A Multi-Objective Green Electric Vehicle Charging Stations Location Problem Considering Central Business District Zone

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Abstract

Depleting fossil fuel reserves will increase the use of electric vehicles. The need to recharge electric vehicles has addressed this issue. In this regard, finding an optimal charging station design is critical. This study introduces a multi-objective battery electric vehicle charging station location problem (BEVCP). As one of the main novelties of this study, we divided the city into two zones, namely inside and outside the central business district (CBD) zone, and designed the charging station network taking these zones into consideration. Furthermore, with regard to the CBD, desired upper and lower bounds of distance (miles) between charging stations are also considered. The proposed two objectives minimize the capital cost of establishing a station and the distance between two stations. In this way, reducing carbon dioxide (CO2) emissions is considered as well. The obtained results confirmed the efficiency of the proposed model.

Keywords
Battery electric vehicle, Charging station location problem, CO2 emission rate, CBD zone.

1. Introduction
Increasing the use of electric vehicles is inevitable due to declining fossil fuel reserves. The need to recharge electric vehicles has addressed this issue (Lord et al. 2019), (Asghari et al. 2021). Modeling electric vehicles to determine the energy capacity of charging stations, determining the optimal location and size of these stations, and charging management methods are essential issues (Paulo et al. 2018). To determine the optimal location of charging stations, various indicators such as distribution network losses, reliability, and accessibility, should be considered (Fei and Ramteen 2017). Currently, the number of electric vehicles around the world is increasing, so that 54 percent of all vehicles in the world are projected to be electric by 2020 (Bahrami et al. 2017). Therefore, it is necessary to design and build charging stations worldwide to charge this type of vehicle.

Essential factors for recharging station are uncertainty of load demand, the uncertainty of the number of connected electric vehicles, distance, power consumption of vehicles, battery charging time, the energy required for battery charging, number of electric vehicles, and determination of time charging profile, number of charging stations and determination of station input power capacity (Fei and Ramteen 2017).

In 2016, Middle East Countries established the Electric vehicle and infrastructure development center, focusing on charging infrastructure and electric propulsion. They introduce its products in the field of fast and slow chargers for electric cars and motorcycles after designing, manufacturing, and performing accurate tests according to the international standard IEC61851. The center's fast chargers support three standards: CHADEMO (Japanese cars), CCS (European cars), and GB/T (Chinese cars). Also, the upstream connection of all chargers is based on the standard OCPP (Open Charge Point Protocol) (Miralinaghi and Srinivas 2019).

Both battery capacity and fast charging capability are improving, but the need of improved charging methods is still felt. Other charging methods have been proposed, including mobile charging stations and wireless chargers. The various needs and solutions offered by manufacturers have slowed down the emergence of standard charging methods. Since 2015, measures to standardize charging processes need more attention (Miralinaghi et al. 2020).

In 2017, TESLA issued a credit card to owners of S and X cars so that they could use the company's 400 kWh of superchargers for free. Owners of TESLA electric vehicles will have to pay per kilowatt-hour when using superchargers at charging stations after the free quota expires. The price range for using these superchargers in the United States is between $ 0.06 and $ 0.26 per kilowatt hour. These TESLA superchargers can only be used for TESLA cars.

One of the charging networks that can be used for other electric vehicles (except TESLA) is Blink, which has fast level 2 and DC chargers. The cost of using these chargers varies for members. It varies between $ 0.39 and $ 0.69 per kilowatt hour for members and $ 0.49 to $ 0.79 for non-members depending on the location of the station. By 2013, the company's chargers were overheating, damaging the charger and the car itself. The company's solution to this problem was to reduce the maximum flow (Bahrami et al. 2020).

There are two approaches to optimizing the presence of electric vehicles. The first view is to optimize and plan the charge and discharge time or charge management. The second perspective investigate locating electric car parking or charging station (Bayram et al. 2021). A green multi-objective location problem is taken in this study to design charging stations. All in all, we proposed two objective models for reducing CO2 emissions. In the rest of the paper, another contribution of BEVCP has been reviewed and then will bring up in the literature section. In the next part, the proposed model will be discussed. The last section will allocate to state the conclusion of the research.

2. Literature Review

Locating a charging station is one of the most important issues. The location of charging stations can lead to congestion of power distribution lines. As a result, the reliability is reduced and the energy losses of the distribution network are increased. Therefore, the location of charging stations is important that studied by some researchers (Miralinaghi et al. 2020). To identify the optimal location for charging stations on a network that is under the influence of distributed generation sources, a goal function including two parts of power loss and average voltage deviation is considered.

Zaccagnino (2019) used the Poisson distribution to consider the uncertainty of the presence of the number of electric vehicles per hour, and the normal distribution to uncertain the amount of charge requested by each vehicle. Based on this, 100,000 scenarios per hour have been created and using the Latin super-cube method, the scenarios per hour have been reduced to 10. The results of numerical studies show that uncertainty in the amount of load caused by charging electric vehicles can overload the network in some hours. Determining the right number and location for car charging stations can greatly prevent network overload.

Zhang et al. (2021) studied different operating strategies are expressed and refer to three strategies called uncontrolled charging mode, controlled charging mode and intelligent charging mode. In uncontrolled charging mode, the charge rate is maximum and we have no control over it. In vehicle-to-grid (V2G) controlled charging mode, we can adjust the charging rate according to the peak load point. In smart charging mode, in addition to V2G method, we can also have V2G charging and discharging. It can be done in two ways. The complete model of the probabilistic behavior of the presence of grid-to-vehicle (G2V) vehicles in parking lots (as the best idea for charging stations) is expressed. In this study, the simultaneous effect of charging and discharging cars and driving pattern losses on working days and weekends of different seasons of the year has been done.

Thomas and Josef (2013) discussed hybrid vehicles, a combination of fossil fuels plus electric. In all electric vehicles the capacity of the relevant batteries is higher than in hybrid car batteries. Relationships between losses and load coefficient and load variance are investigated in this paper. Xiao-Hui et al. (2016) minimized the objective function, which includes costs related to construction, operation and charging using a particle swarm optimization algorithm. It shown that by adopting intelligent strategies in the operation of electric vehicles, the adverse impact of these vehicles on the transmission system is reduce. Paulo et al. (2018) explored multi-purpose locating of electric vehicle charging stations to improve voltage and reliability and reduce cost's objective, regardless of the car battery charging model.

Miralinaghi and Srinivas, (2019) and Bayram et al. (2021) parking location has been done to reduce power losses without considering the probabilistic model of electric car charging station and the need for car batteries to be charged.

Fei at al. (2018) employed genetic algorithms and Monte Carlo simulation to locate and determine the capacity of electric car charging stations and scattered production sources. Zhang et al. (2021) focused on the location of fast charging stations to reduce the charging time of electric vehicles. In a type of technology and structure proposed in the fast-charging station, the charging time of electric vehicles has reached less than 7 minutes.

In this paper, a new method for locating fast electric charging stations with a regional perspective and the coefficient of interchange between regions is proposed. First, the city must be divided into specific are. By focusing on CO2 emitted from electric vehicle (route, node-tripe time emission), the initial candidate points in each area are determined. Land price and distance from the network substation are main parameters. Capital cost of the fast-charging station is defined as an objective function as well as station location and then solved by the Cplex solver. In the proposed method, in addition to the location of the fast-charging stations, the distance and capacity of fast charging unit's capacities at each station is also determined.

3. Model description

The proposed multi-objective battery electric vehicle charging station location problem considering CBD zone is presented in this section. Total network cost and CO2 emission rate are defined as objective functions. Additionally, two upper and lower distance bounds are considered to determine where charging stations are located. The symbols corresponding proposed model is described as follows.

Sets:

i	Index of candidate sites for charging stations in the network, $i \in \widetilde{N} \subset N$, where $\widetilde{N}$ is the set of candidate sites and N is the node set. Also $\widetilde{N} = \{\overline{N} \cup \overline{\overline{N}}\}$ where $\overline{N}$ is the set of candidate sites which are located in the CBD area and $\overline{\overline{N}}$ is the set of candidate sites which are located outside the CBD area.
t	Index of time stages $t \in T$.
r	Index of origins in the network, $r \in R \subset N$.
s	Index of destinations in the network, $s \in S \subset N$.
k	Index of the paths for an O-D pair, $k = 1,2,\dots,K^{rs}$, Where K^{rs} is maximum number of deviated path allowed between an O-D pair (r,s)
a	Index of arc set A, $\mathrm{a} = (i,j) \in A$

Parameters:

f_i	Fixed capital cost ($) of opened charging station at node $i \in \widetilde{N}$
D_t^{rs}	Number of BEV inter-city trips between O-D pair $r \in R$ and $s \in S$ in time stage $t \in T$
$\bar{B}$	Maximum SOC measured by vehicle range (miles)
M	A sufficiently large number
$P^{rs\,k}$	The sequence of nodes on the k^{th} path between O-D pair $r \in R$ and $s \in S$
d_{ij}	Distance (miles) between node $i \in N$ and $j \in N$
γ	CO_2 emission rate of using electricity (kg/mile)
γ'	PEVs' the electricity consumption rate (kWh/hr)
τ	The desired upper bound of distance (miles) between two located charging station at node $i \in \widetilde{N}$ and $j \in \widetilde{N}$
π	The desired lower bound of distance (miles) between two located charging station at node $i \in \widetilde{N}$ and $j \in \widetilde{N}$

φ A certain threshold $(0 \leq \varphi \leq 1)$

W_{it} A waiting time of a BEV in a queue at node $i \in \bar{\bar{N}}$ which is located outside the CBD zone in time stage $t \in T$.

Decision variables:

Z_{it} Is equal to 1, if a charging station is open at node i in time stage t, 0 otherwise.

$Y_t^{rs\,k}$ Is equal to 1, if the k^th path between $r \in R$ and $s \in S$ is taken in time stage $t \in T$, 0 otherwise.

$\bar{Y}_t^{rs}$ Is equal to 1, if at least one path is satisfied for an O-D pair $r \in R$ and $s \in S$ in time stage $t \in T$, 0 otherwise.

$I_{it}^{rs\,k}$ Is equal to 1, if trips along the k^th path between $r \in R$ and $s \in S$ will be charged at the station at node$i \in \widetilde{N}$ in time stage $t \in T$, 0 otherwise.

$B_{it}^{rs\,k}$ Remaining SOC (miles) on a PEV at node $i \in N$ on the k^th path of an O-D pair $r \in R$ and $s \in S$ in time stage $t \in T$

$l_{it}^{rs\,k}$ Restored SOC (miles) to an PEV at node $i \in N$ on the k^th path of an O-D pair $r \in R$ and $s \in S$ in time stage $t \in T$

Different assumptions may be contemplated to construct the proposed model including:

- The model is proposed for battery electric vehicle.
- Vehicles are homogeneous and fully charged at origins.
- Energy consumed is unified in terms of travel distance.
- Charging stations are uncapacitated.
- Considering congestion and also vehicle range limitation, the lower and upper distance bounds are considered, respectively.

The proposed BEVCP model is defined in form of a mixed-integer programming as follows:

$$\text{Min } \omega = \sum_{i\in N}\sum_{j\in N}\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}}\sum_{t\in T}\left(B_{it}^{rs\,k} + l_{it}^{rs\,k} - B_{jt}^{rs\,k}\right)\gamma + \sum_{i\in \bar{\bar{N}}}\sum_{t\in T} W_{it} Z_{it}\gamma' \tag{1}$$

$$\text{Min } \emptyset = \sum_{i\in \widetilde{N}}\sum_{t\in T} f_i Z_{it} + \sum_{r\in R}\sum_{s\in S}\sum_{t\in T} u_t^{rs} D_t^{rs}(1-\bar{Y}_t^{rs}) \tag{2}$$

s.t.

$$d_{ij} \leq \tau + M\left(2 - Z_{it} - Z_{jt}\right) \quad \forall\,(i,j)\in A,\ \ i,j \in P^{rs\,k}, t\in T \tag{3}$$

$$d_{ij} \geq \pi - M\left(2 - Z_{it} - Z_{jt}\right) \quad \forall\, i\in \bar{N}, j \in \bar{N}, (i,j)\in A,\ \ i,j \in P^{rs\,k}, t\in T \tag{4}$$

$$B_{it}^{rs\,k} \leq \varphi\bar{B} + M\left(1 - I_{it}^{rs\,k}\right) \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{5}$$

$$B_{it}^{rs\,k} \geq \varphi\bar{B} - M I_{it}^{rs\,k} \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{6}$$

$$\bar{Y}_t^{rs} \leq \sum_{k\in K^{rs}} Y_t^{rs\,k} \leq 1 \quad \forall\, t\in T, r\in R, s\in S \tag{7}$$

$$I_{it}^{rs\,k} \leq Y_t^{rs\,k} \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{8}$$

$$l_{it}^{rs\,k} \leq M I_{it}^{rs\,k} \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{9}$$

$$I_{it}^{rs\,k} \leq M l_{it}^{rs\,k} \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{10}$$

$$B_{it}^{rs\,k} + l_{it}^{rs\,k} \leq \bar{B} + M(1 - Y_t^{rs\,k}) \quad \forall\, i\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{11}$$

$$B_{it}^{rs\,k} + l_{it}^{rs\,k} - d_{ij} \leq B_{jt}^{rs\,k} + M(1 - Y_t^{rs\,k}) \quad \forall\,(i,j)\in A,\ \ i,j\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{12}$$

$$B_{it}^{rs\,k} + l_{it}^{rs\,k} - d_{ij} \geq B_{jt}^{rs\,k} - M(1 - Y_t^{rs\,k}) \quad \forall\,(i,j)\in A,\ \ i,j\in P^{rs\,k}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{13}$$

$$B_{rt}^{rs\,k} = \bar{B} \quad \forall\, t\in T, r\in R, s\in S, k\in K^{rs} \tag{14}$$

$$\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}} I_{it}^{rs\,k} \leq M Z_{it} \quad \forall\, i\in P^{rs\,k}, t\in T \tag{15}$$

$$Z_{it}, Y_t^{rs\,k}, \bar{Y}_t^{rs}, I_{it}^{rs\,k} \in \{0,1\},\ \ B_{it}^{rs\,k}, l_{it}^{rs\,k} \geq 0\,, \quad \forall\, i\in \widetilde{N}, t\in T, r\in R, s\in S, k\in K^{rs} \tag{16}$$

The first objective function in equation (1) is to minimize the total CO2 emissions during charging stations and routes. Equation (2) minimizes the total system cost while allowing a penalty cost, namely the range limitation cost, to penalize uncovered trips. A total system cost includes fixed capital costs, variable capital costs, and range limitation costs for BEV trips that cannot be fulfilled. According to constraint (3), the maximum distance between two charging stations is less than τ. As a result of constraint (4), the minimum distance between two charging stations in CBD zones is greater than π. Constraints (5) and (6) demonstrate that when the battery charge of a BEV is less than a pre-defined value $\varphi\bar{B}$ then it refers to a charging station located nearby. The constraint (7) ensures that trips along O-D pairs in each stage can be fulfilled. For each O-D pair, no more than one path is taken in order to prevent double counting. Constraints (8), (9) and (10) convey two principles of charging activities: charging activities can occur along one path of a trip only if the path is taken, and a BEV can receive a positive amount of energy at a station only if the charging activity occurs at the station. For each selected path. Constraint (11) ensures the onboard battery's SOC does not exceed the battery capacity while constraints (12) and (13) concurrently enforce the energy consumption conservation. Constraints (11)-(13) are relaxed for paths that are not taken. Constraint (14) assumes that all BEVs start with a full battery SOC at origins. The constraint (15) confirms the possibility of restoring nodes where a charging station is located. Finally, constraint (16) defines decision variables.

Finally, a linear composite objective function, namely, the weighted sum method, is used to define an equivalent integrated single-objective model (Deb and Kalyanmoy, 2001). As there are different units in the objective functions, a scalarization strategy is needed. In this regard, the ideal and nadir values of the objective functions are given by $\omega^*, \emptyset^*$ and $\omega^{max}, \emptyset^{max}$, respectively. Moreover, symbols θ_n ($\sum_n \theta_n = 1$, $\theta_n > 0$), n = 1, 2 denote the weights of the objective functions. Now the composite objective function is given by the following equation.

$$\begin{aligned} Min\ \aleph &= \theta_1\left(\frac{\sum_{i\in N}\sum_{j\in N}\sum_{r\in R}\sum_{s\in S}\sum_{k\in K^{rs}}\sum_{t\in T}\left(B_{it}^{rs\,k}+l_{it}^{rs\,k}-B_{jt}^{rs\,k}\right)\gamma+\sum_{i\in\bar{\bar{N}}}\sum_{t\in T}W_{it}\,Z_{it}\,\gamma'-\omega^*}{\omega^{max}-\omega^*}\right) \\ &+ \theta_2\left(\frac{\sum_{i\in\tilde{N}}\sum_{t\in T}f_i Z_{it}+\sum_{i\in\tilde{N}}\sum_{t\in T}v_{it}c_{it}Z_{it}+\sum_{r\in R}\sum_{s\in S}\sum_{t\in T}u_t^{rs}D_t^{rs}(1-\bar{Y}_t^{rs})-\emptyset^*}{\emptyset^{max}-\emptyset^*}\right) \end{aligned} \tag{17}$$

Subject to: (3)- (16)

where, $\aleph$ is the optimum value of the equivalent single objective function.

4. Computational Results

The obtained results were carried out to evaluate the performance of the proposed model. All numerical experiments were solved by an Asus Studio PC with an Intel Core i7 CPU at 1.73 GHz and 4 GB of RAM. GAMS 25.5 optimization software and CPLEX solver were employed to code the proposed model. All numerical experiments were constructed based on the realistic transportation network of Zanjan city, which is described in the next subsection.

4.1 A case study: Zanjan transportation network

Zanjan city is the capital city of one of the western provinces in Iran, with a population of 380,000. To assess the proposed RSLP behavior in a real-world situation, a case study on a part of an entire urban transportation network of Zanjan city was conducted, which covered an area of 43 directed links, and 30 nodes .This part of the urban transportation network is selected from the east of ZTN with a low-traffic volume. Figure 1 demonstrates the geometry of the Zanjan transportation network. Some traffic data such as flow, travel time, and network distance were extracted from the Zanjan city transportation master plan on Dec 10, 2010, during the AM peak period (7–8 am) (Tarh-e-Haftom-Consulting-Engineers 2012).

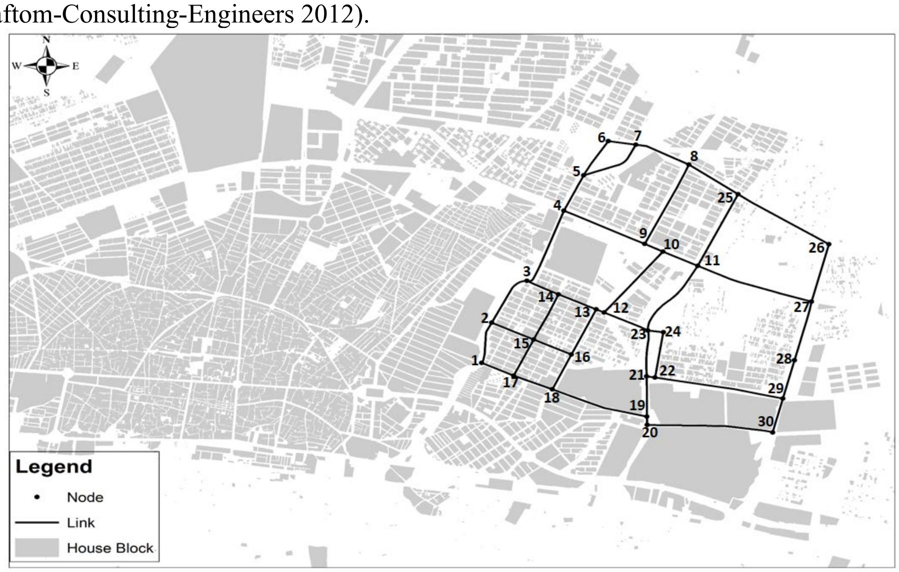

Figure 1. The study site of the Zanjan transportation network

The setup cost for different charging station candidate nodes varied in the interval [100, 200]. The value of u_t^{rs} varied randomly in the interval [20, 50]. The desired lower and upper bounds of distance between two located charging station are set 705 and 1200 miles, respectively.

The proposed model was solved by GAMS software for different sizes of the problem and the obtained results are summarized in the Table 1. Some symbols that were used in the tables are as follows:

- |N|: The number of total nodes.
- |T|: The number of time stages.
- ω^*: The optimal value of first objective function.
- $\emptyset^*$: The optimal value of second objective function.
- *%Gap*: The percent deviation between integer solution and relaxed integer solution corresponding Cplex solver.
- *Time(s):* The total time in seconds.

Table 1. Results of different-sized instances for BEVCP

|N|	|T|	No of variables		No of constraints		Cplex		Time (s)	%Gap
		Continues	Binary	Equality	Inequality	ω^*_{Cplex}	$\emptyset^*_{Cplex}$		
8	3	12288	7128	768	142680	7322694	6144808	32	0
8	4	16384	9504	1024	190240	10343340	8193085	43	0
8	5	20480	11880	1280	237800	12419180	10241350	74	0
8	6	24576	14256	1536	285360	16053690	12276230	243	0
8	7	28672	16632	1792	332920	19274930	14314460	371	0
15	8	216000	117120	7200	4008720	46084900	10048900000	896	10^{-6}
15	9	243000	131760	8100	4509810	50203400	11305000000	1367	10^{-5}
15	10	270000	146400	9000	5010900	55337800	12561100000	1639	10^{-4}
15	11	297000	161040	9900	5511990	60798110	13817200000	1802	10^{-4}

The obtained results confirm the validity of the model in which by increasing the network size, the objective function value is also increased and all different size instances could be solved, efficiently. Also, the gap percent is always less than 10^{-4} % that is an acceptable value.

Additionally, some candidate nodes have been selected in different sizes. It was observed that these nodes were not selected after the setup cost of these nodes was increased and the model was resolved which this event proves the accuracy of the model.

5. Conclusion

A multi-objective battery electric vehicle charging station location problem was proposed in this study where the total network cost and CO2 emissions rate are defined as objective functions. The city was divided into two zones, namely inside and outside the CBD zone. Moreover, two upper and lower distance bounds between charging stations were also considered as another main novelty. The WSM method was employed to transfer the model into a single objective function form. We introduced the ZTN dataset using Zanjan transportation network and applied this data as case-study. The proposed model solved for different instances. Finally, the efficiency of the proposed model was proved by the obtained results.

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Biographies

Sepide Abbasiparizi is an experienced industrial engineer with a passion for solving complex problems through the application of Industrial Engineering, Operations Research, Mathematical Modeling, and Machine Learning techniques. Her academic career began with a Bachelor of Science degree in Industrial Engineering from Shahid Bahonar Kerman University, where she developed her analytical skills and problem-solving abilities. She immersed herself in the world of Operations Research and Mathematical Modeling during her academic studies, exploring innovative solutions to real-world problems. A location of electric vehicle charging stations was the subject of her thesis. This research not only enriched her academically but also contributed to the growth of electric vehicle infrastructure. Keeping up with the latest tools and techniques, she's taken several courses in Operations Research and Machine Learning.

Elham Haji-Sami is a dedicated PhD student in the Industrial Engineering department at Polytechnique Montreal University, actively contributing as a researcher in the Ride Sharing and Pricing Lab at UDEM University. With a strong academic foundation in Applied Mathematics from Tabriz University and an MSc in Industrial Engineering from the Islamic Azad University, where she graduated with distinction and served on the Board of Directors of the Industrial Engineering Society, Elham has established herself as a top student. Her research achievements extend to publishing diverse articles, including mathematical modeling, programming, optimization, operations research, and machine learning (ML). Alongside her academic pursuits, she has amassed valuable experience as a Business Analyst and System and Process Designer, engaging in projects across diverse industries such as Digital, IT, and AI, with a focus on optimizing systems and processes, including ERP and ITSM implementations. Her multifaceted career path underscores her unique ability to excel both as a team player and as an individual contributor, making meaningful contributions to her field.

Saeid Abbasiparizi is a PhD student in the Operation and Decision System Department at Université Laval, Québec, Canada. He graduated as the top student from the Islamic Azad University of Kerman with a B.S. in Industrial Engineering and obtained an M.S. from the Amirkabir University of Technology - Tehran Polytechnic in Industrial Engineering in 2013. With over a decade of experience as a Senior Operations Research Scientist and Data Analyst, Saeid has proven his prowess in Search and Rescue, Transportation Network Design, Mathematical Optimization, and Data-Driven Optimization in academic research as well as industrial settings. His passion lies in the application of mathematical models to tackle complex real-world challenges, and he excels in conveying insights in a comprehensible manner. His research interests include Intelligent Transport Systems, Data-Driven Optimization, Large-Scale Optimization, Combinatorial Optimization, Optimization under Uncertainty, and Machine Learning Algorithms. Saeid's technical skills span programming languages like Python and R, optimization packages such as GAMS, CPLEX, and Gurobi, and his proficiency extends to Machine Learning and Analytics with R.