# pyMassEvac: A Python package for simulating multi-domain mass evacuation operations

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Summary

pyMassEvac is a Python package whose aim is to study mass evacuation scenarios. In particular, it is designed to simulate single- and multi-domain mass evacuation operations in which:

- the individuals to be evacuated are at a remote location, such as in the Arctic, where access to immediate medical care is limited or non-existent;
- each individual's medical condition (modelled as a medical triage system) may change over time, perhaps due to environmental conditions, injury, or care being provided; and
- the individuals must be transported from the evacuation site to a Forward Operating Location (FOL).

An example of a multi-domain mass evacuation operation, where the objective is to maximize the number of lives saved by transporting individuals to an FOL, is depicted in Figure 1.
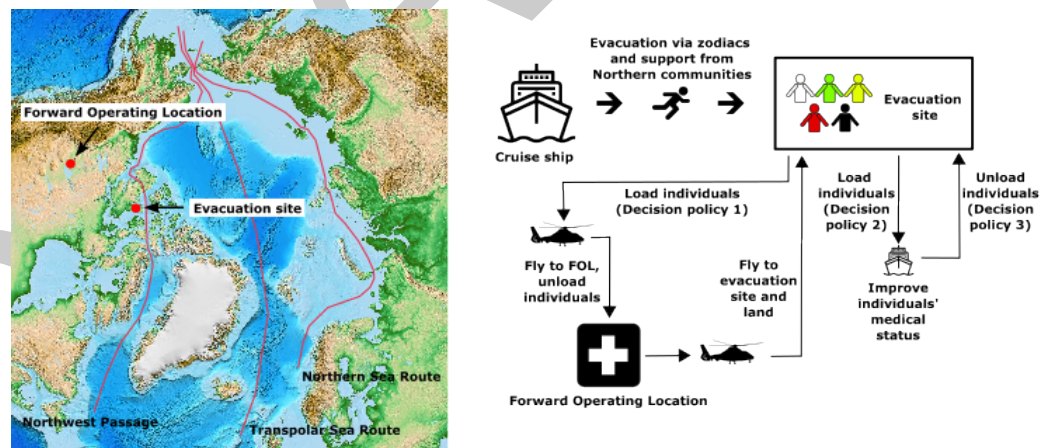
Figure 1: Evacuation plan via air with medical assistance provided at the evacuation site via ship. Colours of individuals at the evacuation site represent those in different triage categories (white, green, yellow, red, black; black represents deceased). For a full description, see Rempel ([2024](#)).

Within this context, pyMassEvac may be used to provide decision support to defence and security planners in two ways. First, through exploring the impact of policies used to make the three decisions depicted in Figure 1 (see right panel):

- **Decision policy 1**: the policy that determines which individuals are loaded onto a vehicle, such as a helicopter, for transport from the evacuation site to the FOL;
- **Decision policy 2**: the policy that determines which individuals receive medical care (if available) at the evacuation site, such as onboard a nearby ship; and

23   ■ **Decision policy 3**: the policy that determines which individuals are removed from the
24   group receiving medical care, for reasons such as limited capacity or that the individuals'
25   medical condition has been sufficiently improved, and returned to the group ready to be
26   transported to the FOL.

27   Second, assuming decision policies are selected, decision support may be provided by using
28   `pyMassEvac` to explore the selected policies' robustness to changes in a scenario's parameters.
29   For example, `pyMassEvac` may be used to explore how robust a set of decision policies are in
30   terms of the number of lives saved with respect to:

31   ■ the initial arrival time of one or more transport vehicles after the individuals have arrived
32   at the evacuation site;
33   ■ the travel time between the evacuation site and the FOL; and
34   ■ the rate at which an individual's medical condition becomes better (through receiving
35   medical care) or worse (due to injury or exposure to environmental conditions) over time.

36   Changes in a scenario's parameters from baseline values may reflect a variety of real-world
37   strategic and operational decisions beyond the tactical decisions made within scenario itself.
38   For example:

39   ■ the reduction in the initial arrival time of transport vehicles may reflect an operational
40   decision to pre-position vehicles during the summer season;
41   ■ the reduction in the travel time between the evacuation site and FOL may reflect a
42   strategic decision to build a new aerodrome; and
43   ■ the decrease in the rate at which an individual's medical condition worsens may reflect
44   an operational decision to invest in improved medical kit.

45   Thus, `pyMassEvac` is designed to be primarily used by operational researchers who study
46   humanitarian or defence and security operations.

47   `pyMassEvac` is accessible at `https://github.com/DRDC-RDDC/pyMassEvac` and is installed via
48   a `setup.py` script. In addition, published evacuation scenarios that have been studied using
49   this package (or one of its earlier developmental versions) are described in Rempel et al. (2021),
50   Rempel & Shiell (2023), and Rempel (2024).

Statement of need

52   The significant decrease in Arctic sea ice in recent decades has resulted in increased activity in
53   the Arctic across a range of sectors, such as oil and gas, mining, fishing, and tourism. With
54   respect to tourism, Arctic nations are concerned with the potential increase in the number of
55   Search and Rescue (SAR) incidents that may occur and the increased size of those incidents in
56   terms of the number of individuals in need of evacuation. This is evidenced by recent exercises
57   that have been conducted, such as the SARex series in Norway (Solberg et al., 2016, 2018), a
58   table-top exercise including the United States, Canada, and the cruise ship industry (McNutt,
59   2016), and the NANOOK-TATIGIT 21 exercise led by the Canadian Armed Forces (National
60   Defence, 2021).

61   While software exists to support planning for and the execution of evacuation operations,
62   it typically either requires a paid license (AVN, 2025; SAR Technology Inc., 2025), focuses
63   on search planning (United States Coast Guard, 2025), or addresses specific situations such
64   as wildfires (Guman et al., 2024). With this in mind, `pyMassEvac` aims to provide an open
65   source software package that enables researchers to (within the context described above) both
66   assess the impact of strategic and operational decisions made prior to an evacuation operation
67   occurring, as well as the impact of tactical decisions made within the operation itself.

Features

Defining an evacuation operation

Mass evacuation operations are modelled in `pyMassEvac` as a sequential decision problem under uncertainty using Powell's universal framework for sequential decisions (Powell, 2022). See Section 4 of Rempel (2024) for the complete description of the model. Given this framework, a scenario's parameters are specified via the initial state variable S_0, which consists of the following elements:

- m^e: Vector of mean time (hours) for an individual's medical condition to worsen and transition from a triage category $t \in \mathcal{T} \setminus \{b\}$ to the next lower triage category $t' \in \mathcal{T} \setminus \{w\}$ at the evacuation site, i.e., m_w^e is the mean transition time from the white (w) to green (g) tag category. The set of triage categories is given as $\mathcal{T} = \{w, g, y, r, b\}$;
- m^s: Vector of mean time (hours) for an individual's medical condition to improve and transition from a triage category $t \in \mathcal{T} \setminus \{w, b\}$ to the next higher triage category $t' \in \mathcal{T} \setminus \{r, b\}$ while receiving medical care, i.e., m_r^s is the mean transition time from the red (r) to yellow (y) tag category;
- c^h: Total capacity for individuals onboard a transport vehicle, such as a helicopter;
- c^s: Total capacity for individuals to receive medical care, such as onboard a ship;
- δ^h: Vector of capacity consumed by each triage category $t \in \mathcal{T} \setminus \{b\}$ onboard a transport vehicle. Individuals in the black (b) tag category are not transported as they are deceased and are assumed to be recovered at the end of the rescue operation;
- δ^s: Vector of capacity consumed by each triage category $t \in \mathcal{T} \setminus \{b\}$ when receiving medical care;
- η^h: Total time (hours) for a transport vehicle to load individuals at the evacuation site, transport them to the FOL, unload the individuals, and return to the evacuation site;
- η^{sl}: Total time (hours) to transfer individuals at the evacuation site to the local facility (such as a ship) in which they will receive medical care, plus the time until a decision is made as to which individuals to transfer back to the evacuation site;
- η^{su}: Total time to transfer individuals from the local facility (such as a ship) in which they are receiving medical care to the evacuation site, plus the time until a decision is made as to which individuals to transport to the FOL;
- τ^h: Vector of initial arrival time (hours) of each transport vehicle after the individuals have arrived at the evacuation site; and
- τ^s: Vector of initial arrival time (hours) of each medical care facility (such as a ship) after the individuals have arrived at the evacuation site.

Note that the initial state in `pyMassEvac` differs from Rempel (2024), specifically including both τ^h and τ^s. In Rempel (2024) these two parameters were specified separately in the case study presented in Section 5.

An example of an initial state, with one transport vehicle and one medical care facility, is given in the tutorial found in `tutorial\tutorial.ipynb`.

Example decision policies

`pyMassEvac` provides a set of decision policies that implements those described in Rempel (2024). All policies are defined in `mass_evacuation_policy.py` and are summarized as follows:

- `green_first_loading_policy`: This policy may be used for either **Decision policy 1** or **Decision policy 2** and puts an emphasis on loading healthier individuals prior to those with worse medical conditions;
- `yellow_first_loading_policy`: This policy is similar to the green-first loading policy, with the exception that it focuses on those individuals that require near-term care, followed by those in descending order in triage category. This policy may be used for either **Decision policy 1** or **Decision policy 2**;

- critical_first_loading_policy: This policy prioritizes those individuals that require immediate attention before moving onto less critical categories. This policy may be used for either **Decision policy 1** or **Decision policy 2**;
- random_loading_policy: This policy randomly selects individuals, regardless of their triage category. This policy may be used for either **Decision policy 1** or **Decision policy 2**;
- random_unloading_policy: This policy randomly selects individuals, regardless of their triage category. This policy may be used for **Decision policy 3**; and
- white_unloading_policy: This policy only removes individuals from the medical facility whose medical condition has improved such that they are assigned a white (w) tag. This policy may be used for **Decision policy 3**.

In addition, a do_nothing policy is provided to model situations in which a decision is to be delayed or to model the lack of transport or medical care.

The tutorial found in tutorial\tutorial.ipynb demonstrates how to use these decision policies. Specifically, it uses the green_first_loading_policy for **Decision policy 1** and **Decision policy 2**, and the white_unloading_policy for **Decision policy 3**.

Ready for reinforcement learning

pyMassEvac is implemented as a custom Gymnasium environment (Towers et al., 2024). An example of its use as an environment with fixed decision policies is provided in tutorial\tutorial.ipynb. pyMassEvac may also be used in combination with a reinforcement learning or approximate dynamic programming algorithm to seek optimal, or at least near-optimal, decision policies. Among the many considerations that must be made when selecting or designing a learning algorithm for this environment is that the set of valid actions are dependent on both the state variable S_k and the parameters defined in the initial state S_0—see Section 4.1 of Rempel (2024). The step function takes this into account and only steps the forward to the next event if the selected action is valid. However, when using a reinforcement learning algorithm a form of invalid action masking (Hou et al., 2023; Huang & Ontañón, 2022) should also be considered.

Acknowledgements

I acknowledge contributions from both Nicholi Shiell and Kaeden Tessier, who are co-authors on related papers (Rempel et al., 2021; Rempel & Shiell, 2023). These collaborations inspired the development of this package.

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