ORMS TOMORROW

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STUDENT CHAPTER SPOTLIGHT
Massachusetts Institute of Technology (MIT)

MINI-POSTER COMPETITION
Undergraduate, Master and PhD winners

THE FUTURE IS ELECTRIC
Cleaner and greener urban logistics

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Letter from the Lead Editors

Dear OR/MS Community Members,

We are pleased to share with you the Fall/Winter 2020 edition of OR/MS Tomorrow!

Congratulations to the winners of our first ever mini-poster competition! We have received very high-quality submissions globally on a wide variety of topics, ranging from evaluation planning for alternative fuel vehicles to parking assignment problems. The first place winning mini-posters in each group (PhD, master and undergraduate) are published in this issue.

In this issue, we discuss a myriad of topics in different areas, including a system dynamic analysis on declining college enrollments, simulation-based optimization, a brief survey on well-known algorithms that changed the world, wind farm layout optimization and the urban planning concept of a 20-minutes neighborhood.

Special thanks to Prof. Michael Bell for sharing his view on green urban logistics. We would also like to thank Mr. Mayank Batra for his time to discuss with us the supply chain strategies of Mint pharmaceutical during COVID-19.

We also spotlight the INFORMS student chapter at Massachusetts Institute of Technology (MIT). Last but not least, don't miss out on the information about competitions held by the Consortium for Mathematics and Its Applications (COMAP)!

Submissions for the Spring/Summer 2021 issue are welcomed. Contact us via email at orms_tomorrow@mail.informs.org!

We hope you enjoy the content.

Jessica Leung and **Amira Hijazi**

OR/MS Tomorrow Family

This issue wouldn't have been possible without the effort of our family members:

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INFORMS Student Chapter Highlight: Massachusetts Institute of Technology (MIT)

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INFORMS student chapters around the United States have been forced to adapt to a "new normal" of remote social interaction amidst the COVID-19 pandemic. We spoke with the leadership team of the MIT INFORMS student chapter to see how one organization is navigating this change. In a Zoom interview at the beginning of the fall semester, Leann Thayaparan (President), Léonard Boussioux (Vice President), and Dan Killian (Treasurer) shared their team's challenges and new approaches to foster a sense of community during the pandemic.

Q: Tell us a bit about the MIT INFORMS student chapter.

Leann: Most of our membership comes from Ph.D. and Masters students in the MIT Operations Research Center (ORC). I would say we have around 100 members though there is no formal membership process. Largely, we just try to create as much community as possible within the people who are doing operations research at MIT. We also try to foster relationships with the alumni group and provide opportunities for the alumni to connect with students.

Léonard: We could describe our roles as social officers because we have to create links and bonds in the community, and we plan several events to do that.

Dan: I would agree. Our organization tries to encourage people to mingle, whether it's across cultural lines or across research interests. Getting people to break out of their comfort zone, especially at a place like MIT, is really important.

Q: What are some activities that your chapter used to organize pre-pandemic?

Léonard: Traditionally, the INFORMS officers organize lunches or afternoon snacks, and often we have a theme. For example, around Christmas, we organized an event where we asked people to build a gingerbread house. I never knew about gingerbread houses before coming here, but I heard it's a very American thing, so we organized a group competition to build the nicest house. A lot of us international students actually loved building this house!

Dan: My personal favorite was a French pastry event where several of the French students introduced us American students to the classic French breakfast. I will say they have it right in France with the waffles. I mean, it was like dessert for breakfast.

Leann: We also planned a bunch of activity-based events. During the MIT open house for admitted students, we would have an event for current and new students to meet each other. Then in the fall, we used to host a retreat where we'd take everybody to Maine and go camping and canoeing and just give people a chance away from school to bond with each other. And even though these events didn't have immediate academic implications, people would form connections and then be able to approach each other later on.

Léonard: And to build on this, we can now see how important these events were at the time. With the pandemic, we cannot organize in-person activities for the new students, so they actually have had a lot of difficulty making friends and forming groups to work together.



Gingerbread houses from a pre-pandemic chapter event.

Q: So how did you shift your activities in response to the pandemic?

Léonard: We had to change everything. The first thing we witnessed back in the spring was that we no longer had a physical place where we could just interact and say hi to people. So we decided to create times, especially Friday night after 5 p.m., to provide **opportunities for people to meet over Zoom.** During these meetings, we make breakout rooms to separate people into groups of seven or eight, and then every 15 minutes we change the breakout rooms so that you can meet other people. However, after two of these events, people wanted to do something new, and we needed to provide something that would attract those who don't like Zoom events. Dan, do you want to describe what we did for the open house, for example?

Dan: Yeah, so normally for the open house for admitted students in the spring, we would host a dinner and happy hour at one of the local restaurants. It's just a very informal way for people to ask your student opinion of the program. But with

all on-campus events canceled, we needed some other way to give people a sense of the ORC community.

So instead we organized a **virtual scavenger hunt** where the INFORMS officers compiled a list of different group tasks that could be completed remotely and assigned points to these tasks. It was things as simple as, take a Zoom picture with everyone wearing their favorite hat, or videotape someone on your team eating an entire banana peel, stem included. Another one was, take your favorite book title and try to write it in emojis. We assigned teams of about six to seven people with a mix of current and potential ORC students, and teams uploaded everything to a website so that everybody could see each other's submissions.

At the end, the INFORMS officers picked out the highlights from the event, and we had an awards ceremony to reflect on everything that was done. That got a ton of really positive feedback. People enjoyed being able to kind of act silly with some of their classmates, and I think it gave the potential students hope that when things are back on campus, there is a supportive, engaged community of students that are willing to help them on their journey through MIT.

Leann: Then this fall, since we didn't have the student retreat, we were very concerned that people would start the school year more or less alone, especially the first years. So we organized a **tournament** similar to what Dan just described but with a focus on sparking conversation and extended over two weeks. Example tasks were things like, recommend a book to somebody, and if they took the time to read it and you guys had a conversation about it, you would get a certain amount of points. Or figure out where every first year is located right now in the world. Things that would encourage people to reach out to each other and find out how they're doing.

Another thing we're organizing is a **buddy system** for our first years. We're forming small groups of about four first years and then one or two second years who are essentially mentors and in charge of getting the group together every month or so for an hour to just chat. We're really hoping that people will find study partners and bond in a way that would have happened naturally if we were all physically in the same location.

Q. Have you had any trouble keeping people engaged despite these virtual events?

Dan: I would say definitely. Some people enjoy being in a Zoom meeting or breakout room with new people, but plenty of people in our department don't have a desire to do that. Our approach has been to try to create events that are welcoming, and we try to highlight the importance of networking and getting to know your fellow students.

Leann: A big challenge in the pandemic is that it's very hard to have variety when your only way of connecting with people is over Zoom, which is why we've been focusing on different types of events, like events with different numbers of people, activity-based things, or maybe tasks where instead of calling someone over the phone, you can just text them.



Group picture from a virtual tournament at the beginning of the fall semester. The two-week long event included individual and team challenges to help students meet and reconnect.

Q. Has it been challenging to navigate newly instituted COVID policies?

Dan: A big challenge has been figuring out funding. There was a lot of uncertainty about how to justify funding or manage reimbursements for remote events, and early on, we did not know whether we would be on campus in the fall and if we could plan in-person events.

Leann: Right, a major challenge we faced in the spring was planning long term. For example, we had to reserve our fall retreat location in February, and there were a lot of contract negotiations in the spring and summer as we were figuring out plans for the fall. But in July or August, the hammer basically came down that we're not going to be in-person, and things became a lot easier to plan.

Q. Have you made any changes that you hope future officers will keep once in-person activities resume?

Léonard: I think the buddy program at the beginning of the year since it helps first years make connections earlier in the semester.

Dan: And I like the idea of continuing Zoom calls in the summer, when you have students doing internships around the world, and being able to make sure that they're included in events. In the past, I think all of the summer events were in-person events.

Leann: I agree that Zoom can enhance some interactions, so I'm excited to see how the balance will be struck between the accessibility of remote events and the opportunity to meet in-person when we have that option.

Q. Any final thoughts that you would like to share with other student chapters?

Léonard: Take advantage of the remote connection. People across the world can access Zoom, and especially with the breakout rooms, it's easier to meet and interact with different people. Also, keeping the sense of community is important whether we are remote or on campus. It feels good to see people happy to reconnect after maybe they felt alone in the first few months of the pandemic. So don't abandon the community, and always try to reach out!

Note: Interview has been edited for clarity and length.

The Consortium for Mathematics and Its Applications Contests Information

The Consortium for Mathematics and Its Applications (COMAP) sponsors and administers a number of mathematical modeling contests open to college and high school students. Here are some information about this year's contests!

Mathematical Contest in Modelling (MCM) and Interdisciplinary Contest in Modelling (ICM)

COMAP'S Mathematical Contest in Modeling (MCM) is an international contest open to undergraduate students of all disciplines. The contest provides students the opportunity to engage in and improve their math modeling, problem solving, and writing skills. During the contest student teams build and analyze a model to address a problem, and then write a paper to showcase their work. In 2020, students formed over 13,700 teams to address one of three open-ended problems (A-Continuous, B-Discrete, C-Data Insights). The *Interdisciplinary Contest in Modeling (ICM)* runs parallel to the MCM with the same requirements. In 2020, students formed over 7200 teams to address one of three open-ended problems (D-Operations Research/Network Science, E-Environmental Science, F-Policy). Each team can have up to three students, and there is no limit on the number of teams a school can register for the contest. Scholarship prizes are awarded to top teams.

NEW for 2021: Team members may work virtually! Let our contests be part of your in-person, hybrid, or virtual classroom. Registration required by **Thurs. Feb. 4, 2021**. Follow us on Twitter @COMAPMath.

Contest Flier and Registration: https://www.comap.com/undergraduate/contests/

High School Mathematical Contest in Modeling (HiMCM)

COMAP's High School Mathematical Contest in Modeling (HiMCM) was held on November 4-17, 2020! HiMCM is an international contest designed to provide students with the opportunity to work as team members to engage in and improve their modeling, problem solving, and writing skills. Teams from your school apply mathematics to model and develop a solution to a real-world problem. Each team can have up to four students from the same school, and there is no limit on the number of teams a school can register for the contest. See www.himcmcontest.com Follow us on Twitter @COMAPMath for up-to-date contest information.

For more information and to view past problems and results visit: https://www.comap.com/highschool/contests/himcm/about.html







Declining College Enrollments: A System Dynamics Approach

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Through the 20th century, a university education was lauded as the pathway for success in adulthood for American students. However, in the past decade this view has shifted. College enrollment peaked in 2011, and has since been in decline most years for all but fifteen states, and even there the increases weren't more than 2% in 2019; in contrast, the states with declines experienced drops of 4% or more (Nietzel, 2019).

In the United States, a shrinking pool of college-bound high school graduates - a trend related to a stronger economy, lower birth rates in the last generation, and lower state contribution to education - endangers the vitality of the higher education landscape (Nadworny, 2019). In their recent publication, Pavlov & Katsamakas (2020) of Worcester Polytechnic Institute in Massachusetts and Fordham University in New York investigated the effects of college-level responses to these declining enrollments.

Drawing on system theory, Pavlov & Katsamakas (2020) framed the collegiate ecosystem as a system dynamics computational model involving the four interconnected sectors of Students, Faculty, Facilities, and Financials. The causal structure of the model is drawn below, where the elements in squares are the stocks and the other elements are the influencing variables.

The directed arrows of this model indicate the positive or negative impact of a cause X on an effect Y. For example, an increase in Students would increase Facilities shortage - that is, there would be an even greater shortage - while an increase in Facilities would decrease Facilities shortage.

Simulated scenario analysis measures the impact, based on the above causality understanding, on the student body, faculty load, net revenue, endowment, and debt of three strategies:

- **The "do nothing" strategy**, the base case, wherein the college "does not actively mitigate the declining applications"
- **The cost strategy**, wherein the college reduces faculty to offset revenue losses from lower enrollment
- **The revenue strategy**, wherein the college develops campus facilities, such as dorms, to attract students and thus increase revenue

Using the enrollment drop for Massachusetts of 15%, Pavlov & Katsamakas (2020) suppose receipt of 6,500 applications to a generic college in 2010 and a decline starting in 2015 and running to 2025, at which point the college expects only 5,525 applications per year.

As expected, the "do nothing" strategy has adverse effects on all but faculty load. As applications decline, student enrollment declines, so the college has less revenue from tuition, board, and other mandatory university costs that provide the majority of funding. The causal structure indicates this: Student enrollment is proportional to revenue (increase desired) and to faculty load (increase not desired). Therefore, declining enrollment harms revenue but helps faculty load. Moreover, expenditures per student increase as the university must spread fixed expenses, such as facilities and faculty, over fewer students.

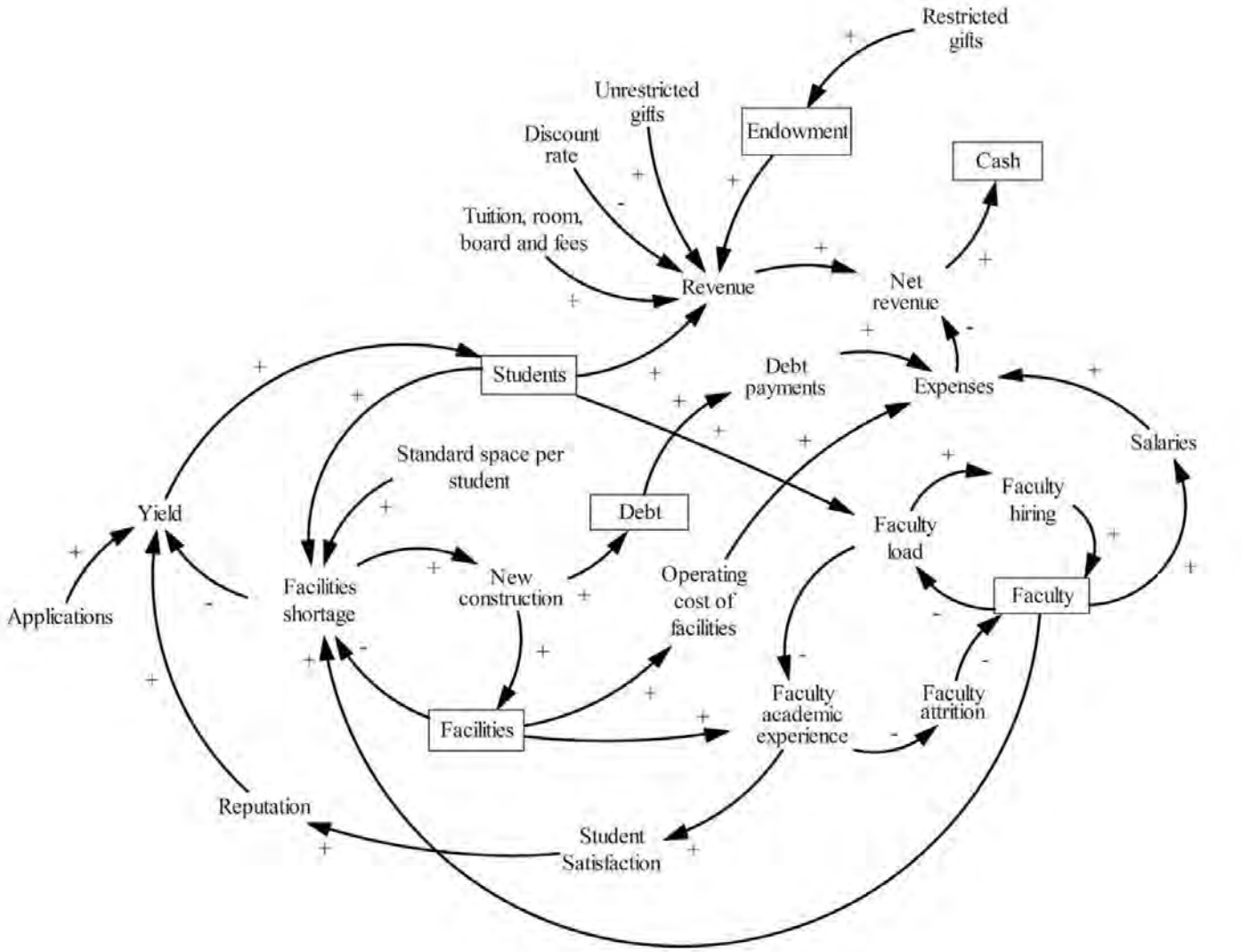


Figure 1: Causal structure of the college model (Adapted from Pavlov & Katsamakas, 2020)

For a few years, the simulation predicts that the revenue, lesser though it is, will be sufficient to cover expenses. Come 2018, the university must draw from their endowment to stay out of the red. Endowments, often employed during emergencies, are fit for the task of bridging the revenue-expense gap, but only for so long. Within five years, the university will fall back on loans, which add to operating expenses through interest payments. This, of course, won't support the university long-term since no new revenue is coming to pay off the new debt.

Without increasing tuition, the "do nothing" strategy is self-destructive. Instead, some universities try cutting costs. Simulations for the cost strategy have four levels: 100%. 75%, 50%, and 25% faculty retention. The first is basically the "do nothing" strategy. It maintains a zero net revenue for about 5 years before the college begins to experience negative net revenues from which it never recovers.

Under 75%, 50%, and 25% faculty retention, the college sees surpluses despite lower enrollment, ergo lower revenue, because the staff reduction provides sufficient expenditure cuts for a few years. The causal structure models this in the proportionality between faculty hiring, salaries, and expenses. Cutting faculty eliminates salaries needing to be paid, so the university can spend less on instruction.

Eventually, net revenue declines whether 25% or 100% of the faculty positions are filled, but the cost strategy creates a problem particularly when too low a level of faculty retention is attempted. The more faculty that the university lets go, the greater the instruction pressure is on the remainder; fewer faculty translates to greater faculty load. Consequently, faculty academic experience declines, as foreseen by the inverse proportionality between faculty load and faculty academic experience. The ultimate impact on student enrollment is lower student satisfaction, worsened reputation, and declining application yield.

Altogether, the cost strategy entails numerous unintended consequences that make the university less attractive to students, which cuts student application and enrollment even further.

The most common strategy to combat declining student enrollment is to compete with other colleges over facility quality. To

determine the impact of this revenue strategy on student enrollment, the simulation assumes a per student classroom space expansion of 10% and analyzed five scenarios: 1) the do nothing strategy, as a control, 2) no change in enrollment despite expansion, 3) 5% increase in enrollment in response to the expansion, 4) 10% increase, and 5) 20% increase.

That the expansions will entail significant construction costs is a given; the chart shows that new constructions will demand the taking on of debt that contributes to operational expenses. The question is, will the revenue from increased student enrollment be enough to offset these costs? The simulations suggest not.

From the causal model we see that facility growth benefits, directly or indirectly, faculty academic experience, student satisfaction, school reputation, and student enrollment. However, as the on-campus growth attracts more students and the university spends to maintain the per student classroom expansion of 10%, by 2023, in all four of the non-base scenarios, the debt-inflated expenses overwhelm whatever revenue the university gains from increased enrollment. It stumbles into negative net revenue again.

From a competition standpoint, the university that pursues a revenue strategy will have a significant advantage over a university that does not, but as with the cost strategy there are unintended consequences. In this case, operating costs, and expenditures per student, grow beyond what the set tuition of a slimmer student body can fund. The "solution" would be to adjust tuition accordingly, but experience tells us that a bigger price tag will only deter more students from enrolling.

Barring regular tuition hikes, in all these strategies the college will, in the long-term, run with an operational deficit. This does not bode well for colleges that must keep tuition affordable to attract a shrinking pool of economics-conscious college applicants while also generating enough revenue to maintain and develop academic and campus quality.

The character of this generation's high school graduates is changing. The opportunities afforded by a changing economy and society have enabled many to circumvent the college route long-travelled before, pursuing families and careers without diplomas.

The simulations from Pavlov Katsamakas (2020) suggest that colleges, to survive declining enrollments and attract students back to their campuses, must do more than tweak the number of professors, the size of classrooms, or the quality of the facilities. The truth of the matter is that colleges are businesses, and businesses must adapt to satisfy the changing preferences of their target audience (Kasperkevic, 2014). It may be that what rescues higher education is a complete re-engineering of college as it is now.

What would you, as a student or educator, recommend that colleges implement or transform?

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Cleaner and Greener Urban Logistics: The Future is Electric

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The pandemic is offering planners and politicians an opportunity to rethink city logistics. Before the pandemic, there had been growing public concern about urban air quality and the contribution made to emissions (and noise) by trucks used in city logistics. This spans trucks used for deliveries to retail outlets, offices, and homes as well as trucks used in the construction industry and refuse collection. The culprit is generally seen to be the diesel engine, because of the greenhouse gases (GHG), nitrogen oxide (NOx), and particulates they emit, along with the noise they produce.

Progress is being made in designing cleaner diesel engines and the Euro standards are providing a lever to help phase out the use of older, more polluting diesel engines in urban areas. The Euro 1 standard of 1992 limited NOx emissions to 9 grams per kilowatt-hour (kWh) and particulates to 0.4 grams per kWh. By 2014, the Euro 6 standard limited NOx emissions to 2 grams per kWh and particulates to 0.02 grams per kWh (National Infrastructure Commission, 2019). In the UK, London introduced a Low Emission Zone in 2008 followed by an Ultra Low Emission Zone (ULEZ) in 2019. All vehicles entering the ULEZ not meeting the Euro 6 emissions standard pay a penalty of GBP100 per day for trucks and GBP12.50 per day for vans and cars.

While cleaner diesel engines clearly help, electric vehicles are seen as the ultimate solution. Electric vehicles have many advantages for city logistics. Firstly, they produce zero emissions at the point of use. Secondly, they are relatively quiet. Thirdly, small electric vans can be operated safely and unobtrusively in shared and pedestrianized spaces.

The use of electric vehicles in city logistics is by no means new. In 1930 the first electric milk float (a small open-sided electric van) was introduced and for 70 years delivered milk in UK cities. Due to changes in cost, diesel vehicles replaced the electric milk floats in 2000. However, StreetScooters (electric vans produced for DHL by Ford of Europe) entered into service in 2016, reflecting improvements in electric vehicles, in particular, battery technology (see https://www.milkandmore.co.uk/electric-pioneers, accessed 6/4/20).

One problem with the use of trucks in city centers is the difficulty in finding free parking spaces or loading zones that are close to the cargo destination. In this respect, cargo bikes are attractive as they can use bike lanes, enter pedestrianized areas and, if parked on street, need less space. A wide range of cargo bikes are available. The Armadillo electric cargo bike from Velove, Sweden, together with the 'city container' (sometimes referred to as the 'meter cube box') is proving to be a popular alternative in Europe (Erlandsson, 2019).

In some cities, specialized electric vehicles are allowed to operate in pedestrianized areas, which are otherwise closed to vans and trucks. For example, the Cargohopper found in Utrecht, Holland, consists of an electric tractor pulling a series of trailers and is designed for narrow streets and cobbled surfaces (Eltis, 2015).

Many vehicle manufacturers are now active in the electric vehicle market offering a range of vehicle types and sizes, attracted by improvements in battery technology (McKinsey, 2017). Since 1990, battery energy density measured in kWh per kg has more than doubled while the cost measured in US$ per kWh has fallen by more than factor six. Energy density may continue to improve linearly, but cost reductions seem to be leveling out (National Infrastructure Commission, 2019).

Electric propulsion is not only attractive for small goods vehicles. Volvo Trucks has been developing electric trucks with a payload of 12.4 tonnes (Pink, 2019). These vehicles, which are particularly suited to the construction industry and waste collection, are nearly silent with near-zero emissions at the point of use. Battery capacity can be chosen to suit the application and charging opportunities.

One issue with electric vans is their limited range and the time it takes to recharge their batteries. To increase the range of electric vehicles, they can be equipped with hydrogen tanks and fuel cells to convert the hydrogen to electricity. In this way, the range of electric vehicles can be at least doubled and refueling can be performed quickly. However, hydrogen as a fuel for vehicles is not energy efficient. Where hydrogen is generated by electrolysis, the energy consumed by electrolysis, compression of the hydrogen, the fuel cell, the inverter, and the electric motor is such that only about a quarter is left for transporting cargo. Batteries are much more energy efficient. The energy consumed by the charger, the inverter, and the motor leaves about three quarters for transporting cargo. There are technologies other than electrolysis for producing hydrogen, but these are neither energy-efficient nor green as they generate GHG emissions (Baxter, 2020).

In summary, the pandemic is offering an opportunity to change the way city logistics is delivered. Electric vehicles offer a cleaner and greener solution.

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An Interview with Mint Pharmaceuticals on Supply Chain Strategies during COVID-19



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The COVID-19 pandemic has posed new challenges across diverse industries. In this article we highlight the challenges facing the supply chain of a leading pharmaceutical company. Mint Pharmaceuticals is a Canadian pharmaceutical company located in Mississauga, Ontario that delivers high quality and affordable generic pharmaceuticals and healthcare solutions to the Canadian market. Mayank Batra, the director of supply chain at Mint Pharmaceuticals, has experience conceptualizing, implementing, and anchoring initiatives to improve business outcomes with exposure to major international markets. Mr. Batra spoke with OR/MS Tomorrow to share his insights on the challenges and supply chain recovery strategies during the pandemic.



Mr. Mayank Batra
Director of Supply Chain
Mint Pharmaceuticals

Q: How has COVID-19 impacted your company?

The COVID-19 pandemic is a global crisis with unprecedented impact on supply chains all over the world. It has created unique opportunities and challenges for our organization. Mint Pharmaceuticals has helped avert 15 national drug shortages on 10 different molecules since 2014.

Sales of hydroxychloroquine doubled in Canada during March-April as various preliminary reports touted it as an effective treatment for COVID-19. This anti-malaria drug is mainly prescribed to treat auto-immune diseases such as lupus or rheumatoid arthritis. We provided a unique solution by collaborating with the Government of Canada for supplying and storing 7.5 million doses of this product, which has helped secure safety stocks for Canadians in need. Similarly, we have contributed immensely by creating sufficient supply and unique distribution solutions for all our other products, managing the ups and downs of the demand curve during the pandemic.

There have been disruptions at every node and touchpoint of our supply chain. Starting from running operations of our manufacturing plants, availability of raw materials (RM), increased RM prices, caused local shutdowns, disrupted manufacturing schedules, reduced air shipment capacities, increased freight costs, curtailed workforce availability and so on. We have been challenged on all the fronts in the supply chain. However, so far we have been able to ensure sufficient supply for all products,

navigating through all these challenges.

Q: What are the strategies that your organization has taken to tackle this situation?

To deal with the present situation, we have done intense coordination and collaboration across the front end and back end of our supply chain. We have worked very closely with our customers, plants, vendors, suppliers of our vendors, logistics service providers, transportation companies, and so on.

For example, in one case we went beyond pre-pay and arranged RM for our supplier so that she could supply on time to meet our increased requirements. In another case, we loosened the contract of one supplier so that he could take on increased plant sanitation expenses. There are so many examples of our collaboration with stakeholders in navigating these tough times. In my opinion, when the whole ecosystem must win, the individual wins are less important.

Q: What are some of the planning challenges your team faces?

Demand forecasting has been a significant challenge for planners. Regulations on prescriptions have changed twice this year which has significantly impacted demand and order patterns. Competitors are also facing significant supply challenges which have led to a disruption of their products and contributed to exponential surge in demand for our portfolio. Supply planners have faced huge issues around supply timelines because of disrupted manufacturing schedules and raw material and workforce availability. Planners are continuously collaborating with suppliers on innovative solutions to clear backorders and maintain safety stocks.

Q: How have you enhanced your supply chain resilience amidst COVID lockdowns?

We are working towards quick turnarounds on contracts to create alternate vendors and logistics service providers. We have identified suppliers and materials that pose high levels of supply chain risk in both our direct supplier base and the extended back-end supply network and have started working on alternate supply sources and solutions. We have started looking for logistics solutions that help us track our shipments and alarm us in case of possible disruptions and delays. We are revisiting inventory guidelines for our portfolio to create the right balance of working capital and availability. With consideration towards manufacturing plant constraints, we are conducting multiple scenario planning exercises, mapping different demand, supply and commercial levers to prepare ourselves for different cases and create resilience in our supply chain.

Q: How have COVID lockdowns and the shift to a work-from-home model impacted the workforce within your company's supply chain?

Lockdown has impacted the supply chain workforce significantly. Our manufacturing operations have faced many challenges to maintain an adequate workforce to run plants and distribution centers smoothly. This challenge has impacted supply planning, logistics planning, and allocation activities. Lockdown has also shifted customer behavior and buying patterns drastically. We responded by increasing scenario planning activities, which has become an important part of the sales and operations planning (S&OP) process. Work-from-home has also brought more focus on the ongoing digital transformation of supply chain management (SCM) processes and systems so that we are prepared to provide infrastructure for collaboration and smooth SCM operations if required to work remotely in future, too.

Q: What skill sets would be useful for budding supply chain managers in the post-COVID era?

Looking at every challenge from the lens of how an action will impact the whole system is very important. Network collaboration, scenario planning, working capital impact analysis, periodic inventory policy reviews, S&OP, alternate suppliers mapping, and many other tools equip supply chain managers to bring resilience to the supply chain. There is a fine balance between service level, working capital, and availability. With the flexibility to review and rebalance, SCM managers can better navigate these situations.



Simulation-based Optimization: Stimulate to Test Potential Scenarios and Optimize for Best Performance

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Simulation is a primary tool to model complex systems, especially when the typical analytical techniques are not available due to modeling assumption complexity. Simulation helps decision-makers to define various scenarios to test the influence of alternative pre-specified decisions on system performance. Because simulation cannot find and suggest optimal decisions for a complex system, it is integrated with optimization techniques such as exact, heuristic, and metaheuristic methods. This combination, a developing area of research in operations research, is called "simulation-based optimization" or "simulation-optimization". Decision-makers are facing unprecedented challenges with increasing complexity and faster innovation cycles in the industry. On the other hand, advanced simulation techniques and high computational power have expanded simulation-based optimization methodologies as a powerful tool. Simulation-based optimization techniques have been utilized to optimize environmental systems, communication networks, complex supply chain networks, healthcare systems, and energy systems. The first step in a simulation-based optimization algorithm includes system analysis, parameter setting, and data collection. The second step consists of selecting and applying a suitable optimization algorithm to find the optimal decisions.

Three areas in simulation-based optimization have demonstrated vast developments and still need improvement. The first development uses dynamic simulation and optimization techniques to run real-world case studies. In dynamic simulation-based optimization, a varying behavior of system parameters for different time or scenarios is defined. Then, in the optimization section, time-dependent decision variables will be added to the model with analytical dynamics. Advancement in modeling and high-speed computational power has enabled engineering, and business research to involve dynamic simulation optimization in various operation research and management science topics such as supply chain, logistics, healthcare system, and transportation [1,3]. Dynamic simulation-based optimization has been addressed on large scale urban transportation and supply networks with time-dependent continuous decision variables to provide more practical scenarios that require high accuracy of solution [3]. For instance, a decision support system has been developed by performing a dynamic simulation to model water distribution system contamination and dynamic optimization to track time-varying optimal response protocols [12]. The dynamic simulation has been utilized to develop model complexity and enriches the optimization solution's accuracy by providing time-dependent variables. In healthcare research, dynamic simulation-based optimization has been used to optimize staff reallocation at an emergency medical center with arbitrary structures located in Austria. The results demonstrate a 7% system performance improvement [13].

Another enhancement is applying metaheuristic optimization algorithms. Various metaheuristics such as local search, random search, and simulated annealing, have been deployed to solve large-scale dynamic problems and find the local or near-global optimum solution within a reasonable time. Metaheuristics are also required when decision-makers or managers are willing to run simulations to optimize a complex multi-objective system. These objectives usually involve trade offs (e.g., increase service level by reducing cost), and their solution is not unique. For instance, multi-objective simulation-based

optimization with an efficient heuristic algorithm has been employed in a residential area in the Italian city of Naples. The results show up to 56% cost reduction and around 20% energy transition improvement [4]. In a real case study, the decision tree and tabu search have been proposed for dispatching rules for shopping by Shahzad and Mebarki (2016). They represent metamodels that can generate similar results to the real simulation within a very reasonable time [5]. Integrating metaheuristic algorithms with simulation-based optimization has also been proposed for scheduling and production problems because decision-makers are dealing with two opposite objectives, which reduce cost and increase outputs [16]. Therefore, this integration can turn into a practical tool for managers and decision-makers.

The final development is employing machine learning to enrich simulation-optimization related techniques. Operation researchers' attention has been driven to employing modern methodologies, such as data mining, artificial intelligence, and machine learning, that can offer more tactical techniques to tackle complexity and challenges. A combination of Artificial Intelligence / Machine Learning (AI/ML), simulation and optimization helps industries enhance understanding of problems and make smarter and faster decisions. Especially, using AI/ML is a critical opportunity in simulation-based optimization to create metamodels that can deliver valuable insights into large scale and complex systems, such as using artificial intelligence in a material handling system [6]. Growing trends in Industry 4.0 make machine learning an appropriate tool to solve various manufacturing prediction problems [7]. The world's most innovative companies and industrial consultants bring up AI/ML to find the best optimal solutions for complex systems [8,9]. The most widely-known simulation-based optimization commercial tools, such as AnyLogic, are spearheading these changes and creating a new generation of simulation models by adding machine learning technology [10]. Many optimal models are computationally expensive due to system complexity, while the current AI/ML can solve such a problem efficiently to achieve better results. For instance, IBM combines the AI/ML with simulation-based optimization techniques and a new platform to overcome the lack of transaction and inventory visibility, which creates a lot of challenges and costs for industries [14].

To conclude, future simulation-based optimization studies should endeavor to investigate these developments and optional improvements. Simulation-based optimization is now recognized as a powerful tool for academics and industry to obtain the best solutions to challenging problems. Therefore, applying machine learning methods and heuristic algorithms to optimize solutions and improving the simulation phase by introducing dynamic parameters is particularly critical.



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Algorithms that Changed the World

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With the advancement of technology and computing capabilities, computer science and optimization have come a long way in solving complex, large-scale real-world problems. How are these challenging problems solved? Algorithms. Algorithms work hard to systematically search the solution space for the desired goal. Many different algorithms could be used to search the solution space, but it is critical we use the 'best' algorithm in this fast-paced, outcome-based world. Deciding on the 'best' algorithm depends on key performance indicators (KPI) like speed, efficiency, run time, and space complexity. KPI's change based on the type of problem and the objective of the algorithm. Some methods demand a quick solution with reasonable quality, while others search for optimal solutions like a global maximum or minimum.

This article was inspired by an analytics webinar series conducted by Opex Analytics titled "Five algorithms that changed the world", presented by Dr. Larry Snyder. I borrowed excerpts from that webinar and added my own flavor to present the top five algorithms that have changed the world of problem-solving, optimization, and operations research.

Our first algorithm is **Gradient Descent (GD)**, proposed by Cauchy in the early 1850s to find the minimum of any function. Consider a convex function shaped like a bowl (Figure 2). If the objective is to minimize the convex function, then the GD algorithm guarantees a global optimum. The idea is to start the search direction from the top of the surface and reach the feasible bowl-shaped region's lowest point. The pseudo-code of GD is shown below in Algorithm 1. GD starts with an initial guess of the minimum point, X_0. The traversing direction (slope) is given by the negative gradient ($\nabla f(X_n)$) while the step length, or the incremental distance which moves the minimum point from X_0 to X_1, is determined by the learning rate α_n. This process of deciding on a direction to move and taking a step in that direction continues until the gradient becomes zero or the algorithm reaches the desired epsilon (10^{-8}) change in the value of the function value at subsequent iterations.

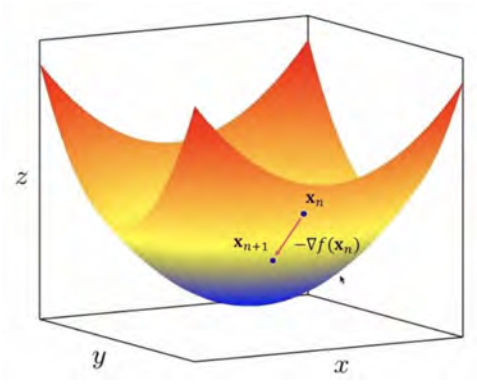


Figure 2: Gradient Descent algorithm

Many machine learning models utilize the GD algorithm to select and tune parameters. For instance, regression models use GD to find the best fit intercept and slope for each predictor variable. Similarly, the back-propagation algorithm uses GD in artificial neural networks and deep learning models. Updates to the GD algorithm have adapted it to today's complex problems like learning from big data and fast computation requirements. Big data demands mini-batch gradient descent, a version of GD which uses a sample batch of data as the starting points. This mini-batch GD uses a predefined set of batches in each epoch, which helps the back-propagation algorithm converge to find the best weights and reach the best possible minimum value. Stochastic gradient descent (SGD) is used in fast computation requirements. The training set is randomized and in every iteration only one training data point is used to find the gradient of the cost function. Thus, SGD might not achieve accuracy but wanders around the region close to the global minimum.

Algorithm 1 Gradient Descent Algorithm [4]

1: Choose an initial guess X_0
2: **repeat** ▷ Main loop
3: new point = current point - step size * gradient direction
4: $i \leftarrow i + 1$
5: **until** X_n and X_{n+1} are sufficiently close

Second, we move on to the random number generator proposed by Lehmer in 1951 and known as **Linear Congruential Generator (LCG)**. LCG is used to generate independent and uniformly distributed random numbers in a long sequence without repetition. The pseudo algorithm is shown below in the Algorithm 2. The algorithm works with the residues of successive powers of the random number generated in each iteration with good randomness properties. This algorithm requires only a few initial conditions to decide the parameters a, c, and m.

Algorithm 2 Mixed Linear Congruential Generator Algorithm [1]

1: Choose an initial number (seed) X_0
2: Initialize a, c and m ▷ m=large number, c=nonzero
3: **repeat** ▷ Main loop
4: $X_{n+1} \leftarrow (aX_n + c)$ mod m
5: **until** done

LCG is faster than other random number generators and requires less memory to store state space. As such, LCG is often used in cryptography to secure pseudo-random number generators. The fields of computing and random processes use advanced versions of LCG, such as the Mersenne twister (M_{31}). This version of the LCG, developed by Matsumoto and Nishimura in 1997, generates one of the most extended random number sequences, ($2^{19937} - 1$) numbers before repeating. Many machine learning applications use the latest versions of LCG to predict the future state of random processes in the technology

space and genetic engineering and biomedical engineering.

Third, we discuss one of the most important contributions in mathematical optimization and computer programming: the recursive algorithm known as **Dynamic Programming (DP)**, proposed by Richard Bellman in the late 1950s. This algorithm works to decompose a master problem into smaller, easier-to-solve sub-problems, which are sequentially solved until it works back to the master problem's solution. The sub-problems are nested recursively to find the solutions which give optimal substructure to the master problem. Thus, the sub-problems' solutions compose the solution to the master problem. Some applications of this classic sequential decision-making algorithm include inventory management, database access, flight control, routing, and RNA structure prediction. For example, the Bellman equation, used for a general recursive minimization problems, is shown in Equation 1.

$$\Theta_t(X) = \min_{a \in A(s)} \left\{ C(X,a) + \gamma^t \, \mathbb{E}\left[\Theta_{t+1}(X'/X,a)\right] \right\} \quad (1)$$

where C is the immediate reward or cost for state-action pair (X, a), $\Theta_t(X)$ is the optimal expected cost with the starting state X and calculated as the sum of the immediate cost for (X, a) and the future expected cost for all X' with the given (X, a) state. γ is the discounting factor such that the value of \$1 in period $t+1$ is equal to γ in period t.

There are many DP extensions in optimization applications; value iterations used in the Markov Decision processes, Hamilton Jacobi Bellman equation for solving partial differential equations, and optimal control theory. In supply chain theory, DP has been applied in both the Bellman-Ford algorithm for finding the shortest distance between two nodes and in backward induction for finite horizon discrete multi-stage or multi-period problems. Many stochastic optimization problems demand DP as a benchmark solution method because DP assumes full knowledge of the random variable's underlying distributions. For instance, Clark and Scarf used DP to prove the optimality of base-stock policies for serial supply chain systems, which led to significant breakthroughs in finding the optimal global solutions to various supply chain topologies. The stochastic version of DP gives an exact optimum for stochastic problems, unlike stochastic programming, chance-constrained linear programs, and robust optimization techniques. However, due to the curse of dimensionality, if the number of state spaces grows exponentially then DP fails to solve the large problem in reasonable run time. Hence, faster algorithms imitating the DP concept have been developed. Computer scientists use algorithms like reinforcement learning, while operations researchers use approximate dynamic programming (ADP), an algorithm widely used in stochastic optimization, deep reinforcement learning, and artificial intelligence applications.

Fourth in our list is the **Fast Fourier Transform (FFT)**. Tukey and Cooley proposed FFT in 1965 as an advancement of Joseph Fourier's Fourier Transform (FT) developed in the early 1800s. In essence, FT is used to reconstruct the sine waves from a combined wave format. Joseph Fourier showed that some functions could be expressed as an infinite sum of harmonics. Since the Fourier series represents signals in terms of sines and cosines based on the frequency and phase-type, the oscillating wave structure can be decomposed to select the signals of choice. In other words, any signal can be decomposed into sine waves based on their frequency (pitch) and amplitude (volume). The basic FT equation for function f(x) is given here

$$\hat{f}(\psi) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i x \psi} dx \quad (2)$$

where $e^{2\pi ix} = \cos(2\pi x) + i\sin(2\pi x)$ is based on Euler's formula. Unfortunately, FT fails to process signals in a reasonable time. For instance, if a signal has 1,000,000 data points, FT takes 20 hours, not practically feasible for real-world applications. In order to speed up computation time, John Tukey and James Cooley invented a faster version of FT in order to detect nuclear tests by the USSR during the Cold War. If a signal has 1,000,000 data points, FFT solves it in 0.05 seconds, an impressive improvement from 20 hours. The pseudo-code for FFT is shown below in Algorithm 3. Today, FFTs are widely used in engineering, music, science, and mathematics and was included in 'Top 10 Algorithms of 20th Century' by the IEEE magazine Computing in Science & Engineering.

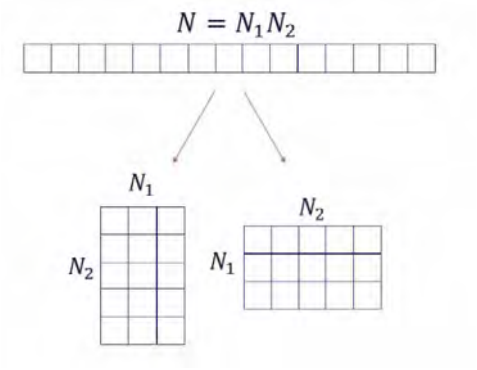


Figure 3: FFT algorithm

To illustrate FFT algorithm, the discrete version of the FFT is added below. The discrete Fourier transform (DFT) of *f* at frequency *k* is given by

$$\hat{f}(k) = \sum_{j=0}^{N-1} f(j) e^{2\pi i j \frac{k}{N}} \quad (3)$$

where $i = \sqrt{-1}$. The basic idea is to divide and conquer recursively by breaking down the DFT into smaller DFT's for any composite number N=pq. The smaller DFT's are multiplied by twiddle factors (complex roots of unity). If N has prime factorization $N = p_1, p_2 ... p_m$, then FFT requires only $N * \sum_i p_i$ operations.

Algorithm 3 Discrete Fast Fourier Transform [2]

1: Choose N=pq ▷ N is a composite number
2: Initialize variables N_1, N_2 ▷ as shown in Figure 3
3: $\hat{f}(k_1, k_2)$ is calculated using Equation 3
4: **repeat** ▷ Main loop
5: $\hat{f}(k)$ is computed in two stages
6: perform N_1 FTs of size N_2
7: multiply FTs using complex numbers ▷ twiddle factors
8: perform N_2 FTs of size N_1
9: **until** done
10: **return** $\hat{f}(k) \quad \forall k$

The final algorithm topping our list has revolutionized operations research: the **Simplex Algorithm** developed by George B. Dantzig during World War II. Formulating linear inequalities was first presented by Motzkin in his Ph.D. thesis in 1936, later by Kantorovich in 1939 in economic analysis, and finally by Hitchcock in 1941. However, Dantzig was the first person to collectively solve a linear program (LP) with linear constraints and a linear objective function [3]. Both Koopman and Dantzig formulated the initial LP problem as a maximization objective and named the algorithm as "climbing up the bean pole" [3]. Initially, the US military used the Simplex Algorithm for planning and transportation problems. However, now the algorithm is used in the vast majority of optimization problems, including airline scheduling, production planning, vehicle routing, and supply chain network design.

Linear inequalities are defined as half-spaces of the hyperplanes, thus, form a convex polyhedron (Figure 4). This way, the optimal solution will be a corner point or one of the extreme points of the polyhedron. Therefore, an effective algorithm is to quickly traverse extreme points in the polyhedral hyperspace to satisfy the objective type. For two variables, the LP problem can be easily solved using a graphical method.

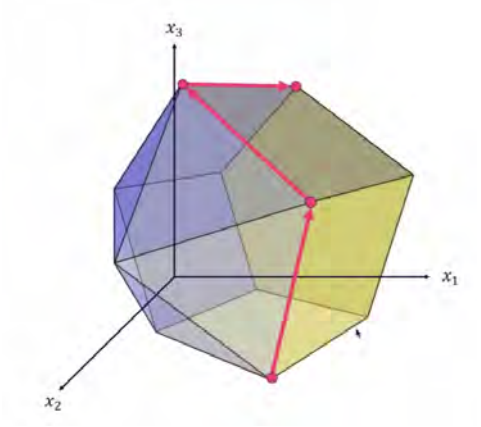


Figure 4: Corner points of the polyhedron

The linear programming objective is to find $z = min \quad c^T x$ such that $\mathbf{A}x = b$, for all $x \geq 0$, where $x = (x_1, ...x_n)$, **A** is an m x n matrix and *b* and *c* are column vectors. The pseudo code for the simplex algorithm is shown in Algorithm 4.

Algorithm 4 Simplex Algorithm [4]

```
Initialize A, c, b        ▷ A= m x n matrix, c is a row vector, b is column vector
Choose an initial solution vertex p
if there is a better neighboring solution        ▷ Main loop for each equation through p do
    end
    Relax equation to get a better performing edge
Update cost vector, objective, and the basic solution if edge improves objective then
    end
    replace p by neighbouring vertex
go to 4 if no improvement then
    end
    return p
```

Several extensions of the simplex solution method, such as Wolfe decomposition and Benders decomposition, have been developed to reduce the run time and solve large scale LP problems. High performing cutting plane algorithms and branch & bound algorithms were developed to find integer solutions, essential for real-life applications. Solving integer programs requires a fast computing LP algorithm. In 1972, Klee and Minty presented an LP problem using a corner point search to evaluate all extreme points and proved the Simplex algorithm has a worst-case exponential runtime. Several authors tried developing algorithms to solve LP problems in polynomial run time. Leonid Khachiyan theoretically proved that the proposed Ellipsoidal method is a polynomial-time algorithm. At the same time, Karmarkar's breakthrough was an interior point algorithm used to solve large LP's in polynomial run time. As a result of all these improvements, today, complex mixed-integer linear programs (MIP) with millions of variables and constraints are solved using commercial software in reasonable run times. For example, IBM ILOG Cplex shortened its runtime by a factor of 30,000 from 1991 to 2007. In addition, Gurobi claims that their solver is the world's fastest for solving LP and MIP problems.

The discovery and improvement of algorithms is a continuous process. Several commercial software companies are pushing their R&D scientists to implement advanced machine learning techniques like neural networks, deep learning coupled with cloud computing, and parallel computing approaches in advanced hardware and computer architecture. We cannot wait to see what algorithms are being created by such researchers to change the world. In short, we can expect some breakthrough algorithms are coming in the future, which will solve the most complicated and complex problems in shorter run times.

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Everything Within 20 Minutes: Travel Infrastructure & the 20-Minute Neighborhood

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The 20-minute neighborhood is an urban planning concept that has gained public policy attention in the last decade. The cities of Melbourne in Australia and Portland, Oregon in the United States have set multi-year action plans to transform most if not all of their neighborhoods to fit this model. In 2016 Detroit, Michigan proposed its own 20-minute neighborhood plan.

The idea is that every home will be within 20 minutes, by foot, bike, or public transport, of daily facilities and services like grocery stores, parks, and schools. The creators of Plan Melbourne, launched in 2017, anticipate that the 20-minute neighborhood will fulfill two of the United Nations' Sustainable Development Goals: 1) good health and well-being and 2) sustainable cities and communities (Victoria State Government, 2012).

Three pieces must come together to create a 20-minute neighborhood: residential density to accommodate local retail, good local transport, and an adequate supply of expected facilities and services (Stanley & Stanley, 2014). Summarized another way, a neighborhood must answer the three D's:

- Density: How many houses are there per acre?
- Distance: How far can people go in 20 minutes, and how?
- Destination: What is in that 20-minute radius?

Each of these goals has its difficulties. This article will focus on the second: the ability of a city to build travel infrastructure for public and active transport.

For Melbourne, Stanley & Hansen (2020) calculate that achieving the 20-minute neighborhood will require local public transport services to run every 20 minutes or from 5 am to 11 pm, with "a minimum of 55 services per stop per day per direction." In any urban planning scheme the various transportation modes must coordinate to provide a complete, quality system that brings citizens easily around the city. In a 20-minute neighborhood, the fine integration of this system is even more important. Moreover, to support more walking and cycling, city planners need to, among other measures, create distinct bike lanes on the road, widen footpaths, design bridges that accommodate vehicles and pedestrians, and make travel easier by adding appropriate light and shade along routes. The logistical demands of this model are considerable.

Stanley & Stanley (2014) identify local buses as the public transportation option best suited to meet the heavy, high-frequency travel demands of a 20-minute neighborhood, and echo the previous emphasis on trip frequency and duration, as well as speed of service, to make travel by bus convenient and attractive for passengers. According to Plan Melbourne 2017-2050,

the city's transport network will need to increase its services by over 80%, amounting to 10 million more trips per day, by 2050 to support this growth and integration (Wynne, 2017)! Stanley & Hansen (2020) estimate that increasing bus service to this scale would cost $250 million per year over sixteen years, or $4 billion total, which is a modest sum compared to Melbourne's $30-40 billion budgetary commitment to rail.

Planners often use heat maps of residential density, area walkability, access to mixed-use centers (MUCs), also called neighborhood activity centers (NACs), and other topographical features to judge where transportation services should expand and where they are achieving or have achieved the 20-minute neighborhood. Data on existing travel patterns and community input will further help in determining infrastructure needs (Wung, 2014). Melbourne's Principle Public Transport Network provides state and local governments and communities data of this ilk, outlining the presence of public transport services and candidates for future routes (Wynne, 2017).

A top priority is building a transportation network that grows 'without gaps or circuitous routing', connecting newer developments with older ones and promoting land use initiatives that accord with the 20-minute goals (Stanley & Stanley, 2014). Tempe, Arizona, provides a good example of a transportation environment supporting this accessibility: Tempe boasts an average commute time of 20 minutes, border-to-border light rail, and an extensive neighborhood circulator, or bus system that has enabled it to develop with less reliance on private automobiles (Graves, 2017; Silva, King & Lemar, 2019).

The previous discussion concerns public transport. The active transport aspect of infrastructure planning focuses on the bikeability and walkability of neighborhoods. One consideration for making a city more bikeable and walkable is plain practicality: In an interview, Mark Mitchell, the recent mayor of Tempe, AZ, noted that the desert climate of the state added shade availability to the list of needs presented to urban planners (Graves, 2017).

The suitability of a city to accommodate active transport, and the consequent evaluation of places in which a city can improve, may be assessed in a manner similar to Silva, King & Lemar (2019). They analyzed the performance of five network scenarios in relation to 12 non-work destinations and travel sheds and coverage at each destination. The scenarios were all-roads bicycle network, low-stress bicycle network, all-roads pedestrian network, sidewalk-only pedestrian network, and transit network. The metrics for network compliance to 20-minute city guidelines were the "number of residential units that could reach at least one point of the destination groups and the number of destinations that each parcel could reach" (Silva, King & Lemar, 2019). In Tempe, all networks except the sidewalk-only pedestrian network accommodated an average of over 75% of residential units per the 20-minute neighborhood goal. Heat maps further indicated the exact areas where city planners could channel more attention and investment to improve accessibility.

In a 2017 study in Melbourne, Gunn et al. employed a different technique to determine the walkability of NACs: cluster analysis. Using data for 534 NACs, including adult travel patterns and activity center data like supermarket availability, the researchers identified walkability cluster types, finding only 9% of NACs in Melbourne had high walkability, 50% had medium walkability, and about 41% had low walkability. Comparison of the sociodemographic profiles, community designs, movement network, and lot layout could inform policy decisions to increase walkability and travel patterns in medium and low walkability areas.

Though urban planners have developed better methods to realize these concepts in cities like Melbourne and Tempe, understandable skepticism about the viability and impact of 20-minute cities has been voiced. The editor of a Melbourne-based consultancy, for instance, questions whether these urban plans are more "good politics than good policy" or whether reduction of walking times will necessarily lead to reduction of car use (Davies, 2013).

Regardless, greater consciousness of sustainable transportation demands and growing appeal toward connected urban and suburban living will continue to place the 20-minute neighborhood on the policy and planning horizon of city design and network decision-makers.

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Optimization of Wind Farm Layout

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The University of Sydney



Wind energy is a vast potential source of renewable energy as wind supply is inexhaustible. Wind energy is generated using wind turbines. When the wind blows past a wind turbine, its blades capture the kinetic energy of the wind currents to spin an electric generator, which produces electricity.

For a given piece of land (wind farm), it is crucial to find the optimal positions of the wind turbines as the electricity power output of each turbine depends heavily on their locations and relative positioning with other turbines. Sub-optimal wind farm layout design often leads to lower net wind power yield and increased maintenance costs.

The process of determining the locations to maximized power production is called Wind Farm Layout Optimization (WFLO). While it may seem attractive to simply build a larger number of turbines in order to capture more kinetic energy from the wind current, densely packed turbines may lead to reduced energy production due to wake effects, an aerodynamic phenomenon that occurs between upwind and downwind turbines.



Figure 5: A wind farm layout optimization illustration

Modeling Wake effects

When the wind passes a wind turbine (denoted as Turbine 1), a part of the wind kinetic energy would be absorbed by Turbine 1 and transformed into electricity, leaving the wind velocity reduced in the downwind direction. The downwind turbine would produce less power than Turbine 1, and this phenomenon is called the wake effect.

WFLO aims to optimize the trade-off between energy generation and wake effects. Yet, a wind turbine can be affected by multiple wake effects generated by other turbines nearby in a wind farm. The resulting wake interference adds an extra layer of complexity to the optimization model. In 6, we provide an illustration of the multiple wake effects. We display a single wind wake effect on the upper panel and multiple wake effects on the bottom. The x- and y-axis are the standardized distances from the turbine blade center along and perpendicular to the wind direction, respectively. The color represents the rate of reduction of wind velocity. From the right panel, we can see that the multiple wake effects affect the wind velocity significantly and therefore must be taken into account in the WFLO problem formulation.

A wide range of wake modeling approaches has been developed to capture the wake effects, for instance, the Ainslie model, the G. C. Larsen model (see [8][9]), and the Gaussian 3D model[2]. Yet, the Jensen model[1] remains the most popular analytical model due to its simplicity and accuracy.

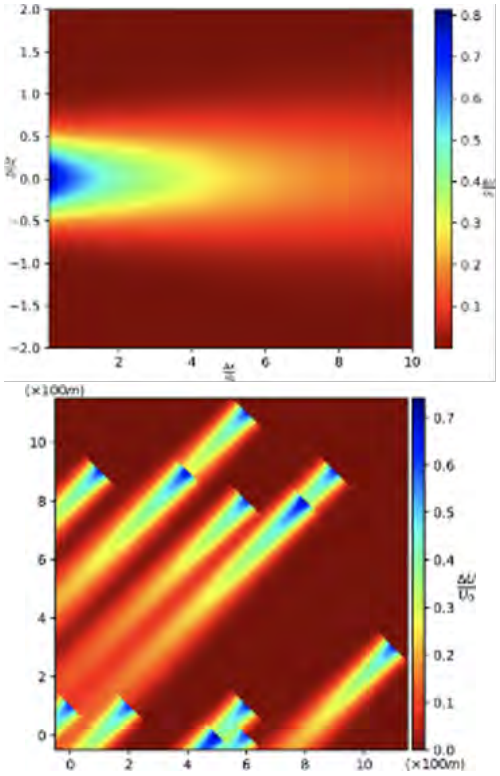


Figure 6: Wind wake effect illustration: one wake effect and multiple wake effects

Solving WFLO with the advancement in Artificial Intelligence and Machine Learning

A myriad of optimization algorithms are used to solve the WFLO problem, and many of them are heuristic algorithms, such as Genetic [3], Particle Swarm Optimization [4], and Ant Colony [5]. With the recent development in artificial intelligence and machine learning, various powerful methods such as support vector machine [6] and deep learning [7], were used to guide the heuristic algorithm and developed into new optimization strategies with insights into the characteristic of the wind power distribution and computations of wind velocity.

Representation of wind farm layouts

The wind farm layout can be encoded as discrete or continuous variables. In a discrete representation, the farmland is divided into small grids as shown in 7. The width of each grid is at least the diameter of the turbine blades such that two turbines are at least one diameter apart as long as wind turbines are placed in distinct grids.

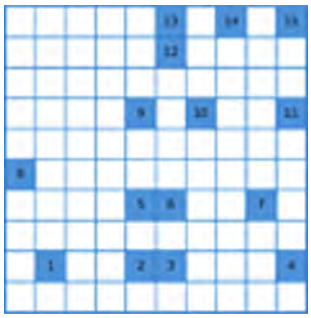


Figure 7: Discretize the wind farm into grids

In a continuous setting, the wind farm layouts can be encoded using real-valued representations such as coordinates of turbines. Yet, the high precision often comes with computational cost. Given the same number of variables and the same inherent underlying problem complexity, the computational burden in continuous problems is typically greater than that of discrete problems in light of the larger variable-domain size of continuous variables [10].

Future Research

Designing wind farm layouts requires insights in managing the trade-offs between energy generation, operational costs, and capital investments. To gain insight in optimizing these trade-offs, the WFLO can be formulated as a multi-objective optimization problem. Given some of the constraints and complexities mentioned above, the best way to formulate and solve the WFLO problem remains largely an open question. It will be exciting to find a wind farm layout that achieves a global maximum power output in a continuous space with new strategies and algorithms, and we are looking forward to it.

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Mini-poster Competition (PhD level) Winner: *Denissa Purba*

EVACUATION PLANNING FOR ALTERNATIVE FUEL VEHICLES

Denissa Purba | Collaborators: Eleftheria Kontou PhD (Advisor), Chrysafis Vogiatzis PhD
Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign | dpurba2@illinois.edu

BACKGROUND

Despite of the economic and environmental benefits[1,2,3], alternative fuel vehicles are vulnerable during emergency states due to limited driving range and lack of charging infrastructure[4,5].

2 possible vulnerability scenarios during evacuation:

- Evacuation distance exceeds the driving range limit
- Traffic congestion that forces vehicle to recharge

OBJECTIVE

determine *evacuation routes*, considering the vulnerabilities and needs of alternative fuel vehicles due to limited driving range and recharging needs

METHODOLOGY

The formulation considers 5 attributes of evacuation routes



Fast

Route should enable reaching shelters fast
Objective #1 : Minimize total travel time

Safe

The route is safe for evacuees to move, e.g., no road blockage/damage and no traffic conflict
Constraints Set #1 : No Traffic Conflict
- *Links have only one direction*

Seamless

The route should have at least one clear path to avoid confusion
Constraints Set #2 : Tree Problems
- *All evacuees are headed to the shelters*

Capture Recharging Needs

Evacuees should have access to a recharging station if needed before reaching the shelter
Constrain Set #3 : Hop Constraint Problem
- *If distance of evacuees to shelter, L hops $\geq$ driving range limit, τ hops $\rightarrow$ recharge*

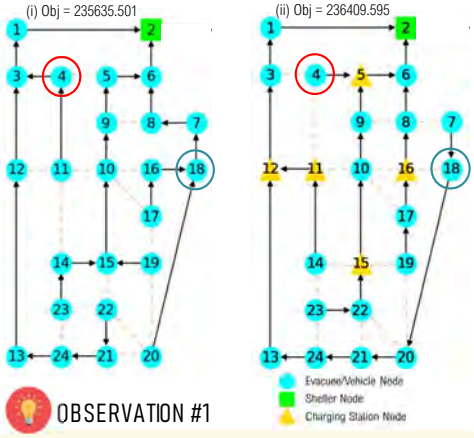
Account for Charging Delays

charging delay $=$ charging rate, r $\times$ distance of evacuees to shelter, L *hops*

Objective #2 : Minimize total charging delays

RESULTS

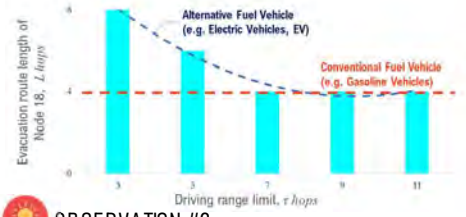
Figure 1. Evacuation Route of (i) Conventional Fuel Vehicles (e.g., Gasoline Vehicles); (ii) Alternative Fuel Vehicles (e.g., Electric Vehicles, EV) with driving range, $\tau = 3$ hops



OBSERVATION #1

- ✓ The total evacuation time increases due to recharging
- ✓ Each evacuation route for each vehicle type is unique and not feasible for the other type
  - See Node 4. In gasoline case, vehicles from node 4 can evacuate directly without recharging. In EV case, vehicles from node 4 need to recharge

Figure 2. Effect of increasing driving limit, τ, to the evacuation route length of Node 18



OBSERVATION #2

- ✓ As the driving range limit is relaxed (τ increased), there are more opportunities for vehicles to choose the shortest route without recharging

CONCLUSIONS

- The characteristics of the vehicle (driving range and fuel capacity) are important in determining the evacuation route
- Each evacuation route for each vehicle type is unique and not feasible for other types
- Even though there may exist shorter routes to safety, each alternative fuel vehicle type will detour to recharge before reaching safety

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Mini-poster Competition (Master level) Winner: *Stefanie Walsh*

Practicing What We Preach: Applying ORMS to Curriculum Decisions to Improve Student Outcomes

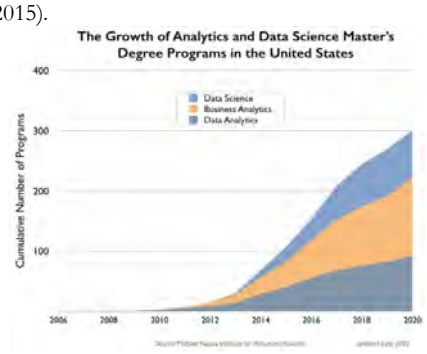
Stefanie Walsh, Matthew A. Lanham
Purdue University, Krannert School of Management
walsh88@purdue.edu; lanham@purdue.edu

ABSTRACT

We develop models to predict key performance metrics (i.e., placement rate, starting salary) of master's in business analytics and data science programs based on curriculum offerings. The motivation for this study is that students and program administrators want to know which courses among potentially many offerings best help students get where they want to go professionally. We reviewed and collected data from all 250+ programs and have developed a predictive model that we are working to integrate into an optimization model to help students identify which courses to take based on which have the most impact on them getting placed and possibly improving their starting salary.

INTRODUCTION

As the number of data science and analytics programs rise, also comes a diverse set of curricula available to students (Mamonov, et al., 2015).



Research questions

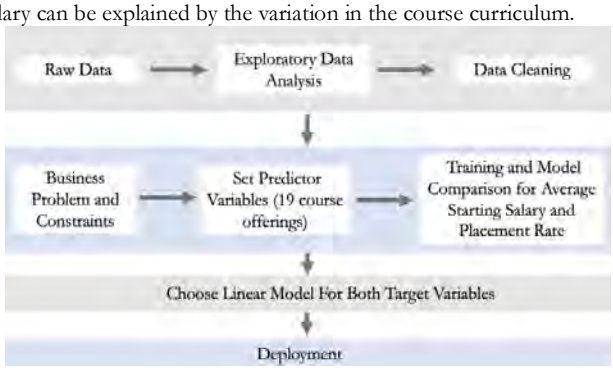
RQ1: What courses are being offered?
RQ2: How well can we predict success metrics based on course offerings?
RQ3: Which courses should a student take?

LITERATURE REVIEW

The literature has many articles that discussed BA/DS curriculum (Turel & Kapoor, 2016; Parks, Ceccucci, & McCarthy, 2018). Particularly, they looked at what courses were offered and whether those courses were sufficient in preparing students for industry. Beyond that, we did not find any research that attempted to predict and program success metrics and prescribe an optimal set of courses to take to maximize these important performance measures.

METHODOLOGY

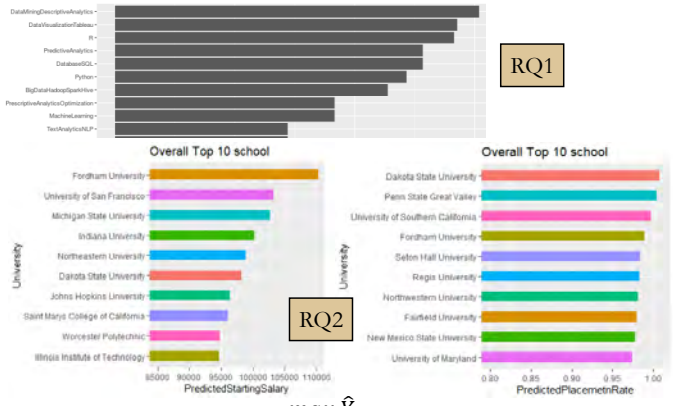
We found mostly new programs did not report too much on their programs success or were vague in their course descriptions. Our methodology is detailed in the figure below. Our predictive models current reveal that ~40% of the variation in placement rate and starting salary can be explained by the variation in the course curriculum.



RESULTS AND DECISION-SUPPORT TOOL

To explore and discuss our current we have provided an R shiny app that program managers and students can use to see what courses are available at a program and predict their placement and salary:

https://hsu230.shinyapps.io/MasterProgram/



RQ3

$$max\ \hat{Y}_{Placement}$$
$$subject\ to\colon \sum_i x_i \leq N$$
$$x_i \epsilon \{0,1\}$$

CONCLUSIONS

Data mining and **Data Visualization** were the most offered courses in programs. Our predictive models suggest the most important courses for starting salary and placement are **Predictive Analytics** and **Data Visualization,** respectively. We believe course offerings do play a critical role in successful program outcomes. We are currently developing an IP model to add to our shiny app to recommend the optimal set of courses to take given a student's curriculum constraints.

Mini-poster Competition (Undergraduate level) Winner:
Menna Hassan and Daniel Jacobson

Exploring the Effect of Clustering Algorithms on Sample Average Approximation

Danniel Jacobson[1],
Menna Hassan[2],
Zhijie (Sasha) Dong[3]

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[2]School of Electrical and Computer Engineering, Purdue University, Lafayette, IN 47907,
[3]Ingram School of Engineering, Texas State University, San Marcos, TX 78666

Abstract

Stochastic Programming (SP) is defined as modeling optimization problems in which a portion of the dataset being inputted into the function or constraints of the function are uncertain. SP is used in disaster management, supply chain design, and other complex problems. Many of the real-world problems that SP is applied to, produce large models, and it is important that they are optimized quicky and efficiently. Existing optimization algorithms are limited in capability of solving these larger problems. **Sample Average Approximation (SAA)** method is a common approach for solving large scale SP problems by using the Monte Carlo simulation. SAA approximates the SP objective function by a sample average estimate derived from a random sample. The resulting SAA problem is solved deterministically. The process is repeated with different random samples to obtain potential solutions. This project focused on applying clustering algorithms to the data before the random sample is selected. Once clustered, the random sample is randomly selected from each of the clusters instead of from the entire dataset.

Research Objective

This project looks to analyze five clustering techniques compared to each other and compared to the original SAA algorithm in order to see if clustering improves both the speed and the optimal solution of the SAA method for solving stochastic optimization problems.

Stochastic Programming Optimization Model

$$\min f = fc + pc + \sum_s p_s (tc_s + hc_s + wc_s) \quad (1)$$

$$\sum_a y_{a,i} \cdot V_a \le \sum_l U_l \cdot x_{i,l}, \quad \forall i \quad (2)$$

$$z_{a,i,s} = y_{a,i} - \sum_j q_{a,i,j,s} \quad (3)$$

$$w_{a,j,s} = D_{a,j,s} - \sum_i q_{a,i,j,s} \quad (4)$$

$$\sum_l x_{i,l} \le 1, \quad \forall i \quad (5)$$

$$x_{i,l} \in \{0,1\}, \quad \forall i,l \quad (6)$$

$$y_{a,i,s}, q_{a,i,j,s} \ge 0, \quad \forall a,i,j,s \quad (7)$$

(1) minimizes the overall cost (*f*), including fixed cost (*fc*), procurement costs (*pc*), transportation, costs (*tc*), holding costs (*hc*), and shortage costs (*wc*)

(2) restricts that at each facility the total procurement quantities would not exceed the storage capacity

(3) calculates surplus quantity of type a items at facility *i* in scenario *s*

(4) calculates shortage quantity of type a items at location *j* in scenario *s*

(5) makes sure one facility will be operated at most.

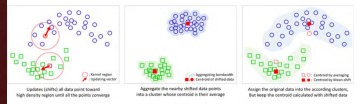
(6) and (7) define the integrity of the variables

Methodology

Original Sample Average Approximation (SAA)

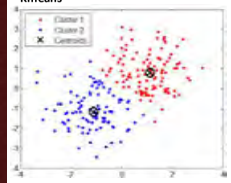
The SAA is a Monte Carlo simulation-based approach. The basic idea is to randomly generate samples and then approximate the expected value function by the corresponding sample average function.

Mean Shift



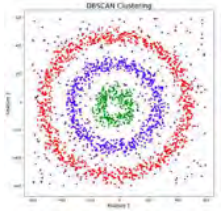
- Centroids store all neighbors within radius *r*
- Centroids move to the mean of all of their neighbors
- Does not require preset number of clusters

Kmeans



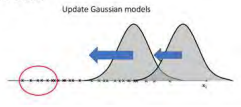
- Stratified and Random
- Data assigned to centroid
- Centroid moves to data's average
- One parameter: *k* the number of clusters

Density-Based Spatial Clustering (DBSCAN)



- Two parameters: *minP* and epsilon
- cluster begins if a data point has *minP* points within epsilon distance
- all points within epsilon of cluster are added

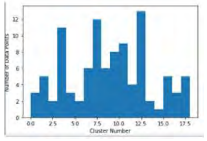
EM-GMM



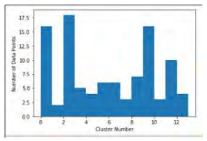
- Assume Gaussian distribution
- Mean and standard deviation describe a cluster
- EM algorithm used to optimize parameters

Parameter Estimation

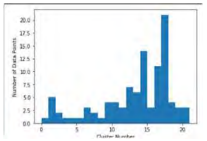
One of the major factors in the quality of clustering is the selection of the parameters. Every clustering algorithm has at least one parameter that needs to be preset before the clustering begins. The assumption made was that in order to get the best results out of the SAA algorithm, the samples need to be chosen from robust, well distributed clusters. To subjectively select the parameters, histogram graphs were analyzed in order to view the distribution of the clusters. The goal was to not allow any one cluster to have too many data points (ideally under 25) and to have the majority of the clusters contain multiple data points.



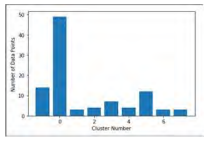
The distribution of data points in the Random Kmeans cluster with k = 18.



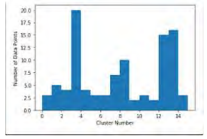
The distribution of data points in the Stratified Kmeans cluster with k = 13.



The distribution of data points in the Mean Shift cluster with radius = 1050.

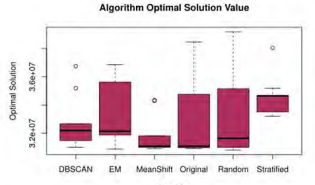


The distribution of data points in the DBSCAN clusters with minP = 3 and epsilon = 650.

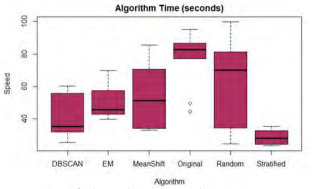


The distribution of data points in the EM-GMM clusters with k = 15

Results



Stratified sampling Kmeans clustering algorithm gave the worst optimal solution value, mean shift performed the best
Only the stratified sampling Kmeans algorithm had a statistically significant difference from other algorithms



Stratified sampling Kmeans clustering algorithm performed fastest, the original SAA algorithm performed the slowest
No algorithms showed a statistically significant difference in time

Conclusion

All 5 Clustering algorithms increase the speed of the SAA algorithm. However, they don't appear to improve the optimal value by a statistically significant amount. Further testing is needed along with gathering a larger sample (only ran each 10 time). Parameter estimation can also be investigated to see if the parameters can be selected objectively rather than subjectively.

Acknowledgement

This work has received the financial support from National Science Foundation (NSF) Research Experiences for Undergraduates (REU) program.