearable devices [11]. The areas of DCRT and NOCS have also grown, which can be seen through the growth in manycore systems, network-on-chip architectures, and efficient wireless technologies [40], [41], [42]. For instance, dynamic power management algorithms can help optimize energy consumption in distributed computing systems [43]. Edge devices like micro data centers or edge servers use low-power processors and storage to efficiently handle computations at the edge of the network instead of a centralized data center [44]. Growth in these areas has also greatly benefited from Moore's Law as exponential gains in computational efficiency have allowed for Internet-of-Things, distributed computing, and wireless technologies to grow rapidly [2].

The areas of SSCO and SECU have also seen significant growth that can be attributed to the rise of low power technologies. Within the SSCO domain of embedded systems, the many advancements in operating systems have enabled running real time operating systems on power constrained embedded systems [4], [45], [46]. In recent times, many works within SECU focus on resource-efficiency, enabling progress on energy-efficient security for power-constrained systems and novel data compression algorithms for wireless sensors [47], [48]. Research within SECU also focuses on the tradeoffs between security, low power, and cost in low power technologies and how security can be achieved while meeting other technological requirements [3].

One recent area of growth for low power has been MLAI. MLAI has seen explosive growth in the past decade and MLAI models can now even be deployed on mobile devices [49], [50]. Though initially mobile MLAI models were only convolutional neural network (CNN) based,

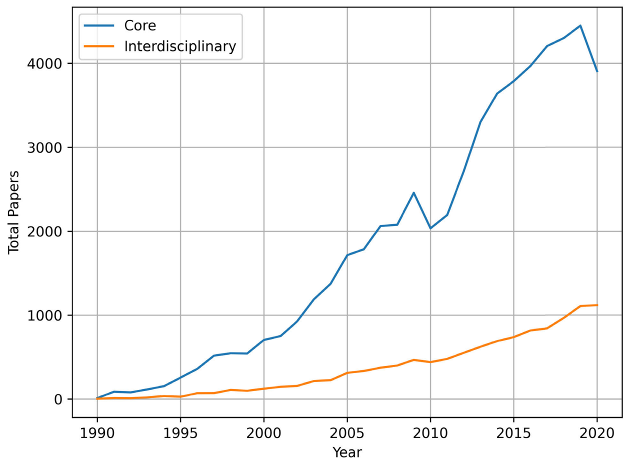

FIGURE 2. Total core and interdisciplinary low power papers per year.

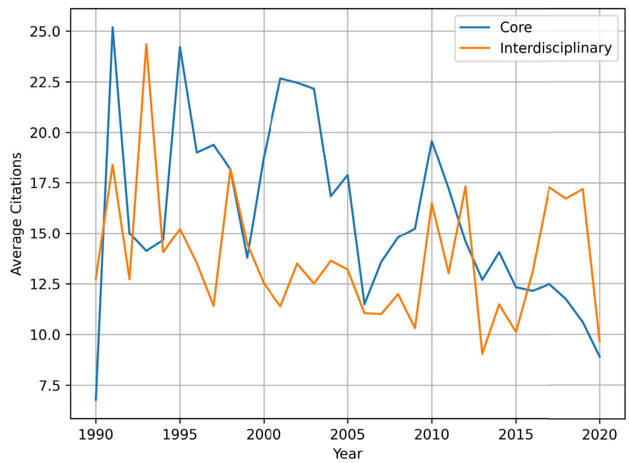

FIGURE 3. Average citations for core and interdisciplinary low power papers for the year they were published.

recent models have used vision transformers (ViTs) [51], [52], [53], [54] and vision graph neural networks [55], [56], while others have continued to focus on CNN based models [57], [58], [59]. Beyond computer vision, mobile models for natural language processing tasks exist as well, such as MobileBERT [60]. The aforementioned algorithmic innovations in MLAI have made massive strides toward enabling low-power, mobile-friendly MLAI applications. This progress is coupled with low power technologies like NVIDIA's Jetson Nano series and Google's Edge TPU chips, which leverage novel hardware designs to empower the deployment of MLAI applications in resource-constrained environments [61]. Likewise, MLAI has also been leveraged to push the boundaries of low power technologies. For instance, replacing heuristic-based policies with reinforcement learning has demonstrated notable improvements in performance for cache eviction, branch prediction, and task scheduling [62], [63], [64].

III. THE GROWTH OF LOW POWER

Throughout the history of engineering, major technological breakthroughs, such as the invention of the transistor or the development of the internet, have spurred growth in many research areas. These types of advances have birthed new fields like computer architecture and spurred growth in others like wireless technologies. Low power research papers in particular have also seen this kind of growth as new technologies develop. We can see this growth in Figure 1 where the growth of the percentage of low power papers as a part of total engineering papers indexed in WoS can be seen from 1990 to about 2005 where we reach a peak of inflated expectations. We then see a trough of disillusionment coinciding with the Great Recession in the United States followed by a recovery and a flat lining of low power papers as a percentage of engineering papers.

We can also see the growth of low power papers in terms of the total papers published from 1990 to 2020 in Figure 2, with a significant growth of low power papers indexed in WoS from 1990 to 2020. We can see the growth of low power papers both in what we classify as core low power papers (AMSC, SEMI, CAIM, DCRT, WIOT, and NOCS) as well as what we classify as interdisciplinary low power papers (MLAI, SECU, and SSCO). We classify MLAI, SECU, and SSCO as interdisciplinary low power research since they are fields that are less central to low power research. Despite this growth in the number of low power papers we can see the average number of citations of papers published in a given year for both core and interdisciplinary papers does not show the same growth (Figure 3). In fact we can see a decrease in the average number of citations in recent years, which can be explained by the shorter amount of time to gather citations for recent papers (post 2018). We also notice numerous spikes of average citations in particular years, which are driven by a few significant papers with very large citation counts. This offers an interesting insight that citations of low power papers are concentrated on specific impactful papers. This leads to the fact that in the years when these impactful papers are published the average citations for those years is greatly increased.

Examination of how the keywords in abstracts have changed over the past three decades provides additional insights into how the field of low power has evolved. Figure 4a-b shows word clouds of the most common words in abstracts from the 68,000 low power papers we examine in our dataset for the time periods of 1990-1992 and 2018-2020. When examining these word clouds we can see some interesting changes emerge over the three decades. In the time period from 1990-1992 papers more commonly had *device*, *circuit*, *logic*, and *optical* in their abstracts as research trends were more focused on hardware design, parallel processors, optical electronics, and introducing more transistors onto each chip. In the time period from 2018-2020 we can see *communication*, *networks*, *wireless*, *IOT*, *energy*, *neural networks*, and *algorithm* appear more often in abstracts in comparison to 1990-1992 showing their rise in importance. This shows that low power papers published now are much more heavily focused on the fields of wireless technology,

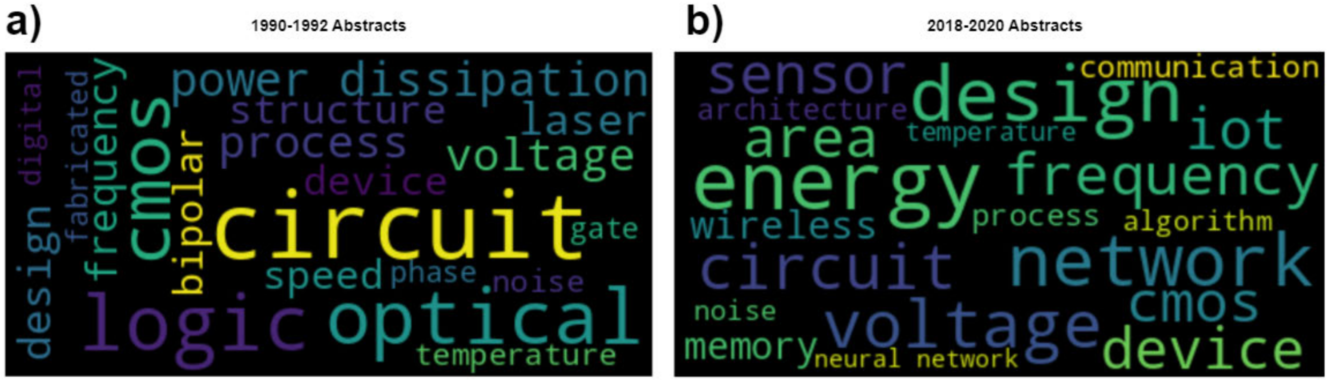

FIGURE 4. Word clouds of most common words in abstracts for our dataset of over 68,000 low power papers. a) Word cloud of most common words in abstracts for low power papers from 1990 to 1992. b) Word cloud of most common words in abstracts for low power papers from 2018 to 2020.

Internet-of-Things, and machine learning as compared to in 1990. Despite this major change, papers published in the areas of circuit design and semiconductor technologies remain important, which can be seen by the presence of *design*, *CMOS*, and *circuit* in the word cloud from 2018-2020 in Figure 4b. From the changes in the word clouds from 1990 to 2020 we can see that the growth of future low power papers is trending towards those in connected technologies (wireless and Internet-of-Things technologies), efficient artificial intelligence and algorithms, and energy-efficient computing.

IV. LOW POWER COMMUNITIES

Within research the most important metric to determine links between papers are their citations and references, which can be represented as directed edges in a graph. We can see how in Figure 5a that the dataset of over 68,000 low power papers published between 1990 to 2020 indexed in WoS has a total of 945,000 citations. Our dataset has 56,200 core low power papers and 11,800 interdisciplinary low power papers. We classified these low power papers into one of nine topic areas of: Analog and Mixed-Signal Circuits (AMSC), Semiconductor Technologies (SEMI), Computer Architecture and In-Memory Computing (CAIM), Distributed Computing and Real Time Computing (DCRT), Wireless and Internet-of-Things Technologies (WIOT), Networks-on-Chip (NOCS), Machine Learning and Artificial Intelligence (MLAI), Security (SECU), and Systems, Software, and Controls (SSCO). We can see the relations of these communities in Figure 5b and 5c, which show the connections between these communities and a broad grouping within the areas of computation, communication/networks, and software & applications.

Through the past three decades there has been consistent growth in the field of low power, but how have each of the individual communities developed? With the growth in these communities did the average impact of papers published grow in terms of average citations per paper or only in terms of the total number of papers published within the communities? To answer these questions, we examine our low power communities through the average citations of papers published in that year for that community to see the average impact of papers published. We further look at the total papers published in a given community in a year to see the growth of the individual communities and their total impact. In Figure 6 we can see that in terms of average citations for papers published in a given year, papers published in the space of MLAI have had increasing citations after 2015. We can also see that papers published in SEMI and WIOT have a higher number of average citations compared to papers published in NOCS, CAIM, SSCO, SECU, AMSC, and DCRT. It is important to note that papers published in recent years are at a disadvantage as they have less time to gather citations. In Figure 7 we can see the total papers published within a given community for a given year. Through this we can see the extremely fast growth of papers published in WIOT and MLAI, the consistent growth of papers within SEMI and the relative flatlining of papers published in the fields of CAIM and AMSC, even though they are still very large communities.

TABLE 1. Comparison of our LPN to Cora, CiteSeer, and ER in terms of nodes, edges, and clustering coefficient (CC).

Dataset	Nodes	Edges	CC
LPN (Ours)	3294	5547	0.06
Cora	2708	5429	0.13
CiteSeer	3312	4732	0.08

V. LOW POWER NETWORK (LPN) ANALYSIS

To create the 5,161 paper low power citation network we used papers from core low power conferences and journals, as well as low power papers from conferences and journals that are not focused on low power technologies. We call our proposed network of 5,161 low power papers the Low Power Network (LPN). We compare our LPN to other benchmark citation networks, Cora [6] and CiteSeer [7], as well as to a random network created using the Erdos Renyi (ER) model [65]. Cora and CiteSeer are benchmark citation networks of computer

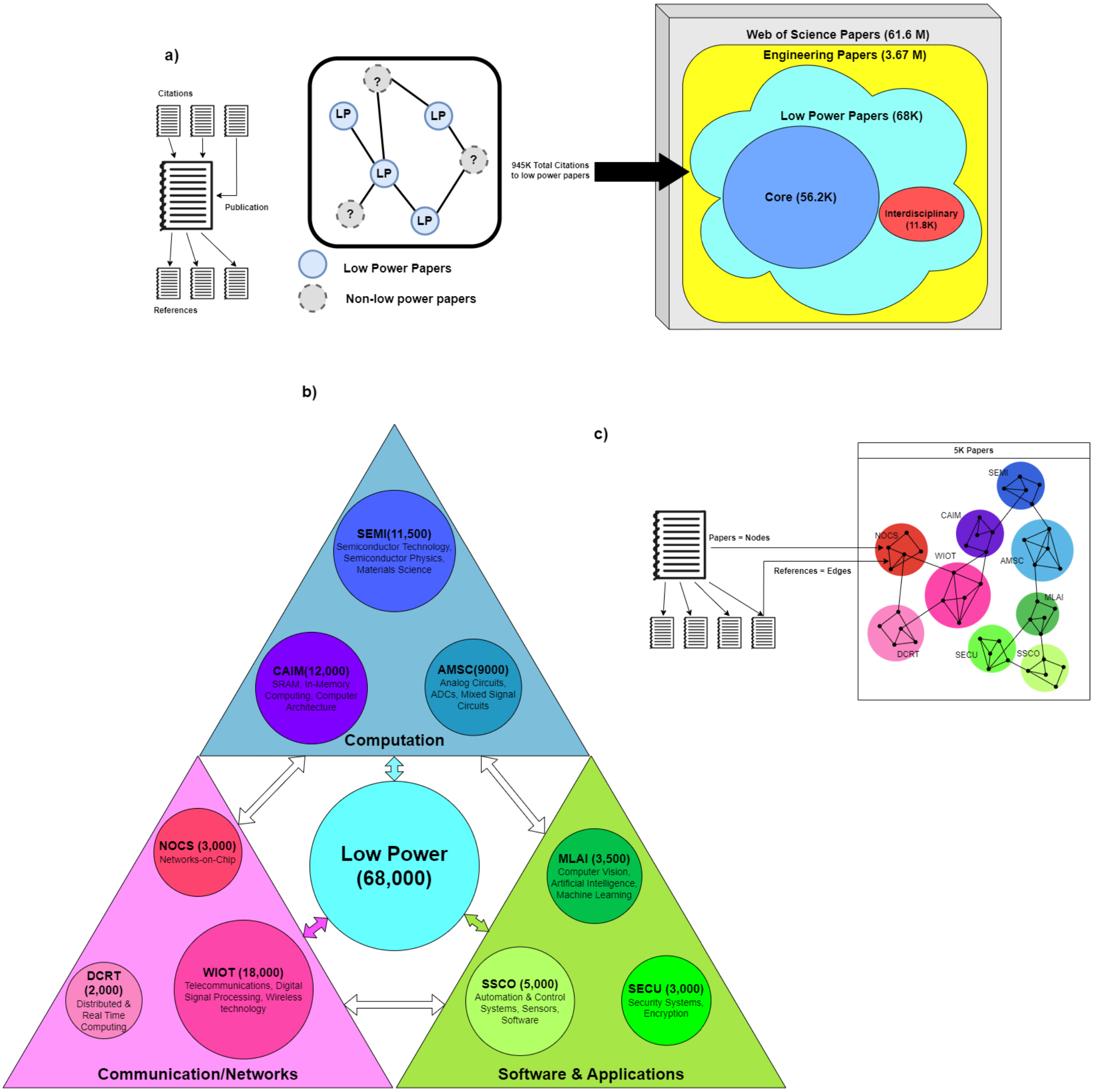

FIGURE 5. a) Shows the relation of the references and citations of a paper to our overall 68,000 low power papers dataset. We can see there are a total of 945,000 citations to our 68,000 low power papers. We can also see that the 68,000 low power papers can be broken into 56,200 core low power papers and 11,800 interdisciplinary low power papers. b) We classify each of the 68,000 low power papers into one of nine topic areas of: Analog and Mixed-Signal Circuits (AMSC), Semiconductor Technologies (SEMI), Computer Architecture and In-Memory Computing (CAIM), Distributed Computing and Real Time Computing (DCRT), Wireless and Internet-of-Things Technologies (WIOT), Networks-on-Chip (NOCS), Machine Learning and Artificial Intelligence (MLAI), Security (SECU), and Systems, Software, and Controls (SSCO). We can see the communities of AMSC, SEMI, CAIM fall within the area of computation, the communities of DCRT, WIOT, NOCS fall within the area of communication/networks, and the communities of MLAI, SECU, and SSCO fall within the area of software & applications. c) We create a network using 5,161 papers using the references as edges and the papers as nodes. We can see our nine communities within the network as well.

science papers frequently used to compare various graph neural network architectures.

In Table 1 we can see a comparison of our LPN to Cora and CiteSeer in terms of nodes, edges and clustering coefficient (CC). Our LPN has 3294 nodes (5161 papers with the disconnected nodes removed), 5547 edges, and a CC of 0.06 giving us the most edges, second most nodes, and the lowest CC showing that low power papers are less centralized

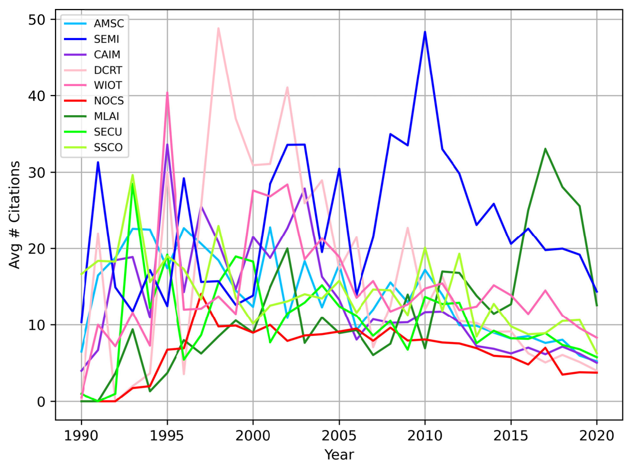

FIGURE 6. The average citations of papers published in a given year for the nine communities in our low power dataset.

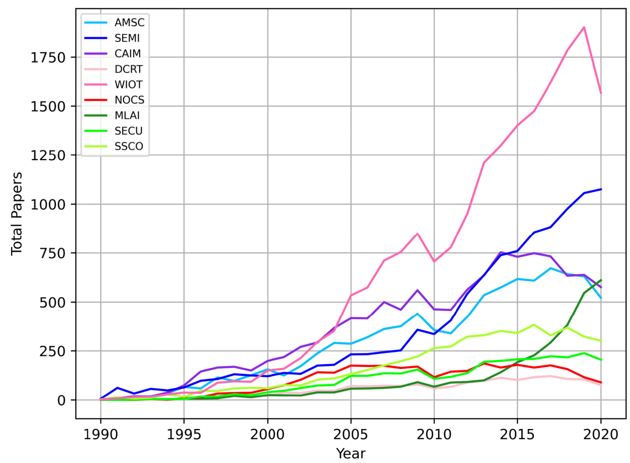

FIGURE 7. The total number of papers published in a given year for the nine communities in our low power dataset.

and possess less papers that are "hubs" for citations (i.e., have high degrees) compared to the papers in the Cora and CiteSeer datasets. We also generated an ER random network [65] for comparison using Gephi [66] to generate a network with 3000 nodes and approximately 5000 edges in order to have a similar average degree to our LPN. The ER network was generated with a probability of edge creation of 0.0011 to get the correct proportion of nodes and edges, which lead to a CC of 0.0 (so small Gephi rounds it down to 0). A comparison of the ER network to our LPN, Cora, and CiteSeer can be seen in Table 2 as the ER network has an average degree of 1.65, similar to our LPN's 1.69, Cora's 2.01, and CiteSeer's 1.42. Our LPN has a highest degree of 93 (lower than Cora or CiteSeer, but higher than the ER network), an average path length of 2.83 (lower than Cora, higher than CiteSeer, and slightly higher than the ER network), and a diameter of 11 (higher than CiteSeer and the ER network, but lower than Cora). From these network statistics we can determine that our LPN is less centralized compared to Cora or CiteSeer as its network statistics show it

TABLE 2. Comparison of our LPN to Cora, CiteSeer, and ER in terms of highest degree (HD), average path length (APL), average degree (AD), and diameter.

Dataset	HD	APL	AD	Diameter
LPN (Ours)	93	2.83	1.69	11
Cora	169	4.79	2.01	15
CiteSeer	100	1.82	1.42	8
ER	11	2.8	1.65	10

does not have as many large "hubs" for citations as Cora or CiteSeer.

To properly compare our network to Cora, CiteSeer, and a random ER network, we visualize all four networks in the open-source graph visualization and network analysis tool Gephi [66] using the Fruchtermann Reingold layout format [67] in Figure 8. Figure 8a shows Cora when it is partitioned by modularity class showing some of the natural communities that form within its network. Similarly Figure 8b shows CiteSeer partitioned by its modularity class and Figure 8c shows an ER random network partitioned by its modularity class. One noticeable attribute of the ER random network is that the partitioning of the network also appears random as their are no real communities to be formed in a random network. Figure 8d shows our LPN network partitioned by modularity class showing the interactions between the natural communities that form in our network. From these plots in Figure 8 we can visually see the natural formation of communities in a network even without providing the proper class labels to the network. We can also see that a random network does not have any natural communities form, unlike citation networks.

We also visualize our LPN when highlighting specific communities. In Figure 9, we visualize papers published in IEEE Transactions on Applied Superconductivity (IEEE TAS) as orange, papers published in the International Symposium on Low Power Electronics and Design (ISLPED) as red, papers published in the IEEE Journal of Solid-State Circuits (IEEE JSSC) as blue, and low power papers published in AAAI Conference on Artificial Intelligence, Conference on Computer Vision and Pattern Recognition (CVPR), Conference on Neural Information Processing Systems (NeurIPS), Journal of Machine Learning Research (JMLR), and Proceedings of Machine Learning Research (PMLR) as green. From these visualizations we can see low power papers tend to cluster into communities based on their topic. Specific journals like IEEE TAS also appear to be much more likely to cite and to be cited by papers published within the IEEE TAS journal as compared to papers published in ISLPED or IEEE JSSC. Low power papers published within the machine learning conferences are also much more likely to cite and be cited by papers published within those conferences and journals as compared to papers published in other venues. This makes sense as low power

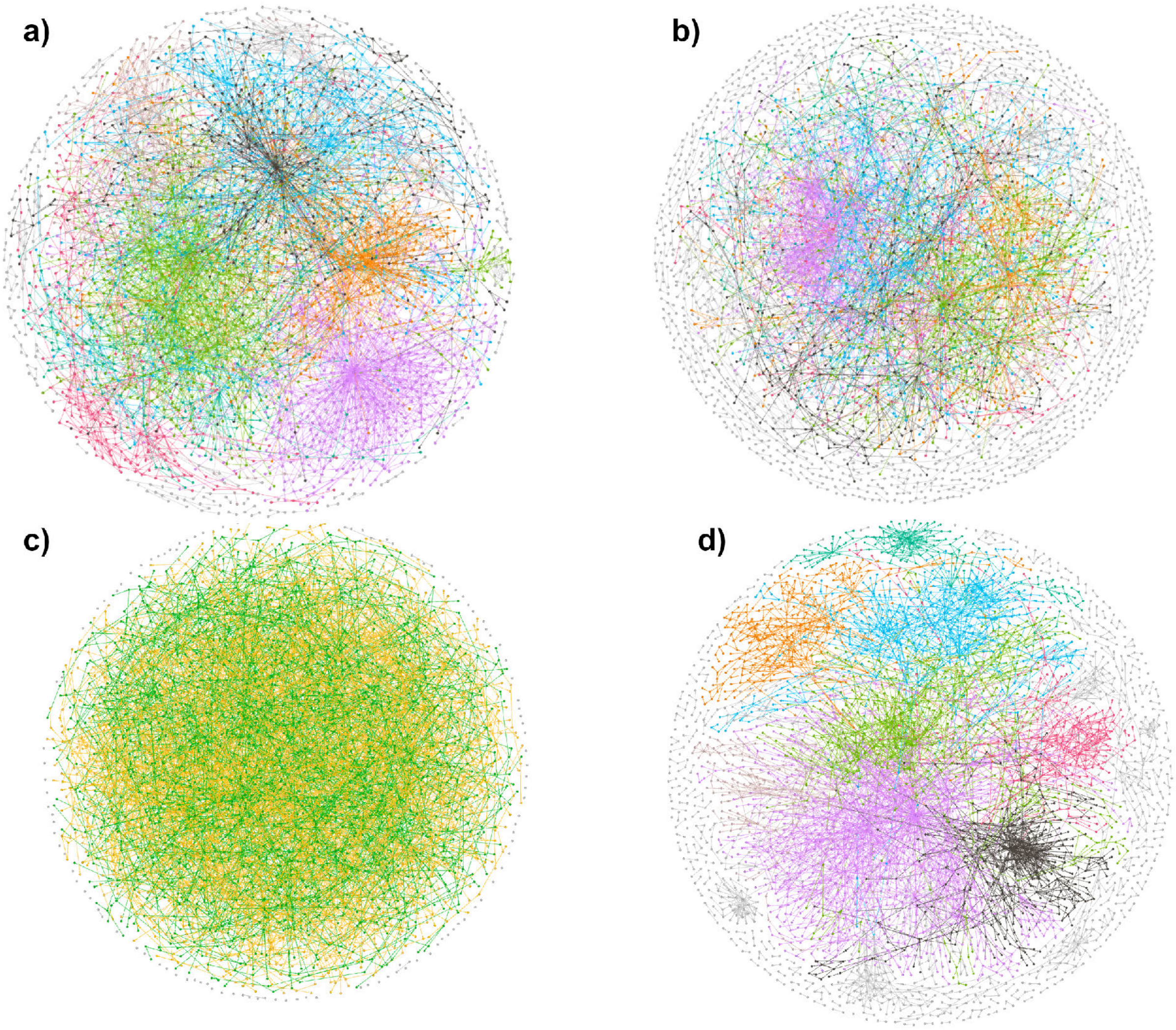

FIGURE 8. a) Shows Cora when it is partitioned by modularity class and visualized using the Fruchtermann Reingold format. b) Shows CiteSeer when it is partitioned by modularity class and visualized using the Fruchtermann Reingold format. c) Shows an ER network when it is partitioned by modularity class and visualized using the Fruchtermann Reingold format. d) Shows our LPN when it is partitioned by modularity class and visualized using the Fruchtermann Reingold format.

machine learning papers are uncommon in pure machine learning conferences and journals and it is also uncommon for papers published in low power conferences to cite or be cited by papers in pure machine learning conferences and journals leading to a more closed community compared to the community that publishes low power papers in ISLPED for example. This shows that diverse low power papers in a variety of topics tend to be published in venues such as ISLPED, IEEE Transactions on VLSI, IEEE Transactions on Computers or other similar venues as opposed to specialized venues such as the machine learning conferences and journals or IEEE TAS, which tend to have less diverse low power papers as low power research is not their focus.

We also want to see the complex interactions of all nine communities within our network. In Figure 10 we visualize our network using the graph editor software, yED [68], which allows us to see natural separation and clustering of communities within our network. For example, we can see that papers in MLAI are frequently clustered together with other MLAI papers, but SEMI papers are more often connected to papers outside of the SEMI community when compared to the MLAI community, showing the more diverse nature of low power papers within the SEMI community.

VI. LEARNING TO PREDICT

Within a research network we want to be able to determine, how different areas of research interact, but this is impossible to do without the ability to classify interdisciplinary papers into research categories. Node classification using a GCN helps alleviate this issue as it allows for labeling new research papers (unlabeled nodes) into the corresponding research areas based on their connections in the network and the words present in their abstracts, keywords, or text. Node classification is also directly useful to journal reviewers in the

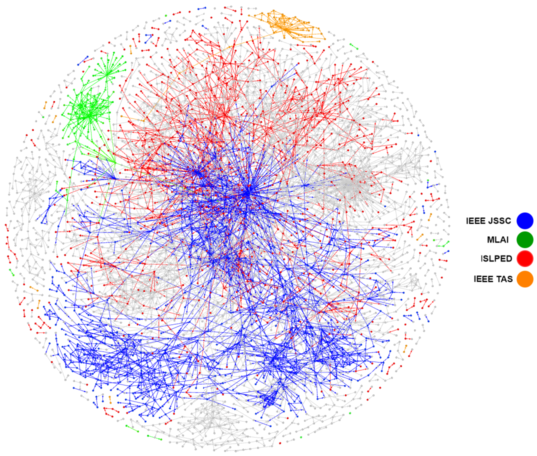

FIGURE 9. Fruchtermann Reingold visualization of papers published in our LPN highlighting papers published in different conferences and journals. IEEE Journal of Solid-State Circuits (IEEE JSSC) are blue, papers from MLAI conferences and journals are green, International Symposium on Low Power Electronics and Design (ISLPED) papers are red, and IEEE Transactions on Applied Superconductivity (IEEE TAS) papers are orange.

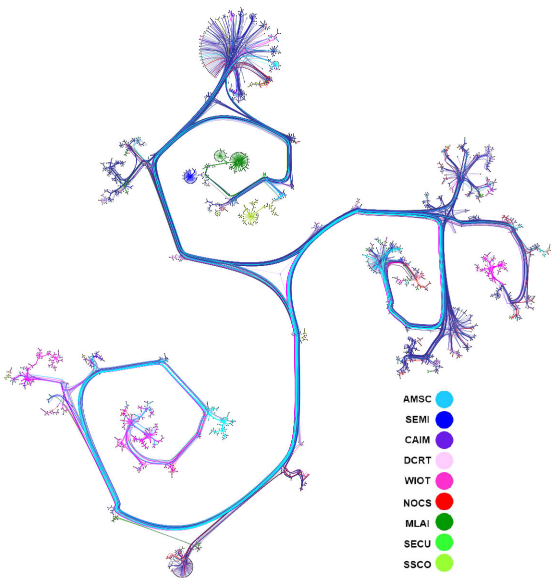

FIGURE 10. Visualization of papers published in our LPN highlighting papers published in the nine different classes in our network. AMSC papers are in light blue, SEMI papers are blue, CAIM papers are purple, DCRT papers are pink, WIOT papers are magenta, NOCS papers are red, MLAI papers are green, SECU papers are light green, SSCO papers are yellow-green.

scientific community, for example if a paper is submitted and it is unclear what research area it belongs to for assigning a reviewer, a GCN can be applied to determine the research area to which the paper belongs. We also want to be able to predict the connections between research papers, even when some of the connections are unknown. Link prediction enables this through predicting the edges (citations) between research papers, which allows us to see how different research papers interact with each other and where connections are likely to occur.

To verify the usefulness of our network in node classification and link prediction, we used a two layer GCN with ReLU activation trained for 30 epochs to perform node classification and trained for 60 epochs to perform link prediction to compare against Cora [6] and CiteSeer [7]. To create the GCN we used Deep Graph Library [69] and the GCN layer from [70]. To perform our experiments for node classification and link prediction we split the data into an 80:20 split between training and testing data. For both node classification and link prediction we used the transductive setting, meaning that training and inference occur on the same graph but the testing data labels are masked during training.

We also perform training on data from 1990-2016, then test on data from 2017 to 2020 in order to show the predictive power of GCNs on future data when only training on past data. This is useful since when a GCN is used in practice it is not being tested and trained on a random train test split, but will only have access to past data for training and then need to classify papers from after its training years.

For node classification we are classifying the class label of unlabeled nodes using a words vector of size 1873 generated from the most common words used in the abstracts of the LPN papers. The unlabeled nodes are thus classified based on their connections in the graph and the words present in their abstract. Link prediction works similarly, but instead of classifying nodes we are predicting the masked links (i.e., edges) of the already labeled nodes. In Figure 11 we can see the node classification of an example node that is classified as the WIOT with a probability of 0.85 when trained on the input citation network where the node embeddings are the bag of words vector.

In Table 3 we can see when using a two layer GCN and training for 30 epochs for node classification and 60 epochs for link prediction that our LPN provides the highest link prediction accuracy and a node classification accuracy in between Cora [6] and CiteSeer [7]. For node classification our GCN achieves an accuracy of 75.4% on our LPN, 80.4% on Cora, and 73.8% on CiteSeer showing that our network is more difficult to predict the topic area as compared to Cora, but easier than CiteSeer. This could be due to Cora's higher average degree, highest degree, and clustering coefficient making it more easy to classify papers clustered together. Interestingly in terms of link prediction, our LPN actually achieves the highest accuracy showing that determining connections from nodes is actually easiest in our LPN. This could be because our LPN has more diverse categories of papers as compared to Cora or CiteSeer. For example, it is easier to determine that an applied superconductivity paper should have a link to another applied superconductivity paper as compared to a paper in machine learning.

We also performed node classification to predict future labels (of 2016-2020) from training on past labels (1990-2015). This yielded lower accuracy achieving 74.1% as opposed to 75.4% on node classification showing that since topic areas importance change over time that training on past data is worse as compared to using a random 80:20 split for

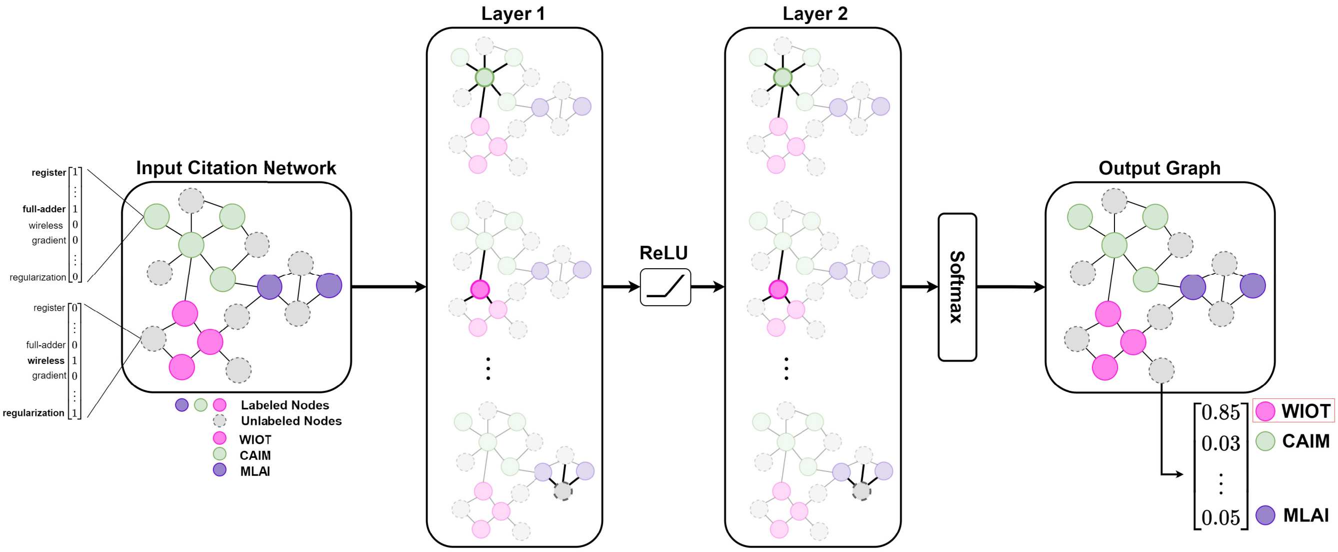

FIGURE 11. Two layer GCN operating on citation network where the node embeddings are a bag of words vector. The output is a classification of the unlabeled node based on the probability of belonging to a given class.

TABLE 3. Node classification and link prediction accuracy on Cora, CiteSeer, and our LPN when using a two layer GCN and training for 30 epochs for node classification and 60 epochs for link prediction.

Method	LPN (Ours)	Cora	CiteSeer
NC (%)	75.4	80.4	73.8
LP (%)	91.13	85.60	81.13

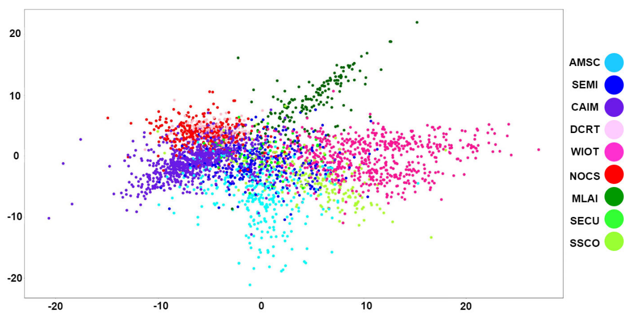

FIGURE 12. Feature vectors generated by the GCN trained on our LPN dataset for node classification projected into 2D space using Principal Component Analysis.

training data. An example of why this would be worse is for the low power machine learning research papers, from 1990-2015 papers that could be classified as low power machine learning were significantly fewer as compared to from 2016-2020 leading to much less training data to learn what types of words indicate a machine learning paper.

To better understand how our GCN is able to distinguish between our nine classes, we plot the feature vectors generated by the two layer GCN trained on our LPN dataset for node classification projected into 2D space using Principal Component Analysis (PCA) in Figure 12. The plotted features are well clustered and easily separable for some classes like MLAI and WIOT, but for other classes (e.g., SEMI) it is harder to distinguish the feature vectors. The better separated and clustered features align with our classes clustered together in Figure 10, showing the communities that have easily separable feature vectors also have more intra-community connections. We can also see that the classes that are not easily separable in Figure 12 also have more inter-community connections in Figure 10, resulting in less distinguishable clusters.

VII. THE FUTURE OF LOW POWER

Our network based analysis of low power evolution over the last 30 years highlights the dynamic and evolving nature of the low power field. Over time, many topic areas have waned in significance, while others have sprung up and lead to new sparks of creativity within the field. Low power has grown from being a field purely within computer architecture and semiconductor technologies to a field that impacts a diverse array of topics from wireless technologies, to machine learning and artificial intelligence, to distributed computing, and superconducting electronics. As computational demands continue to increase and the importance of sustainable computing continues to grow, the field of low power will continue to grow and impact our everyday lives.

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