One of the benefits of swarm intelligence is graceful degradation of the swarm's performance. As the simulation progresses, the swarm will incur losses. However, by dynamically shifting its resources, the swarm is able to maintain both tasks, defending the base while still searching for enemy units. It is only when the swarm loses a large percentage of its population that the swarm begins to break down and is no longer able to successfully work on both objectives. The swarms in this project were evolved with an initial population size of 40 units. This number allowed the group of units to be large enough to be considered a swarm while still being small enough to encourage unique, emergent behavior. The concept of how large a swarm needs to be in order to be considered a swarm is a fuzzy one and often depends on the application. The question of how size affects a swarm's performance will be explored further in future work.

VI. Conclusion

One of the advantages of swarm intelligence is a swarm's ability to autonomously reorganize itself in a dynamic environment. In our work, we have used techniques found in nature to allow swarms to manifest this behavior in simulations where the swarm is required to perform well in two objectives. In the Point Attack & Point Defense swarms, agents have to balance themselves between both defending their base and finding and attacking their enemy's base. Swarms in the Search & Destroy simulation have to use recruitment methods to form groups to destroy a large opponent. And finally, these scenarios are combined in the Base Attack swarm, in which a single swarm has to complete defensive and offensive objectives, using both threshold functions and recruitment techniques. By using an evolutionary learning algorithm, the weighting functions that defined the swarms' behavior in each of the three simulations are optimized to maximize the swarms' fitness scores.

We believe that these concepts can be expanded upon in future work. One topic to consider is the effect of size on a swarm's performance. For the purposes of these simulations, a population size of 40 was chosen because it is small enough to be feasible in a real-world application but also large enough to demonstrate swarm characteristics. A more in depth exploration of the effects of population size could provide more insight as to when a large group of agents begins functioning as a swarm.

This paper has demonstrated the application of a multi-state swarm that was able to use state-switching capabilities to adapt to a dynamically changing environment. While previous work has shown swarm intelligence as a viable solution to single objective missions, we have expanded these swarm techniques to accomplish multiple objectives using threshold functions to control the switching between states. The emergent behaviors of the swarms are robust and allow the swarm to continue achieving its objectives until a large percentage of its population is lost.

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