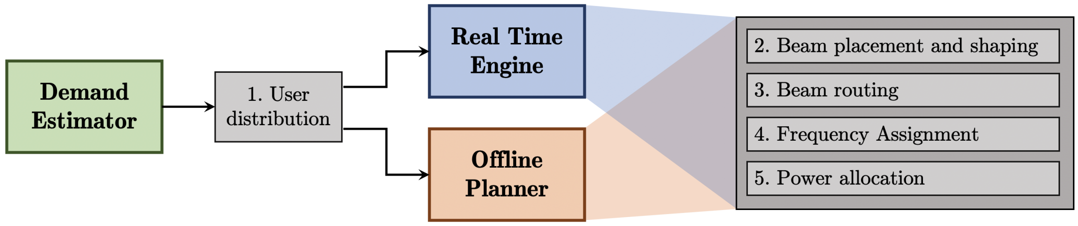

Figure 3: Necessary components in a resource management system. The *Demand Estimator* is responsible for predicting changes in the user distribution (demand and location) at different time horizons. The *Offline Planner* then addresses long-term resource allocation tasks, while the *Real Time Engine* works on a time scale of seconds to minutes, fixing any service failure and leveraging resource-efficient opportunities.

by training a model with an asymmetric loss function that places a heavier penalty on underestimations. Furthermore, the forecasts being probabilistic instead of point estimates gives insight into the amount of uncertainty at the prediction level. This allows the OP to better plan for worst-case scenarios and reduce the number of times the RTE needs to take action. To avoid producing overly-conservative allocations, the OP and RTE subsystems could also incorporate robustness mechanisms against uncertainty, as explored in the literature for both metaheuristic frameworks (**??**) and RL (**??**).

OP and RTE. The interaction between OP and RTE is more subtle since it is a consequence of the shared control of the constellation's resources. While the OP does a long-term recurrent allocation of all resources, the RTE should only react when nominal demand predictions are out of distribution. We envision this happening under six circumstances: 1) demand spike, when the real demand is significantly higher than expected; 2) demand diminish, when real demand is significantly lower than expected; 3) new user, when a new user connects to the system using a new (non-allocated) beam; 4) mobility re-route, when a ship or plane follows a different route than the one expected; 5) gateway failure, when a gateway antenna temporarily or permanently fails; and 6) satellite failure, when a satellite temporarily or permanently fails. Both the RTE's type of action and time to react significantly vary depending on the event. Nevertheless, all these situations can be considered as out-of-distribution occurrences, which have traditionally been a challenge to AI and learning-based models as a form of non-stationarity or high stochasticity. Recent studies (**???**) propose generalization mechanisms which might be able to address these scenarios.

The challenges emerging from system interactions pose additional problems to AI and have been traditionally understudied in satellite communications literature. We consider these issues as one of the remaining open challenges when it comes to the Dynamic Resource Management problem and a necessary direction of future work. In the next section we extend on this idea and other open challenges and future work directions.

5 Open Challenges

Different challenges remain regarding the use of AI and learning-based technologies for the Dynamic Resource Management problem. These can be analyzed from a subproblem perspective, a system-level perspective considering interactions, and from the perspective of autonomous systems. In this section we cover all three and propose directions of future work, highlighting those areas where AI is still not present.

5.1 Limitations on subproblem performance

We first address the performance limitations that subproblem-oriented AI algorithms face and which recently-proposed frameworks could help mitigate them.

- **High-dimensionality**. All four subproblems covered in this work (beam placement and shaping, gateway routing, frequency assignment, and power allocation) have been traditionally under-studied in high-dimensional scenarios (**?**), such as those dealing with tens of thousands of users or thousands of beams. Although some works do try to address this issue (**??**) by simply running tests on high-dimensional scenarios, recently-proposed mechanisms against high-dimensionality are still to be explored in the satellite communications context. This is the case, for instance, of specific RL frameworks (**??**).
- **Time limitations**. Time convergence is often an overlooked factor in current approaches, and can be especially critical for some of the metaheuristic-based algorithms presented. While most works focus on a static picture for which all resources can be allocated without a time horizon, future studies should incorporate new findings on speeding up the convergence time (**?**). Learning-based approaches are more robust against this issue given their quick online evaluations and offline training frameworks.
- **Constellation Dynamics**. Constraints imposed by constellation dynamics are usually neglected. Most works focus on single satellites, disregarding dependencies between the different satellites of the constellation and how they change over time. Constraint-based frameworks have been studied for both metaheuristic algorithms (**?**) and RL (**???**).

1. **Out-of-distribution events.** As highlighted in Section 4.4, most events requiring the RTE involvement occur due to out-of-distribution events such as demand spikes or system failures. This issue has traditionally been a

challenge for AI and learning-based methods, although recent works propose different methods to increase environment diversity (**???**) and consequently the agents' robustness.

5.2 Limitations due to interactions

When the DE, OP, and RTE act together, additional limitations might emerge. These are mainly related with forecasting quality and the OP-RTE interaction.

2. **Long-horizon forecasting**. The DE is faced with challenging prediction windows when a delay exists between the current and the target times. Uncertainty in these situations might be too large using traditional methods. Newer models that use attention mechanisms that learn complex patterns in data like (**?**) or (**?**) could be explored. 3. **Multiuser prediction**. To forecast future user distributions and demands, the DE can do it on a per-user basis or rely on multivariate output models (**??**). The latter is not sufficiently-explored and can be the basis of frameworks to leverage low amounts of data (e.g., new users, non-stationary patterns) (**?**). 4. **Search space complexity.** As a consequence of the OP-RTE interaction, once the OP sets a long-term resource allocation, the RTE will amend some parts of it as real-time operations take place. While maybe no more than tens of beams will be part of this process during a RTE cycle, the related search space will be notably more complex, as the RTE will be required to simultaneously make decisions on multiple variable types (e.g., beam center, bandwidth, power) instead of following a sequential process.

5.3 Areas of future work

We finally address unexplored research directions that are related to more advanced problems in the context of autonomous constellations.

5. **Transfer learning for satellite architectures**. All models and algorithms so far have been designed in the context of specific satellite architectures. This assumption limits the application of one model to multiple satellite architectures. In the future, it is expected that satellites will have flexibility in their own configurations (**?**), to better address operators' needs. Being able to successfully transfer the models to these new configurations will be essential to maintain service quality. 6. **New prediction models**. Historical data of current user bases might be rich enough to forecast using simple neural architectures. However, it is possible that this is not always the case, especially if new users choose on-demand services more frequently. In those cases, more complex neural architectures including Graph Neural Networks to leverage spatiotemporal data (**?**), attention mechanisms to improve performance (**?**), or transfer learning frameworks capable of few-shot-learning (**?**) might be better suited. 7. **Orbits as resources.** In this paper, like most studies on satellite communications, we assume all satellites are located on the same orbit. This might not always be the case, especially for megaconstellations. In that sense, we could consider allocating orbital resources as the fifth subproblem from a constellation perspective. It is likely that AI and learning-based methods can also be applied in that context. 8. **Multiagent systems.** Finally, we want to highlight the possibility that the resource control is decentralized as opposed to a centralized DE, OP, and RTE. These scenarios align with the literature on multiagent systems (**??**), and satellite constellations are a specific use case that is starting to be explored (**??**).

6 Conclusion

In this work, we propose an AI-based framework to tackle the system-level challenges in the Dynamic Resource Management problem for satellite communications. This framework incorporates three necessary components (Demand Estimator, Offline Planner, and Real-Time Engine) to address the sequence of subproblems (beam placement and shaping, gateway routing, frequency assignment, and power allocation) that lead to the complete resource allocation. We identify potential component interactions that are often overlooked by current approaches and discuss why AI and learning-based methods are well suited to handle them. In this context, we examine the benefits of applying AI to solve the complete resource allocation problem, highlighting prevailing performance limitations that AI could overcome, as well as unexplored areas of future work.

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