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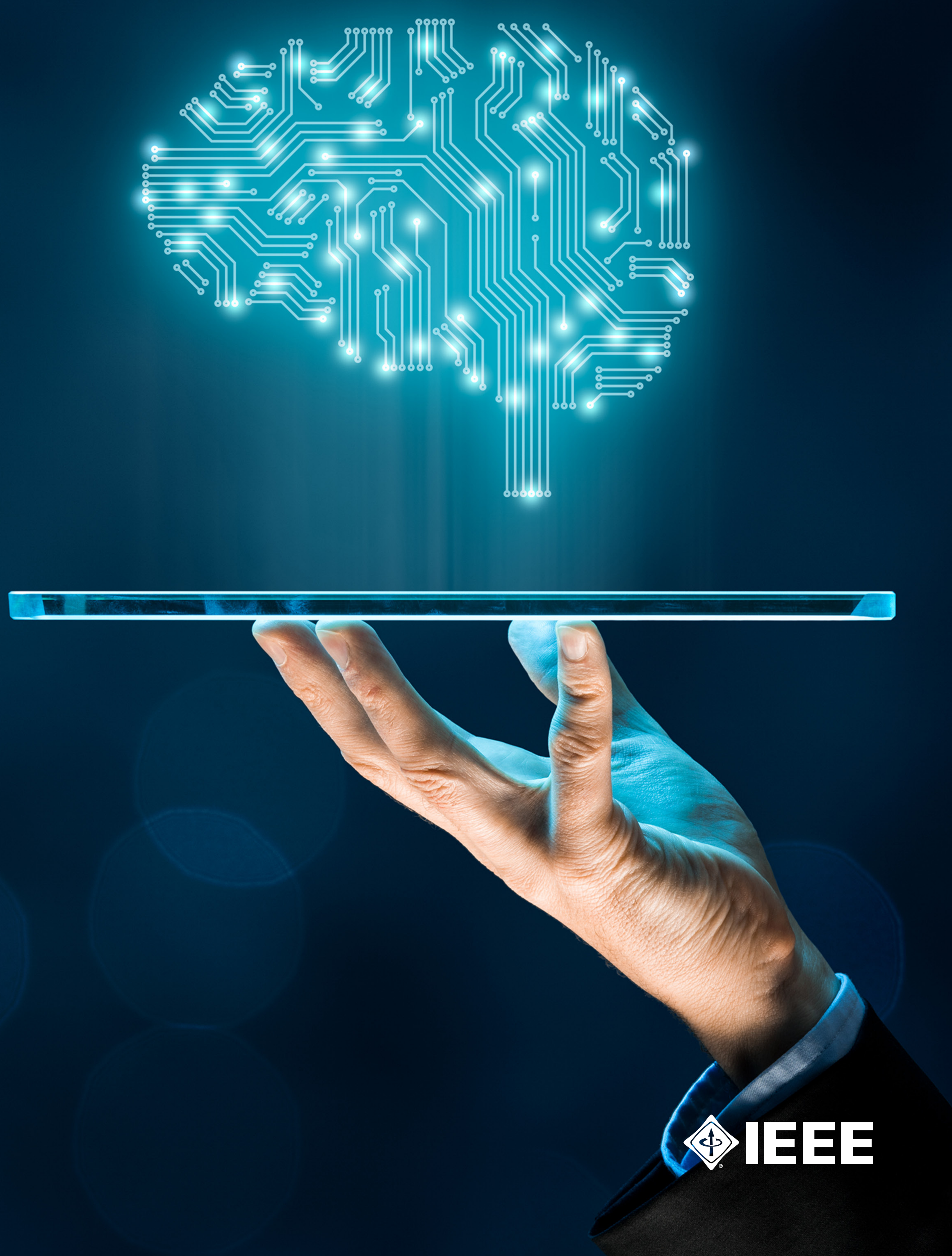
THE BRIDGE

The Magazine of IEEE-Eta Kappa Nu



Neural Networks

Outsmart Moore's Law with Machine Learning

Determining Optimum Drop-out Rate for Neural Networks.

Distributed Stochastic Optimal Flocking Control for Uncertain Networked Multi-Agent Systems

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THE BRIDGE

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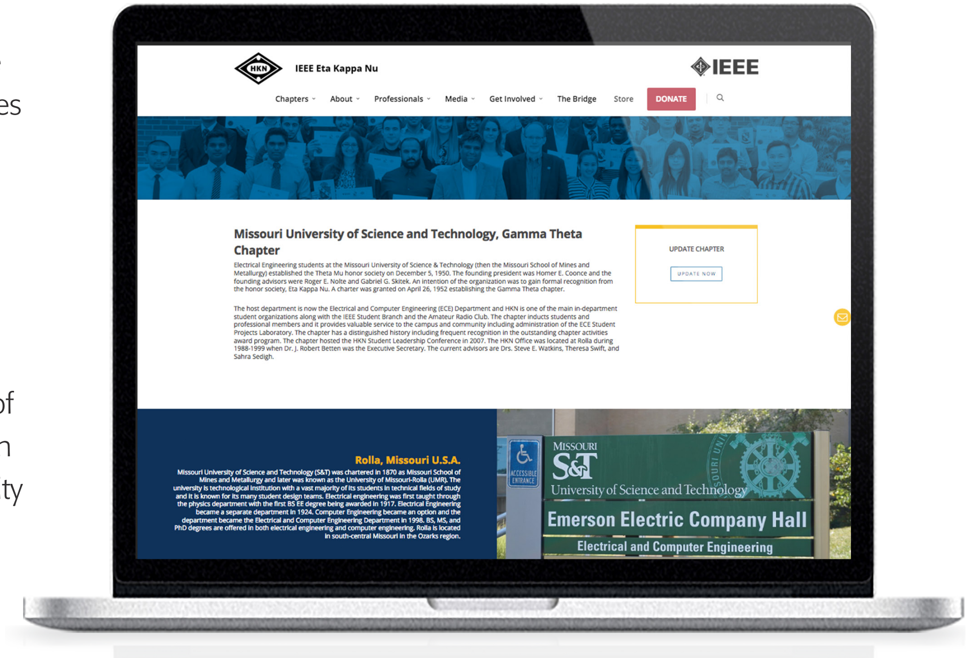
Dear Eta Kappa Nu (HKN) Members and Friends

The first few months of the 2018 year have been busy. Our Student Leadership Conference gave many opportunities for learning and networking. (Thank you University of Florida for being an excellent host.) Two top undergraduates were recognized with our Zerby/Koerner Award and twenty-four chapters received chapter activities recognition. Six new chapters have joined our HKN community and several others have charter ceremonies pending or have started the application process. Eta Kappa Nu is on the move!

When we talk about HKN membership, we like to mention the facets of our honor society that are expressed so well in the induction ritual. First, individuals are invited to join based on our ideals of scholarship, character, and attitude. Membership recognizes accomplishments as a student or as a professional, reputation within ones professional circle, and willingness to be part of a service-oriented community. Second, HKN provides opportunities for continuing personal improvement. The ritual notes "you have a new way in which to improve yourself. … [through HKN involvement] you make yourself a better engineer and citizen." Third, HKN has the express aim of encouraging excellence in the profession, especially in education. The ritual challenges members "to improve your chapter, your organization, your community, and yourself" as an HKN community. The intents of HKN membership are not limited to college scholarship and college experience. HKN is a lifetime designation of continuing accomplishment and willingness to contribute to society, especially through the HKN community.

IEEE-Eta Kappa Nu has a new Chapter Directory section on the website. This section has been designed to provide useful information on your chapter and to highlight your chapter and your campus. A chapter has options for a chapter description, a campus description, images, links, multimedia, and more. An example page for the Gamma Theta Chapter is shown. See hkn.ieee.org/chapters/university-chapters/ for other examples and for the online form to submit content. Let us know more about your HKN Chapter and University.

We hope that our chapters will start planning for the latter portion of the year. Our chapters have opportunities to add to our member community (do not forgot possible professional inductions) and to compete for an Outstanding Chapter Award. We encourage chapters to transfer knowledge to the next group of officers and to begin a plan for fall of 2018. In particular, Founders Day on 28 October is our unique opportunity to celebrate HKN and to engage locally and with your alumni.



Example Page from the Chapter Directory

SOME REMINDERS TO CHAPTERS:

- Nominate candidates for the Board of Governors and the Outstanding Student Award
- Submit your spring induction paperwork
- Order your graduation regalia

REMINDERS FOR ALUMNI:

- Contact info@hkn.org to see how you can get involved or contribute to support HKN and to invest in our future.

Regards,

Steve E. Watkins

Nancy Ostin

Outsmart Moore's Law with Machine Learning

by: Dustin Tanksley and Donald C. Wunsch

Over the last half century, computing has transformed most aspects of society due to a rapid increase in computation power. With the possible end of Moore's Law in sight, much of this growth could come to an end. This paper will discuss why machine learning will continue growing even after Moore's Law, and demonstrate why it is a great time to enter the field.

WHAT IS MACHINE LEARNING?

At the most fundamental level, machine learning is the process of using advanced function approximators and large amounts of data to create a mathematical representation of a problem. As an example, one could take a group of pictures of cats and dogs, and identify them. To do this, some function would have to map these pictures to a numeric value, possibly 0 for cats and 1 for dogs. The art of machine learning is creating these complicated functions and then apply meaning to the mathematical representations. Three major approaches to such tasks are supervised learning, reinforcement learning, and unsupervised learning.

Supervised learning is typically the most intuitive. In this type of learning, labeled data are fit to an appropriate function; for example, matching the price of a house to the size, other factors. For simple problems, a linear (or higher order) regression algorithm works just fine, however as more parameters such as; bedroom and bathroom count, location within or distance to a major city, population density, and other factors are considered, nonlinear models are often needed. Nonlinear versions of regression exist, but neural networks and other methods are often competitive with those, and the whole family of such approaches can be considered types of machine learning. Perhaps the best example of supervised learning success can be seen in ImageNet, an effort to identify the object in an image. ImageNet consists of more than 10 million internet images that have been identified and labeled by humans, and as of 2017, the best algorithm achieved a 97.7% correct classification, which is better than most humans (typically 90-95%) [1][2].

Reinforcement learning typically uses similar neural network architectures as supervised learning, with the key difference that data usually must be generated/gathered, so that performance functions replace the role of labels. Reinforcement learning is easiest to visualize in games, such as tic-tac-toe. Several actions are available, allowing the agent to place a mark in one of the squares, and in doing so generates a new data-point, but the agent does not know if this was a good or bad move. When the game ends, the agent is told if it wins, loses, or draws and must use this data to determine if all the actions it took were good or bad. Classifying moves as good or bad is a somewhat difficult process, but many improvements have been made in the field, with the most recent being AlphaGo, an effort by Google to master the game of Go (a far greater computational challenge than Chess). AlphaGo's most recent achievements include beating a former world champion in a 5-game match (AlphaGo Lee) and beating 60 of the top Go players in the world without any losses (AlphaGo Master). Beyond this, an even stronger version has been released, AlphaGo Zero, which defeated AlphaGo Master 89-11 and is notable for being completely trained by reinforcement learning from playing, without the benefit of any initial supervised learning [3][4].

Unsupervised Learning is very different from supervised and reinforcement learning, in that it does not have a training target. Clustering, the most common form of unsupervised learning, groups inputs together based on similarities, and determines it has succeeded based on how tightly the groups are packed, and how many outliers are present. In this way, unsupervised learning is typically very good at finding patterns in the data, though with complex datasets, the pattern found may be difficult to interpret. While this can make it unsuitable for some of the problems in supervised and reinforcement learning, it does have some very profound applications. For example, it can be used to divide and conquer other problems such as the combinatorically-demanding Traveling Salesman Problem. Unsupervised learning was used as a heuristic to divide the problem and achieve a dramatic speedup over the best previous solution. [5] Whether the final processing is done by another algorithm or a human, reducing the complexity of data analysis is among many applications of unsupervised learning.

Overall, each method to machine learning has its own strengths and weaknesses. It is clear that humans exhibit traits from each, being able to learn from either a teacher (supervised), or trial and error (reinforcement), or being able to classify objects based on their similarities to find patterns (unsupervised). While human level AI may be far away, these methods can be applied to most problems with very good results.

WHY WILL MACHINE LEARNING OUTLIVE MOORE'S LAW?

While Moore's law has certainly helped machine learning, it is not needed for the continued growth of the field. Algorithmic advances are continually improving the field, with new methods for learning along with better parallel processing constituting the most significant increase in performance. Furthermore, increasingly specialized hardware that focuses on the operations needed for machine learning has led to tremendous growth.

To put this in perspective, IBM Deep Blue managed to defeat the reigning world champion of chess, Garry Kasporov, in 1997. Deepmind's AlphaGo Lee defeated Lee Sedol, 18-time world champion of Go, in 2016. Chess has a state space complexity of 10^47, while Go has a state space complexity of about 10^170. This means in those 19 years, computational efficiency would have increased by 123 orders of magnitude, or 297,600,000% per year. While this figure is very approximate, it highlights just how impressive the growth of machine learning is.

To further highlight the growth of AlphaGo particularly, the original version used 176 GPUs, and required months of training. When it defeated Lee Sedol, it had switched to 48 Tensor Processing Units (TPUs), which are optimized for machine learning. Just months later Deepmind launched AlphaGo Zero, which started learning without any human game data, and in 3 days was stronger than the version that beat Lee Sedol (AlphaGo Lee), and ultimately after 40 days was fully trained, far outmatching any previous results. This newest version only runs on 4 TPUs, and even despite this is many times stronger then AlphaGo Lee.

Just as algorithmic advances have accelerated machine learning, newer, more optimized hardware has made its impact as well. When self-driving car research took off around 2010, GPU acceleration had started to become mainstream. Since then, programs that could utilize these resources became more common, and has since become the de-facto standard for machine learning. The more specialized TPU that is aimed solely at deep learning applications has finally stepped into consumer grade products with Nvidia's release of the Titan V, which claims up to 110 TFlops of compute power in deep learning applications. This shows a large step towards creating specialized hardware specifically for machine learning, and the potential demand for such systems.

THE BARRIERS TO ENTRY ARE COMING DOWN.

Getting into machine learning has become much easier over the past decade. Many APIs are available for all programming languages. With a host to choose from including; Tensorflow, Caffe, Keras, DeepLearning4J, or even MATLAB's Machine Learning Toolbox, it requires very little time and fairly little code to start applying machine learning. Many tutorials are available to help people get started with machine learning, and while there will be some learning time for people unfamiliar with the subject, very little knowledge of machine learning algorithms is needed to successfully use these tools.

Another barrier that has been coming down is the need for supercomputing. While the CPU in a standard computer can usually run most algorithms especially after they are trained, to effectively train on large amounts of data in a reasonable time requires much more power. Fortunately, many APIs nowadays are automatically GPU accelerated, allowing for massive speedup. Specialized hardware is even reaching consumer levels, as can be seen in products such as the Intel Movidius, a USB stick that can be used to accelerate machine learning. As well, several cloud services from companies such as Amazon and Google offer GPU and TPU nodes for use, allowing for models to be trained without buying hardware.

It is important to note that these growths are not a direct result of Moore's Law. While Moore's law clearly benefits newer hardware, allowing for more transistors in the same area, GPUs don't necessarily rely on these and many of their gains are simply from increasing core count. Furthermore, specialized hardware simply boils down to configurations of the transistors that allow for faster computation, at a cost in speed for general purpose computation.

CONCLUSION

The world is fast becoming AI centric as autonomous vehicles are becoming more of a reality every day, autonomous drones/delivery bots are being developed, robots are becoming more adaptable, and the ability of computers to sell to us is growing dramatically. With the rapid advancement of machine learning into nearly every area, it is fast becoming commonplace. With the continued innovations in machine learning algorithms and specialized hardware, the growth in this field will continue far beyond the limits of Moore's Law.

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Donald Wunsch is the Mary K. Finley Missouri Distinguished Professor at Missouri University of Science and Technology (Missouri S&T).

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His education includes: Executive MBA - Washington University in St. Louis, Ph.D., Electrical Engineering - University of Washington (Seattle), M.S., Applied Mathematics (same institution), B.S., Applied Mathematics - University of New Mexico, and Jesuit Core Honors Program, Seattle University.

Key research contributions are: Clustering / Unsupervised Learning; Biclustering; Adaptive Resonance and Reinforcement Learning architectures, hardware and applications; Neurofuzzy regression; Traveling Salesman Problem heuristics; Games; Robotic Swarms; and Bioinformatics.

He is an IEEE Fellow, previous INNS President, INNS Fellow, NSF CAREER Awardee, 2015 INNS Gabor Award recipient, and Eta Kappa Nu member. He served as IJCNN General Chair, and on several Boards, including the St. Patrick's School Board, IEEE Neural Networks Council, International Neural Networks Society, and the University of Missouri Bioinformatics Consortium, Chaired the Missouri S&T Information Technology and Computing Committee as well as the Student Design and Experiential Learning Center Board.

He has produced 20 Ph.D. recipients in Computer Engineering, Electrical Engineering, Systems Engineering and Computer Science; has attracted over $10 million in sponsored research; and has over 450 publications including nine books. His research has been cited over 15,000 times.

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He has previously earned an associate's degree in Science from the Missouri Academy, and a bachelor's degree in Computer Engineering from Missouri University of Science and Technology, as well as being the youngest person to pass the Qualifying Exam in Computer Engineering at Missouri S&T.

He has participated in several chess AI competitions and has placed several times in the top three. He has been recognized for his achievements on several occasions, notable receiving both a GAANN Fellowship and Chancellor's Distinguished Fellowship. He is an active Gamma Theta member of HKN.

Determining Optimum Drop-out Rate for Neural Networks

by: Josiah A. Yoder

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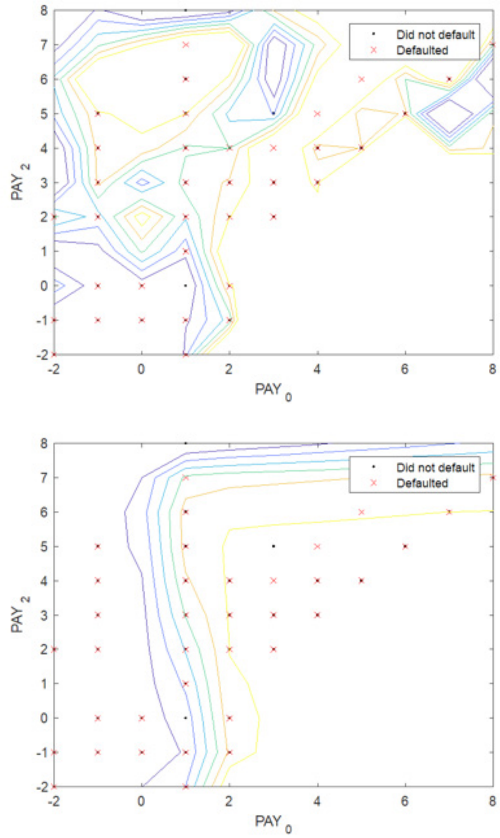
Undergraduate Research Project

ABSTRACT

Dropout is used to reduce overfitting in neural networks. Past research determines the optimum dropout rate for a dataset but does not compare optimal dropout rates across datasets. The purpose of this project is to investigate a correlation in optimum dropout rates between datasets that are non-spatial, non-time series, and have heterogeneous inputs. One dataset with these properties is credit card default data, which contains each client's age, education, etc., and whether they defaulted on their credit card. A dropout rate of 0.5 is widely used but does not always optimize performance. For each dataset, deep neural network models were trained over various dropout rates and training-set sizes. The experimental results presented here show that the optimum dropout rate falls anywhere within its possible range from 0 to 1, that even 10% dropout can significantly improve performance over no dropout, and that dropout can be effective even on small datasets.

INTRODUCTION

Data is more available than ever before. However, basic data analysis often does not result in accurate predictive models. To model the complex patterns within many of today's datasets, scientists often apply neural networks and other machine learning algorithms to detect complex nonlinear relationships in a dataset. One drawback to expressive networks is overfitting. Deep neural networks are very expressive, but that expressiveness allows them to overfit the training data, learning subtle distinctions that are merely artifacts of some particular training set. Figure 1a shows an example of overfitting. The samples deviate from the true function, or signal, because of noise, an effect that is common in real world applications. The overfitting model shown by the contour lines fits so well to the data that it also captures the noise. Such a model would perform extremely well during training but would perform poorly during testing or live implementation. A more versatile and useful model is shown in Figure 1b.



(a)

(b)

Figure 1: An example of an overfitted model. (a) A neural network trained with 100 nodes on the PAY0 and PAY2 fields of the credit card default data set. (b) A neural

network trained with 3 nodes. The contour lines show decision surfaces at different thresholds of the network.

One technique to reduce overfitting is dropout. The dropout technique avoids overfitting by dropping out different random nodes during training (Figure 2).

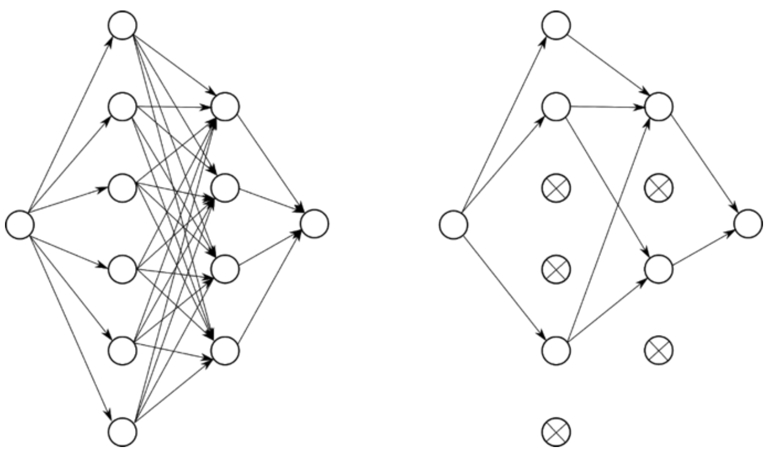


Figure 2: The application of dropout to a neural network (a) A network without dropout (b) One iteration of training the network with a dropout of 50% on the hidden layers.

The contributions of this work are:

- The effect of varying the dropout rates on datasets that are non-time series, non-spatial, and consist of heterogeneous inputs is studied for three datasets.
- There is not an optimum dropout rate shared by the datasets with similar properties. The experiments show that the optimal dropout rate can be anywhere within its range from 0 to 1, influenced by both the dataset selected and how many training samples are used from the dataset.
- While previous publications show that high dropout rates hurt performance of models trained on small datasets (Srivastava 2014), the experiments presented here show that dropout can improve performance even with a training set as small as 450 samples.

BACKGROUND

Artificial neural networks (ANN) are one type of machine learning model. Similar to the human brain, ANNs contain a network of nodes, or neurons, that are interconnected. A deep neural network (DNN) is simply an ANN with multiple hidden "layers".

A common obstacle with the application of neural networks is overfitting. Overfitting occurs when the network aligns too closely to the training data set. This leads to the network having a high predictive power with the training data set but a much lower success rate with the test data set or live data.

Dropout

Dropout is a technique for addressing this problem. The technique involves randomly dropping, or eliminating, neurons from the network during training (Srivastava 2014). This prevents units from co-adapting too much.

For each backpropagation, a new set of nodes is dropped out. At testing time, no dropout is applied. Because each backpropagation drops out so many nodes during training, the expressiveness of the model must be sustained by increasing nodes, layers, epochs, etc.

Following Baldi et. al (2013), this paper denotes the fraction of nodes dropped out during a backpropagation as q (this is the dropout rate), and the number of nodes remaining as p (this is the retention rate). This terminology helps to avoid confusion between the dropout rate and the parameter p, which both appear widely in the literature, but mean different things.

While dropout is most often applied to the hidden layers of a neural network, it can also be applied to the model's input nodes. This can reduce overfitting because the input layers can become redundant. With dropout, the model learns to consider redundant input nodes instead of relying on one. Dropout also increases the number of iterations required for the model to converge during training. For each epoch, a new random set of nodes is "dropped". Thus the model is consistently being trained with a lower number of nodes, requiring more iterations to converge. For example, using a dropout rate of q=0.5 roughly doubles the amount of iterations required to converge (Krizhevsky 2012). The model would train half the number of nodes for roughly twice the number of iterations. The additional computing time would come from the overhead computation time for each iteration. Thus, using a dropout rate of 0.5 increases computing time but by less than a factor of two. Along with adjusting the number of iterations during training, the weights must be adjusted during testing. For example, using a dropout rate of 0.5 during training requires the weights to be multiplied by 0.5 during testing.

The value of q=0.5 is often used for dropout. AlexNet, the network which achieved a step up in performance on the ImageNet classification challenge, used a dropout rate of 0.5 (Krizhevsky 2012). In a thorough review of dropout on very large problems, Srivastava commented that a dropout rate of 0.5 seemed to be close to optimal (Srivastava 2014). However, a similar image classification system using a deep neural network trained in MATLAB did not agree with the optimum dropout rate of 0.5 (Boddy 2017). For linear networks, a dropout rate of 0.5 provides the highest level of regularization (Baldi 2013). Most neural networks, however, are not applied to linear relationships. A contribution of this study is to demonstrate that the optimum dropout for a problem varies widely from one dataset to another and when a dataset's size is artificially reduced during training. Indeed, the optimum dropout could fall anywhere within the valid range for the parameter (0 to just short of 1).

ReLU: Rectified linear activation function

The rectified linear (ReLU) activation function is the most popular activation function for deep neural networks. It has an output range from 0 to infinity. It is 0 for $x < 0$ and is x for $x > 0$ (linear output). It reduces computation time over the softplus and sigmoid functions. (Krizhevsky 2012)

Producing a probability prediction with a Neural Network: The Softmax Function

The softmax function is used as the final layer of a neural network to produce a probability outcome instead of a classification. It essentially normalizes the sum of the values of the output layer. In the case of predicting the likelihood of credit card default, the softmax function would produce two values (default and non default probabilities) that add up to 1. The softmax function can be used in training through back propagation. (Krizhevsky 2012)

EXPERIMENTS

Python was used to develop the deep neural network models. Specifically, the Python library TensorFlow was used to facilitate the model training and testing. Other libraries used include the Pandas and MatPlotLib.

The TensorFlow method DNNLinearCombinedClassifier and DNNLinearCombined-Regressor are used to train the models. Two hidden layers are used with the first consisting of 100 nodes and the second consisting of 50. Ten epochs are used for training the model. Furthermore, a variable representing the dropout rate is passed as an argument into the TensorFlow method used.

TensorFlow Accuracy Determination and Decision Threshold

The model accuracy is an output of the "evaluate" method within TensorFlow. It is calculated by first feeding the testing set through the trained model. The accuracy is then the number of correctly predicted classifications divided by the number of predictions made, or the size of the testing set.

The DNNLinearCombinedClassifier method within TensorFlow is thought to use a default threshold of 0.5 when training the DNN. This can be changed by using the predict_proba method within DNNLinearCombinedClassifier to return a predicted probability for a given feature set, or sample. The return predicted probability can then be compared to a threshold and converted to the original binary classification.

Datasets used in our experiments: The Credit Card Default, Breast Cancer, and Bank Marketing Datasets

Due to their prominence, datasets that are non-time series, non-spatial, and have heterogeneous inputs are commonly used to create predictive models. The Taiwanese credit card default dataset (Yeh & Lien 2009) used in this study contains client attributes such as education level, marriage status, and past payments for approximately 30,000 clients. In addition, it includes whether or not each client defaulted on the credit card, which is necessary to train the model.

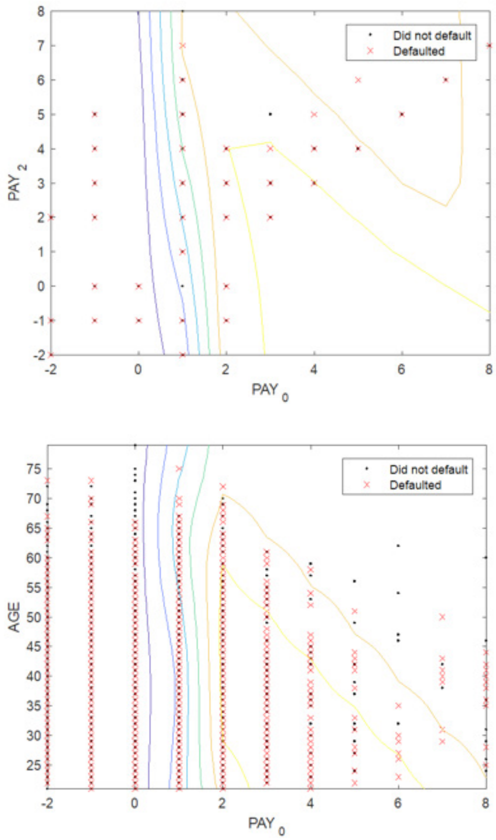
The breast cancer dataset (Wolberg & Mangasarian 1990) includes cancerous cell size uniformity, other diagnosis metrics, as well as the definitive diagnosis of whether a cancerous clump exists. This dataset consists of 699 samples.

The bank marketing dataset (Moro, Cortez, & Rita 2014) includes each clients financial background, marital status, amount of exposure of marketing campaigns, etc. and whether or not they subscribed to a term deposit. Models trained on this dataset contained a training size of 28,000 samples and a testing size of 15,000 samples.

Visually evaluating the separability of the credit card default dataset

A separable dataset is one which can be classified perfectly — a surface exists in the feature space which divides the categories perfectly.

To evaluate the separability of the credit card default dataset visually, a neural network was trained on just three of the input variables: age, pay0, and pay2 (The dataset does not include a pay1 field). The attributes pay0 and pay2 each represent the payment status of a month before the possible default. Negative values represent payment that was on time, and positive values represent the number of months a payment was late. Figure 3 shows the trained network's decision surfaces with various thresholds. The credit card data is far from separable when only these inputs are considered. There are many points with exactly the same inputs but both default and non-default outputs. Pay0 is a much stronger indicator of default than pay3 or age; the vertical decision lines show that changing the second variable does not change the prediction significantly.



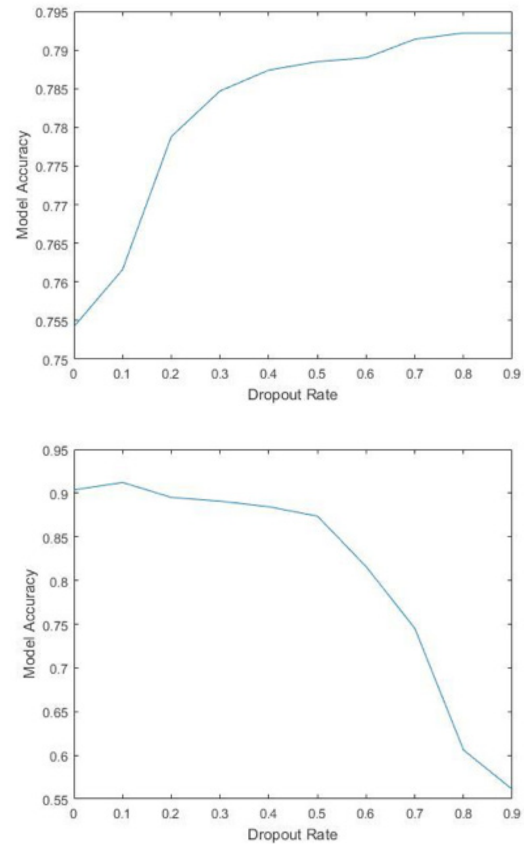
(a)

(b)

Figure 3: The credit-card dataset is not separable when considering age, pay0, and pay1. A three-hidden node network trained on two inputs from the credit card dataset. Red X's indicate clients who defaulted and black dots those who did not. The red values are slightly offset to avoid overlap. The decision surface is shown in blue. The side to the right of decision surface represents clients predicted to default (the side with higher pay0 values). Two experiments are shown with different inputs: (a) pay0 vs pay2 and (b) age vs pay0

Evaluating the optimum dropout rate of different datasets

Figure 4(a) shows the accuracy of a model trained on the credit card default dataset that contains 18,500 samples. Figure 4(b) corresponds to a model trained on a breast cancer dataset that contains 450 samples. Both of the models were trained using two hidden layers consisting of 100 nodes and 50 nodes. As can be seen, an increased dropout rate improved the model accuracy with a large dataset but decreased the accuracy with a considerably smaller dataset.

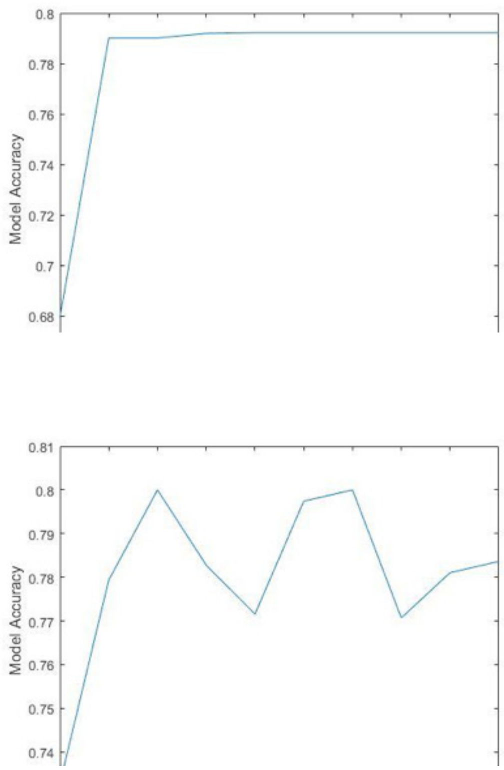


(a)

(b)

Figure 4: Impact of dropout rate on a large and a small dataset (a) The credit card dataset containing 18,500 samples in the training set (b) The cancer dataset containing 450 samples in the training set.

To attempt to replicate the small training size effect seen in Figure 4(b) on the credit card default dataset, models were trained using 450 credit card clients across different dropout rates. Figure 5(a) shows the model accuracies that were determined with the previously used testing set of 1000 samples. As can be seen, the accuracy increases to an approximate maximum when any amount of dropout is present. In an attempt to keep parameters consistent between datasets, the 450 credit card training set was also paired with a testing set of 230 samples, which is the testing set size used in the breast cancer dataset. Five trials of this configuration were run across the dropout rates, and the averaged resulting model accuracies are shown in FIgure 5 (b).



(a)

(b)

Figure 5: Impact of dropout rate on a credit card training set of 450 samples while using large and small testing sets (a) The credit card dataset containing 1000 samples in the testing set (b) The credit card dataset containing 230 samples in the testing set

Much of the variation shown in Figure 5(b) is not repeatable from one set of trials to another. Figure 5(b) averages the results of five different trials. Figure 6 shows the first four trials that were used to construct the averaged curve in Figure 5(b). Figure 6 shows that the model accuracy is inconsistent between trials. This negates the confidence of possible conclusions drawn from Figure 5(b). The credit card default dataset likely has too many variables and complexity for a 230 sample testing set to consistently gauge the model accuracies.

Furthermore, the occurrence of default is relatively uncommon. Therefore, the randomly picked 230 sample testing set can range significantly in its proportion of defaulting clients.

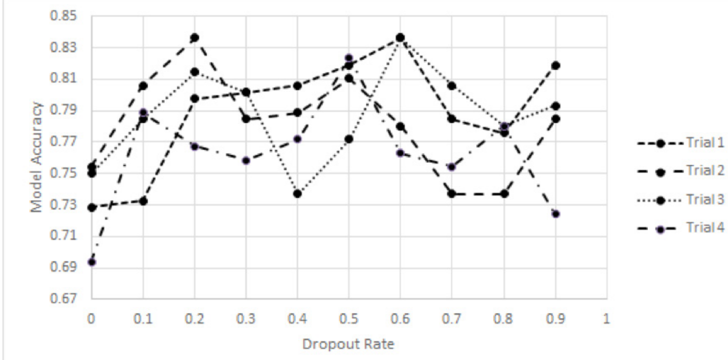


Figure 6: Different trials for the averaged data seen in Figure 5(b).

Figure 7 shows that the model performance for the bank dataset is not significantly affected by the dropout rate. It is difficult to determine an optimum dropout rate with a high of confidence due to the small change in performance, which is less than 0.5%. If models trained on such datasets are not affected by the dropout rate, then no optimum dropout rate can be determined. Thus, it is not possible for such datasets to share an optimum dropout rate.

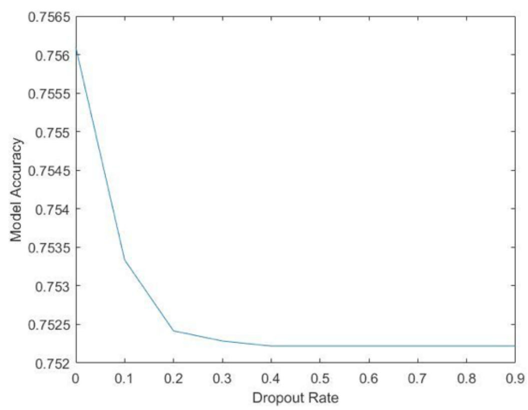


Figure 7: Performance of model trained on a 28,000 sample bank marketing dataset

RELATED WORK

Although the specific form of dropout that we experimentally study here appeared in the literature only recently, the idea of dropping out nodes or edges has been in the literature for some time. For example, in the 1990's genetic algorithms were used to learn which nodes belonged in a neural network (Ronald and Schoenauer, 1994).

Dropout is considered as a sort of bootstrap aggregation or bagging technique (Breiman 1996) in which multiple models are trained on subsets of the data and then combined. Unlike the most straight-forward bagging implementation, all of the models share weights even though they have different structures at each step of training due to dropout (Krizhevsky 2012).

This work has emphasized the relationship between overfitting and neural network expressivity. Curiously, neural networks have a built-in ability to avoid overfitting even when they are capable of memorizing the input set (Zhang et al. 2016). It is not clear how this finding relates to the current work.

CONCLUSIONS

The optimum dropout rates for the credit card default, breast cancer, and bank marketing datasets were not consistently similar. Furthermore, the dataset size seemed to have a large effect on the optimum dropout rate, with smaller datasets performing better with low dropout rates. Due to the variance in optimum dropout rates for the studied models, the implementation of a universal dropout rate is not recommended. It is likely there are too many varying factors between different datasets that prohibit a common optimum dropout rate. Therefore, it is recommended that for each application of the deep neural network studied, the dropout rate be optimized before live implementation of the model.

FUTURE WORK

We plan to expand our experiments to include a larger variety of datasets. We plan to further explore the parameters that could influence the optimum dropout rate, including dataset size, number of features, number of hidden nodes, and separability.

We would like to consider the number of hidden nodes in addition to dropout rate and dataset size. This is important because the dropout rate affects the number of hidden nodes used during training. We would expect that increasing the number of hidden nodes would have a similar effect to reducing the dropout rate, except when the dropout rate gets close to zero. Varying the number of hidden nodes also allows us to control the expressiveness of the neural network and provides an alternative way to avoid overfitting.

Another parameter we could explore is the number of hidden layers used during training. This parameter was not varied in this study because the network cannot be trained with more than approximately three hidden layers without becoming too expressive.

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Distributed Stochastic Optimal Flocking Control for Uncertain Networked Multi-Agent Systems

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ABSTRACT

This paper addresses the finite-horizon distributed stochastic optimal flocking control design problem for uncertain networked multi-agent systems (MAS) in presence of network imperfections (e.g. network-induced delays and packet dropouts) and unknown disturbances. First, through adopting a stochastic modeling technique, the networked MAS dynamics are generated by effectively integrating the effects from network imperfections. Moreover, to handle the unknown disturbances, the networked MAS is formulated as a two-player zero-sum game, with control input and disturbance signal acting as two players. Using the Neuro Dynamic Programming (NDP) technique, a novel stochastic actor-critic identifier scheme is proposed. The proposed scheme can optimize the networked MAS performance even when the system dynamics and disturbances are completely unknown. Eventually, simulation results demonstrate the effectiveness of the proposed scheme.

Index Terms— networked multi-agent systems; neuro dynamic programming (NDP); zero-sum game

I. INTRODUCTION

FLOCKING is a behavior observed in nature by which a large number of distributed interacting entities or agents execute a common group objective, in a harmonic way, and without collisions. Due to these characteristics, flocking techniques are considered as a promising solution for solving some of the challenges encountered in multi-agent systems (MAS) operations, such as consensus, collision prevention, and obstacle avoidance. However, in order to harvest the benefits from flocking, a proper distributed flocking control scheme is needed. According to Reynolds's pioneering work [1], a suitable flocking control needs to maintain three critical rules, i.e. cohesion, separation, and alignment. In [2]-[3], the authors represented a theoretical framework for the design and analysis of distributed flocking algorithms. Recently, [3] developed a flocking control with obstacle avoidance for MAS. Moreover, [4] derived a distributed event-triggered hybrid flocking control for MAS.

Most of the existing control schemes in [2]-[5] focus on maintaining the stability of each one of the three critical flocking rules. However, if compared with stability, the criterion of optimality is much more preferred. In [6]-[7] the authors proposed an optimal control for MAS to simultaneously achieve consensus while avoiding obstacles. Unfortunately, the methodologies in [6]-[7] cannot be used to solve the optimal flocking problem when considering realistic networked MAS which are commonly affected by unknown network imperfections (e.g. network-induced delays and packet dropouts) and disturbances due to three drawbacks, i.e., i) the effects from network imperfections and disturbance need to be carefully considered, ii) [6]-[7] considered simple linear system as the model of the MAS, whereas most of the real-time MAS are nonlinear, and iii) the practical networked MAS dynamics are commonly unknown beforehand due to the real-time uncertainties. To address these deficiencies, in this article we propose a novel distributed stochastic optimal flocking control scheme for practical networked MAS with uncertain dynamics, unknown network imperfections, and disturbances.

First, to ensure the execution of the three flocking rules in an optimal manner, we propose an innovative flocking cost function which includes three parts, i.e., cohesion cost function, separation cost function, and alignment cost function. Subsequently, the distributed stochastic optimal flocking control for networked MAS can be obtained by minimizing the proposed flocking cost function. According to classical optimal control theory [8], the minimized flocking cost function can be obtained by solving the Hamiltonian-Jacobi-Isaac (HJI) equation. However, due to nonlinearity, the HJI equation is very difficult to be solved mathematically. Inspired from computational intelligence, a novel neuro dynamic programming (NDP) technique is developed to approximate the HJI equation solution [9]. The authors in [10]-[11] developed an NDP-based near optimal control for nonlinear continuous-time systems and discrete-time systems respectively. Recently, the authors in [12]-[17] extended the policy or value iteration-based NDP scheme to attain the optimal control strategies when considering more general nonlinear systems. However, to compute the optimal solutions, these iteration-based NDP schemes require a significant large number of iterations which is not applicable for real-time nonlinear system applications.

In order to overcome this issue, the authors in [18]-[19] introduced a time-based NDP approach to solve the optimal control of both nonlinear continuous-time systems and nonlinear discrete-time systems, which makes use of the system historical information instead of iteration-based information. However, these schemes require the exact knowledge of the system dynamics, which cannot be known beforehand.

In order to fill this research gap, in this paper a novel time-based distributed stochastic optimal flocking control is developed for networked MAS. The proposed methodology engages the NDP technique with the innovative flocking cost function which includes cohesion, separation, and alignment aspects. The main contributions of this paper include: 1) the networked MAS optimal flocking design problem is effectively formulated by developing the flocking cost function in an intelligent way, 2) a novel time-based NDP scheme is proposed to obtain the distributed stochastic optimal flocking control of the networked MAS even in the presence of network imperfections and disturbances, and 3) the requirement of exact knowledge of the MAS dynamics is relaxed.

II. BACKGROUND

Similar to [3]-[4], distributed agents in a MAS are connected through a communication network whose topology is expressed by using graph theory. The network communication graph can be represented as $G=\{V,C\}$. Here, $V=\{1,\ldots,i,\ldots,N\}$ denotes a set of vertices, where is the i^{th} agent, and the relevant edge set C is defined as $C \subseteq \{(i,j): i,j \in V, i \neq j\}$, where the edges indicate the potential communication links and sensing capabilities among the distributed agents in the MAS.

Moreover, an unweighted adjacency matrix is introduced as $A=[a_{ij}]\Re^{NxN}$, $\forall i, j=1,2\ldots,N$, with the element a_{ij} defined as $a_{ij}=1$ if $(i,j)\in C$, and $a_{ij}=0$ if $(i,j)\notin C$. Then, the communication graph can be defined as connected when there is a data exchange path connecting each pair of distinct vertices. The MAS with a connected communication graph can be defined as a connected MAS [1]. Similar to [1]-[2], distributed agents in the MAS are assumed to have identical omni-directional communication and sensing capabilities, which indicates that there is a mutual communication within the connected MAS. Mathematically, the adjacency matrix is symmetric, i.e. $A^T=A$, and then the communication graph is undirected. An undirected communication graph topology example is provided in Figure 1.

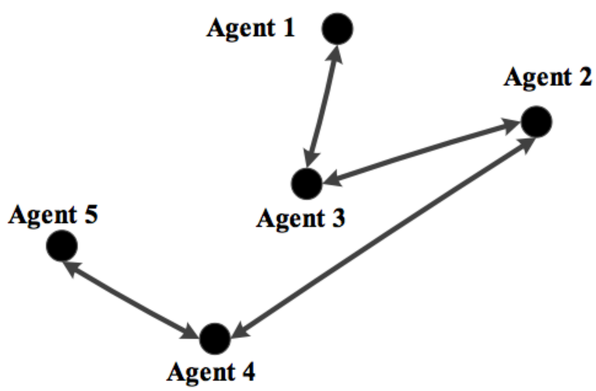


Figure 1. An undirected graph topology for MAS with five agents

III. DISTRIBUTED STOCHASTIC OPTIMAL FLOCKING CONTROL

A. Two-Player Zero-Sum Game Formulation

Considering the original nonlinear continuous-time MAS dynamics given as

$x_i(t)=f_i(x_i)+g_i(x_i)u_i(t)+h_i(x_i)d_i(t),\ \forall\ i=1,...,L$ (1)

where $f_i(x_i)\in\Re^m, g_i(x_i)\in\Re^m, h_i(x_i)\ \in\Re^m,\ \forall i=1,...,L$ denote the heterogeneous nonlinear MAS dynamics, $x_i=[p_i^T\ v_i^T]^T\in\Re^m, u_i\in\Re^m, d_i\in\Re^m,\ \forall i=1,...,L$ are the MAS states, control inputs, and disturbance, where p_i , v_i represent i^{th} agent's position and velocity, respectively, and is the number of agents. Next, based on the *Assumption 1* and [20]-[21], the network-induced delays and packet dropout are incorporated into the MAS dynamics as

$x_i(t)=f_i(x_i)+\gamma_i(t)g_i(x_i)u_i(t-\tau_i)+\ \gamma_i(t)h_i(x_i)d_i(t-\tau_i)$, (2)

with $\gamma_i(t)=\begin{cases} I^{mxm} & \text{if control is received by the actuator at the time } t \\ 0^{mxm} & \text{if control is lost} \end{cases}$, and is identity matrix, and

$\tau_i=\tau_{i,sc}+\tau_{i,ca}$.

According to [20], by discretizing equation (2) with network-induced delays and packet dropout, the networked MAS dynamics can be derived as

$$\begin{aligned} \underset{\tau_i,\gamma_i}{E}[z_i(k+1)]&=\underset{\tau_i,\gamma_i}{E}[F_i(z_i(k))]+\underset{\tau_i,\gamma_i}{E}[G_i(z_i(k))]u_i(k) \\ &+\underset{\tau_i,\gamma_i}{E}[H_i(z_i(k))]d_i(k),\quad \forall i=1,2,...,L \end{aligned} \tag{3}$$

with augment state $z_i(k)=[x_i^T(k)\ u_i^T(k\text{-}1)\ \dots\ u_i^T(k\text{-}b)\ d_i^T(k\text{-}1)]^T$,

$\underset{\tau_i,\gamma_i}{E}[F_i(x_i)]$, $\underset{\tau_i,\gamma_i}{E}[G_i(x_i)]$, $\underset{\tau_i,\gamma_i}{E}[H_i(x_i)]$ are networked MAS dynamics with $\|G_i(z_i)\|_F\leq G_{i,M}$ and $\|H_i(z_i(k))\|_F\leq H_{i,M}$, where $\|\bullet\|_F$ denotes the Frobenius norm, $G_{i,M}$, $H_{i,M}$ are positive constants, and $E\{\bullet\}$ is the mean operator [20].

B. The Novel NN-based Identifier Design

In diverse recent NDP literatures, e.g., [15]-[17], either partial or complete system dynamics of the networked MAS (i.e. $F_i(\bullet), G_i(\bullet), H_i(\bullet)\forall i=1,2,...,N$ are needed for attaining the optimal flocking control. However, due to uncertainties and modelling inaccuracy, the networked MAS dynamics are very difficult to be known beforehand. To circumvent this challenge, we propose a novel online NN-based identifier as follows.

According to the universal function approximation property from neural network (NN), the networked MAS heterogeneous nonlinear system dynamics (4) can be represented as

$$\begin{cases} \underset{\tau,\gamma}{E}\left[F_i(z_i(k))\right]=\underset{\tau,\gamma}{E}\left\{W_{F,i}^T\sigma_{F,i}(z_i(k))+\varepsilon_{F,i}\right\} \\ \underset{\tau,\gamma}{E}\left[G_i(z_i(k))\right]=\underset{\tau,\gamma}{E}\left\{W_{G,i}^T\sigma_{G,i}(z_i(k))+\varepsilon_{G,i}\right\},\forall i=1,...,L \\ \underset{\tau,\gamma}{E}\left[H_i(z_i(k))\right]=\underset{\tau,\gamma}{E}\left\{W_{H,i}^T\sigma_{H,i}(z_i(k))+\varepsilon_{H,i}\right\} \end{cases} \tag{4}$$

where $W_{F,i}\in\Re^{l_Fx2m}, W_{G,i}\in\Re^{l_Gx2m}, W_{H,i}\in\Re^{l_Hx2m}$, $\forall i=1,2,...,L$ represent the target weights, $\sigma_{F,i}(z_i)\in\Re^{l_F}, \sigma_{G,i}(z_i)\in\Re^{l_Gxm}, \sigma_{H,i}(z_i)\in\Re^{l_Hxm}, \forall i=1,...,L$ are the activation functions $\varepsilon_{F,i}\in\Re^{2m}$, $\varepsilon_{G,i}\in\Re^{2m}$, $\varepsilon_{H,i}\in\Re^{2m}, \forall i=1,2,...,L$ denote the reconstruction errors, and l_F, l_G, l_H, are the number of neurons.

Based on relevant NN literature [14]-[15], the networked MAS system state, $z_i(k)\forall i=1,...,L$, can be approximated as

$$\underset{\tau_i,\gamma_i}{E}\left[\hat{z}_i(k+1)\right]=\underset{\tau_i,\gamma_i}{E}\left\{\hat{W}_{I,i}^T(k)\sigma_{I,i}(z_i(k))\chi_i+\varepsilon_{I,i}\right\},\quad \forall i=1,2,...,L;\forall k=0,1,...,N-1 \tag{5}$$

where $W_{I,i}(k)\in\Re^{(l_F+l_G+l_H)x2m}, \forall i=1,2,...,L$ is the estimated weights of the NN-based identifier at time kT_s.

Using (4) and (5), the networked MAS system state identification error can be derived as

(6)

$$\underset{\tau_i,\gamma_i}{E}\left[e_{I,i}(k+1)\right]=\underset{\tau_i,\gamma_i}{E}\left[z_i(k+1)-\hat{z}_i(k+1)\right]$$
$$=\underset{\tau_i,\gamma_i}{E}\left\{W_{I,i}^T\sigma_{I,i}(z_i(k))\chi_i+\varepsilon_{I,i}\right\}-\underset{\tau_i,\gamma_i}{E}\left\{\hat{W}_{I,i}^T(k)\sigma_{I,i}(z_i(k))\chi_i\right\}$$
$$=\underset{\tau_i,\gamma_i}{E}\left\{\tilde{W}_{I,i}^T(k)\sigma_{I,i}(z_i(k))\chi_i+\varepsilon_{I,i}\right\},\forall i=1,...,L;k=0,...,N-1$$

with

$$\underset{\tau_i,\gamma_i}{E}\left\{\tilde{W}_{I,i}(k)\right\}=\underset{\tau_i,\gamma_i}{E}\left\{W_{I,i}-\hat{W}_{I,i}(k)\right\},\forall i=1,...,L;k=0,...,N-1$$

defined as the weight estimation error of the NN-based identifier. According to [20] and equation (6), the main objective of the NN-based identifier design is to force the identification errors and the NN weight estimation errors close to zero. To accomplish this, a novel update law is developed for the NN-based identifier as

$$\underset{\tau_i,\gamma_i}{E}\left\{\hat{W}_{I,i}(k+1)\right\}=\underset{\tau_i,\gamma_i}{E}\left\{\hat{W}_{I,i}(k)+\alpha_{I,i}\frac{\sigma_{I,i}(z_i(k))\chi_i e_{I,i}^T(k+1)}{\left\|\sigma_{I,i}(z_i(k))\chi_i\right\|^2+1}\right\}, \quad \forall i=1,...,L;\forall k=0,...,N-1 \tag{7}$$

where $\alpha_{I,i},\forall i=1,2,...,L$ is the tuning parameter for NN-based identifier, and $\|\bullet\|$ denotes the 2-norm [20]. NDP-based Flocking Cost Function Approximation

According to [20], the ideal stochastic optimal cost function of a networked MAS two-player zero-sum game, $J_i^*(x_i)\forall i=1,...,L$ can be represented by using a novel critic NN as

$$J_i^*(z_i(k))=\underset{\tau,\gamma}{E}\left\{W_{J,i}^T\varphi_{J,i}(z_i(k),z_{-i}(k))+\varepsilon_{J,i}\right\}, \tag{8}$$

where $W_{J,i}\in\Re^{l_J},\forall i=1,...,L$ is the target weights of the critic NN, with l_J being the number of hidden-layer neurons, $\varphi_{J,i}(z_i(k),z_{-i}(k))\in\Re^{l_J},\forall i=1,...,L$ denotes the activation function of the critic NN with $z_i(k)$ being the system state of i^{th} agent, $z_{-i}(k)=\{z_j(k)\}_{j\in N_i}$ being the system state from the neighbors of the i^{th} agent, and $\varepsilon_{j,i}\in\Re,\forall i=1$ represents the reconstruction error of the critic NN. According to relevant NN literatures [14]-[15], [18], the reconstruction error can be forced close to zero while increasing the number of hidden-layer neurons.

Next, putting equation (8) into the HJI equation, it can be represented as

$$0=\underset{\tau,\gamma}{E}\begin{bmatrix}r_{CA,i}(z_i(k),u_i(k),d_i(k))+r_{VM,i}(z_i(k),u_i(k),d_i(k))\\+r_{FC,i}(z_i(k),u_i(k),d_i(k))\end{bmatrix}+\underset{\tau,\gamma}{E}\left\{W_{J,i}^T\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))\right\}+\underset{\tau,\gamma}{E}\left\{\Delta\varepsilon_{J,i}(k)\right\} \tag{9}$$

with $\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))$ being defined as $\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))=\varphi_{J,i}(z_i(k+1),z_{-i}(k+1))-\varphi_{J,i}(z_i(k),z_{-i}(k))$, and $\Delta\varepsilon_{J,i}(k)=\varepsilon_{J,i}(k+1)-\varepsilon_{J,i}(k)$.

Similar to [20], the ideal stochastic optimal cost function (8) can be approximated by using the critic NN as

$$\hat{J}_i(z_i(k))=\underset{\tau,\gamma}{E}\left\{\hat{W}_{J,i}^T(k)\varphi_{J,i}(z_i(k),z_{-i}(k))\right\}, \quad \forall i=1,...,L,k=0,...,N-1 \tag{10}$$

where $W_{J,i}(k),\forall i=1,...,L$ denotes the estimated weights of the critic NN and $\varphi_{J,i}(z_i(k),z_{-i}(k))$, $\forall i=1,...,L$ is selected from an activation function set whose elements in the set are linearly independent [19]. However, substituting the estimated stochastic optimal cost function (10) into the HJI equation (9) does not hold. To evaluate the effects from inaccurate stochastic optimal cost function estimation, an HJI equation estimation error is introduced and defined as

$$\underset{\tau,\gamma}{E}\left[e_{HJI,i}(k)\right]=\underset{\tau,\gamma}{E}\begin{bmatrix}r_{CA,i}(z_i(k),u_i(k),d_i(k))\\+r_{VM,i}(z_i(k),u_i(k),d_i(k))+r_{FC,i}(z_i(k),u_i(k),d_i(k))\\+\hat{W}_{J,i}^T(k)\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))\end{bmatrix} \tag{11}$$

Furthermore, to incorporate the effects from the terminal constraint, the relevant terminal constraint estimation error $\underset{\tau,\gamma}{E}\left[e_{FT,i}(k)\right],\forall i=1,...,L$ is defined as

$$\underset{\tau,\gamma}{E}\left[e_{FT,i}(k)\right]=\underset{\tau,\gamma}{E}\left[\phi_N(z_i(N))\right]-\underset{\tau,\gamma}{E}\left\{\hat{W}_{J,i}^T(k)\varphi_{J,i}(\hat{z}_i(N),\hat{z}_{-i}(N))\right\} \tag{12}$$

where $\hat{z}_i(N),\hat{z}_{-i}(N)$ are the estimated networked MAS states, obtained by using the available system information (i.e. $\underset{\tau,\gamma}{E}\left[\hat{F}_i(\bullet)\right]$, $\underset{\tau,\gamma}{E}\left[\hat{G}_i(\bullet)\right]$, $\underset{\tau,\gamma}{E}\left[\hat{H}_i(\bullet)\right]$) at time kT_s.

Similar to recent NDP literatures [14]-[15], [18], the HJI equation estimation error and terminal constraint estimation error are two important factors to evaluate the critic NN approximation performance. To better learn the ideal stochastic optimal cost function, the critic NN can be tuned by using two estimation errors (i.e. $\underset{\tau,\gamma}{E}\left[e_{HJI,i}(k)\right], \underset{\tau,\gamma}{E}\left[e_{FT,i}(k)\right]$

$$\underset{\tau,\gamma}{E}\left\{\hat{W}_{J,i}(k+1)\right\} = \underset{\tau,\gamma}{E}\left\{\hat{W}_{J,i}(k)\right\} + \alpha_V \underset{\tau,\gamma}{E}\left\{\frac{\varphi_{J,i}(\hat{z}_i(N),\hat{z}_{-i}(N))e^T_{FT,i}(k)}{\left\|\varphi_{J,i}(\hat{z}_i(N),\hat{z}_{-i}(N))\right\|^2+1}\right\} \quad (13)$$

$$+\alpha_V \underset{\tau,\gamma}{E}\left\{\frac{\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))e^T_{HJI,i}(k)}{\left\|\Delta\varphi_{J,i}(z_i(k),z_{-i}(k))\right\|^2+1}\right\}, i=1,..,L, k=0,..,N-1$$

C. Actor NNs Estimation of Stochastic Optimal Flocking Control and Worst Case Disturbances

The two actor NNs for optimal control and worst case disturbances can be estimated as

$$\begin{cases} \underset{\tau,\gamma}{E}\left\{\hat{u}_i(z(k))\right\} = \underset{\tau,\gamma}{E}\left\{\hat{W}^T_{u,i}(k)J(z_i(k))\right\} \\ \underset{\tau,\gamma}{E}\left\{\hat{d}_i(z(k))\right\} = \underset{\tau,\gamma}{E}\left\{\hat{W}^T_{d,i}(k)\psi(z_i(k))\right\} \end{cases}, i=1,..,L, k=0,..,N \quad (14)$$

where $\underset{\tau,\gamma}{E}\left\{\hat{W}_{u,i}(k)\right\}, \underset{\tau,\gamma}{E}\left\{\hat{W}_{d,i}(k)\right\}$ are the approximated weights for control and disturbance actor NNs, respectively. Specifically, the estimation errors can be derived as

$$\underset{\tau,\gamma}{E}\left\{e_{u,i}(k)\right\} = \underset{\tau,\gamma}{E}\left\{\begin{array}{l}\hat{W}^T_{u,i}(k)\vartheta(z_i(k)) + \frac{1}{2}\left[R_{CA,i}+R_{VM,i}+R_{FC,i}\right]^{-1} \\ \times\hat{G}^T_i(z_i(k))\frac{\partial\varphi^T_{J,i}(z_i(k+1),z_{-i}(k+1))}{\partial z_i(k+1)}\hat{W}_{J,i}(k)\end{array}\right\}$$

$$\underset{\tau,\gamma}{E}\left\{e_{d,i}(k)\right\} = \underset{\tau,\gamma}{E}\left\{\begin{array}{l}\hat{W}^T_{d,i}(k)\vartheta(z_i(k)) - \frac{1}{2}\left[S_{CA,i}+S_{VM,i}+S_{FC,i}\right]^{-1} \\ \times\hat{H}^T_i(z_i(k))\frac{\partial\varphi^T_{J,i}(z_i(k+1),z_{-i}(k+1))}{\partial z_i(k+1)}\hat{W}_{J,i}(k)\end{array}\right\} \quad (15)$$

To better tune two actor NNs, the novel update laws are proposed by using the estimation errors defined in (34) as

$$\begin{cases} \underset{\tau,\gamma}{E}\left\{\hat{W}_{u,i}(k+1)\right\} = \underset{\tau,\gamma}{E}\left\{\hat{W}_{u,i}(k)\right\} - \alpha_u \underset{\tau,\gamma}{E}\left\{\frac{\vartheta(z_i(k))}{\left\|\vartheta(z_i(k))\right\|^2+1}e^T_{u,i}(k)\right\} \\ \underset{\tau,\gamma}{E}\left\{\hat{W}_{d,i}(k+1)\right\} = \underset{\tau,\gamma}{E}\left\{\hat{W}_{d,i}(k)\right\} - \alpha_d \underset{\tau,\gamma}{E}\left\{\frac{\psi(z_i(k))}{\left\|\psi(z_i(k))\right\|^2+1}e^T_{d,i}(k)\right\} \end{cases}, \quad (16)$$

with two actor NNs tuning parameters α_u, α_d satisfying and $0<\alpha_u<1$ and $0<\alpha_d<1$. Overall,

The flowchart of proposed design is shown in Figure 3.

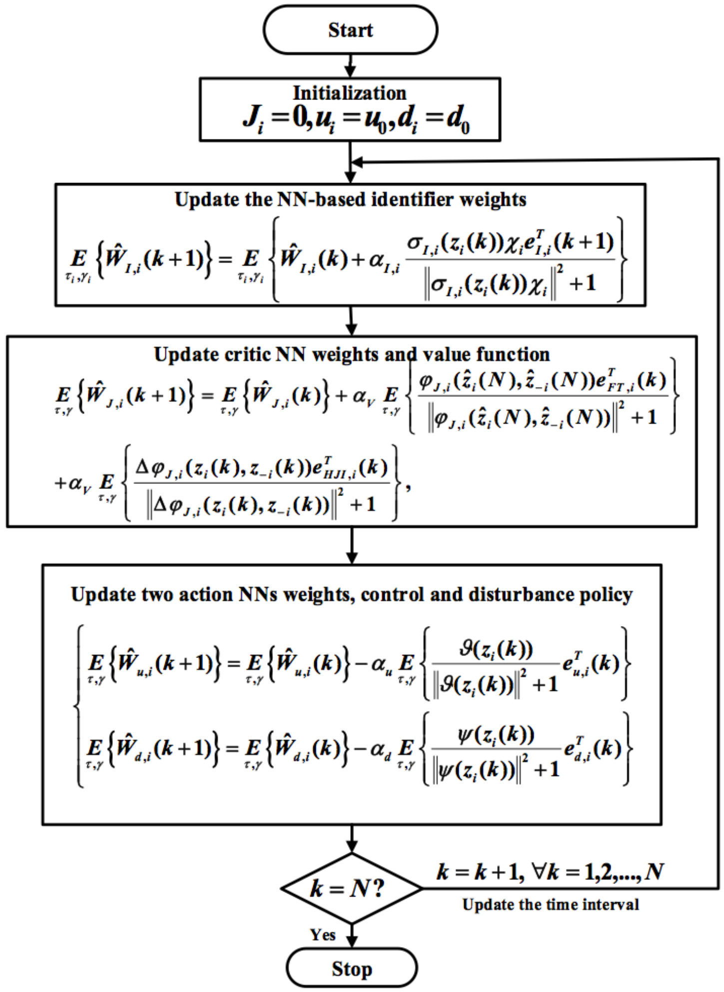


Figure 3. Flowchart of the proposed finite horizon optimal design

IV. SIMULATION RESULTS

In this section, a practical networked nonlinear MAS example is used to evaluate the proposed stochastic optimal flocking control design. Consider the following nonlinear multiple unmanned aircraft system (multi-UAS) as:

$$\dot{x}_i(t) = f_i(x_i(t)) + g_i(x_i(t))u_i(t) + h_i(x_i(t))d_i(t) \quad (17)$$

where the dynamics of the multi-UAS, $f_i(x_i(t)), g_i(x_i(t)), h_i(x_i(t))$, are defined as in [2]. Furthermore, assuming that all the UAS are operating at the same height [3], then, the position of each UAS can be represented in a two-dimensional space. The initial positions of the UAS are generated randomly in a 100m*100m region by using the norm distribution function. Moreover, velocities for multi-UAS are initialized as zeroes.

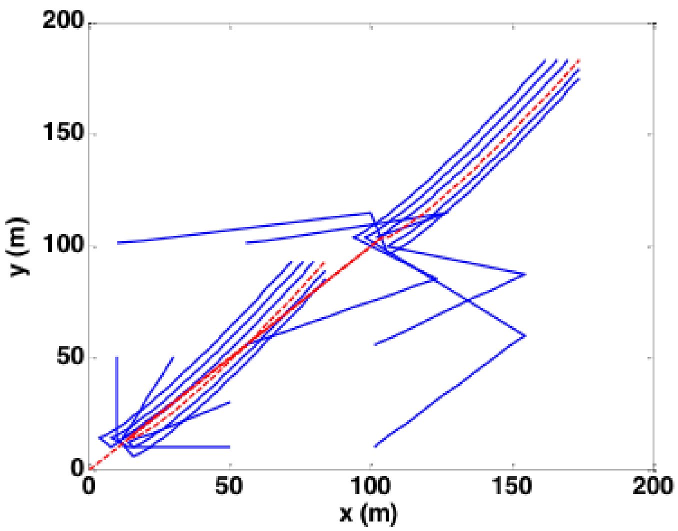
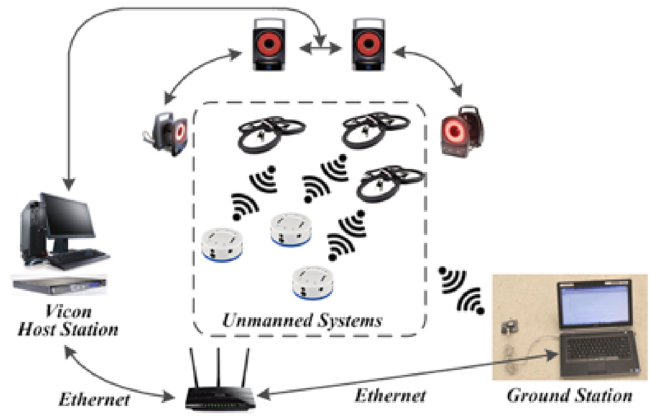


Figure 3. The trajectories of ten UAS

To evaluate the generality of proposed scheme, the flocking performance of the proposed MAS algorithm considering ten agents has been studied. Based on the communication graph, the ten UAS have been separated as two sub-groups, and only a cluster head UAS in each sub-group was allowed to communication between sub-groups. As shown in Figure 3, each sub-group is able to ensure its optimal flocking performance. Moreover, using the communication between the sub-groups, the ten networked UAS can also achieve the overall optimal flocking simultaneously.



(a)

(b)

Figure 4. (a) Networked MAS testbed; (b) Experimental application where networked UAS perform an autonomous mission to track a moving ground vehicle.

Furthermore, the effectiveness of the proposed finite horizon stochastic optimal flocking design has been evaluated through a networked multi-UAS platform. As shown in Figure 4 (a), multiple aerial and terrestrial unmanned systems were connected to a remote controller through aWiFi network. Moreover, the indoor GPS system (i.e. Vicon system) has been used to instead of traditional outdoor GPS. As shown in Figure 4 (b), the proposed scheme can effectively control three UAS (AR Drones) to track the moving target on the ground (i.e. unmanned ground agent) even in presence of network imperfections and unknown disturbance.

According to the simulation and experimental results presented from Figure 3 to Figure 4, the proposed design is not only maintaining the stability of the networked multi-UAS, but also achieving the ideal optimal flocking performance closely, even in presence of complete unknown system dynamics, unknown network imperfections, and disturbance.

V. CONCLUSION

A novel NDP-based distributed stochastic optimal flocking control is designed for uncertain networked MAS with unknown system dynamics and disturbance. To attain the optimal flocking design, a novel optimal flocking cost function is developed first for the networked MAS. Subsequently, a novel NN-based identifier is proposed to relax the requirement of the networked MAS dynamics. Further, a novel critic NN is designed to approximate the HJI equation solution forward-in-time, while satisfying the terminal constraint of the networked MAS two-player zero-sum game over a finite horizon. An initial admissible control and disturbances guarantee that the networked MAS system is stable during the tuning period of the NN-based identifier, critic, and two action NNs. Using Lyapunov theory, the networked MAS system states, identification error, weight estimation errors of the NN-based identifier, critic and two action NNs, are demonstrated to be ultimately uniformly bounded (UUB) in the mean square sense. Simulations and experimental results verify the theoretical solution.

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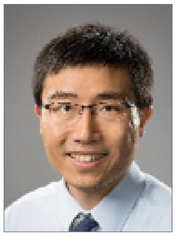

Hao Xu (M'12) was born in Nanjing, China. He received the master's degree in electrical engineering from Southeast University, Nanjing, in 2009, and the Ph.D. degree from the Missouri University of Science and Technology, Rolla, MO, USA, in 2012. He is currently with University of Nevada, Reno, where he is an Assistant Professor with the Department of Electrical & Biomedical Engineering. His current research interests include intelligent control design for advanced power systems, smart grid, autonomous unmanned aircraft systems, and wireless passive sensor network.

Wenxin Liu (S'01–M'05–SM'14) received the B.S. degree in industrial automation, and the M.S. degree in control theory and applications from Northeastern University, Shenyang, China, in 1996 and 2000, respectively, and the Ph.D. degree in electrical engineering from the Missouri University of Science and Technology (formerly University of Missouri–Rolla), Rolla, MO, USA, in 2005. Currently, he is an Assistant Professor with the Department of Electrical and Computer Engineering, Lehigh University, Bethlehem, PA, USA. His research interests include power systems, power electronics, and controls.

IEEE Computational Intelligence Society

IEEE Computational Intelligence Society (CIS) is a vibrant community of researchers, students, and industry professionals engaged in the development and applications of bio-inspired intelligent computational paradigms. The three major pillars of computational intelligence (CI) are neural networks, evolutionary computation,and fuzzy logic and systems. CIS is the home for advanced machine learning techniques such as deep learning, evolutionary games, and computing with words. CIS publishes a number of highly reputed journals covering different facets of Computational Intelligence. The activities of the society evolve depending on the demand of time. Recently, we have started a new publication, titled Transactions on Emerging Topics in Computational Intelligence, to embrace and promote new topics in CI. The society also organizes many premier conferences in the area of computational intelligence. This year two of our major events are: (i) IEEE World Congress on Computational Intelligence (WCCI 2018), which will be held during 8-13 July in Rio de Janeiro, Brazil and (ii) IEEE Symposium Series In Computational Intelligence (SSCI 2018) , which will be held during 18-21 November in Bengaluru, India. WCCI consists of three major conferences, IEEE International Conference on Fuzzy Systems, IEEE Congress on Evolutionary Computation, and International Joint Conference on Neural Networks; while SSCI is a unique event that co-locates about 30 symposia each on a focused topic related to CI. Every year we also organize several other conferences focusing on the use of computational intelligence in areas like Smart World, Data science and Advanced Analytics, Robotics, Bioinformatics and Computational Biology, and Games.

In CIS we assign the highest importance to the academic, scientific, and social needs not only of CIS members but also of the humanity as a whole. Keeping this in mind CIS organizes a wide spectrum of programs such as distinguished lectures, webinars, competitions (including games), summer schools, summer research grants, students' travel grants to attend our conferences, educational videos, and many more. CIS recognizes that Young researchers are the future leaders and makes concerted efforts to promote participation of young researchers in every sphere of its activities.

In order to have a better interaction between the community interested in CI (not necessarily CIS members) and the members of the CIS Executive Committee (ExCom), we carefully choose the locations for our ExCom meetings and usually organize a one-day workshop on CI. Typically, the workshop is jointly organized with a local host, which could be the local CIS Chapter or a university/engineering institute. Usually, all ExCom members give a talk and sometimes one or two local researchers also speak at the workshop. Such workshops are free to anyone (CIS member or not), who is interested in computational intelligence.

Often we end the workshop with a panel discussion with the participants. This is an initiative we started in 2011 and successfully organized workshops in Brazil, Cyprus, Peru, Rhode Island, Spain, Ecuador, Chile, and Argentina. Each of these workshops was very well attended by local students, researchers and professionals, they provided us excellent opportunities to interact with the local community more closely. Sometimes it rejuvenated a chapter and sometimes it motivated people to become interested in CI, and even to start a CIS chapter. This year our first ExCOM is going to be held in Sydney, Australia on April 8 and we are going to organize two workshops on advances in computational intelligence. The first workshop will be held at the University of Technology Sydney and the second one at the University of New South Wales Canberra. In Canberra, we are inviting young high school students, particularly female students, to attend the talk by one of our ExCom members, Professor Bernadette Bouchon-Meunier. This talk will be adapted for the high school students. After the talk, the students will get an opportunity to closely interact with Professor Bernadette Bouchon-Meunier and Professor Julia Chung (also an ExCom member). This initiative is taken to motivate young female students to be interested in engineering in general and computational intelligence, in particular.

CIS is a big happy family, which is driven by a large set of very friendly and dedicated volunteers. To get involved in various CIS activities please write to us at cis-info@ieee.org. To know more about us, please visit http://cis.ieee.org/

IEEE Policy on GDPR

IEEE understands that, in an increasingly data-driven world, keeping personal data private is becoming more difficult. Most importantly, we care about you and respect and value your time. IEEE wants to ensure that we provide to you the tools necessary to perform your IEEE responsibilities in a compliant and efficient way.

A new regulation called the General Data Protection Regulation (GDPR) takes effect on 25 May 2018 and is expected to have far-reaching impact on how business will be conducted worldwide.

IEEE has been carefully reviewing and redesigning its privacy policy, business processes, and how IEEE collects, uses, shares and retains the personal data of its members, customers, volunteers, and professional staff worldwide.

As HKN is a lifetime membership, HKN has a legitimate business interest and will be able to contact you regarding HKN matters. Your right to privacy does allow you to opt out of recieving communications from HKN

For IEEE volunteers, the current process of collecting personal data and emailing on behalf of IEEE will change and impact your day-to-day IEEE volunteer activities. A new process for collecting and using personal data will be communicated.

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IEEE-HKN "Pathways to Industry"

As a strategic initiative, the IEEE-HKN Board of Governors sponsored a pilot workshop program "Pathways to Industry" with partners IEEE-USA and the Electrical and Computer Engineering Department Heads Association (ECEDHA) on 19 March 2018.

The purpose was to offer innovative programs to HKN Graduate Student Members, Young Professionals, and graduating students. This workshop focused on the transition from school to industry; bringing students and professionals together to discuss personal career paths, share hard-earned insights, and offer practical advice in an interactive workshop format.

Topics and Speakers Included:

Ok, I'm About to Graduate. Now What?

Speaker:

Orin Laney

What Does a Career in Financial Services Look Like?

Speaker:

Stan Janowiak, Morgan Stanley

Industry Connections - Industry Panel

Panelists:

Doug Phillips, Texas Instruments

Mike Curcic, EMWorks

Safa Salman, ANSYS

Ye Cheng, MathWorks

Flying With Confidence: Navigating the First Steps of Your Career

Speaker:

Leo Szeto, Owner, Codeate

Panel Session - The Next Big Thing

Moderator:

Tom Coughlin, President, Coughlin Associates

Speakers:

Dennis Leitterman

Leo Szeto, Owner, Codeate

Orin Laney

Students reported that this workshop met their needs and interests in career and personal development, personal financial management, project management, management, negotiating, presentation skills, professional development, and business. These topics will be incorporated and expanded in future IEEE-HKN programs and partnerships.

The workshop was made possible by Texas Instruments, EMWorks, ANSYS, MathWorks, and Codeate as industry partners and IEEE-USA and ECEDHA as sponsors.

President Steve E. Watkins (left center) with the speakers and attendees of the Pathways to Industry Workshop

The Prehistory of Quantum Engineering

by: Michael Geselowitz, Ph.D.,
Senior Director, IEEE History Center

We are on the dawn of an age where the physical implications of quantum theory will result in new technologies. Superposition can lead to greater accuracy in sensing. Quantum states allow quantum computing to surpass anything made possible by traditional electronics. Quantum entanglement holds out the promise of instantaneous and securely encoded telecommunication. Thus, a field of quantum engineering is born.

As novel as quantum engineering is, quantum physics is of course far older, dating at least to Einstein's quantum solution to explain the photoelectric effect in 1905 (though Einstein was later put off by some of the implications of quantum mechanics). Therefore, not surprisingly, physicists and electrical engineers have been at work since at least the 1940s applying quantum mechanics to real-world problems, particularly in the development of solid-state electronics. In one of IEEE's oral histories, laser inventor and IEEE Medal of Honor winner Charles Townes describes how he coined the term "Quantum Electronics" for an IRE (Institute of Radio Engineers, which along with the American Institute of Electrical Engineers was the predecessor to IEEE) conference…in 1959. This might be considered the "prehistory" of quantum engineering.

As a technology advances ever more rapidly, it becomes increasingly critical to preserve its history, both to commemorate the past and to provide lessons for the present and future. That is the role of the IEEE History Center—an organizational unit of IEEE that is located at and co-sponsored by Stevens Institute of Technology in Hoboken, NJ, USA (home of the Iota Delta Chapter of Eta Kappa Nu). Overseen by the IEEE History Committee, the professional staff of the center carry out a number of programs that promote preservation of, research into, and communication of the proud heritage of IEEE-related fields.

Most of the information preserved by the History Center is made available on the Engineering & Technology History Wiki (www.ethw.org), a site that we developed and run on behalf of a consortium of engineering associations. An important section of the site is the IEEE Oral History collection—over 800 interviews of important engineers whose thoughts were captured even before their memories become "history" (one such interview, of Charles Townes, has already been noted). One of the most interesting programs administered by the History Center is the IEEE Milestones Program, which recognizes events in electrical history—defined as being at least 25 years old—by the placement of a bronze plaque. There are to date over 185 Milestones.

Since the Milestones Program is for achievements older than 25 years, some of this prehistory is starting to be recognized. One of the most recent Milestones is the Fermilab Tevatron in Batavia, Illinois, USA, dedicated in November 2017 (http://ethw.org/Milestones:Fermilab_Tevatron). Specifically, Fermilab was recognized for its pioneering use of superconducting magnets, beginning in 1973, which made it for almost 25 years the most powerful particle collider in the world. This power made it the epicenter of the quantum discoveries in the 1970s and 1980s that are now being applied. At the dedication ceremony, the History Center conducted oral history interviews to preserve the memories of those who were responsible for, and continue to be responsible for these exciting developments.

One may wonder what quantum engineering developments of the next 25 years will be recognized by the IEEE Milestones program?

Hello HKN! We are Michael Benson and Katie Lewis, your TWO HKN student governors for 2018. We're thrilled to work together and with you this year and we're excited and honored to serve you for the 2018 calendar year.

It's hard to believe that we're nearly half way through 2018! The first half of this year has flown by and our chapters and alumni have accomplished a great deal in terms of activities on campus, community service, and inducting new members. Given this great start, we're truly excited and eager to see where we go together in the 2nd half of the year. However, we need to continue to build momentum. The summer months are a phenomenal time to practice the skills learned in the classroom and to unwind after a fast-paced academic year. It is also a great time to reach out to alumni and to plan for the upcoming semester. For alumni and students alike, we implore you to reach out to one another and for alumni specifically, to re-engage with your chapter of induction. No matter how far removed you might be from your days as a student, you have experience and wisdom to share with our new members. I encourage you to contact our staff at info@hkn.org to get in touch with your chapter's current leadership team and with other local alumni.

In addition to rekindling your connection to your chapter and the larger world of HKN, we also would like to encourage you (students and alumni alike) to join one of our committees to help do the important work of our society at an international level. If you're interested in helping to define and promote the HKN Brand or further defining and developing the chapter experience, please reach out to us! either at info@hkn.org or via our slack channel

For chapter officers, you've likely already heard from one or both of us by now. If you haven't, please don't hesitate to contact us… some of our chapters don't have the most up-to-date contact information on file. If you aren't sure when you last updated your chapter leadership contact information, please email info@hkn.org and check that it is current, we want you to have the most current information and resources available!

During your induction ceremony, you were told that as a society we value three characteristics above all others: scholarship, character, and attitude. These are the cornerstones of our society and a set of common traits that every member embodies. Individually, each attribute contributes to make a well-rounded and successful professional. However, when taken together, these three attributes combine to set us apart. A strong character and positive attitude coupled with high scholastic achievement can mean only one thing: excellence. Be excellent, enjoy the warm weather, and please don't hesitate to reach out to one or both of us; we're here to serve you!

Michael Benson

2018 HKN Student Governor
Beta Epsilon Chapter

Katie Lewis

2018 HKN Student Governor
Kappa Sigma Chapter

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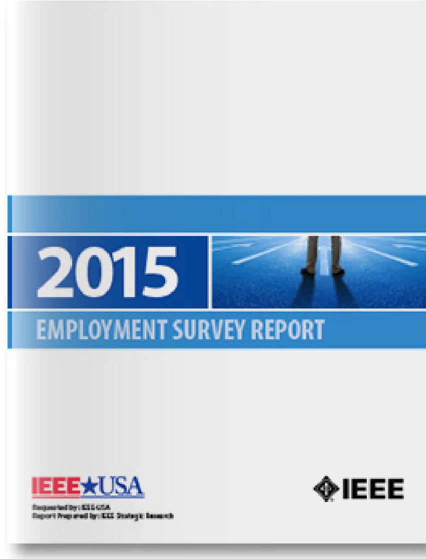

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BY IEEE-USA

The 2015 IEEE-USA Employment Survey was conducted to gain a better understanding of the problem of unemployment among U.S. IEEE members. 3,411 U.S. IEEE members who reported being unemployed during 2014 were surveyed, using a self-administered, online questionnaire.

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IEEE-HKN Outstanding Student Award

The IEEE-Eta Kappa Nu (IEEE-HKN) Board of Governors and the HKN Los Angeles Alumni Chapter are pleased to announce the winners of 2017 Outstanding Student Award: Katelyn Brinker, Gamma Theta Chapter, Missouri University of Science and Technology and James Smith, Xi Chapter, Auburn University. For the sixth time in the fifty-two year history of this award multiple students have been recognized.

Miss Brinker graduated from Missouri University of Science and Technology (Missouri S&T) in May of 2017 with degrees in Electrical Engineering and Computer Engineering and is currently pursuing her master's in Electrical Engineering at Missouri S&T with the support of a NASA Space Technology Research Fellowship. Throughout her undergraduate career she was heavily involved with the Missouri S&T world champion Mars Rover Design Team, IEEE Student Branch, and Eta Kappa Nu Gamma Theta Chapter. She served as the IEEE Instrumentation and Measurement Society Undergraduate Representative, in addition to working at the campus Writing Center as a Peer Writing Consultant and at the Applied Microwave Nondestructive Testing Laboratory as a Research Assistant. After completing her master's she hopes to pursue a career in the field of space science and engineering and develop new technologies that will advance our exploration capabilities.

Mr. Smith is originally from Huntsville, AL and completed his undergraduate degree at Auburn University. He graduated as a University Honors Scholar with a Bachelor of Electrical Engineering and minors in Computer Science and Political Science. While at Auburn, James completed several internships and held an undergraduate research fellowship, conducting research in antenna optimization by genetic algorithms. In addition to his academic pursuits, James held leadership positions in several organizations including Eta Kappa Nu, Spring Up Leadership Programs, and Auburn for Water, a philanthropic organization he co-founded with friends. He was also a member of the Auburn Triathletes and competed in several marathon and ultramarathon distance races. In April 2017, James received the Auburn University College of Engineering President's Award and was the Auburn University Electrical Engineering Student of the Year. Currently, James is enrolled in a PhD program at Auburn University, conducting research in machine learning with a focus in artificial neural networks.

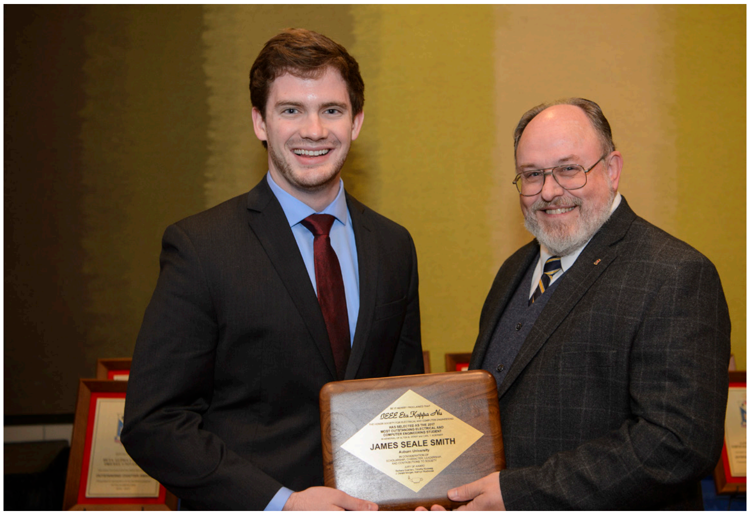
The committee confers Honorable Mention to the following students:

Alex Mages, Epsilon Xi Chapter, Wichita State University

Keith Doggett, Epsilon Omicron Chapter, University of Delaware

The Alton B. Zerby and Carl T. Koerner Outstanding Student Award recognizes outstanding scholastic excellence and high moral character, coupled with demonstrated exemplary service to classmates, university, community, and country.

The award was presented at the Electrical and Computer Engineering Department Heads Association (ECEDHA) Awards Dinner on 19 March 2018.



President Steve E. Watkins presents the OSA Plaque to James Smith of Xi Chapter, Auburn University

President Steve E. Watkins presents the OSA Plaque to Katelyn Brinker of Gamma Theta Chapter, and Daryl Beetner, Department Chair, ECE, all are from Missouri University of Science and Technology.

IEEE-HKN Outstanding Chapter Awards

IEEE-HKN was proud to honor its most accomplished chapters with the Outstanding Chapter Award, this award is presented to IEEE-HKN Chapters in recognition of excellence in their chapter administration and programs, service to the community, and others is an expectation of IEEE-HKN Chapters.

Chapters are selected on the basis of their annual chapter report. Winning Chapter reports showcase chapter activities and impact.

The Outstanding Chapter Award committee focuses on activities to: improve professional development; raise instructional and institutional standards; encourage scholarship and creativity; provide a public service; and further the established goals of IEEE-HKN. A total of 24 chapters were honored at a special ceremony held on 19 March at the Electrical and Computer Engineering Department Heads Association (ECEDHA)

The Department Heads of our Oustanding Chapters gather to recieve their 2017 Awards

This year the Student Leadership Conference was hosted by the excellent Epsilon Sigma Chapter, at the University of Florida, Gainsville.

Between the 13-15 April, chapter representatives from across the world congregated at the Reitz Union building.

Dr. Kent Fuchs (HKN Alpha Chapter), President of the University of Florida, welcomed fellow HKN members and students, alongside other distinguished speakers, including Jennifer Hunter of Microsoft and Terence Yeoh of Aerospace Corp. Dr. Cammy Abernathy, the Dean of the College of Engineering, presented the opening keynote session.

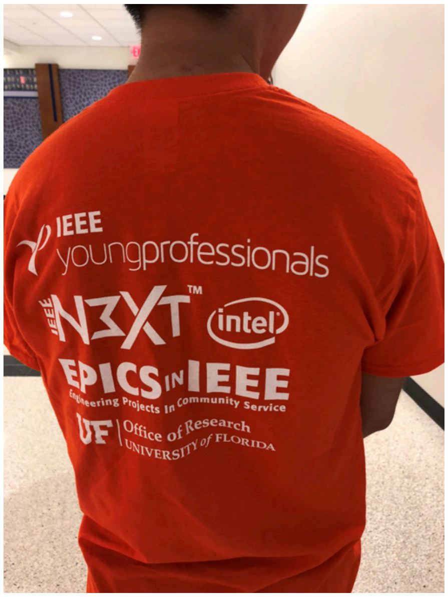
Several members of HKN's own Board of Governors were also in attendance, inspiring and engaging through their own sessions, as well as impromptu meetings and discussions throughout the conference.

Thank you Epsilon Sigma chapter for being an amazing host, and to our Sponsors and Partners: Intel, IEEE Young Professionals, IEEE N3XT™, EPICS in IEEE and the University of Florida for their generous support.

Engaged students and volunteers listen as Brian Malin charts his career from University of Florida Alumni to Launch Engineer.

SLC 2018 Group Photo taken outside of the Ritz Student Union building

For more photos, please visit [our website]



Thank you to all our great Sponsors and Partners!

Go Gators!, The campus gator paid a visit during the photo session

Students from across the world take a moment to pose at our HKN photo booth.

Shane Owens, Laine Powell, Robert Reynolds and Courtney Powell (left to right) engage the students at the N3xt ™ Entrepreneurship panel.

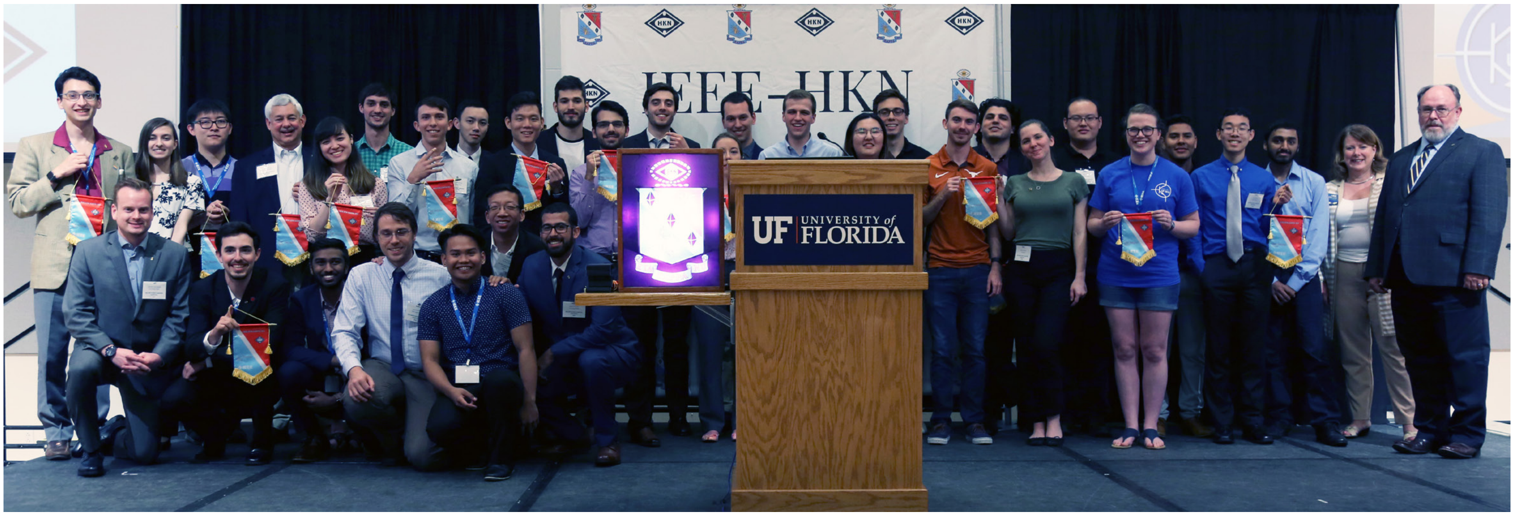
Dr. Kent Fuchs, President of the University of Florida (HKN Alpha Chapter) welcomes IEEE-HKN to the University of Florida

Dean Abernathy delivers an impassioned keynote to an attentive audience

IEEE-HKN Key Chapters

Congratulations to the 2017 IEEE-HKN Key Chapters. The Key Chapter recognition celebrates chapters that participate in activities identified as the best practices of successful chapters. The Key Chapters recognized at the 2018 SLC were:

- Alpha Chapter
- Beta Alpha Chapter
- Beta Delta Chapter
- Beta Epsilon Chapter
- Beta Gamma Chapter
- Beta Kappa Chapter
- Beta Lambda Chapter
- Beta Mu Chapter
- Beta Nu Chapter
- Beta Omega Chapter
- Beta Psi Chapter
- Beta Rho Chapter
- Delta Chapter
- Delta Epsilon Chapter
- Delta Omega Chapter
- Delta Xi Chapter
- Epsilon Beta Chapter
- Epsilon Eta Chapter
- Epsilon Kappa Chapter
- Epsilon Xi Chapter
- Gamma Chapter
- Gamma Alpha Chapter
- Gamma Beta Chapter
- Gamma Delta Chapter
- Gamma Epsilon Chapter
- Gamma Iota Chapter
- Gamma Kappa Chapter
- Gamma Rho Chapter
- Gamma Tau Chapter
- Gamma Theta Chapter
- Iota Chapter
- Iota Gamma Chapter
- Iota Omega Chapter
- Iota Upsilon Chapter
- Iota Xi Chapter
- Kappa Chapter
- Kappa Lambda Chapter
- Kappa Omicron Chapter
- Lambda Beta Chapter
- Lambda Sigma Chapter
- Lambda Upsilon Chapter
- Lambda Xi Chapter
- Mu Chapter
- Mu Alpha Chapter
- Mu Nu Chapter
- Mu Xi Chapter
- Mu Zeta Chapter
- Nu Chapter
- Psi Chapter
- Sigma Chapter
- Theta Epsilon Chapter
- Theta Kappa Chapter
- Theta Mu Chapter
- Upsilon Chapter



President Steve E. Watkins and HKN Director Nancy Ostin (far right) present the key chapter banners to Chapter officers who earned the recognition

For more information abouit the requirements to become a Key Chapter, please visit our website.

PROFESSIONAL PROFILE:

John Seiffertt

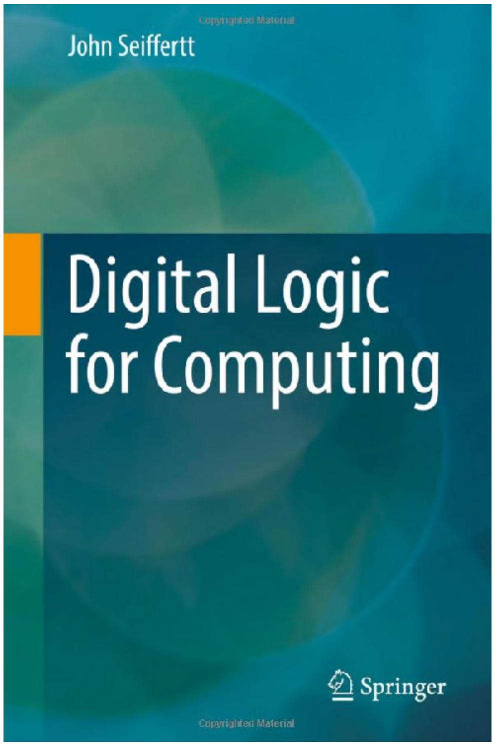
Assistant Professor of Computer Science
Truman State University

Gamma Theta Chapter

John Seiffertt is an Assistant Professor of Computer Science at Truman State University in Kirksville, MO. He received his Ph.D. in Computer Engineering from the Missouri University of Science and Technology in 2009 and also holds graduate degrees in Mathematics and Economics. His research is in the areas of machine learning and agent-based modeling. He has published work in IEEE Transactions journals, presented papers at international conferences, and his most recent book is the "Digital Logic for Computing" (Springer, 2017). With interests across the field, from embedded systems to Turing machines, he is an award-winning teacher committed to helping undergraduates grow both intellectually and professionally.

Why did you choose to study the engineering field?

Computers are the transformative technology of our time and I was drawn to learning all about them, from their abstract capabilities to how to effectiely deploy them.



What do you love about it?

Through computing, you can reach so many fields across all of science and technology. You get to work with many domains and see the power of the computer realized in many exciting environments.

What don't you like about it?

Though engineers don't talk about it, computing does have its limits. Computer scientists discuss this a great deal, but in engineering it's not quite front-of-mind yet. We must be careful to consider what algorithms do and not let them loose without close supervision in some contexts.

Whom do you admire and why?

These days I admire many of my students who trust the process, code on their own outside of class, read widely, value personal as well as professional development, and are grateful for having a breadth of knowledge. From among these will come our best engineers over the next few decades

How has the field of engineering changed since you've started?

Even in computer engineering, more and more tasks are automated than they used to be. The job of engineer keeps working at a higher and higher level of abstraction.

What direction do you think that the engineering field is headed in the next 10 years?

We have a way of creating new challenges every time we introduce a new technology to overcome an old one! The problems we face in pervasive mobile computing, global networking, and energy storage and delivery are unlike the planet has seen before, and are exciting extensions of what computing has given us in the early going of the 21st century.

What's the most important thing you've learned in the field?

Algorithms have their limits. Let's not blindly trust them just yet.

What advice would you give to recent graduates entering the field?

Build up a broad knowledge base outside of engineering. The most important applications and solutions require a wide human perspective.

If you weren't in the engineering field, what would you be doing?

If I weren't seeking to understand through computing, I'd be back in mathematics where I began my academic career. Mathematics is so important to really understand the machine learning algorithms at the center of the most exciting developments in computing.

Finish this sentence. "If I had more time, I would …"

Finish writing my own programming language! Who doesn't have a half-finished language or three stashed among their files somewhere?

Note: Dr. Seiffertt is the guest editor for this issue

The HKN monument at the Gamma Theta Chapter, Dr. Seiffertt's chapter of induction as a professional member.

STUDENT PROFILE:

Stephanie Engelhardt

Nu Chapter

Originally from Iowa City, Iowa, Stephanie Engelhardt attends Iowa State University in Ames, Iowa. She is the current president of Iowa State's IEEE-HKN Nu Chapter and is working towards her B.S. in Computer Science. Additionally, she is involved in a dance company on campus, Orchesis II, and is an undergraduate research assistant. Some of Stephanie's accomplishments include: Academic ranking in the top 2% of her class; HackISU 1st place for the best retail hack (Fall 2017); named as one of the best coders in her software project class as well as her group's project being selected as the honorable mention for best project.

What has it meant to you to be inducted IEEE-HKN?

Being inducted into IEEE-HKN has opened numerous doors for me. One way IEEE-HKN has helped me to improve as an individual is by giving me the chance to take on leadership roles. I have served as the website chair, vice president, and now am currently the president of the Nu Chapter. Prior to serving as the website chair, I had no website programming experience and was able to learn a lot during my elected time. Additionally, being vice president and now president has given me numerous opportunities to develop both my leadership and public speaking abilities. Another important thing that IEEE-HKN has done for me is given me opportunities to network with my colleagues and future employers. I have made some incredible, lifelong friendships through the Nu Chapter. I am forever grateful for all IEEE-HKN has done for me.

Do you have a best HKN story to share

One of my favorite HKN memories is when our chapter hosted a "Nerd Out" trivia night at our school's program, ISU AfterDark. Our club had a lot of fun putting together different trivia questions and then at the program, we had a phenomenal turn out! The school helped to fund prizes, so people got really excited to win, which made the night even more exciting.

Why did you choose to study the engineering field?

In high school, I was torn between physical therapy, mathematics education, and forensic science. Majoring in an engineering field hadn't even crossed my radar. When I came to Iowa State University to major in mathematics education, I had to take a programming course due to state initiatives to teach more programming in schools. When I took this course, I fell in love with programming but was afraid to make a big change to my major. So, I tried doing a Hackathon and taking online programming courses to see if this was something I truly did love, and I realized that the common theme of my original prospective careers was problem solving. I decided to change my major to computer science, which enables me to solve all kinds of different problems all day. I am so excited to be pursuing something that is my passion and have never regretted changing majors.

What do you love about engineering?

I love the problem solving aspect to engineering and how there are many different ways to solve one problem. It is an amazing feeling when you finally solve a problem that you have been working on for a long time. Another aspect that I love about engineering is that you can change the world around you. If you find something that needs changing, you can actually make it happen instead of just sitting on an idea.

What is your dream job?

My dream job would be a job where I get to code a majority of the time. Ideally, I would like to be a full-stack developer or a back-end developer.

Whom do you admire (professionally and/or personally) and why?

I really admire Dr. Tavanapong Wallapak, who is both a professor at Iowa State University and the CTO of EndoMetric (a software company that offers computer-aided technology for colonoscopies). As one of the 16 females (of 179 total students) in my graduating class [1], it was hard for me to find a professional, female role model in my field. However, once I met Dr. Wallapak, it was easy for me to be inspired by her on a daily basis. She leverages all of her abilities to improve the world around her. For example, her hard work to improve colonoscopies could help to save over 50,000 lives that colon cancer takes every year [2]. In addition to her work to fight colon cancer, she also encourages and helps freshman in computer science adjust to Iowa State University. I originally met Dr. Wallapak when I was a TA for her class, and many students commented how much they respected and were thankful for all Dr. Wallapak did for their class. I too respect and am thankful for Dr. Wallapak.

What is the next BIG advance in engineering?

Personally, I believe the next big advance in engineering will be artificial intelligence. Artificial intelligence advances will be seen in every field (medicine, education, etc) to improve the accuracy of products or services given.

What is the most important thing you've learned in school?

The most important thing I've learned while studying computer science is to always challenge yourself to see if you can make it better. Since there are always multiple ways to program something, when you first write a program, it is probably not the most efficient program you could write. So, when you have finished a program, always go back and try to think of other ways to write the code or to store the data to improve the quality of your program.

What advice would you give to other students entering college and considering studying your major?

If the task at hand seems too hard or too complex, start with a smaller problem and solve that. Then, solve the next smaller problem and continue this until you have solved the problem you originally found to be too complex. With that being said, don't be afraid to try and fail. Even if you don't know the solution to the smaller problem, write down what you are thinking and then go from there. You will often find that the solution is not that far away once you have written down your thoughts.

REFERENCES

[1] Enrollment Statistics for Fall Semester 2017 (Fall 2017): n. pag. Iowa State University of Science and Technology Office of the Registrar. Web.

[2] American Cancer Society. Cancer Facts & Figures 2017. Atlanta, GA: American Cancer Society: 2017.

Nu Chapter at Iowa State University

New Chapters

IEEE-HKN is proud to welcome six new chapters:

- Lambda Lambda Chapter at the American University of Sharjah, Sharjah, UAE
- Lambda Phi Chapter at Khalifa University, Abu Dhabi, UAE
- Mu Beta Chapter at the Arab Academy for Science, Technology and Maritime Transport, Alexandria, Egypt
- Mu Pi Chapter at G.H. Raisoni College of Engineering, Nagpur, India
- Mu Rho Chapter at Valparaiso University, Indiana, USA
- Mu Sigma Chapter at National Chiao Tung University, Hsinchu, Taiwan

Lambda Lambda Chapter members proudly take the HKN pledge as they are inducted into HKN

Congratulations and welcome to the HKN worldwide network of Chapters. We look forward to supporting you and to all of the wonderful programs and service work you will bring to your Universities, fellow students and community.

Mu Beta Chapter elebrates their official installation and induction

Mu Sigma Chapter is our our first Chapter in Taiwan

The official HKN charter is presented to Mu Pi chapters

Mu Rho Chapter receive their official HKN member Certificates

Share Your IEEE-Eta Kappa Nu Pride

Official Society Merchandise Now Available

Medal $20	Honor Stole $20
Three Pin Types:	Honor Chord . . . $30
Crest $12	6" Table Covers . $99
Emblem $12	Key Pendant . . . $14
Key $12	Scarf $22
	Necktie $25

Save $10 by purchasing the "honor combo" one honor cord and one honor stole for $40

Save $21 by purchasing 10 of the same style pin for $99

All items available at the IEEE-HKN store at:
https://hkn.ieee.org/get-involved/store/

HKN IEEE *Advancing Technology for Humanity*

IEEE-HKN Founders Day

What is IEEE-HKN Founder's Day?

Founders Day is a way for us to share the Eta Kappa Nu story, raise awareness of the value that an IEEE-HKN Chapter brings to a University, show the many ways a chapter serves fellow students and community and encourage industry to support us. Today's IEEE-HKN students are the leaders of tomorrow.

What do you have to do?

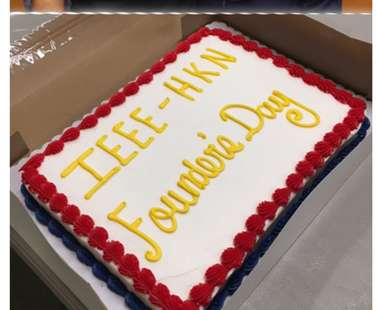
Plan an on-campus event on or around **28 October** to promote your chapter and IEEE-HKN. Each chapter who hosts a Founder's Day activity and completes the online form (available on the IEEE-HKN website), including photos or video from the event, will receive $100 store credit for the HKN store

Why should your chapter participate?

- To raise awareness of the value of your chapter?
- To interest more student in accepting your invitation to join the chapter.
- To remind your department and faculty of the importance of IEEE-HKN.
-To help reconnect with your alumni.
- To spread the message to industry leaders that membership in IEEE-HKN is a sign of a future successful professional.

Contact Information

For any Founder's Day Questions or comments, please contact us at info@hkn.org



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