ORMS TOMORROW

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EXTENSIVE INTERVIEW WITH
the 2020 Judith Liebman Award Winners

COVID-19 VACCINE SUPPLY CHAINS
Strategies to overcome the barriers of vaccinating the entire population

MIGHT DATA HELP THE DESTITUTE?
Analytics to Address Homelessness

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Letter from the Lead Editors

Dear OR/MS Community Members,

We are pleased to share with you the Spring/Summer 2021 edition of OR/MS Tomorrow!

In this issue, we discuss a myriad of topics in different areas, including analytics to address homelessness, operations management within the sharing economy, algorithmic perspective of metaheuristics in optimization and transportation, air quality and health impacts during COVID-19.

We also reached out to the 2020 Judith Liebman Award Winners Sebastián Barriga, Wesley Marrero, and Hyame Alameddine to share with us their experience as inspiring student volunteers in their universities, their student chapters, and INFORMS.

Many thanks to Associate Professor Minh-Ngoc Tran and Tiffany Li for sharing their work on cognitive modelling of consumer preferences. We would also like to thank Associate Professor Evrim Dalkiran for sharing a large variety of modern tools for operations research and Dr. Shubhabrata for sharing with us about the COVID-19 vaccine supply chain strategies. Thank you to Dr. Robert James for sharing on the topic of Dynamic Time Warping.

Submissions for the Fall/Winter 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

We are very excited to have 9 new members joining our editorial team. We also would like to say thank you to our alumni members for their committed services. This issue wouldn't have been possible without the effort of our family members:

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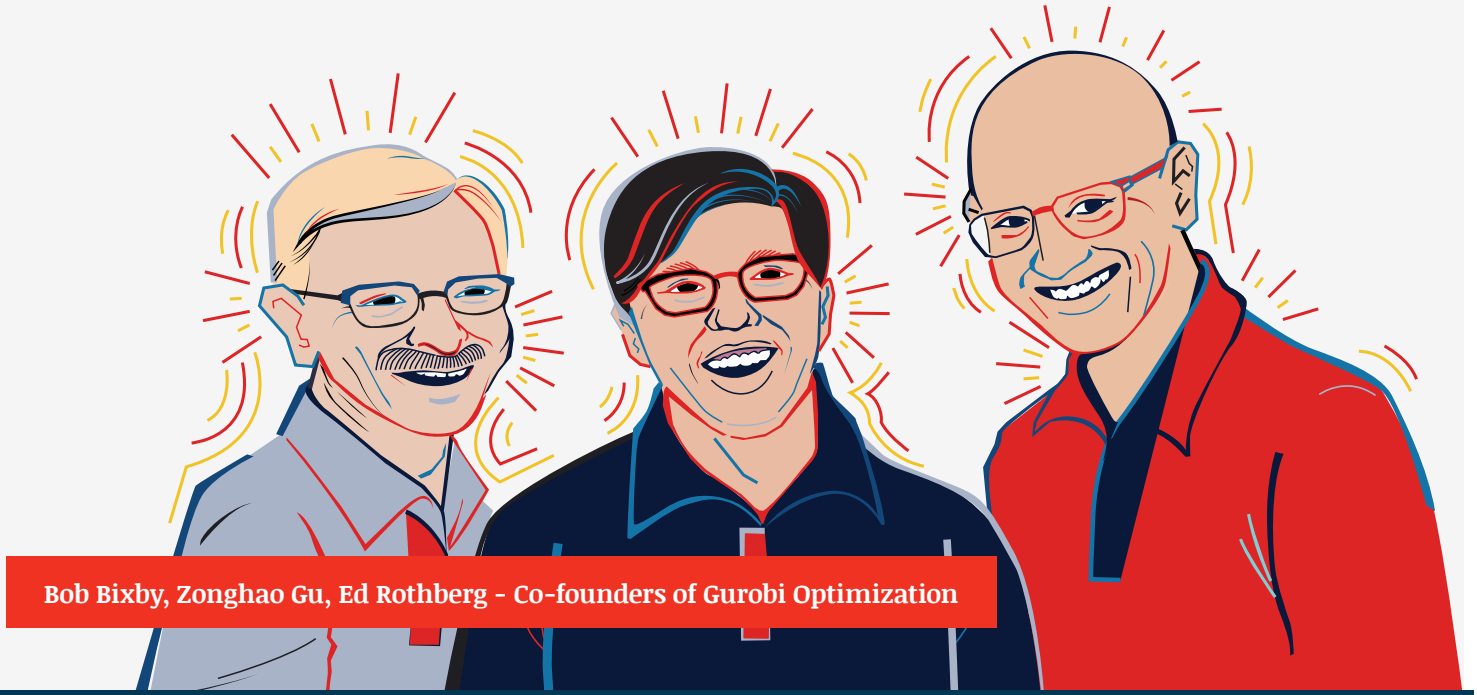
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Might Data Help the Destitute? Analytics to Address Homelessness

Abigail Lindner
Regent University



Homelessness is a worldwide social and economic challenge; the United Nations Human Settlements Program estimates that the homeless population, defined as those individuals not in a permanent housing situation, is about 100 million. Because of the lack of data and political sensationalism in the matter, homelessness does not receive the amount of discourse and treatment that it should. However, in the past five years, data and social science researchers have explored the application of data technology and predictive analytics to confront this human tragedy.

The Chair for the Institute of Global Homelessness, Dame Louise Casey, lists a three-pronged approach to addressing homelesseness, which may be summarized as Prevention, Provision, and Reformation (Beckwith, 2020). Behind each, the force of data and modern technologies has been rallied to re-evaluate the policies undergirding homelessness programs.

Prevention

This first prong of Casey's approach uses predictive analytics to determine what factors aggravate the risk of homelessness and what public policies ameliorate the risks. Like most social problems, homelessness does not follow a linear path; it involves a "complex interplay of individual, interpersonal, and socioeconomic factors" (Fowler, Hovmand, Marcal & Das, 2019). Mashariki (2018) emphasizes an urban analytics approach that layers data on poverty, unemployment, affordable housing, individual health, substance abuse, and other factors to create a more robust picture of homelessness.

In Los Angeles County in California, where about 141,000 people experience some amount of homelessness every year, researchers from the California Policy Lab, the LA County Homeless Initiative, and others collaborated to analyze the 85 million service utilization records from the County's Enterprise Linkages Project. The goal: predict return to homelessness, or RTH, and first-time homelessness, or FTH, based on inpatient and outpatient visits with state service agencies, such as the Department of Health Services and the Department of Mental Health. A preliminary model produced from this project indicated that "[t]he majority of single adults who will experience [FTH] or a [RTH] are already clients of mainstream County agencies" (Wachter, Bertrand, Pollack, Rountree & Blackwell, 2019). By targeting the 1% with the highest risk for homelessness, the county could prevent nearly 6,900 instances of homelessness in a year.

In New York, the Allegheny County Department of Human Services introduced an algorithm in the late 2010s to likewise identify high-risk individuals, as determined by use of mental health services, emergency rooms, and substance abuse services or interaction with the criminal justice system (Castillo, Zamorana, Jaramilla & Gonzalo, 2020). In both California and New York, these metrics are used because consistent research in the past

two decades has demonstrated that, among the homeless in developed countries, an interaction between mental health, physical health, substance abuse, family conflict, and crime can predict the risk of homelessness. Structural disadvantage, including specific policy and group-based discrimination, is another consideration. This algorithm, judged to be accurate and non-discriminatory for dimensions like race and age, enables Allegheny County to identify high-risk individuals and allocate resources accordingly, confronting homelessness before it happens.

Provision

The second prong of Casey's approach acknowledges that prevention does not help the already homeless. The insight gained from predictive analytics provides direction for public response to homelessness. As homelessness is not a homogenous condition, a heterogeneity of systematic responses is demanded. In 2015, the Built for Zero movement at Community Solutions spear-headed a data-driven approach to meeting the needs of homeless populations in, as of writing, more than 80 communities in the United States. Whereas previously agencies acted separately and relied on census data to measure homelessness, Built for Zero creates a database of comprehensive, real-time, multi-agency data for each single adult experiencing homelessness in a given community so that solutions can be individualized and program success based on individual change rather than organizational outcomes (Broom, 2019). Provisions include food, shelter, and medical treatment that care for the impacted individuals in the short-term.

The construction of these databases assumes knowledge about the identities and locations of homeless individuals. The truth, however, is that this population, by dint of lacking permanent residence, is among the hardest to track. The introduction of mobile and GIS technologies, such as the Homeless Outreach Portal in Los Angeles County, has facilitated the collation of real-time data on homelessness in recent decades (Kelkar, Frey, Suriya & Engel, 2019). In the United Kingdom, the Homeless Data England project, operating within the Ministry of Housing, Communities & Local Government, is working on a national scale to improve data on homelessness program outcomes and homeless population (Wu, Man, Taylor & Aldridge, 2020).

Reformation

The third prong of Casey's approach draws from the insights from the first prong and the measurable results from the second to inform the restructuring of the entire homelessness system; it moves from a short-term and immediate care framework to long-term and sustainable solution. Any hope of eradicating homelessness - eradication in the sense that supply of services for homelessness exceeds demand - requires a coordination among agencies at a number of action levels, not just the federal, state, or local governments.

Data and digital technology are essential for this multi-stakeholder coordination. The Principal at Community Solutions, Beth Sandor, names five traits that communities that have reduced homelessness share in common: a commitment to a shared target across all programs and investments, data and feedback on system progress and human outcomes, a dedicated team with the capacity to work in and change the system, proven practices that can be tested and adapted in every community, and access to flexible resources to quickly respond to new information or needs (Beckwith, 2020).

Consider this broader "ecosystem approach" to homelessness (Kelkar et al., 2019) as applied to housing policy. As the unifying factor among the diverse individuals of the homeless population is want for a permanent housing situation, it makes sense that a key focus is on providing housing.

Early experimental studies in the late 20th century and large-scale studies in the United States and Canada in the 2010s suggest that a housing first philosophy, wherein housing is arranged quickly and without preconditions, results in better social stability than the treatment first philosophy, wherein an individual receives housing after demonstrating readiness or service plan compliance (Fowler et al. 2019). The National Alliance to End Homelessness emphasizes that the Housing First model, often accused of being "one-size-fits-all", in fact recognizes that one size does not fit all. A Housing First model provides flexibility in that it does not prescribe services, but rather provides the one service that every person who is homeless needs (National Alliance to End Homelessness, 2019). Consequently, Housing First actually goes beyond the shelter question of homelessness.

Fowler et al. (2019) describes a complex systems perspective of Housing First and homeless services, with a top layer of homeless and residential services that screen for need, middle layers that move in a staircase model from shelters to temporary housing to permanent supportive housing, and a bottom layer that supports investigation of household instability and creation of safety nets. This complex systems view acknowledges the multiplicity of actors, including nonprofits and landlords, and the nonlinearity of their actions. Via a series of computer simulations of policy experiments for homelessness, the researchers found that homelessness declines the most when Housing First and the first prong of prevention are combined and that broad-scale prevention works best in the context of rights-based housing policies (Fowler et al., 2019).

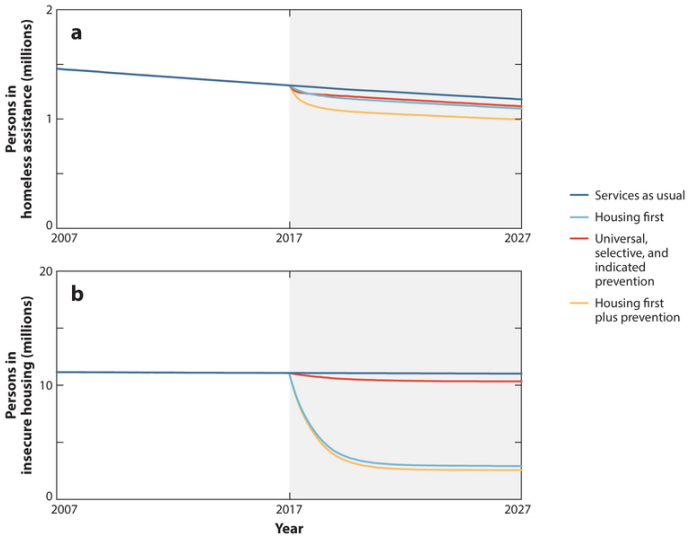


Figure 1: Policy experiments showing the impact of housing first and prevention efforts on the number of people in homeless assistance. Graphic from Fowler et al. (2019).

Cho (2014) considers Housing First a "whole-system orientation", not a single program, because its aims - reduction of homelessness frequency, across-the-board permanent housing, and care and support for housing maintenance and quality of life improvement - require a shared commitment. There must be engagement among "a variety of programs and services including homeless outreach, emergency shelter, permanent supportive housing, affordable housing, rapid re-housing, along with case management supports, health care, income supports, employment services, and more." This reinvention achieves that third prong of system reformation.

Homelessness affects all of us, no matter how well-to-do we may be. While awareness has risen, research in the U.K. discovered a disproportionately small amount of action is subsequently undertaken by the public, in part because of misunderstandings about homelessness and its prevention, belief that homelessness is an individual problem, and a fatalistic sense that a single person's actions will do basically nothing to help so large an issue (Teixeira, 2017). The work being done to organize, clarify, and analyze the data on this population is helping to change this story.

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Meet the 2020 Judith Liebman Award Winners



Amira Hijazi
North Carolina State University

The Judith Liebman Award has been established to recognize outstanding student volunteers who have been "moving spirits" in their universities, their student chapters, and INFORMS. We interviewed the 2020 Judith Liebman Awardees Sebastián Barriga, Wesley Marrero, and Hyame Alameddine. We start with introductions of these outstanding students:



Sebastián A. Barriga
M.Sc. (c) Industrial and Systems Engineering
Pontificia Universidad Católica de Chile

I am Chilean and pursuing a Master's degree in Operations Research at Pontificia Universidad Católica of Chile, conducting research on scheduling chemotherapy patients. I was elected as Operations Research Major Delegate in my junior year (2017) and that's how I got involved with our newly-formed INFORMS Student Chapter. In the following years, I took on the responsibility of being its Secretary, Vice President and President. This year I am volunteering with INFORMS Subdivisions Council as a student chapter representative. I'm not really sure what will come next, but I think going abroad either for studying or working would definitely be in my plans.



Wesley J. Marrero
MGH Institute for Technology Assessment
Harvard Medical School

I completed my B.S. in Industrial and Management Engineering from what was formerly known as the University of Turabo (now Ana G. Mendez University). Afterward, I received my Ph.D. and M.S. in Industrial and Operations Engineering and an M.A. in Statistics from the University of Michigan. I am currently working as a postdoctoral research fellow at Harvard Medical School and the MGH Institute for Technology Assessment. In the future, I aspire to become a faculty member in a research-intensive institution. My end goal as a researcher is to narrow the gap between decision-making theory and practice.



Hyame Alameddine
Ph.D. Information Systems and Multimedia
Concordia University, Canada
Experienced Researcher
Ericsson, Canada

I am an experienced researcher at Ericsson, Canada; working on the security and optimization of 5G and virtualized networks. Before joining Ericsson, I served as a postdoctoral fellow at the University of Waterloo, Canada in 2019-2020. I also worked as a programmer and application developer in multiple national and international companies in Lebanon, my home country, between 2009 and 2014.

I received my Ph.D. degree in Information and Systems Engineering from Concordia University, Canada in 2019. During my Ph.D., I developed and applied multiple optimization techniques

to solve the problem of network and computing resources management and scheduling in virtualized networks. I earned a Master's degree in Computer Engineering - Information, Systems and Multimedia in 2015 from Conservatoire National des Arts et des Métiers (CNAM) University, France.

As an active researcher in the areas of cloud and edge computing, network functions virtualization, software-defined networking, 5G and security, I aim at elevating today's technological experience to provide better active learning experiences in a world in which we redefined the basics of living.

Can you summarize your involvement with INFORMS?

Sebastian Being part of a Latin American Student Chapter of INFORMS isn't always ideal, as most of INFORMS amazing activities are held in the US. Despite this geographical constraint, we've participated in the 2017 Student Leadership Conference in Baltimore, MD, and in 2019 we traveled to Seattle, WA, to receive the Cum Laude level award for our Student Chapter at the Annual Meeting. This was made possible with the support we received from INFORMS and our own School of Engineering, for which I am extremely grateful. During these events, I learned from INFORMS' unique culture and met people with whom I have continued contact. It opened my mind as the OR/MS community in the US is much wider and bigger than in Chile, and I'm very thankful for having had that opportunity for growth.

Wesley I first became engaged with the INFORMS student chapter at the University of Michigan (INFORMS at UM) through my service as the volunteering and outreach chair in 2018. In this position, I had the privilege of co-organizing outreach activities as well as starting the INFORMS at UM Pro-Bono Initiative, a program of service to the community. As a result of my efforts, a new position was created for the 2019-2020 term: the pro-bono chair position. I had the honor of being the first to take on this chair position and continuing with the development of the INFORMS at UM Pro-Bono Initiative.

During the 2019-2020 term, I steered the Pro-Bono Initiative towards developing new collaborations with organizations in our community. I was able to establish relationships with several non-profit and community organizations, including United Way for Southeastern Michigan, Habitat for Humanity, the New West Willow Neighborhood Association, and the University of Michigan's Shared Services Center. The pro-bono group greatly benefited from these projects. By the end of the year, the pro-bono group grew from 9 to over 40 volunteers at the undergraduate and graduate level from multiple departments at the University of Michigan.

To ensure the continuation of the initiative after my term as the pro-bono chair, I identified and trained my successor for this position. Currently, I serve as an advisor for the pro-bono group. I am proud to say that the current pro-bono chair along with INFORMS at UM volunteers are still working on projects, even in the light of the current pandemic.

Hyame I was introduced to INFORMS by one of my friends in 2016 when we were discussing the idea of co-founding a student chapter to promote collaboration between graduate students. Since then, I joined INFORMS and became a member. I also co-founded the Montreal Operations Research Student Chapter (MORSC). The co-founders and I decided to register MORSC under INFORMS to become an INFORMS student chapter. I served as the Academic Events Director of MORSC in 2016-2017 and as a Vice President in 2017-2018.

During those years, I introduced INFORMS and promoted MORSC to friends, colleagues and professors in the field and motivated them to join INFORMS, the chapter and its organizing committee. I assisted in setting up the chapter strategy. For instance, in 2016-2017, when we co-founded the chapter, we focused on organizing many events to promote the chapter within Concordia University and other universities in Montreal. In 2017-2018, we decided to expand our social media and host wider events to reach colleagues in other countries. We moved from local events to national and international events organized in collaboration with other organizations such as the Canadian Operational Research Society (CORS), Airo Young part of the Italian Operational Research Society (AIRO), GERAD, Centre Interuniversitaire de Recherche sur les Réseaux d'Entreprise, la Logistique et le Transport (CIRRELT), the Mechanical Industrial and Aerospace Engineering Graduate student committee at Concordia University and the Operations Research Challenge (TORCH). We invited professors and researchers from universities inside and outside Canada to share with us their latest research.

Furthermore, my contributions to MORSC included ensuring that the chapter by-laws and strategies are respected, coordinating MORSC activities and events with the MORSC executive board and other MORSC teams, organizing events and managing the academic events team. In addition, I was following up on administrative tasks related to the chapter registration under INFORMS and Concordia University, application for funds, yearly reports about the chapter achievements, and setting up and organizing the call for elections for a new executive board.

What were the challenges, benefits, and disadvantages of your involvement?

Sebastian My first year in our INFORMS Student Chapter I was part of the Social commission, the one that gets involved with different low-income public organizations and develops a project to help them via OR/MS. I think that that experience was what started my passion for my career, as I could see firsthand that what we were doing could have an impact on society. It was challenging, as solving a real-life problem isn't like a course's homework: data is disorganized, people aren't always very clear of what their needs are and most of all, you have to take into account the human factor in any implementation that you want.

After carrying out this project, I started getting involved even more in our Student Chapter as a Board Member, where I had to foresee the global picture of the commissions. What I've always

been very thankful about is our own team, full of bright and talented men and women, mostly undergraduates, who give their time and passion for the community. Sometimes it might be hard to keep organizing events when there are exams or for example a remote year (i.e. COVID19 pandemic), but the motivation that our chiefs of commissions have is wonderful, as they were the ones who pushed and kept carrying out their activities.

Wesley Being involved in outreach activities and pro-bono work has challenges, benefits, and even disadvantages.

Challenges: The most difficult part of my involvement with INFORMS at UM has been to identify community partners and assess the potential for collaboration. It requires several meetings to clearly define a potential partner's needs and evaluate if our areas of expertise are a good fit to address the problems. Another challenging area has been to ensure that the volunteers are developing their skills and that both the students and the community organizations are benefiting from the partnerships.

Benefits: Outreach activities reinforce relationships among INFORMS at UM members by providing us with the common goal of inspiring the future generation of operations research and analytics professionals, while simultaneously igniting the interest of future potential INFORMS members. Additionally, these activities allow us to connect with other student organizations at the University of Michigan and learn from each others' successes and failures.

Pro-bono projects give INFORMS at UM members the opportunity to obtain real-world experience while serving the community and underserved populations. Volunteers also get the chance to showcase their work in internal and external research conferences as well as in media articles. We were fortunate to present our decision support model for the placement of mobile pantries at the Michigan Student Symposium for Interdisciplinary Statistical Sciences, where the volunteers working on the project were awarded the Societal Impact Award. Also, we have had the privilege of our work being featured by local news outlets, such as Concentrate.

Disadvantages: For me, the greatest drawback of volunteering was the time it took away from my research and studies. I have found that it's best to address this issue by sharing and distributing the workload with my peers. It is an immense privilege to serve the next wave of operations research and analytics professionals as well as the community.

Hyame Great question indeed. I do not know where to start. Perhaps, I should start by elimination and mention that I cannot think of any disadvantages. This might be too "cliché", but I would say all the struggles are learning experiences even if they were confused with disadvantages at some point in time. One of the earliest challenges I faced was when we launched MORSC. It was very difficult to promote the chapter and incentivize students to contribute and become active members.

Another challenge was project and time management. Many times, members of the organizing committee of MORSC events fail to accomplish their assigned tasks due to personal reasons or upcoming exams. With the limited number of members in the organizing committee, it was very challenging to re-distribute the tasks and ask the help of others. Many times, the executive board members and I had to take over and figure out the time and project management to make the event a success.

Despite these challenges, I personally learned a lot. My communication skills along with my marketing skills improved significantly. I practiced project and time management and learned from colleagues how to better handle those and adjust to all the uncertainties. I had the chance to expand my network and meet colleagues and researchers working in different areas. I was also delighted to meet, discuss and learn from many professors who served as distinguished speakers in MORSC events. Last but not the least, I was involved in periodic discussions with other organizations and student chapters such as the Canadian Operational Research Society (CORS), GERAD, Centre Interuniversitaire de Recherche sur les Réseaux d'Entreprise, la Logistique et le Transport (CIRRELT), the Mechanical Industrial and Aerospace Engineering Graduate student committee at Concordia University and The Operations Research Challenge (TORCH) with which we organized many joint events. I would like to take the opportunity to thank every member of those organizations for their continuous support of MORSC.

Being a student, it's usually difficult to spare time for volunteering. How did you manage that given your busy schedule?

Sebastian Since I started my undergraduate degree, I've always participated a lot in everything I liked, therefore I guess it hasn't been that hard for me. Of course, sometimes time is scarce, yet if you really like what you are doing then it's not a big problem. And I think that's the key: to be involved in something that you really like will be totally worth it. The experience, the people, and the personal growth will always be a great investment.

Wesley Volunteering has always been a priority for me. Scheduling a few hours to serve others every week has given me the best results. I have had to be intentional in the time I set apart to volunteer. Also, it helps to work with others. Teamwork typically makes the tasks more enjoyable and they get done quicker.

Hyame Taking the decision to co-found and contribute to MORSC was a big step for me with all the tight deadlines I had. However, at the time, I asked myself the following questions:

Does contributing to such an initiative fit my long-term goals and career?
My answer was: yes.

Do I have time to spend on this initiative?

My answer was: Hyame, you are always afraid when it comes to getting out of your comfort zone. You never tried contributing to a student chapter before. This is your last opportunity to make the best of your student life. You always work by deadlines, challenge yourself and figure out your time management.

Just like any other work experience, there is a probation period and a notice time before you leave. You should at least try!!!

How many hours do I need to allocate per week for this volunteering work?

The answer was: 2-3 hours per week.
Nonetheless, I ended up allocating much more time to this volunteering work. This only proves that when you have the passion for something you will figure how to work it out. Also, your environment has a great impact on you and your performance. I confess that without the motivation of my friends, the co-founders, I would have not volunteered. We were all Ph.D. students with limited time and a lot of research struggles. When I saw them motivated, I told myself, if they can do it why would I not be able to do it as well? We supported each other very well. Whenever one was busy, the others covered for him/her and were understanding.

How do you feel about the award you received?

Sebastian It was totally unexpected yet a very pleasant surprise. I have been part of my INFORMS student chapter for a few years now, and I couldn't be more grateful for the experiences INFORMS and my Student Chapter have given to me. I had the chance to travel, to learn organization and leadership skills, and to love even more my career, but most of all to meet amazing people and feel part of its community.

Wesley I am honored to receive the 2020 Judith Liebman Award. It is my hope that the INFORMS at UM Pro-Bono Initiative continues to serve as a bridge between the University of Michigan and the Ann Arbor community for the years to come.

Hyame I feel extremely blessed and accomplished. I am very happy to be recognized by INFORMS for my contributions to MORSC. Receiving the Judith Liebman Award is yet another great motivation to continue giving back to the community, supporting students and researchers all around the world just like they supported me. I believe that sharing knowledge is my duty and a very important step to build a better world.

What would you suggest to your fellow students who are interested in getting involved with INFORMS?

Sebastian To take part in their student chapters and try the things that make you happy! There's nothing better than trying new experiences and carrying them out as far as you can. If you have an idea, propose it to your student chapter and organize yourselves to make it. Also, there are many ways that the OR/MS community can help others, so don't forget it and do your best always! And if you think I can personally assist you in something please feel free to reach me and I'll try to help as much as I can.

Wesley Getting involved with INFORMS provides a unique opportunity to expand your network, share your work, and potentially develop collaborations. I would encourage my fellow students to take advantage of their student chapters. If they do not have one, I urge them to start a new chapter. The benefits vastly outweigh the effort. I also exhort my peers to attend INFORMS conferences and their networking events. Reach out to people after their talks and make sure to follow up with them after. It is important to dig the well before you get thirsty!

Hyame For all the students out there, I say: Do not overthink the responsibilities, this is the challenge that you must try. Volunteering is the work experience you are looking for. It builds your entrepreneurship skills, leadership and communication skills. It teaches you time and project management. And on top of all that, it introduces you to great souls that will accompany you through your journey. Working in operations research or not, does not allow/prevent you from getting involved with INFORMS. Despite being an international society for practitioners in the fields of operations research, management science, and analytics; INFORMS is a great welcoming, supportive community which strives to support its members, acknowledge and reward their hard work. Getting involved with INFORMS is an exceptionally rewarding investment if you strike to evolve and make a difference among your colleagues, your community, your research and around the world.



Essay on COVID-19 vaccine supply chains

Piyal Sarkar
Department of Mechanical and Industrial Engineering
Ryerson University



Dr. Shubhabrata Das
Department of Medicine
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The COVID-19 pandemic caused by the severe respiratory syndrome coronavirus 2 (SARS-CoV-2) is a threat to humanity in the 21st century. More than 1.7 million people died due to this pandemic. Research findings show that SARS-CoV and SARS-CoV 2 bear similar genetic properties [4]. Thus, the previous scientific efforts to develop SARS-CoV vaccine has certainly paved the foundation to design vaccines for COVID-19. To minimize the deadly impact of COVID-19, the need of this hour is to roll out an effective vaccine to eradicate this global pandemic. With increasing cases of COVID-19 everyday, there is a huge demand for a reliable vaccine. In this article, we discuss the challenges, and the possible strategies to overcome these barriers associated to the COVID-19 vaccination to the entire population. Also, we mention some of the key strategies that can be learnt from Influenza or measles vaccine supply chains to develop an efficient supply chain. The main aim of this article is to make the ORMS coomunity aware of the COVID-19 vaccine supply chain and to discuss on some feasible solutions to develop an effective framework to distribute the COVID-19 vaccines to the whole population. The article finally concludes with some effective policies that can be practiced so that the world is ready to address such global pandemics.

Hospitals are trying to increase their efforts to administer the vaccines. Vaccines manufactured by companies such as Pfizer, and Moderna have been proved to be 90 percent effective. Dr Anna Nagurney, Professor of Operations Management at the University of Massachusetts, Amherst recently stated in an interview that “It’s going to be a massive logistics operation on a scale the world and the United States has never seen” [6]. The challenges underlie in delivering the products to the points of demand from the manufacturing houses. There will be several challenges in managing the supply chain of COVID-19 vaccines. The two major factors that make the vaccine supply chain complex can be attributed to: variability in demand, complicated storage requirements.

The demand of vaccine is huge. However currently almost all countries can not match the demand as these manufacturing companies have started vaccine production recently, and the production is not enough to vaccinate the whole population at once. Moreover, the vaccination strategy is different for different countries based on geopolitical factors as well as healthcare delivery system in these countries. Furthermore, improper utilization of vaccine which depends on these factors mentioned can lead to wastage. For a particular country, the demand for vaccines may be stable or relatively stable. But the challenge may lie for predicting the daily or weekly demand of vaccines

in the individual vaccination sites. People may sometimes miss or skip appointments and moreover many hospitals may do not have the infrastructure to share the real time usage and inventory information to the relevant public authorities. Hence, whenever there is a mismatch in demand and supply, there is a chance of wastage of vaccines. Experts predict that a substantial amount of vaccine may get wasted if they are not used before, they expire [3]. Delivering a vaccine for a global will definitely require a logistical effort of extraordinary complexity. The three leading vaccine candidates, from AstraZeneca/Oxford, Pfizer/BioNTech, and Moderna, have very different requirements when it comes to shipping and storage, and even after the vaccines arrive at the vaccination points—the health clinics, hospitals, and pharmacies where vaccinations will occur—there are a host of logistical hurdles that must be overcome to ensure efficient and equitable distribution. Some vaccines need to be stored at extremely cold temperatures. The Pfizer vaccine can be stored at minus-70 degrees Celsius, plus or minus-10 degrees Celsius, for six months. It is definitely a super tough temperature requirement that few hospitals or health centers can offer. Essentially, hospitals would need to purchase an ultra-cold freezer, each of which can cost as much as US $20,000 and preserve more than 100,000 doses. Hence, Pfizzer has made a make-shift arrangement of thermal shipper which can keep vaccines at ultra-cold temperatures for as long as 10 days. However, these shippers can only be opened for vaccine retrieval only twice in a day posing inadequate delivery. Moreover, after 10 days, dry ice needs to be added to these shippers every five days. Furthermore, once vaccines are taken out of the shippers and put it into regular refrigerator, these need to be used within five days. In this context the other two vaccine candidates are much more flexible. The Moderna vaccine can be stored between 2 to 8 degrees Celsius for a month. Hence, a regular refrigerator can be used to preserve this vaccine. Moreover, it can be stored for six months at -20 degrees Celsius in a regular freezer. Besides, the Moderna vaccine can be stored at room temperature for around 12 hours. AstraZeneca's DNA vaccine is also easier to store. It can be stored between 2-8 degrees Celsius for six months. This is really a very, very basic requirement. For this flexible storage requirements, many consider AstraZeneca's vaccine to be the one that's going to be widely distributed around the world. To explore about other vaccines in the market, readers are encouraged to refer to the following link: https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/.

In the light of these above mentioned stringent logistical requirements, let us focus now some key strategies that can be practiced for maximizing COVID-19 vaccine usage as well as strategies to reduce wastage of the same. The supply chain ideas practiced by Amazon and Walmart can be of great value in this regard. Instead of shipping vaccines directly to different hospitals and health units, government could set up regional "fulfillment centers" in different areas with pooled inventory—much like the practice followed by Amazon's. These fulfillment centers can restock the vaccination sites as per daily or weekly demand. By using this just-in-time distribution strategy, supply could better match demand at specific sites and reduce unnecessary wastage of vaccines. Also, if there is a fluctuation in demand within the adjoining sites under a same fulfillment center, vaccines cam be circulated immediately from one vaccine site to another vaccine site. Large retailers such as Walmart and Amazon have developed time-tested supply-chain tools that public health authorities could learn from. These time tested tools will help creating a database of the possible number of inventories in different vaccine sites and capture the demand information much effectively which can be used effective supply of COVID-19 vaccine supply. As mentioned above the other challenge for the COVID-19 vaccine management lies in the complicated storage requirements. As discussed. the storage requirement for COVID-19 vaccines are quite expensive. To overcome this challenge the approach of cross-docking may help. Cross docking is a logistics procedure where products from a supplier or manufacturing plant are distributed directly to a customer or retail chain with marginal to no handling or storage time. Walmart is a pioneer in cross-docking. The cross-docking approach will skip the storage in ware-houses. If the cross docking approach is followed, the vaccines can be directly delivered to the regional fulfillment centers from the vaccine manufacturing house or, the airports (for vaccines coming from facilities in other countries). The cross-docking approach for vaccine distribution would greatly reduce the need for strict cold storage requirement eliminating the need for freezers at intermediate warehouses. However, in order to apply this cross-docking approach for vaccine distribution there should be a very good coordination between the vaccine manufacturers, transport companies, health care providers and patients.



Practitioners can get certain guidance on managing the corona vaccine supply chain from the Influenza vaccine supply chain [2]. Here are some of the takeaway points. At risk early production to ensure timely delivery, flu vaccine manufacturers such as GlaxoSmithKline PLC and Sanofi often start manufacturing flu vaccines in January, well before the US Food and Drug Administration (FDA) determines which strains to produce. This practice is known as "at-risk early production". Unfortunately, at an instance when such production does not match the FDA's recommendation, the manufacturers must discard entire batches of vaccine strains. Thus, supply chain pressures cause manufacturers to balance between improving on-time delivery performance and reducing the likelihood of producing the wrong strains. This is one of the challenges for any flu vaccination

Proactive contracting, complex business contracts administer the vaccines supply chain from manufacturers to health centers

and retail pharmacies. The supply chain contracts minimize the supply and demand mismatch. Instead, incentive alignment is key to the design of medical supply chain contracts that band together the otherwise divergent interests of vaccine manufacturers and health-care providers [2]. In the case of flu vaccine contracting, early contracts that shares risks and rewards between a manufacture and a vaccine provider can create a virtuous circle of incentives—it provides incentives for vaccine providers to stick to sufficiently large orders and encourages manufacturers to produce early to ensure on time delivery. More importantly, early contracting influences the health-care providers to collect demand information and share it with manufacturers to plan production and delivery. In the U.S., flu vaccine manufacturers enter into early or "pre-book" contracts with their customers (hospitals, clinics, and retail pharmacies) nearly one year before the flu season [1]. These committed pre-book orders provide sure shot payments, which can reduce manufacturers' financial risks of producing vaccines. Most of the pre-book contracts contain terms that incentivize manufacturers to produce early. They also provide incentives for health-care providers to order early, place large orders, and allow revisions to their orders as their demand forecast changes. Discounts are sometimes provided for early commitments. For example, in a 2012 contract offered by Novartis Vaccines and Diagnostics Inc. to the New York state, the price was $77.52 per 10 dose if the order is pre-booked before February 1, $82.37 between February 1 and March 1, $87.21 between March 1 and April 1, and $96.90 after April 1. Now, the return policy is based on the pre-book time schedule: the maximum returnable proportion of the pre-book orders ranges from 20% (for pre-book orders placed before February 1) to 15% to 10% and finally to 0 (for orders placed after April 1) [3].

While the distribution is challenging, another challenge lies in motivating the public to get vaccinated. Every country has their vaccine regulatory body to control and monitor the guidelines related to vaccines. For example, the Centre for Drug Control (CDC), USA has guidelines for priority vaccination groups, including people of 65 years and older, pregnant women, children, and those living with infants. In addition unlike the COVID vaccines, the side effects of flu vaccines are known and the benefits has been known to outweigh potential risks. Yet, many individuals are still reluctant to get vaccinated, in part due to deep-seated "anti-vax" beliefs that have grown more influential in recent years. As all stakeholders— hospitals, clinics, retail pharmacies, flu vaccine manufacturers, vaccine regulatory body, and the public—learned the above lessons over the years, incentive contracting, effective campaigning, and proactive planning can help balance the supply and demand of flu vaccines despite the threats of uncertainties. To explore more about the distribution strategies of the vaccines, we strongle encourage to refer to the study of Matrajt et al. [5].

Thus, the main challenge for any vaccine supply chain is to minimize the demand-supply mismatch. Regional fulfillment centers, and cross-docking can be major strategies for managing a vaccine supply chain. Also, designing supply chain contracts that minimizes the risk of "at-risk early production." The COVID-19 pandemic has given a lesson to the entire world. The world has to be ready to combat such pandemics. The World Health Organization (WHO) must develop health policies and more effective internationalization strategies such that all countries can work together closely to design sustainable, cost-effective vaccine supply chains.

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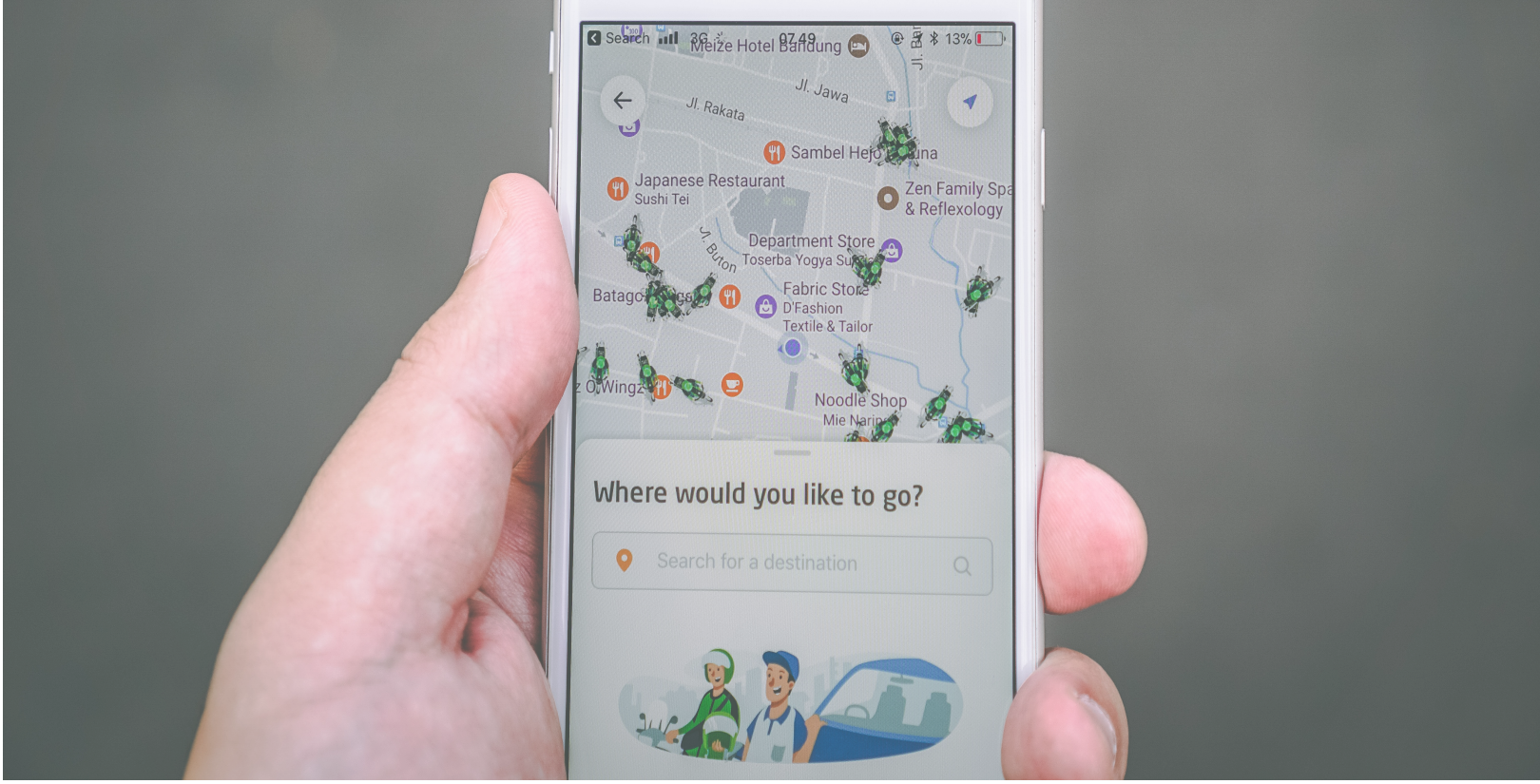
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Operations Management within Sharing Economic Industries

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Nearly 40% of customers worldwide have purchased products or requested services through firms such as Doordash, Uber, Amazon situated in the sharing economy. In operation management, the sharing economy is a business model built around the on-demand case to product and service facilitated on an online platform such as ride-hailing platforms that find a driver for individual riders. It can also be considered the business model that provides products or services to many buyers by a single entity, for example, vehicle sharing service, which makes available vehicle rentals to individual users [1].

During the COVID-19 pandemic, tremendous growth has been seen in the food delivery industry and online ordering, attracting leadership attention. The new movements in traditional operation and supply chain models have been seen among decision-makers in sharing economy industries involving: 1) technology, 2) transaction type, 3) platform type, 4) governance model, 5) business approach, and 6) shared resources [2].

1. Transmitting from old to new perspectives

In the sharing economy, every business model needs to apply the new approaches for modeling on three central pillars of OM theory: inventory theory, revenue management, and queuing theory. In the following, I will describe differences in the new perspective of each theory:

1-1 Inventory Theory

In classical inventory theory, the main decisions are around how much needs to be ordered and when. However, in the sharing economy, effective matching between supply and demand is considered a primary priority because sometimes supply cannot be controlled at a short time scale [1]. For instance, in the food delivery industry, the process in which drivers become available on the platform is mainly independent of customers' arrival process. Therefore, the final decisions are less about orchestrating the supply and finding the best solution to match each unit of demand with each available supply unit [3]. In operation research, the dynamic optimization formulation can be employed to formulate the problem. In the dynamic modeling, the platform can earn a reward as a function of quality matches reported the number of supply units left unmatched (like excess inventory in the classical inventory problem) and the number of unsatisfied customers (shortage in inventory problem). A few articles are discussing using dynamic optimization techniques in sharing economic areas. For instance, Zipkin (2008) minimizes the number of lost sales by providing a new modeling inventory [4]. Chen et al. (2014, 2019) consider the dynamic optimization to reformulate the perishable inventory

model for the food industry. They demonstrate how economy sharing needs to readjust their models by considering reward structure to reduce the number backlogs and increase their profits [5,6]. Baccara et al. (2020) demonstrate the vital role of trading off between centralized vs. decentralized matching in the online labor market such as uber and Lyft to minimize the lost demand [7]. Techniques and insights developed for the old concept (classical inventory management) can transfer to the new perspective (economic sharing). All sharing economic business managers and researchers are expected to use many inventory techniques and computational methods to move to a new platform [8].

1-2 Revenue Management

Classical revenue management focused on how prices should be adjusted to sell a fixed amount of capacity on the finite time horizon. The process should be dynamically modified based on available capacity, which means less capacity can be translated to a higher price [9]. However, economic sharing has embraced classical revenue management's basic idea, which needs to be considered that capacity is crowdsourced and extremely sensitive to the paid wages [10]. Overall, the two-sided dynamic pricing (wages paid to workers and prices charged to the customer) can be considered the best approach for sharing the economy and spatially distributing the nature of supply and demand. In the Doordash or uber platform, higher wages in one location draw supply away from other locations and low demand in one location and force supply to search elsewhere. There are some examples in academic applications; for instance, Zhang et al. (2018) discussed the role of value co-creation in the sharing economy, especially when customers want to pay an affordable value to receive the ontime service, but the providers face capacity limitations. They present how pricing adjustment can help to satisfy customer demand with limited capacity [11]. Another example is Zipcar, which could be competitive with other rental car companies by providing an efficient pricing method to attract customers [12]. Zipcar makes the cars available for customers in public parking lots, and customers could reserve the car for short or long trim at an affordable price [12]. Therefore, based on these businesses' complex behavior, new evolution is needed to apply operation research techniques and methodologies to optimize the current economic sharing models.

1-3 Queuing theory

Queuing theory is a mathematical formulation to examine the congestion and delays of waiting in line, and it studies every component of waiting in line and needs to be served, such as arrival process, service process, number of capacities, and customers [3]. Queuing theory is a natural tool for sharing economy applications because of its on-demand access to products and services[3]. The queuing theory needs to be extended to employ in sharing economy businesses in some directions: 1. Sharing economy relies on when and how much workers decide to work, therefore a multi-server queueing system considering that the number of servers is not fixed and can be varied over time. 2. A double-ended queue modeling can be suitable because arrival customer and servers' functions are independent. The server (workers) will not necessarily return to the original location after service completion. For instance, Benjaafar et al. (2019) provide a multi-server queuing system to study product sharing in a food industry case study [13]. Kim (2019) applies a bulk input G/M/1 type queuing model with stochastic congruent properties to find the optimal solution for a car rental company[14]. It needs to be modeled very dynamically over time-of-service providers to be available or not. Operation Research provides an acceptable solution to the model, formulation and solves this type of problem.

2. The role of ORMS to overcome challenges in the sharing economy

These business models face various challenges, and ORMS techniques and methods can be practical solutions. One challenge that needs to be discussed is the cannibalization effect, which can curtail ownership because any individual can rent instead of the owner. ORMs techniques can help decision-makers find a suitable solution regarding how a platform should price its products and under what conditions a platform would benefit from resource and product sharing. For instance, Doordash Inc starts to benefit from operation research and machine learning to identify optimal prices for services and products. The first challenge can come up with managing available resources and leveraging capacity. Compared to the traditional service system, capacity can be controlled in a different way which is indirectly by wages and prices. In these businesses such as Doordash and Uber, capacity is related to independent workers' decisions (meaning drivers in Doordash and Uber) because they will decide when, how much, and where to work and accept the demand and wages. Operation research algorithms show that the optimal price can be a trade-off between market size and labor pool size or the waiting cost [1]. Resource allocation and price management are challenging parts of economic sharing that can be handled by implementing the operation research concept in optimization formulation and algorithms. Gan (2019) proposes a novel distribution logistic network considering Big Data analysis to optimize resource allocation by investigating customer preference. The author assumes that all logistic partners follow their policy, and the idle logistic resources can be recognized and assigned to distribution needs. The author provides an objective function model based on high speed, low cost, and low pollution for different logistic preferences and uses the heuristic algorithm to solve the model [15,16]. Kim et al. (2015) introduce three resource allocation methods for a sharing economy industry by minimizing transaction costs and the level of idle resources. They use game theory to solve this complex problem and find more realistic solutions [17].

Another challenge that can be discussed is matching with minimum cost and high trust between customer and ownership, how the sharing economy platform can match customer demand and supply with max satisfaction and minimum cost. Most platforms benefit from the recommendation algorithm and machine learning to match the best supplier (for instance, for Doordash best restaurant) to customer demand. Operation research opens a new perspective in this area by introducing a complex business model. In the sharing economy, much information is available to help decision-makers optimize the decisions and strategies if they implement the appropriate algorithms and tools with high security [18].

How can we deal with Uncertainty (Demand and Capacity) We are living in a significantly fluctuating environment, and uncertainties are surrounding the businesses and personal life. One example is COVID 19 pandemic, in which everything has been changed. All customers were forced to switch to the online platform from using restaurant services to regular shopping tasks. Online platforms such as Doordash, Grubhub, and amazon were faced with vast and unpredictable demand with a lack of resources (workers). So, they started to adjust the pricing management to attract more suppliers (resources) because some other workers lost their jobs who never thought about working at the online platform. So, these businesses benefited from these opportunities and tried to attract more resources by offering acceptable prices. On the other side, restaurant and shopping center owners who never collaborated with the online platforms, and now pandemic gave them the chance to move to the new online platform [19,20]. For instance, Doordash introduced the Main Street Strong plan for restaurant owners to attract them to join its online platform. The main Street Strong plan aimed the restaurant owners to build their brands, launching various programs to attract customers, and handling customer reviews to boost their qualities. This platform can be helpful for businesses because they could easily adjust their traditional approach based on customer demand and move to online platforms. However, this platform still needs to be optimized by employing operation research methods for providing the best solutions in revenue management and resource allocation. Still, business owners are not satisfied with available resources, and they lost their customers because of the lack of resource sharing provided by doordash. Pandemic verifies that uncertainty can impact all sides of different businesses, and using operation research to optimize the best strategies with minimum cost and maximum revenue, all businesses can eliminate the consequence of uncertainties [21].

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A measure of distance between time series: Dynamic Time Warping

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Many important phenomena are recorded as time series data, for instance, audio signals, electrocardiogram (ECG) signals from heartbeat monitors, returns of a financial asset and even the intensity of light emitted from a distant star. In many applications, it is of interest to measure the similarity (distance) between different time series samples. For example, voice recognition systems compare the audio signal of a spoken word against a database of template signals. Another example is heartbeat monitoring systems that compare real time patterns against a database of ECG patterns of known heart conditions.

When measuring the similarity between time series sequences, it is important to consider the alignment path, that is, the mapping between observations in the two time series. The Euclidean distance is a widely used measure of similarity between two vectors which, by definition, enforces a lock-step one-to-one mapping between corresponding observations in any two time series samples. Yet, the similarity between two time series measured by the Euclidean distance can be severely distorted when minor misalignments along the time axis, for example due to instrument measurement error, are present between the two time series. As a consequence, time series data mining tasks such as classification and clustering will break down if misalignments are not first corrected. Figure 2 demonstrates this idea for two starlight curves that belong to the same class of star but are misaligned in time[1]. The second panel of Figure 2 illustrates the lock-step Euclidean alignment path between the two time series. Since we know that the two time series belong to the same class of star, it is clear that the Euclidean distance does not provide an intuitive measure of similarity for these misaligned time series.

[1]The starlight curve data is available at https://www.cs.ucr.edu/%7Eeamonn/time_series_data_2018/

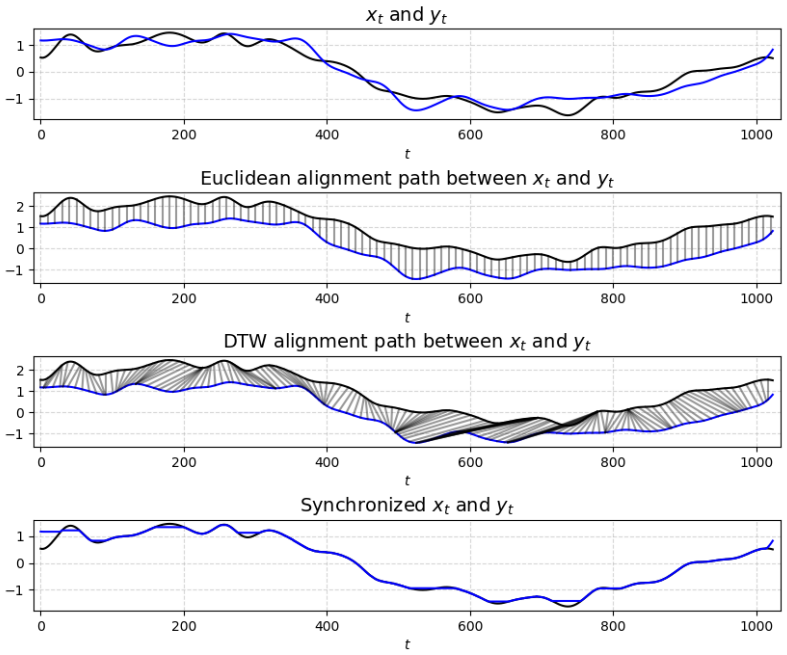


Figure 2: Comparison of Euclidean and DTW alignment between two starlight curves for an identical star.

To accurately measure the similarity in these cases, we must account for the potential misalignment between the two given time series samples. Dynamic Time Warping (DTW) offers one possible solution to this misalignment problem. DTW shrinks or stretches regions of one time series so as to best fit the other. In other words, DTW allows a non-linear alignment between observations and is therefore invariant to misaligned data. The third panel of Figure 2 plots the alignment path that is constructed by DTW. Using this alignment path, the final panel of Figure 2 plots the synchronized time series. It is now clear that the starlight curves belong to the same class of stars.

To construct the DTW alignment path, we first build a cost matrix that contains the exhaustive combination of all possible pairwise Euclidean distances between observations in the two time series. Contiguous alignment paths can be traced through this cost matrix and the distance between the two time series under any given alignment path is the sum of distances along the path. The goal of DTW is to construct the alignment path with the least cost. This path of least cost is found by using a recursive equation that defines the cumulative cost at the current observation as the current cost plus the minimum cost in the adjacent cells corresponding to the previous observation. Typically we compute the optimal alignment path subject to a constraint, known as the warping window width constraint, that restricts where the warping path is located to a region around the main diagonal of the cost matrix. Intuitively, this constraint ensures realistic alignments by prohibiting cases where one observation is matched with many observations in the other time series, a circumstance known as pathological warping.

Figure 3 plots an example of the cost matrix together with the DTW alignment path (solid white line) for the two starlight curves plotted previously in Figure 2. The dashed line along the diagonal of the cost matrix corresponds to the Euclidean alignment path. Therefore a Euclidean alignment path is a special case of the DTW alignment path. When the DTW alignment path is above (below) the diagonal we stretch (shrink) time series x to match time series y. For this reason, DTW is often referred to as an elastic distance measure. The cost matrix demonstrates that the DTW alignment path is a path of least resistance. The dotted dashed lines around the diagonal of the cost matrix represent a warping window width constraint set to a value of 20% of the length of the time series. In practice, the optimal value to use in this constraint can be selected using cross validation [1].

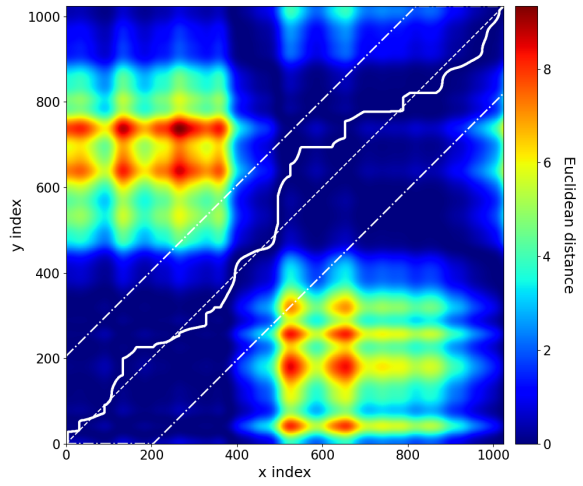


Figure 3: Cost Matrix and DTW alignment path for two Starlight Curves

One of the most prolific applications of DTW is as the distance measure in a nearest neighbour algorithm. For a given query time series, a K-nearest neighbour DTW algorithm is used to find the best match from a database of reference time series. However, the computational cost of a nearest neighbour search that uses DTW distance is considerable. In practice, a K-nearest neighbour DTW algorithm should always use lower bounding and early abandoning techniques to reduce the number of DTW computations that are required. Lower bounds are functions that are faster to compute than the DTW distance but closely approximate the actual DTW distance between two time series. Lower bounds are used to efficiently prune the nearest neighbour candidates and are implemented in cascading order of computational complexity. The three most common lower bounds developed in the literature are those of [7, 3] and [4]. It is also possible to specify early abandoning conditions whereby a current DTW calculation can be stopped if the cumulative distance along the optimal alignment path is such that the reference sequence cannot be a nearest neighbour [7]. These techniques allow DTW to be applied to truly massive datasets. In addition to nearest neighbour applications, time series clustering can also be performed using DTW [6]. For example, STRAVA has demonstrated how DTW averaging techniques in the domain of time series clustering can fix sequences of location data that have been misaligned by GPS sensor noise. It is also possible to generalize DTW for use with multivariate time series sequences [8].

Dynamic Time warping has been shown to perform exceptionally well across a large number of application domains, particularly when considering its relative simplicity [1]. As such, DTW has emerged as one of the most important time series data mining techniques in the last two decades. More recent trends in time series classification have moved towards ensemble models that use K-nearest neighbour DTW as a key algorithm [see e.g., 5]. Moreover, [2] has recently formulated DTW as a classical optimal control problem. This opens up avenues for future research on new methods for analysing signals via extending the optimization formulations.

In conclusion, DTW is a versatile tool that has been used with great success across many scientific fields. It is likely that many more exciting time series data mining problems can be solved by applying DTW in imaginative new ways.

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Cognitive Modelling of Consumer Preferences using the Linear Ballistic Accumulator (LBA)

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Understanding attitudes and preferences is an important topic in many fields. One of the most commonly used analytical methods for measuring preferences is the discrete-choice experiment (DCE) [5]. In these experiments, respondents are given hypothetical scenarios involving several products with different combinations of attributes, such as brand name and price. In each trial, they are asked to choose the product they are most likely to buy. The most commonly used model to analyze these choice data and extract the information behind the choices is the multinomial logit (MNL) model [2]. This model is developed based on the expected utility theory, assuming that each option has a perceived utility and that individuals will choose the option with the highest expected utility [4]. Although the MNL model has been widely adopted in discrete response analyses, it provides only limited insight into understanding the cognitive processes of decision making [3]. This issue can be overcome by using the linear ballistic accumulator (LBA) model in cognitive science, which incorporates not only the choices made but also the time required to make those choices [1].

The LBA model assumes that decision making is an evidence accumulation process [1]. Evidence is accumulated separately and simultaneously for each option, and respondents choose the option whose evidence accumulator first reaches its corresponding evidence threshold. In addition to the choice itself, the LBA model allows for inferences about the latent cognitive aspects of the decision of choice, such as the rate at which evidence accumulates for each option and the amount of evidence each option requires to trigger a choice response.

The key elements of the LBA are the starting points (k), the drift rate (d), the response threshold (b), and the response time (t). The starting points (k) refer to the amount of evidence at the beginning of the decision-making process. Different accumulators have different starting points, which are the random values generated from a uniform distribution: $U(0, A)$. The drift rates (d) refer to the speed of evidence accumulation, which are independently sampled from various normal distributions, with different means $v_1, v_2, \ldots, v_n$, for different accumulators and a common variance s. The response threshold (b) is the amount of evidence required for each accumulator to trigger a response. The response time (t) consists of two parts. The first is a non-decision time (τ), which occurs before and after the evidence accumulation, such as stimulus encoding and motor-response production. The second is the time taken by the accumulator to reach its threshold. We always assume that the response time of non-decision processes to be constant across trials. The accumulation process is illustrated in Figure 4.

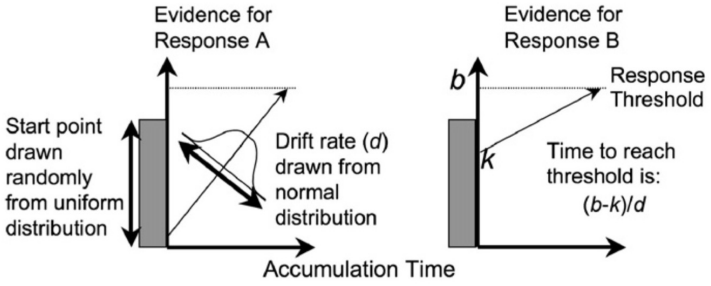


Figure 4: Graph demonstration of a binary-choice version of the LBA [1]

Since both individual and group-wide preferences are crucial for marketing strategies, two levels of parameters are introduced, that is, individual-level parameters $\boldsymbol{\alpha_j} = (\alpha_{j,1}, \ldots, \alpha_{j,5})^T$ and group-level parameters $\boldsymbol{\mu_\alpha}, \boldsymbol{\Sigma_\alpha}$ of the LBA. A normal distribution is applied for the individual-level parameters to capture the between-subject variation, that is, $\boldsymbol{\alpha_j} \sim \mathcal{N}(\boldsymbol{\mu_\alpha}, \boldsymbol{\Sigma_\alpha})$. The individual-level parameters capture the within-subject variation, while the group-level parameters capture the between-subject variation in the underlying cognitive processes of decision-making.

One barrier to applying the LBA to marketing is that it is not practical to obtain response time information, i.e., the time it takes for a customer to make the purchasing choice. However, the response time information is required to compute the likelihood. To resolve this problem, the likelihood function of the original LBA needs to be modified to fit the situation where only choice data is available. We do so by using importance sampling [7], which produces an unbiased estimate of the intractable likelihood that incorporates only the choice data. The likelihood for each individual $p(RE_j|\boldsymbol{\alpha_j})$ can be estimated unbiasedly as in Eq. (1), where RT_k are the samples from $g(RT)$ and $g(RT)$ is a proposal density which is easy to sample from.

$$\widehat{p(RE_j|\boldsymbol{\alpha_j})} = \frac{1}{p}\sum_{k=1}^{p}\frac{p(RE_j, RT_k|\boldsymbol{\alpha_j})}{g(RT_k)} \tag{1}$$

The model parameters include the group-level parameters $\boldsymbol{\mu_\alpha}, \boldsymbol{\Sigma_\alpha}$ and the individual-level parameters $\boldsymbol{\alpha_1}, \ldots, \boldsymbol{\alpha_m}$, where m is the number of individuals. In order to approximate the full joint posterior $p(\boldsymbol{\mu_\alpha}, \boldsymbol{\Sigma_\alpha}, \boldsymbol{\alpha_1}, \ldots, \boldsymbol{\alpha_m}|\boldsymbol{\mathcal{D}})$, we use the manifold Gaussian variational Bayes (Manifold GVB), which is a stable algorithm and less sensitive to the initialisation [6]. The pseudo-code implementation is summarised in Algorithm 1.

Algorithm 1 Manifold GVB with natural gradient [6]

Initialize $\boldsymbol{\mu} = \boldsymbol{\mu_0}$ and $\boldsymbol{\Sigma} = \boldsymbol{\Sigma_0}$
Compute $\nabla_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda}), \nabla_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})$ and the control variate $\boldsymbol{c}$
Compute the natural gradients: $\nabla^{\text{nat}}_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda}) = \boldsymbol{\Sigma}\nabla_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda})$
$\nabla^{\text{nat}}_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda}) = \boldsymbol{\Sigma}\nabla_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})\boldsymbol{\Sigma}$
Initialize the momentum: $\boldsymbol{m_\mu} = \nabla^{\text{nat}}_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda})$
$\boldsymbol{m_\Sigma} = \nabla^{\text{nat}}_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})$
stop = false
while *not stop* **do**
    $\boldsymbol{\mu} = \boldsymbol{\mu} + \varepsilon\boldsymbol{m_\mu}$
    $\boldsymbol{\Sigma}_{old} = \boldsymbol{\Sigma}, \boldsymbol{\Sigma} = R_\Sigma(\varepsilon\boldsymbol{m_\Sigma})$
    if *stopping rule is met* **then**
        stop = true
    else
        Estimate $\nabla_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda}), \nabla_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})$ and the control variate $\boldsymbol{c}$
        Compute the natural gradients: $\nabla^{\text{nat}}_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda}) = \boldsymbol{\Sigma}\nabla_{\boldsymbol{\mu}}\mathcal{L}(\boldsymbol{\lambda})$
        $\nabla^{\text{nat}}_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda}) = \boldsymbol{\Sigma}\nabla_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})\boldsymbol{\Sigma}$
        Compute the momentum: $\boldsymbol{m_\mu} = \omega\boldsymbol{m_\mu} + (1-\omega)\nabla^{\text{nat}}_{(\mu)}\mathcal{L}(\boldsymbol{\lambda})$,
        $\boldsymbol{m_\Sigma} = \omega\Gamma_{\boldsymbol{\Sigma}_{\text{old}}\to\boldsymbol{\Sigma}}(\boldsymbol{m_\Sigma}) + (1-\omega)\nabla^{\text{nat}}_{\boldsymbol{\Sigma}}\mathcal{L}(\boldsymbol{\lambda})$
    end if
end while

The above analysis provides insight into the decision-making processes of past choices. In addition, we are also interested in the choices that individuals are likely to make in the future. In order to predict future choices based on past choices, the posterior

predictive distribution is used. The posterior predictive distribution for new choices $\boldsymbol{y^*}$ can be computed using Eq. (2).

$$p(y^*|\mathcal{D}) = \int p(y^*|\boldsymbol{\alpha_j})p(\boldsymbol{\alpha_j}|\mathcal{D})d\boldsymbol{\alpha_j} \tag{2}$$

Note that $p(y^*|\mathcal{D})$ could be estimated unbiasedly by sampling from the VB approximation of $p(\boldsymbol{\alpha_j}|\mathcal{D})$. Therefore, the pseudo-code implementation to estimate the posterior predictive distribution can be summarised as in Algorithm 2.

Algorithm 2 Estimation of the posterior predictive distribution

for $i = 1, \ldots, N$ **do**
  Sample $\boldsymbol{\alpha_{ji}} \sim p(\boldsymbol{\alpha_j}|\mathcal{D}) \approx q_\lambda(\boldsymbol{\alpha_j}) \sim \mathcal{N}(\boldsymbol{\mu}_{\boldsymbol{\alpha_j}}, \boldsymbol{\Sigma}_{\boldsymbol{\alpha_j}})$
  for $k = 1, \ldots, p$ **do**
    Sample $\boldsymbol{RT_k} \sim g(\boldsymbol{RT})$
    Compute $\widehat{p(y^*|\boldsymbol{\alpha_{ji}})} = \frac{1}{p}\sum_{k=1}^{p} \frac{p(y^*, \boldsymbol{RT_k}|\boldsymbol{\alpha_{ji}})}{g(\boldsymbol{RT_k})}$
  end for
  Compute $\widehat{p(y^*|\mathcal{D})} = \frac{1}{N}\sum_{i=1}^{N} \widehat{p(y^*|\boldsymbol{\alpha_{ji}})}$
end for

We provide marketers with a tool to analyze how various factors affect consumer decision-making and the likelihood of each individual purchasing a specific product. This information can be used to help develop marketing strategies based on the goals marketers aim to achieve. For instance, using predictive probability information, marketers could identify the target groups most likely to purchase their products. By analyzing the characteristics of that specific group, such as gender or age, marketing strategies could be designed accordingly to address a larger group with similar characteristics. Another example is that because preference strength provides information about how sensitive individuals are towards each attribute (e.g., brand name or price), marketers could use this information and incorporate more highly preferred attributes into their marketing strategies.

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Transportation, Air Quality, and Health Impacts During COVID-19

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Traffic congestion adds considerable expense to business operations. Businesses may lose money due to shipment delays, productivity losses, wasted fuel, and refunds for late deliveries [1]. Delays due to traffic congestion have also halted manufacturing lines [1]. Traffic congestion results in up to $27 million in lost time and fuel for businesses [2]. In addition, traffic congestion can cause daily stress and frustration, while exhaust emissions pollute the air [3]. Air pollution was linked to over 30,000 deaths in the U.S. in 2015 [4], with broader implications for patients with lung cancer, heart attacks, strokes and other lung diseases like asthma [5]. Furthermore, car exhaust released into the air can stunt the growing lungs of children living in polluted areas [6]. Preliminary studies indicate that air pollution is associated with a higher number of deaths due to Covid-19 [7].

Although municipalities, states, and not-for-profit entities have been searching for solutions to traffic congestion for decades, the problem persists. Constructing additional roads is a limited solution, since space and capital are limited. And people who see empty roads may opt to use their personal vehicles that lead to congestion, rather than using public transportation, carpooling, or other methods of travel. To summarize a 2009 study [8], creating more roads creates more demand for those roads.

More recently, as the Covid-19 pandemic upended life in the United States and led to massive unemployment [10], studies from the first few months of the pandemic showed significant traffic congestion reductions [11] and correlated improvements in air quality [12]. For example, according to a University of California-Davis study, the number of miles driven by American drivers between early March and mid-April 2020 declined by 71%, and greenhouse gas emissions dropped by 32 million metric tons [13]. Beyond necessitating remote work for many employees, the pandemic required many business operations to be halted. This disruption compelled many businesses to rethink business operations or put into practice alternatives to the standard 9-to-5 workday with its associated rush hour congestion [14]. The number of people working remotely has limited the number of vehicles traversing our roads, greatly reducing traffic congestion and improving road operations.

With lockdown restrictions eased across much of the country, traffic has returned to the roads. However, with an estimated 42% of the workforce now working from home [15], traffic patterns and congestion have shifted. In a study of five major U.S. metropolitan areas from April to July 2020 [16], during the first spike of cases in the pandemic, showed that while miles per vehicle returned to the February 2020 pre-pandemic levels, congestion declined significantly as commuters spread their travel throughout the day. This dispersion in peak traffic is partly due to employees, particularly essential workers, who might typically take public transit but instead traveled in personal cars for fear of contracting Covid-19 [17]. Nevertheless, in spite of the increase in vehicle miles traveled, the amount of time spent waiting in congestion has decreased. This is important for air quality, as idling cars exacerbates the the already nega-

tive impact of pollution from constantly flowing traffic [18]. As the pandemic has shown, reducing traffic clearly benefits public health and business operations.

Through their reduction in congestion, work-from-home policies and flexible work schedules benefit employees, employers, and society at large. Although research pre-dating the pandemic showed that employees working from home were at least as productive as their peers in the office [19] [20], some companies remain hesitant about the benefits of remote work in the long term. Still, early evidence from the pandemic shows that the productivity of remote workers has continued to match or exceed pre-pandemic office-based productivity levels [21] [22]. Just as important, remote work policies are a major component of decreasing traffic congestion, decreasing air pollution, and increasing public health and quality of life [12]. Corporations should strongly consider keeping the flexible working hours and work-from-home options created during the pandemic. As the economy has rebounded from the first round of unemployment, new opportunities present themselves for mitigating traffic reduction. Even as recent research has shown that workers' attitudes towards commuting have changed, policy interventions that encourage these changes are required to ensure that traffic congestion does not rebound after the pandemic [12].

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Using Modern Tools for Operations Research: Concepts & Codes

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Operations research (OR) has been an academic and industry focus that has gained prominence since World War II, being used to optimize, predict and solve challenging problems across many sectors. To help introduce new OR students to the implementation of key optimization techniques, this article reviews several main optimization concepts, as well as implementations in Python and R.

Linear Programming

Linear Programming (LP) is both a fundamental and commonplace form of optimization: many, many problems may be expressed as linear programs (see Figure 5). For example, resource allocation problems and many others from business supply-chain applications may be modeled as LPs. We briefly introduce the basics of an LP problem as well as several repositories that may be helpful for implementing a LP:

(1) A set of variables,

$$x = [x_1, \ldots, x_n]^T, x \in \mathbf{R}^n$$

(2) A linear objective function to minimize or maximize

$$f(x) = c^T x, c \in \mathbf{R}^n$$

(3) A set of linear constraints of the form

$$a^T x \geq b \text{ or } a^T x \leq b \text{ or } a^T x = b$$

where $a \in \mathbf{R}^n$ and $b \in \mathbf{R}$

- Introduction to linear programming with Python
- Linear programming example in R
- Linear programming and regression analysis in Python
- Linear programming and optimization in Python

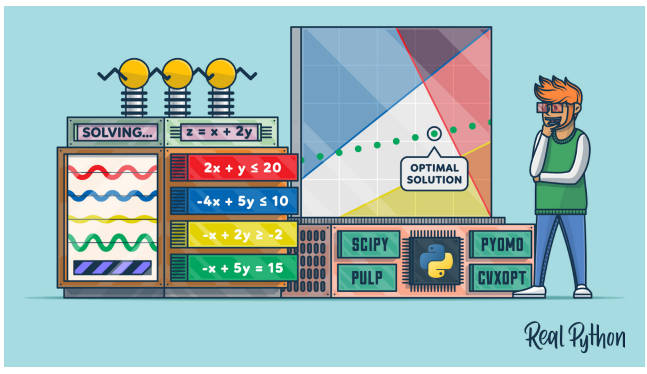


Figure 5: Graphical overview of LP (Source: Stojiljkovic, (2020))

Integer Programming

Integer Programming (IP) operates similarly to LP in that it seeks to optimize a function involving various variables with certain constraints, with the additional restriction that variables assume integer values (see Figure 6). Thus the restriction on variable values determines whether IP or LP should be employed: variables with discrete values (e.g., age) can be assessed via IP; and variables with continuous values (e.g., medicine dosages) can be assessed via LP.

A common problem in IP is set covering. Set covering involves a finite set U and a collection of subsets of U : $S_1, S_2, \ldots, S_n$. As an example, facility location problems employ the idea of set covering.

The goal is to identify the fewest number of subsets such that their union is U. Integer programming is employed to solve a set covering problem by considering a binary variable x_i for each subset S_i, where $x_i = 1$ when S_i is selected for inclusion in the union and $x_i = 0$ otherwise (Trevisan, 2011). A solution is obtained thusly:

$$\text{Minimize } \sum_{i=1}^{n} x_i$$

$$\text{Subject to: } \sum_{i:v \in S_i} x_i \geq 1, \forall v \in U$$

The objective function minimizes the number of subsets comprising the union, while the constraint specifies that each element of U must appear in at least one of the subsets S_i.

Another simple problem that may be solved via IP is the knapsack problem. Consider a knapsack with maximum weight constraint W. Then consider n types of items with corresponding values $v_1, v_2, \ldots, v_n$ and weights $w_1, w_2, \ldots, w_n$. The goal is to pack the knapsack such that the value of the packed items is maximized while respecting the weight capacity of the knapsack. In the 0-1 IP version of this problem, either one item of a given type may be taken or no items of a given type may be taken. A general knapsack problem allows the "packer" to take more than one item for a given type. For delivery companies, the issue of cargo loading is a knapsack problem.

Given time and perseverance, a student could calculate the solutions for simple examples of either of these problem types but solving by hand becomes unwieldy as the number of variables increases. The links below provide implementations for both the set covering and knapsack problems.

- The set cover problem using the Greedy Algorithm in R

- The set cover problem using a method other than the Greedy Algorithm in Python
- The knapsack problem using the cvxpy package in Python
- The knapsack problem using PuLP in Python with Jupyter Notebooks

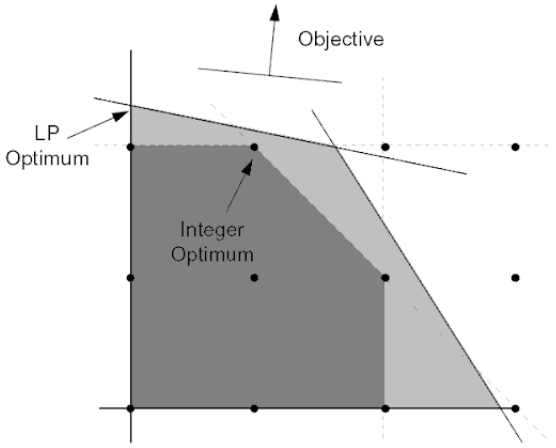


Figure 6: Solution for IP problem (Source: Eudoxus Systems Ltd.)

Mixed-Integer Programming

Mixed-integer programming (MIP) involves problems where some of the decision variables are constrained to be integers (e.g., 0, 1, 2), while other variables take continuous values. Although solution techniques for MIPs have existed for many years, recent advances in computing power, algorithms, and data availability have made it possible to model and solve the world's most complex business problems as increasingly tractable MIPs. A basic mathematical representation of MIP is given as follows:

(1) A linear objective function to minimize or maximize

$$z = c^T x$$

(2) A set of linear constraints of the form

$$Ax \leq b,\ x \geq 0 \text{ and integer}$$

where $x = [x_1, \ldots, x_n]^T$ is the decision variable vector (i.e., the unknowns)
$c = [c_1, \ldots, c_n]^T$ is the objective function coefficient vector
$b = [b_1, \ldots, b_m]^T$ are the constraint bounds (i.e., the right-hand side)

- Mixed integer programming example with stock investment in Python
- Mixed integer linear programming in R

Branch and Bound Method

Branch and bound, often abbreviated BB or B&B, is an algorithm that seeks an optimal solution to a variety of mathematical optimization problems (see Figure 7). The technique improves upon the idea of a complete enumeration, wherein each possible solution of the decision variables is considered and represented in an enumeration tree. For a problem with n variables, a tree that completely enumerates all solutions will have 2^n leaves. For multivariate problems, complete enumeration quickly becomes unwieldy. Rather than fully exploring solutions, BB uses a routine called pruning to eliminate the vast majority of solutions quickly and effectively.

To begin, BB relaxes any integrality constraints for the variables in order to solve for the LP relaxation of the problem, using typical LP techniques. The result provides bounds for subsequent steps. The first node of our branch and bound diagram for a maximization problem, LP(1), will contain the upper bound solution $z^*_{LP}(1)$, with variable values $z^*_{LP}(1)$, found through the LP relaxation and possibly a lower bound solution $z^*_{IP}(1)$ found by a search algorithm, such as rounding down/up each variable value from the LP solution. Whereas $z^*_{LP}(1)$ is a relaxed solution, $z^*_{IP}(1)$ is a feasible solution to the problem. The optimal integer solution exists between these bounds.

Upon completing the bounding step, the branching process continues: one variable is identified (e.g., having the largest fractional part in $x^*_{LP}(1)$) as the branching variable and two child nodes are created. Suppose the variable x_k is selected, having the value x^*_k in $x^*_{LP}(1)$. Two child nodes from node 1 are then created, each with an additional constraint: $x_k \geq$ ceiling(x^*_k) in one; and $x_m \leq$ floor(x^*_k) in the other. The resultant LP relaxations for nodes 2 and 3 are solved and $z^*_{LP}(2)$ and $z^*_{LP}(3)$ are obtained, along with possibly integer solutions $z^*_{IP}(2)$ and $z^*_{IP}(3)$ through a search algorithm. When new integer solutions, $x^*_{IP}(2)$ and $x^*_{IP}(3)$, are found, we update the incumbent solution and lower bound $LB = \max\{z^*_{IP}(1), z^*_{IP}(2), z^*_{IP}(3)\}$. The nodes that have already been explored (branched on), or provide an integer solution to the LP relaxation, or for which $z^*_{LP} \leq LB$ are all fathomed, or pruned from the search tree. As new node problems are solved, we update the upper bound, i.e., $UB = \max\{z^*_{LP}(k), k \text{ is unfathomed}\}$. Once the bounds are updated, the branching step continues. The process ends when all unfathomed nodes have been explored.

- A branch and bound solution in R for the knapsack problem
- A branch and bound solution in Python for the Traveling Salesman Problem (another classic algorithmic problem)

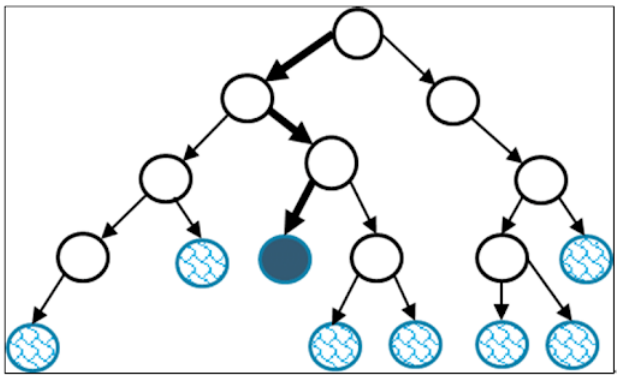


Figure 7: Tree like structure for BB problem

Transportation Problems

To discuss transportation problems, we must first consider network-flow problems, as the former are a special case of

the latter.

Consider an industrial good produced at various plants and desired at various markets. Each plant has a given capacity and each market has a given need. Transportation from plant to market - from origin to destination - may also pass through intermediate points, rather than going directly from the plant to market. The origins, destinations, and intermediate points may be viewed as nodes in a network. The goal of a network-flow problem is to minimize the cost of production and shipment while satisfying the demands of each destination.

The transportation problem removes the intermediate locations. It may be formulated as follows (Bradley, Hax, and Magnanti, 1977):

(1) The parameters:

a_i : the number of units available at source $i, i = 1, \ldots, m$
b_j : the number of units required at destination $j, j = 1, \ldots, m$
c_{ij} : the unit transportation cost from source i to destination $j, i = 1, \ldots, m$ and $j = 1, \ldots, n$

(2) The variables:

x_{ij} : the units transported from source i to destination $j, i = 1, \ldots, m$ and $j = 1, \ldots, n$

(3) The objective function to minimize:

$$\sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

(4) Subject to:

$$\sum_{j=1}^{n} x_{ij} \leq a_i$$
$$\sum_{i=1}^{m} x_{ij} = b_j$$
$$x_{ij} \geq 0$$

The objective minimizes the total cost of transportation for all units, while the constraints ensure that the supply capacity at each origin is respected and the demand at each location is satisfied. This basic formulation assumes that supply meets demand, though this is not always the case.

- Transportation problem in Python using the spaghetti package
- Transportation problem in Python using PuLP
- Transportation problem in R using lp.solve

Decision Analysis

Decision analysis is a formalized method for selecting optimal choices that have uncertain outcomes. This outcome uncertainty can be characterized by probability distributions for variables that represent the key consequences of the considered actions (Howard, 1988). The decision maker's relative preference for the various possible outcomes can then be described by a utility function that also captures the decision maker's attitude toward risk. A logical decision maker thus prefers the action that maximizes a particular mathematical combination of the derived probabilities and utilities. Figure 8 is a graphical illustration of a decision tree.

Multiple-criteria decision analysis (MCDA) is a sub-discipline of operations research that explicitly evaluates multiple conflicting criteria in decision making. Conflicting criteria are typical in evaluating options: cost or price is usually one of the main criteria, and some measure of quality is typically another criterion.

- Management decision analysis using Python
- Multi-criteria decision analysis

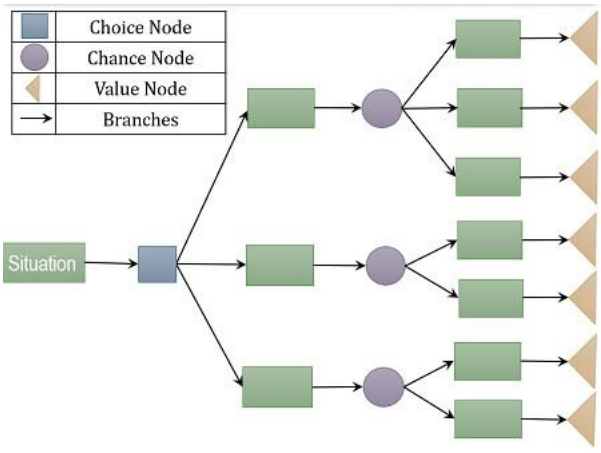


Figure 8: Decision Tree Analysis (Source: Prachi M. (2019))

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Metaheuristics in Optimization: Algorithmic Perspective

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The key motivation of *metaheuristics* is to find a **good-enough solution** to an optimization problem. In this article, some state-of-the-art metaheuristics algorithms along with illustrative examples will be demonstrated.

Introduction

The computer science and operations research communities have been striving to solve complex, large-scale real-world problems. In the previous article (Fall 2020), I described the fundamental algorithms that changed scientific computing in mathematics, computer science, and operations research. While solving a large-scale problem, finding a feasible solution and improving the solution to converge to the optimal global solution is necessary. However, finding exact solutions is difficult because resources are constrained, and most of the optimization problems are complex. Metaheuristic can solve this difficulty by offering *approximate* solutions.

Comprehending computational complexity is crucial to reap the benefits of metaheuristic. In computational complexity theory, we know only a few algorithms that are guaranteed to converge to optimality in reasonable run time (polynomial time-algorithms). However, many real-world problems are NP (non-deterministic). i.e., given a solution to the problem, we can verify the solution in a reasonable amount of time. Is P $\neq$ NP? Finding polynomial-time algorithms for the NP-complete problems is still in progress. NP-complete problems are the hardest in NP. If any NP-complete problem is P-time solvable, then all problems in NP are p-time solvable.

This article is inspired by the previous article on "Algorithms that changed the world" in the Fall 2020 issue. In continuation to this, I share the top five meta-heuristic algorithms (Genetic Algorithm, Simulated Annealing, Tabu Search, Swarm Intelligence Algorithm, Variable Neighborhood Search) to solve complex optimization problems that are difficult to solve to optimality using traditional optimization techniques.

Metaheuristic algorithms

A metaheuristic algorithm is a search procedure designed to find, a good solution to an optimization problem that is complex and difficult to solve to optimality. It is imperative to find a near-optimal solution based on imperfect or incomplete information in this real-world of limited resources (e.g., computational power and time). The emergence of metaheuristics for solving such optimization problems is one of the most notable achievements of the last two decades in operations research.

There are challenges that call for attention to develop better solutions over existing traditional approaches. Different metaheuristic algorithms are described by authors that are pretty extensive to various applications to solve non-linear non-convex optimization problems. In combinatorial optimization, it is impossible to solve specific problems that are NP-hard (i.e., in reasonable run time). Thus, metaheuristics can often find good solutions with less computational effort than optimization algorithms, iterative methods, and simple greedy heuristics. There are different varieties of problems that are impractical to solve using an optimization algorithm to global optimality. For example, an optimization problem becomes complex when there are stochastic random variables present in the objective or constraints. Hence, it is not easy to solve large-scale stochastic programs using stochastic programming or robust optimization techniques.

Metaheuristic can play a key role in different domains. In essence, many optimization problems are multi-objective functions with non-linear constraints. For instance, most of the engineering optimization problems are highly non-linear that demand solutions to multi-objective problems. On the other hand, artificial intelligence and machine learning problems rely heavily on large datasets, and it is difficult to formulate the optimization problem to solve for optimality. Therefore, metaheuristics play a significant role in solving practical problems that are difficult to solve using conventional optimization methods.

Metaheuristic algorithms are classified based on how they operate over the search space [3] such as nature-inspired vs. non-natured inspired, population-based vs. single point search, dynamic vs. static objective functions, one vs. various neighborhood structures, memory usage vs. memory-less methods. The purpose of this article is not to compare search and optimization

techniques. Nevertheless, it is critical to question whether conventional search methods meet robustness requirements. Metaheuristics are suitable for both exploitation and exploration of the solution space.

Now, let us explore some metaheuristic algorithms. In addition to their algorithmic perspective, a real-life scenario of emergency response allocation of marine accidents and the application of metaheuristics will be exemplified.

Genetic Algorithm

The genetic algorithm (GA) is a metaheuristic motivated by the evolutionary process of natural selection and natural genetics. The algorithm [9] combines the fittest's survival among string structures with a structured yet randomized information exchange to form a search algorithm. The key aspect of genetic algorithms is the balance between efficiency and efficacy necessary for survival in different harsh competitive environments.

Genetic algorithms are theoretically and empirically proven to provide robust searches in complex spaces. In GA, a pool of initial solution sequences is generated and stored in a population pool. These sequences represent the genetic representation of a solution domain. A fitness function that describes a solution value of the objective function is determined. Using a selection operator, two-parent solutions from the population undergo genetic operators such as crossover and mutation with an associated probability. The parent chromosomes generate offspring chromosomes by crossover operator to represent child solutions, namely child1 and child2. These offspring chromosomes undergo a mutation (swapping of Alleles) operator. The fitness function (objective) is evaluated for the children's solution, and the population is updated based on the betterness (Elitism) of the fitness function. The algorithm is repeated until maximum generations or by a stopping condition. Generally, the solution sequences are encoded in either binary or bit string structure to represent the solution.

Consider an example of allocating response vessels (e.g., rv_1, rv_2, rv_3, rv_4, and rv_5) in a few accident scenes, say s_1, s_2, s_3, s_4 and s_5. The sequence's chromosome representation would be $[s_1 - s_3 - s_4 - s_2 - s_5]$. The "**Child**" represents the proposed "Accident Scenes" to assign "Response Vessels". There are several types of **crossover** operators used in GA. Crossover operators such as single point crossover, two-point crossover, k-point crossover, priority-based encoding, and uniform crossover are widely used. A sample one-point crossover is shown below that may split the parent chromosome at a certain point.

Response Vessels	rv_1	rv_2	rv_3	rv_4	rv_5	
Parent (Accident Scenes)	s_1	s_2	s_3	s_4	s_5	
Child	s_4	s_5	s_1	s_2	s_3	(Crossover)
Child	s_4	s_5	s_3	s_2	s_1	(Mutation)

In mutation, one of the child sequences is swapped, such as s_1 is swapped with s_3. The stopping condition depends on the type of combinatorial optimization problem. Generally, maximum generations and maximum run time is considered as stopping criteria. However, stopping conditions can be based on stall time and maximum stall generations. A generic process flow of the development of the Genetic Algorithm is shown in Algorithm 3.

Some of the applications of GA are feature selection and hyperparameter tuning in machine learning, game-theory applications, scheduling problems, molecular structure optimization, non-linear programming, and financial mathematics. A response vessel allocation model using GA is proposed in [14] to support the oil spill contingency plan.

Algorithm 3 Genetic algorithm

Initialize parameters: pop_size, max_generations, max_time, max_generations, max_stall_time, elicit_rate, crossover_rate, mutation_rate, seed_count, tournament_selection
Generate initial population (P) randomly
Evaluate fitness function
generation ← 0
while generation ≤ max_generations || time ≤ max_time || stall_time ≤ max_stall_time || sgenerations ≤ max_generations **do** ▷ main loop
    while size(P') < popsize **do**
        generation ← generation + 1
        Selection:
        parent1 ← tournament_selection(P) ▷ Roulette Wheel
        parent2 ← tournament_selection(P)
        Crossover:
        child1 ← crossover(P) ▷ Random restart
        child2 ← crossover(P)
        Mutation:
        child1 ← mutate(P) ▷ Mutation rate
        child2 ← mutate(P)
        Compute fitness function
        Eliticism: ▷ Elite count
        if best fitness individual in P' **then**
            P' ← () ▷ Exploitation
        else
            P ← P' ▷ Exploration
            P' ← ()
        end if
    end while
end while
return the optimal point
Print the fitness value

Simulated Annealing

Simulated annealing (SA) [12] is primarily inspired by the annealing: heating and controlled cooling operation in metallurgy.

A generic process flow of the SA algorithm is shown in Algorithm 4. A neighborhood solution (s) is generated using a local search procedure using an initial seed (s_0) and temperature. The fitness value of the objective function is evaluated for this seed and neighborhood solution. Let δ be the difference between the fitness function values. If $\delta < 0$, the neighbor solution is accepted, else, the neighbor solution is accepted with a Boltzmann probability density of $e^{(\frac{-\delta}{T})}$. Thus, both exploitation (extensive search in a previously known search space) and exploration (explore new opportune wider search spaces) are deployed over the search space. In the process of cooling, the algorithm converged to an approximate solution, escaping from local optima to find the near-optimal solution. This slow cooling implemented in the SA algorithm is interpreted as an exploration process that involves a slight decrease in the probability of accepting worse solutions when the solution space is explored. In summary, the SA algorithm behaves like a hill-climbing heuristics but with more power not to get stuck in the local optima [19].

Algorithm 4 Simulated Annealing algorithm

Initialize parameters: Temperature (T), initial seed, max_iterations, n_rep, cooling rate (α)
while cool_iteration $\leq$ max_iterations **do** ▷ main loop
    cool_iteration $\leftarrow$ cool_iteration + 1 ▷ Update cooling iterations
    temp_iteration $\leftarrow$ 0
    while temp_iterations $\leq$ n_rep **do**
        temp_iteration = temp_iteration+1
        Select a new point from the neighborhood
        Compute current_cost of the new point
        $\delta \leftarrow$ current_cost - previous_cost
        if $\delta \leq 0$ **then**
            Accept the neighbor ▷ Exploitation
        else
            Accept the neighbor with the probability $\exp\left(\frac{-\delta}{T}\right)$ ▷ Exploration
        end if
    end while
    $T \leftarrow \alpha * T$ ▷ 0<α<1
end while
return the optimal point
Print the objective value

Although SA usually achieves an approximate solution to the global minimum, it could be enough for many practical problems and implementation. Applications of SA include traveling salesman problems, graph coloring problems, vehicle routing and extensions, very-large-scale integration and computer design, and scheduling problems. Several variants of SA proposed by authors are quantum annealing, dual-phase evolution, stochastic tunneling, and parallel tempering. Optimal ship routing can be proposed using SA [13] that minimized the time of voyage and maximize the safety of voyage.

Tabu Search

Tabu search (TS), another metaheuristic algorithm, is based on the memory structures and uses local search methods to find a potential solution by checking its neighbors to find a better solution [8]. Generally, local search methods get stuck in suboptimal regions. TS enhances the search process by restricting (henceforth the term Tabu) the same solution's recurrence from coming back to previously visited solutions. TS has many similarities with SA, and both involve hill climbing and exploration possibilities. The memory structure defines a set of rules used to filter solutions from the neighborhood search. More commonly, a Tabu list consists of solutions defined by Tabu tenure (number of iterations) that the solution remains in the solution bucket. The memory structures used in TS can be divided into three categories [7]:

- Short term memory: If a potential solution appears in the Tabu list, it cannot be revisited until it reaches Tabu tenure
- Intermediate memory: Intensification rules are used to improve the search spaces
- Long term memory: Diversification rules that drive the search into new regions. A reset is applied if the solution gets stuck in a plateau or sub-optimal region

A simple local search algorithm is shown below in Algorithm 5. TS uses a local search or a nearest neighborhood (greedy) search procedure to move from one potential solution iteratively, s_0 to an improved solution s by a simple operation σ in the neighborhood s_0, until some stopping criterion has been satisfied. Many local search heuristics are available in practice, including steepest descent, 2-opt, 3-opt, R-opt, nearest neighbor, and random descent.

Algorithm 5 Local Search algorithm [19]

Initialize parameters: tolerance, initial seed
Select a starting solution, s_0
Select a neighborhood solution, s by a suitable method ▷ Steepest descent or random descent
while $f(s) < f(s_0)$ **do** ▷ main loop
    Replace s_0 by s
    Select a neighborhood solution, s by a suitable method
end while
return s_0 ▷ approximation to the optimal solution
Print the objective value, $f(s_0)$

The algorithm is initiated by random initialization and solutions. In each iteration, a new solution is found by making local movements over the current solution. The neighbor solution is the best among all (or a subset of) possible solutions in the neighborhood using operator $N(\sigma)$. In the exploration process, recently visited solutions should not be visited, thereby maintaining a tabu list in order to strict the solution movement in the local search process. Therefore, we have a dynamic neighborhood compared to the static neighborhood obtained by other local search algorithms. Typically, there are three kinds of tabu lists maintained using memory structures: 1) A long term memory that hold the history through all the exploration process and reset the search process getting stuck in local optima, 2) an intermediate memory to improve the search space and 3) a short term memory to keep the most recently visited solutions as tabu movements.

Tabu search is very efficient and escapes from the local solution to find the near-optimal solution. Some of the applications of solving combinatorial problems using Tabu search are Scheduling, communications path assignment, graph coloring, graph partitioning, job shop scheduling, neural network pattern recognition, and routing problems [7]. The optimal allocation of *berth*, similar to a car *park*, for ships is proposed in [4] using the Tabu Search algorithm.

Algorithm 6 Tabu Search algorithm

```
1: Initialize parameters: tolerance, initial seed, maxiterations, max_Tabu_Size
2: s_Best ← s_0
3: best_Candidate ← s_0
4: tabu_list ← empty
5: tabu_list.push(s_0)
6: while iterations < max_iterations do                                   ▷ main loop
7:     s_Neighborhood ← get_Neighbors(best_Candidate)
8:     best_Candidate ← s_Neighborhood[0]
9:     for s_Candidate in s_Neighborhood do
10:        if (not tabulist.contains(s_Candidate)) && (fitness(s_Candidate) > fitness(best_Candidate)) then
11:            best_Candidate ← s_Candidate
12:        end if
13:    end for
14:    if fitness(best_Candidate) > fitness(s_Best) then
15:        s_Best ← best_Candidate                                        ▷ Exploitation
16:    end if
17:    tabu_list.push(best_Candidate)
18:    if tabu_list.size > max_Tabu_Size then
19:        tabu_list.remove_First()                                       ▷ Exploration
20:    end if
21: end while
22: return s_Best
23: Print the objective value
```

Swarm Intelligence Algorithms

Swarm Intelligence Algorithms are inspired by bird flocking's social behavior, animal herding, bacterial growth, and fish schooling. Swarm intelligence systems, initially developed within cellular robotic systems [1], are typically made up of a population of simple agents interacting locally with one another and with their environment. Researchers propose several nature-inspired swarm intelligence algorithms to solve a combinatorial problem to a near-optimal solution. Algorithms such as ant colony optimization [5], particle swarm optimization (PSO) [11], bee colony optimization, cuckoo search are some of the well-known algorithms under swarm intelligence.

PSO [11] is a population-based evolutionary algorithm in which the best solution can be represented as a vector in an n-dimensional space. In every iteration, the velocity (v_{ij}) and the position (x_i) of the particles are controlled to converge to the near-optimal solution that maximizes or minimizes the objective function. Particles move through the solution space and are evaluated based on a fitness function. In each iteration, particles are updated with two values, namely p_{Best} and g_{Best}. p_{Best} (y_{ij}) is the best solution achieved so far, whereas the g_{Best} ($\hat{y}_j$) is the second-best value obtained by any particle in the population. A schematic representation of the p_{Best} and g_{Best} is shown in Figure 9. Thus, exploration happens with neighborhood search and reduces the susceptibility of PSO falling into local optima but slows down convergence speed.

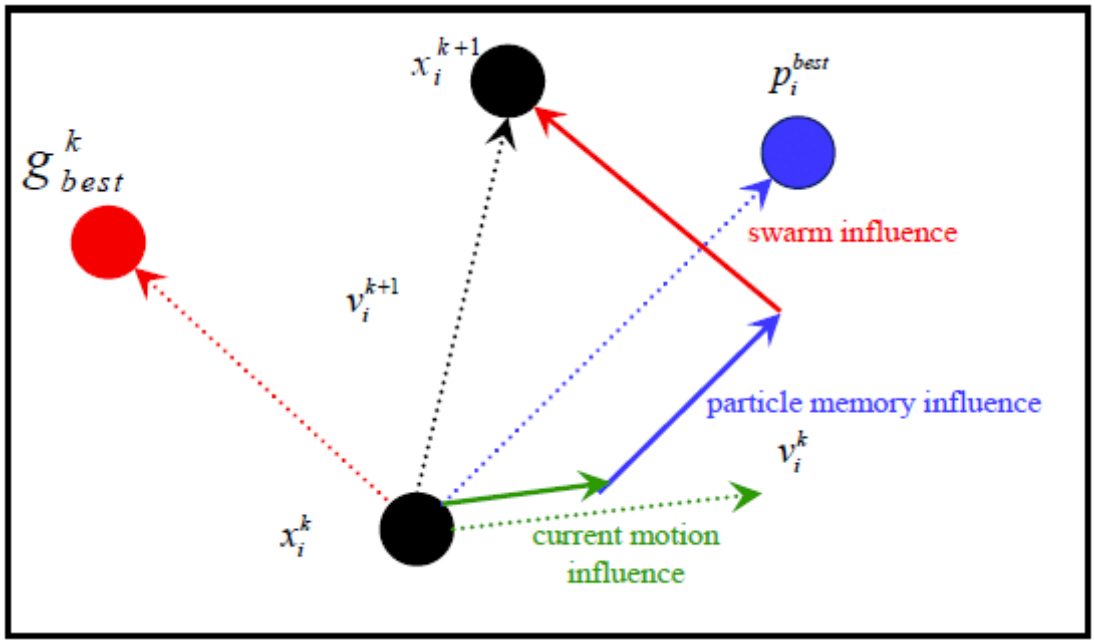


Figure 9: Velocity component construction of a particle swarm

The position of the particle is changed by adding a velocity, $v_i(t)$, to the current position, as in Eq. (3), with $x_i(0) \sim$ U(x_{min},x_{max}).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

For g_{Best} PSO, the velocity of particle i is calculated as in Eq. (4), where c_1 and c_2 are acceleration constants. The PSO algorithm is shown below in Algorithm 7.

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_{1j}(t)[y_{ij}(t) - x_{ij}(t)] + c_2 r_{2j}(t)[\hat{y}_j(t) - x_{ij}(t)] \tag{4}$$

Algorithm 7 Particle Swarm Optimization algorithm

Initialize parameters: tolerance, initial seed, max_iterations
Create and initialize an n-dimensional swarm
while iterations < max_iterations **do** ▷ main loop
    for each particle i=1,...,n_s **do**
        if f(x_i) > f(y_i) **then**
            $y_i \leftarrow x_i$
        end if
        if f(y_i) > f($\hat{y}$) **then**
            $\hat{y} \leftarrow y_i$
        end if
    end for
    for each particle i=1,...,n_s **do**
        Update the velocity using Eq. (4)
        Update the position using Eq. (3)
    end for
end while
return g_{Best}
Print the objective value

PSO can be applied to various optimization problems [20], including civil infrastructure systems, traffic accident forecasting, structural engineering, multi-thresholding modalities for suspicious region detection on mammograms, photovoltaic array reconfiguration, power systems, and rail transit assembly of robot systems. Some exciting applications including NASA's swarm technology investigation for planetary mapping, the movie 'Batman Returns' makes use of swarm technology for rendering, depicting the penguins' movements, and the 'Lord of the Rings' film trilogy made use of similar technology during battle scenes.

To illustrate, in the case of an emergency response system of a marine oil spill, allocation and deployment of response vessels (e.g., rescue ships) can be optimized using PSO, as proposed in [21]. In an oil recovery operation, the key goal is to collect as much oil as possible, and this is a time-contingent operation. The optimal response plan (considering the allocation of resources, recovery behaviors of skimmers, space for carrying equipment of vessel transportation, and resource utilization from response centers) proposed in this research recovered approximately 80.28% of the spilled oil within the first 48 response hours.

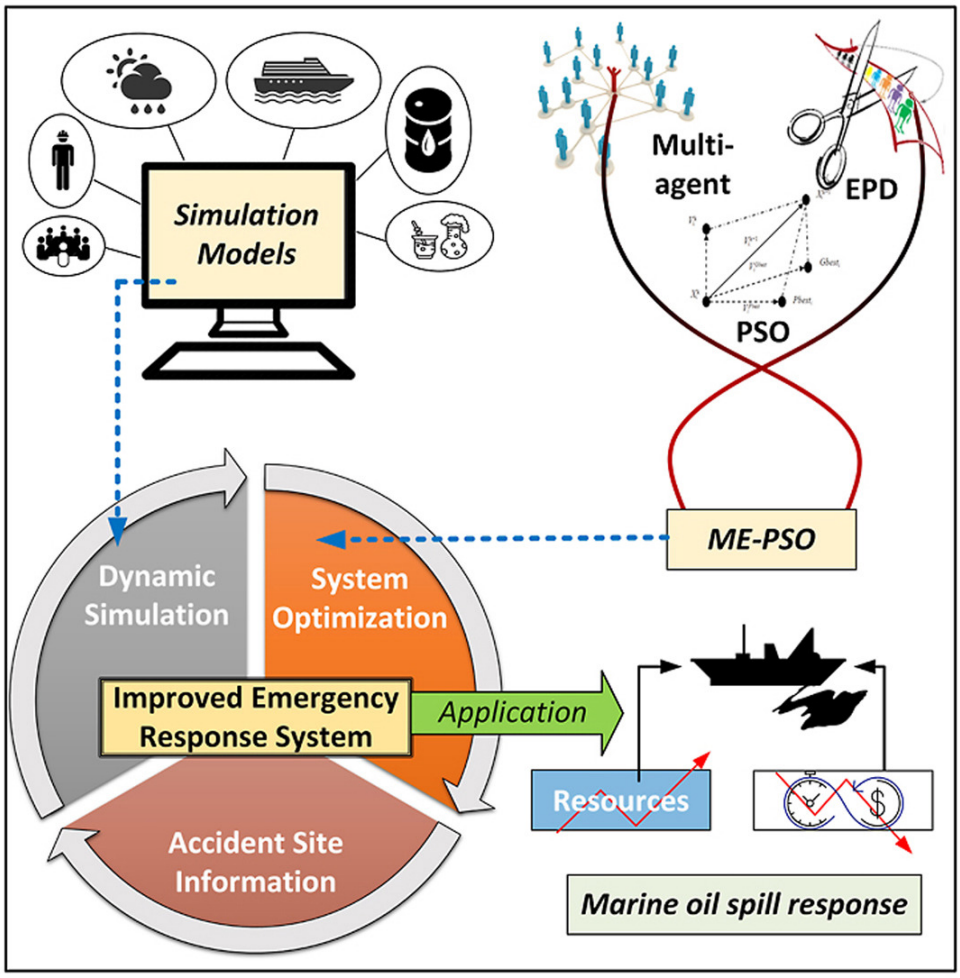


Figure 10: Emergency Response of Marine Accidents, using PSO [21]

Variable Neighborhood Search

Variable neighborhood search (VNS) [16] algorithm explores distant neighborhoods of the initial solution and moves to a new improved solution. Similar to Tabu search, a local search method is applied repeatedly to get from solutions in the neighborhood to local optima and escape from the valleys that contain them. This characteristic helps VNS to solve linear, non-linear, integer, and mixed-integer programs. VNS uses a simple local search coupled with the first improvement heuristic and neighborhood change algorithms; it has both exploitation and exploration process similar to other metaheuristics.

The details of the VNS algorithm are shown in Algorithm 10. At first, a first improvement heuristic is invoked to find the local optima, given the solution's feasible region, as in Algorithm 8. Then, the neighborhood heuristic is invoked to escape from the local optima to find a better solution in the new feasible area, as in Algorithm 9. The algorithm is repeated until maximum preset iterations and CPU run time. In addition to the first improvement heuristic, a simple local search can be used for the local search operation, as in Algorithm 5.

Algorithm 8 First improvement heuristic [10]

```
procedure FirstImprovement(x)
    repeat
        x' ← x
        i ← 0
        repeat
            i ← i + 1
            x ← arg min_x {f(x), f(x^i) }, x^i ∈ N(x)
        until f(x) ≤ f(x^i) or i = |N(x)|
    until f(x) ≥ f(x')
    return x'
end procedure
```

Algorithm 9 Neighborhood change heuristic [10]

```
procedure NeighborhoodChange(x,x',k)
    if f(x') ≤ f(x) then
        Accept the neighbor                          ▷ Exploitation
        k ← 1
    else
        k ← k + 1                                    ▷ Exploration
    end if
end procedure
```

Algorithm 10 Variable Neighborhood Search algorithm [10]

```
procedure VNS(x,tmax,kmax)
    repeat
        k ← 1
        repeat
            x' ← Shaking(x,k)
            x'' ← FirstImprovement(x)                ▷ local search
            x ← NeighborhoodChange(x,x'',k)          ▷ change neighborhood
        until k=kmax
        t ← CpuTime()
    until t > tmax
    return x'
end procedure
```

A variant of VNS [6] uses a deterministic neighborhood search, unlike the single neighborhood structure. 'Shaking' is an additional step performed to find the best alternative solution from the k^{th} neighborhood at random. Similarly, reduced VNS, skewed VNS, variable search decomposition, parallel VNS are widely used techniques to solve mathematical programming problems [10]. Overall, VNS is simple and broadly applicable. It is more efficient to produce good solution quality in reasonable CPU time. Applications of VNS include location theory, network design, lot-sizing, pooling problems, reliability, geometry, and telecommunication design.

Summary

To summarize, metaheuristics are used to find good-enough solutions for an optimization problem. Metaheuristics are simpler to design and implement [17]. A few well-established metaheuristic algorithms that can solve optimization problems in a reasonable time frame are described in this article. Effective algorithm development is a continuous improvement process. Several search procedures, nature-inspired algorithms are being developed to solve a variety of complex optimization problems.

In light of advantages, metaheuristics are strategies that guide the search process. There are simple local search techniques to complex learning processes available in the form of iterative algorithms. Metaheuristics are approximate solution methods and usually non-deterministic [3]. The critical aspect of metaheuristics is not problem-specific, and hence any optimization problem can be solved with ease of understanding. Nevertheless, despite its popularity and practical efficacy, metaheuristic methods give inadequate quality solutions. It heavily relies on proper implementation and hyperparameters tuning, which in itself is another

optimization landscape [2].

Considering implementation platforms of metaheuristics to solve real-world problems, MATLAB [15] has inbuilt GA, SA, and particle swarm algorithms. Similarly, many packages were developed using various programming languages such as C++, Java, and Python (e.g., [18]) to solve optimization problems.

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