The Impact of Morphological Energy Costs on Single-Objective Multi-Robot Evolution

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ABSTRACT

This paper investigates the impact of imposing an energy cost on morphological complexity in the single-objective evolution of multi-robot systems. Robots are evolved for a collective gathering task using NEAT-M (a variation of the state-of-the-art NEAT algorithm which co-evolves morphology and neural controllers). Energy costs are implemented by introducing the functionality of a battery into the robots. The battery is drained at a constant rate throughout task simulation until exhausted, at which point the robot ceases operation. Results indicate that added sensor energy costs are successful in evolving simpler morphologies which achieve equivalent task performance in simple environments but degraded task performance in medium and difficult environments. It is proposed that a more complex sensory requirement for group co-ordination behaviour is the reason for degraded task performance in increasingly difficult environments.

CCS CONCEPTS

• **Computing methodologies → Evolutionary robotics**; **Multi-agent systems**; *Neural networks*.

KEYWORDS

Collective robotics, evolutionary robotics, neuroevolution, morphological complexity

1 INTRODUCTION

An open area of inquiry in the field of *evolutionary robotics* is regarding the impact of energy costs in *artificial evolution*. The interest herein lies with the potential to increasingly mimic the processes of *natural evolution* [10], in which calorific energy costs play an integral role [12, 21]. By refining evolutionary algorithms to more accurately resemble nature, the hope is that better performing (and more economical) solutions to various computational problems can be generated at a faster rate.

Implementing energy costs in evolutionary robotics systems presents a promising approach to developing more efficient robot designs. Recently, there has been increased focus in the targeted evolution of low-complexity, high-performing robots [2, 6, 19]. The measure of complexity in robot agents primarily revolves the structure of their morphology (or body) and neural controller (or brain) [19]. Therefore, morphological complexity is related to the physical sensor/actuator configuration of a robot's body, whereas neural complexity is related to the structure of robot's brain (usually encoded as an *artificial neural network* [13]).

Multi-objective evolutionary techniques have often been employed to achieve the desired progression towards candidate solutions which optimise more than one parameter. Nagar, Furman and Nitschke [19] investigated such a strategy to evolve robots with the objectives of minimising morphological complexity and maximising task performance. However, a potential criticism of this approach is that the artificial selection process is overly stringent and untrue to nature (where morphological simplicity is not *directly* selected for) [15, 16].

This paper aims to address these concerns by investigating the impact of introducing sensor energy costs into the design of the robot, which is expected to engender an indirect selective pressure against morphological complexity. A *single-objective* evolutionary process is used in which only task performance is maximised. It is hoped that this method can achieve similar evolutionary results to previous work, while more closely resembling natural evolution.

We thus propose the following two hypotheses:

- **H_0:** *Morphological energy costs in single-objective evolution do not significantly influence performance in a collective gathering task.*
- **H_1:** *Imposing an energy cost on morphological complexity in single-objective evolution results in the development of morphologically simpler robots which achieve improved performance in a collective gathering task.*

The alternative hypothesis, H_1, is devised on the basis of previous work by Nagar, Furman and Nitschke [19]. This study found that the multi-objective neuroevolution of robots minimised for morphological complexity and maximised for task performance successfully promoted the evolution of simpler morphologies with higher performing task-accomplishing behaviours (see Section 2.4). Our investigation aims to provide additional evidence to support these findings.

2 BACKGROUND

2.1 Collective and Evolutionary Robotics

Collective or *swarm robotics* (SR) is the problem-solving approach whereby a multi-robot system accomplishes specific task goals through collaborative *group behaviour* [14]. There are many real-world applications for SR systems, such as hazardous waste clean-up and oceanic environmental monitoring [24].

Evolutionary robotics (ER) is the field of research into the automatic design of autonomous robot controllers and morphologies

through processes which imitate *natural evolution* [10]. The basic premise of natural evolution is that a population of genetically similar, yet unique, organisms compete in a common environment and, through the process of *natural selection*, the "fittest" individuals survive and reproduce [29]. In this manner, superior traits are inherited over successive generations and the population as a whole tends to become better adapted to its environment.

ER provides a cost-effective approach to robot design whereby variations are automatically assessed for functionality through simulation and iteratively improved over multiple cycles. Additionally, using this method of *artificial evolution*, new models of cognition can be developed that, through experimental analysis, may prove better than existing hand-designed solutions [22].

Furthermore, ER enables the development of robot controllers which facilitate the self-organising, group behaviour patterns required in SR systems. This is possible by simulating environments which require collaboration between individuals for successful task completion and the subsequent selection and propagation of effective controllers.

2.2 Neuroevolution

Neuroevolution is a broad term encompassing an array of approaches to training *artificial neural networks* (ANNs) – using *evolutionary algorithms* (EAs) – for specialised behaviours, all of which draw on insights from neuroscience and evolutionary biology [9]. ANNs are used in many different problem spaces including pattern recognition, prediction, optimisation and associative memory, as well as robot control [13, 28].

2.2.1 Artificial Neural Networks.
ANNs are structured as weighted directed graphs with nodes representing artificial neurons and edges representing the connections between neuron inputs and outputs [13]. Environmental information flows from *input nodes* to *output nodes* via weighted connections which may pass through *hidden nodes* within the network. This alternative approach to computation makes ANNs far more effective in solving certain problems, such as pattern recognition, which traditional computational architectures struggle to handle efficiently [3].

2.2.2 Single-objective Neuroevolution.
In conventional *single-objective* neuroevolution, the optimisation of only one parameter is considered in the evolutionary process. For example, when evolving a robot controller, one might simply specify task accomplishment as the objective for optimisation. No other restrictions are placed on the evolutionary process and any developments which positively, or neutrally, impact achieving this objective are selected and propagated. As a result, the final evolved controller may incorporate unexpected or undesirable traits unrelated to the objective of focus. Although this may initially appear to be a disadvantage, the flexibility of this open-ended approach does allow for the discovery of creative solutions to challenging problems [15, 16].

Another perceived benefit of single-objective neuroevolution is that the evolutionary process is more true to the workings of natural evolution, which also effectively has one objective: survive to reproduce. This can be an especially important factor to consider when using evolutionary algorithms to model and investigate real-world processes. In this context, there are many open areas of research. For example, ER techniques have been used as a novel approach to the study of evolutionary theory itself [7, 22]. Furthermore, the combined use of ER and SR techniques may assist in shedding new light on research into the evolution of human brain size and the social brain hypothesis [8, 20].

2.2.3 Multi-objective Neuroevolution.
Building on work in traditional neuroevolution, multi-objective neuroevolution offers a significantly more refined approach to evolving ANNs. Here, it is possible to specify multiple, often contradictory, parameters to be simultaneously optimised. There are many real-world problems of this nature. For example, consider the case of designing a consumer electronic device, where one might wish to minimise cost and power consumption while maximising performance [30]. A similar ER-related multi-objective problem is in the evolution of high-performing, low-complexity neural controllers for robots, as is being investigated in this study.

As previously mentioned, one potential downfall of multi-objective neuroevolution is that it can end up being overly prescriptive with its multiple optimisation objectives. In this way, many potential solutions may not end up being explored as candidates at all, leading to convergence on local optima [15, 16]. Furthermore, this relatively inflexible quality of multi-objective neuroevolution makes it a poor model of natural evolution.

2.3 NEAT

Neuroevolution of Augmenting Topologies (NEAT) is a state-of-the-art single-objective neuroevolution strategy that uses a direct, genetic encoding scheme of ANNs to evolve both network topology and connection weights [26]. This genetic encoding is a linear representation of the network, with a set of *connection genes* which each indicate a connection between two *node genes*. Node genes consist of a set of inputs, hidden nodes and outputs. During mating, this format of encoding enables the easy lining-up and crossing-over of corresponding genes.

The original idea behind NEAT is based on three main concepts: *historical markings*, *speciation* and *incremental growth* [26]. Historical markings are used to track the origin of each gene in the network over the course of evolution. To achieve this, upon the introduction of a novel gene (through mutation), a unique *innovation number* is assigned to that gene. This information allows the algorithm to correctly identify and line up matching genes (i.e. those with the same innovation numbers) in separate *genomes* (i.e. the genotypes of different individuals) when crossing over, without the need for computationally expensive structural comparison through graph traversals.

Speciation is the process whereby the population is divided into different niches for each topological innovation. This initially protects new topologies from being competed out of consideration and gives them a chance to develop and optimise their structure through competition with others in only their niche [26]. Once again, innovation numbers are used here to improve computational efficiency by avoiding topology matching.

Finally, the concept of incremental growth from minimal structure is contrary to conventional approaches which seed the starting population with many random topologies to encourage diversity. NEAT, in comparison, begins with a uniform set of simple topologies
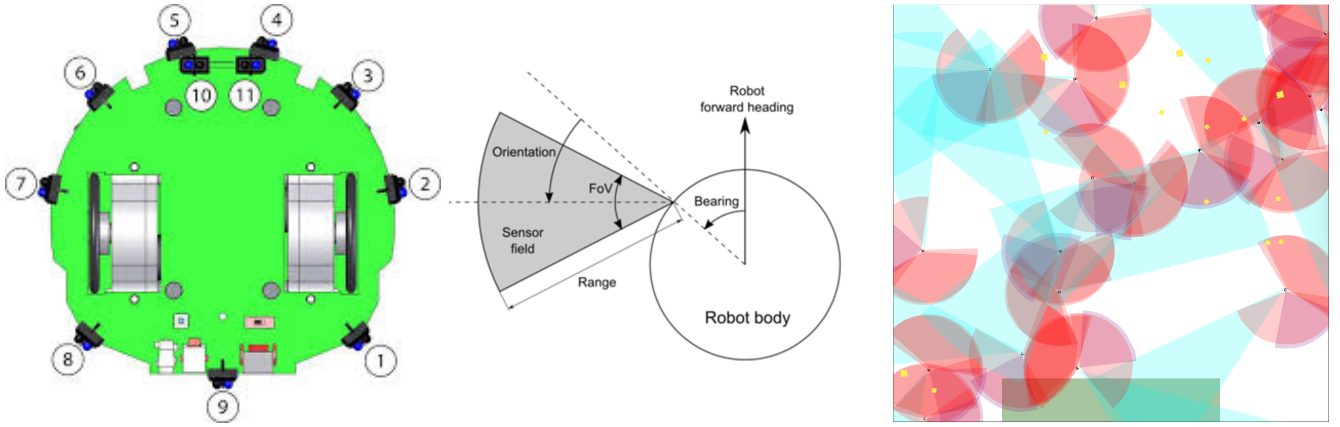
Figure 1: *Left*: The Khepera III robot morphology on which our simulated robots are based [18]. *Centre*: The various parameters for robot sensors which can change throughout the evolutionary process [19]. *Right*: Example of the simulated task environment containing robots with outward-facing, coloured arcs representing different sensor types, yellow blocks of varying sizes and a rectangular gathering zone along the bottom edge of the environment.

consisting only of input and output nodes (i.e. no hidden layers). Therefore, each candidate ANN starts with a minimal topology which increases in complexity through evolution. This approach minimises the dimensionality of the search space and gives NEAT a performance edge over other techniques. Furthermore, through this process of *complexification*, NEAT is able to discover far more complex candidate ANNs than fixed-topology techniques [25, 27].

2.4 Morphological Complexity

Morphological complexity is related to the layout of the physical body of a robotic system, including body shape and the number and arrangement of sensors on the body.

In 2012, Auerbach and Bongard [2] investigated the relationship between a robot's morphological complexity and the complexity of the task environment in which it is evolved. Supporting the hypothesis, it was observed that increasing environmental complexity directly promoted the evolution of more complex robot morphologies. However, contrary to these results, further research in the same year on the relationship between environmental and mechanical complexity found a decrease in more complex task environments [1].

Later research by Auerbach and Bongard [2], in 2014, analysed the evolution of complexity in robots selected for locomotion ability. Firstly, it was seen that these robots tended to increase in complexity over evolutionary time. This supported the "arrow of complexity" hypothesis previously posited [4]. Secondly, as with the 2012 study, results indicated that more complex morphologies evolve in complex environments compared with simple environments.

Research by Nagar, Furman and Nitschke [19], in 2019, applied the strategies of single- and multi-objective neuroevolution of robotic systems to the study of the cost of complexity in evolutionary theory. In this study, robots were evolved for a collective gathering task where the objectives of high task performance and low morphological complexity were optimised. This was in an attempt the simulate the hypothesised selective pressures in natural

evolution, where larger (and thus more complex) brains carry an increased energy consumption requirement. Two independent simulations were run in environments of varying task difficulty, one with the low-complexity optimisation objective and one without. The experiment produced interesting results. In simpler task environments, both simulations produced robots equally effective in task performance. However, seemingly counterintuitively, in more difficult task environments, robots evolved with a cost on morphological complexity achieved higher task performance (with simpler morphologies) than those evolved without such a cost.

3 METHODS

This section outlines the methodology and fitness measurement used in evolving candidate solutions for the collective gathering task. The evolutionary algorithm that has been employed for all experiments is a direct-encoding algorithm known as NEAT-M [11], through which both morphology and neural controller are co-evolved.

3.1 NEAT-M

NEAT-Morphologies (NEAT-M) is an extension to the single-objective NEAT algorithm (see Section 2.3) which directly incorporates the evolution of morphology into the neuroevolution process [11]. The fundamental steps of NEAT remain unchanged in NEAT-M, however, instead of only evolving a controller genotype for each individual, a direct encoding of the morphology is evolved in tandem.

Each input node in the controller's ANN is associated with a direct encoding of the parameter configuration for its corresponding sensor on the robot's body. The parameters stored in this manner includes the sensor type, field of view, range, bearing and orientation (Figure 1). These parameters each have genetic mutation operators to allow for sensor evolution. Furthermore, should an input node be removed from the robot's controller during evolution, the corresponding sensor is also removed from the morphology.

3.2 Fitness Function

The simulated robots are evolved through a single-objective neuroevolution process whereby task performance is the objective being maximised. Therefore, the evaluated fitness of a robot genotype is calculated based only on how competent it is at completing the collective gathering task (see Section 4.2).

A genotype's fitness, F, is determined as the sum of task completion and a time bonus. Task completion is measured as the number blocks successfully collected in the gathering zone, v_c, divided by the total number of blocks in the environment, v_t. A time bonus is rewarded to robot teams that manage to complete the gathering task within the simulation time. This is calculated as one minus the number of simulation time steps elapsed up until the moment of task completion, s_e, divided by the total time steps in the simulation, s_t. Equation 1 summarises this fitness calculation.

$$F = 100 \times \frac{v_c}{v_t} + 10 \times \left(1.0 - \frac{s_e}{s_t}\right) \tag{1}$$

The genotype fitness, F, is maximised throughout the evolutionary process. As is evident by the equation, the theoretical maximum value for F is 110. This represents a robot team that is able to complete the collective gathering task in zero time steps (which is practically impossible).

4 EXPERIMENTAL DESIGN

For this study, we make use of a multi-agent simulator for a collective gathering task, based on the MASON simulator framework [17]. The effect of morphological complexity costs on single-objective neuroevolution is investigated through the execution of two sets of experiments. Robots, with and without sensor energy costs (Section 4.1), are evolved in environments of varying complexity (Section 4.2) and their resulting task performance and morphological complexity is analysed.

4.1 Robot Configuration

In approaching the collective gathering task, homogeneous robot teams of twenty individuals are evolved to collaborate in achieving the task objective. *Homogeneous*, in this context, refers to robots with identical sensor and neural controller configurations. The morphology of the simulated robots used in this investigation is based on that of the Khepera III robot [18], as presented in Figure 1.

4.1.1 Robot Batteries. To investigate our hypothesis regarding the effect of morphological complexity costs on the single-objective evolution of robot teams, the concept of a battery was integrated into the pre-existing robot design. Upon a robot's battery being fully drained (i.e. reaching a level of zero or less), it ceases all movement, thereby rendering it inactive and unable to continue pushing blocks in the environment.

Two variations of the robots have been simulated, each utilising this battery in a different manner. In the first set of experiments (Section 4.1.2), the robot batteries are drained over the course of a simulation run, whereas, in the second set of experiments (Section 4.1.3), the robot batteries are not drained at all.

Sensor Type	Energy Cost
Bottom Proximity Sensor	1
Infrared Proximity Sensor	1
Colour Proximity Sensor	2
Ultrasonic Sensor	5
Low Resolution Camera	10

Table 1: Sensor Energy Costs. Each robot sensor is assigned an energy cost between 1 and 10 (in arbitrary energy units) based on its relative real-world complexity. Least complex is a proximity sensor with an energy cost of 1 and most complex is a camera sensor with an energy cost of 10.

4.1.2 Robots with Energy Costs. For experiments where the robots' batteries are drained, a specific energy cost between 1 and 10 (in arbitrary energy units) is assigned to each of the five sensor types (Table 1). These energy costs are based on the relative real-world complexity of each sensor type, taking a proximity sensor to be the least complex sensor with an energy cost of 1 and a camera to be the most complex sensor with an energy cost of 10.

The *morphological complexity*, M, for a particular robot is thus defined as the sum of the energy costs for all the sensors on its body. This is expressed in Equation 2, where n represents the total number of sensors and $C(S_i)$ represents the energy cost for a sensor, S_i, of a particular type.

$$M = \sum_{i=1}^{n} C(S_i) \tag{2}$$

Since the maximum number of sensors an evolved robot can incorporate is ten, the theoretical maximum value for morphological complexity, M, is 100. This represents a robot with ten low resolution camera sensors.

The battery capacity for each robot is initialised at the outset of a simulation run to 100,000 energy units. As the simulation progresses, the current battery level for these robots is decremented for each passing time step by their morphological complexity value, M. This is expressed in Equation 3, where B_t represents the battery level at time step t.

$$B_{t+1} = B_t - M \tag{3}$$

Since it is possible for the robots' batteries to fully drain before the end of a complete simulation run (consisting of 10,000 time steps), these robots can have their active lifetime restricted. Therefore, it is predicted these energy costs will create a selective pressure that drives robots to evolve simpler, more effective sensor configurations which allow them to remain active in the task environment for longer. In this manner, morphological complexity is expected to be indirectly minimised.

4.1.3 Robots without Energy Costs. In the second set of experiments, robot batteries are not drained at all and remain at full

Neuroevolution Parameters	
Replications per experiment (runs)	14
Generations per experiment run	250
Trial evaluations per generation	5
Population size	150
Initial connection density	0.5
Initial input nodes / output nodes	5 / 2
Simulation Parameters	
Time steps per trial evaluation	10,000
Initial robot battery capacity (energy units)	100,000
Initial robot / block positions	Random (outside gathering zone)
Robot team size (individuals)	20
Robot size (radius)	0.15
Environment / gathering zone size (width × height)	40×40 / 20×4
Small / medium / large block size (width × height)	0.4×0.4 / 0.6×0.6 / 0.8×0.8
Small / medium / large block pushing robot collaboration	1 robot / 2 robots / 3 robots
Bottom proximity sensor	Bottom-facing
Infrared proximity sensor: range / FOV	$(0.0, 0.4]$ / $(\pi/6, 5\pi/6)$
Colour proximity sensor: range / FOV	$(0.0, 0.4]$ / $(\pi/6, 5\pi/6)$
Ultrasonic sensor: range / FOV	$(0.0, 1.0]$ / $(0.0, \pi)$
Low resolution camera: range / FOV	$(0.0, 0.8]$ / $(\pi/9, 8\pi/9)$
Minimum / maximum number of sensors	1 / 10

Table 2: Neuroevolution and simulation parameters. Configuration options used for the neuroevolution process and all experimental simulations of the collective gathering task.

capacity throughout a simulation run. As a result, their active lifetime is unrestricted by their morphological complexity (i.e. robots remain active throughout all 10,000 time steps in a simulation run).

It is predicted that, since there is no selective pressure for simpler morphologies, these robots will evolve more complex sensor configurations. This set of experiments serves as a control for comparison with the robots utilising energy costs.

4.2 Environment Configuration

The simulated environment for the collective gathering task is contained in 40×40 two-dimensional region. Located along the bottom edge of this area is a 20×4 rectangular gathering zone. At the start of a simulation run, a homogeneous team of robots and a blocks of varying sizes are randomly positioned within the environment (outside the gathering zone). The task objective is for the robots to find and push all of the blocks into the gathering zone in the shortest amount of time possible.

Blocks can be one of three sizes (small, medium and large) with larger blocks requiring more robots to move them. Small blocks can be moved by one robot, medium blocks by two robots and large blocks by three robots. This increased collaboration for moving larger blocks is considered more complex behaviour and, thus, three different environment complexity definitions (simple, medium and difficult) have been established, each with different numbers of blocks of each size. Table 3 summarises the block size configurations for each environment complexity.

Environment Complexity	Number of Blocks		
	Small	Medium	Large
Simple	10	5	0
Medium	5	5	5
Difficult	0	5	10

Table 3: Simulation Environment Definitions. Three definitions of environment complexity were used in the simulations of the collective gathering task. Simple (having the most small blocks) requires the least robot collaboration, while difficult (having the most large blocks) requires the most collaboration.

Sensor Energy Costs	Environment Complexity		
	Simple	Medium	Difficult
Yes	E_1	E_2	E_3
No	N_1	N_2	N_3

Table 4: Experiment Sets. Two sets of three experiments were performed. This consists of simulations evolving robots with and without sensor energy costs, in each of the three environment definitions. Abbreviations are assigned to each experiment as indicated.

4.3 Experiment Configuration

Experiments are divided into two test sets: (1) robots with sensor energy costs and (2) robots without sensor energy costs. The second
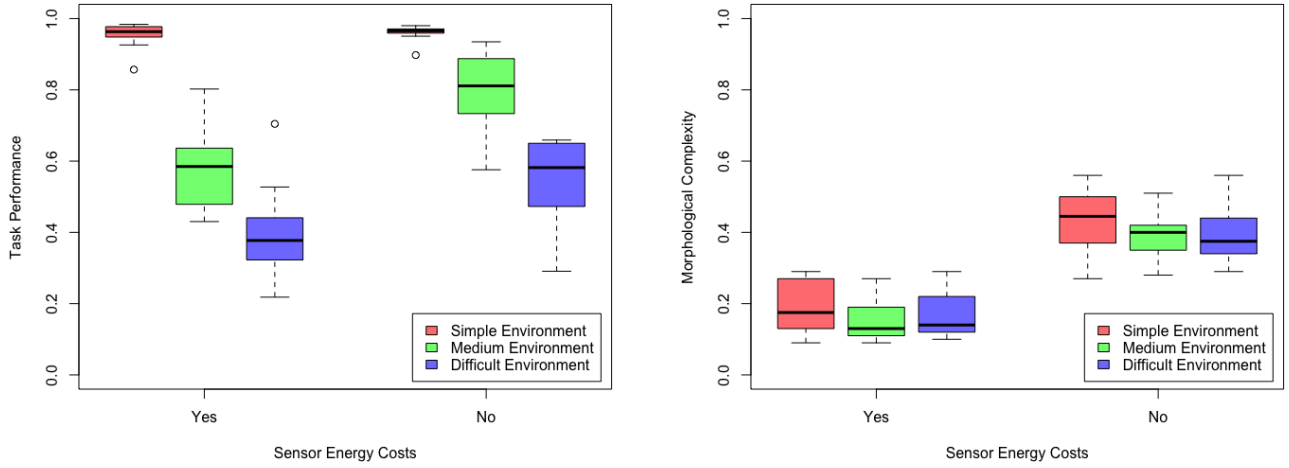
Figure 2: *Left*: Average maximum task performance for robots evolved with and without sensor energy costs, in each of the three environment definitions. *Right*: Average morphological complexity for robots evolved with and without sensor energy costs, in each of the three environment definitions.

test set (without energy costs) represents the experimental control with which the results of the first test set are compared. Each test set consists of three separate experiments, with one for each environment complexity definition. This overall configuration of six experiments is summarised in Table 4.

Every experiment involves an evolutionary process consisting of 250 generations, where each generation undergoes five trial evaluations. Throughout the evolutionary simulation, a robot population of size 150 is evolved. All neuroevolution and simulation parameters are presented in Table 2. Fourteen repetitions (i.e. separate runs) are performed for each experiment to ensure statistical soundness of the results.

5 RESULTS AND DISCUSSION

This section provides a comparative analysis of the results produced from our two sets of experiments (Table 4) in relation to the anticipated outcomes hypothesised in Section 1.

5.1 Validation of Hypothesis 0

H_0: *Morphological energy costs in single-objective evolution do not significantly influence performance in a collective gathering task.*

The best evolved candidate solutions (i.e. having the highest task performance) in each environment have been graphed on box plots for normalised measures of task performance and morphological complexity (Figure 2). Normalisation is achieved by taking the theoretical maximum values for task performance and morphological complexity to be 110 (see Section 3.2) and 100 (see Section 4.1.2), respectively.

T-tests between the experiments with and without energy costs indicate significantly ($p < 0.01$) degraded task performance for robots with energy costs in medium and difficult environments, but

statistically equivalent task performance in simple environments. Specifically, it was found that task performance for robots evolved with energy costs decreased, on average, by 0.6%, 27.9% and 28.1% in the simple, medium and difficult task environments, respectively.

The overarching measure of task difficulty across the various environment definitions is the degree of robot collaboration required to complete the collective gathering task. Simple environments require the least collaboration (with most blocks being movable by a single robot), whereas difficult environments require the most collaboration (with most blocks needing three robots to move). The results demonstrate that morphological energy costs negatively impact task performance in medium and difficult environments but not in simple environments.

Therefore, these findings serve to support H_0 for simple environments where little robot collaboration is required. However, for medium and difficult environments where robot collaboration becomes increasingly necessary, these results strongly contradict H_0. Therefore, we can confidently reject H_0.

5.2 Validation of Hypothesis 1

H_1: *Imposing an energy cost on morphological complexity in single-objective evolution results in the development of morphologically simpler robots which achieve improved performance in a collective gathering task.*

In the investigation of H_1, the impact of sensor energy costs on both morphological complexity and task performance needs to be taken into account. To support the hypothesis, robots evolved with energy costs should demonstrate decreased morphological complexity and increased task performance.

As presented in Figure 2 (right), morphological complexity is impacted by sensor energy costs. T-tests between the experiments with and without energy costs indicate significantly ($p < 0.01$) reduced
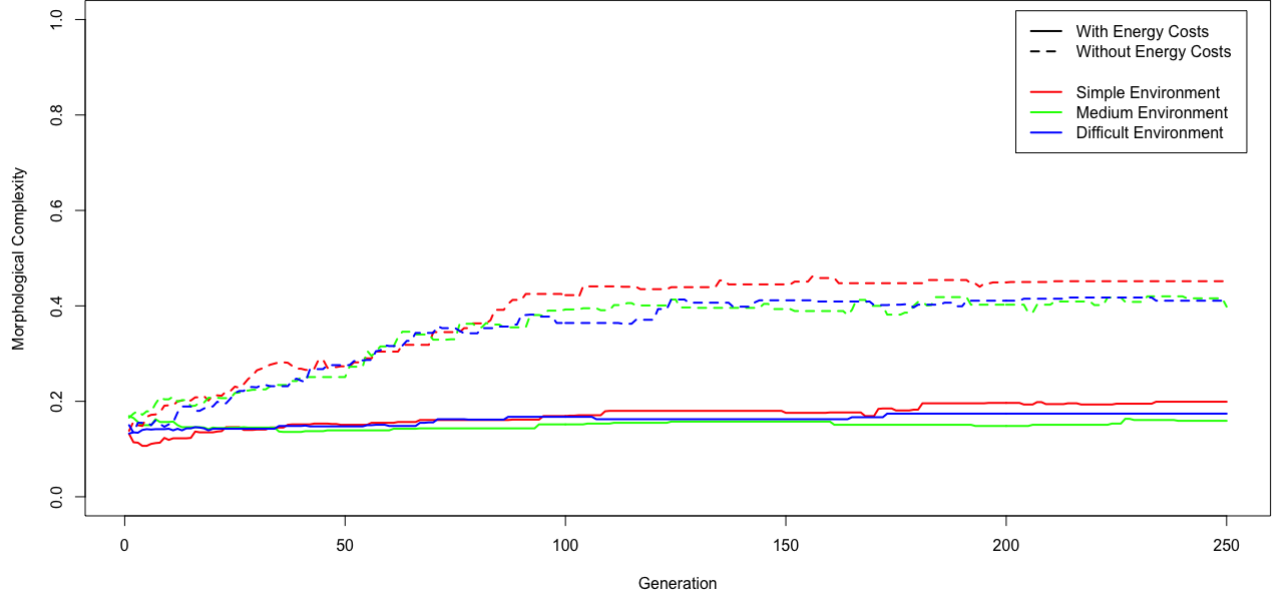
Figure 3: Progression of average morphological complexity for robots evolved with and without sensor energy costs over evolutionary time in each environment.

morphological complexity for robots with energy costs across all environments. Specifically, the evolved morphological complexity for robots with energy costs decreased, on average, by 56.9%, 60.6% and 57.5% in the simple, medium and difficult task environments, respectively.

Figure 3 further illustrates the significant impact of energy costs on evolved morphological complexity. Here, it can be observed how robots without energy costs rapidly evolve more complex morphologies, while those with energy costs remain at the same approximate complexity level throughout the evolutionary process. In line with H_1, these results indicate that the introduction of an energy cost on morphological complexity does successfully evolve simpler robot morphologies.

However, as discussed in Section 5.1, task performance for robots evolved with energy costs is either negligibly affected (simple environments) or significantly reduced (medium and difficult environments). This is contrary to the predictions of improved task performance outlined in H_1.

Therefore, these findings provide strong evidence against H_1 and rather suggest the antithesis is true. That is, imposing an energy cost on morphological complexity in single-objective evolution results in the the development of morphologically simpler robots which achieve *degraded* performance in a collective gathering task.

Although unexpected based on prior work [19], this outcome does follow what might be considered the intuitively correct result. Due to the imposed sensor energy costs, robot morphology is not free to evolve unhindered and is effectively restricted to only a few, simple sensors. The logical extension of this is that these robots have less sensory capabilities and, although perhaps more

energy efficient, they are less effective at performing the collective gathering task [23].

Furthermore, previous research has shown that robots with evolved morphologies tend to perform better than those with fixed morphologies [5]. It is reasonable to classify the robots with energy costs in this study as being between the two extremes, with neither permanently fixed morphologies nor freely evolved morphologies. Thus, this hampering of morphology evolution could further explain the negative impact on task performance.

Since task performance is unaffected by morphological energy costs in simple environments, these results demonstrate that the constrained sensory capabilities do not negatively impact individual robot task performance. However, the degraded task performance experienced in medium and difficult environments (requiring increased robot collaboration) indicates that these energy costs primarily weaken *collective* robot task performance. As such, it is speculated that group co-ordination behaviours require more advanced sensory configurations than individual behaviours [23].

Another possible reason for the discrepancies between this study's results and those of Nagar, Furman and Nitschke [19] is the fact that an alternative measure of morphological complexity was implemented in our study. Specifically, our measure of morphological complexity was based on the number and type of sensors on a robot's body. In comparison, Nagar, Furman and Nitschke [19] calculated morphological complexity based on the number and type of sensors, as well as their range and field of view.

6 CONCLUSIONS

This study investigated the impact of imposing energy costs on morphological complexity in single-objective evolution for a collective gathering task. The aim of the research was to provide further evidence in line with the findings presented in a previous study by Nagar, Furman and Nitschke [19]. Specifically, the results in this previous study suggested that costs on morphological complexity promoted the evolution of simpler robots with increased task performance in difficult environments.

Our results contradict this hypothesis, rather indicating that morphological complexity costs are only effective in evolving simpler robots with equivalent task performance in simple environments. However, in medium and difficult environments, morphological complexity costs result in the evolution of simpler robots at the expense of task performance. It is proposed that the more complex sensory requirement for group co-ordination behaviour is the reason for degraded task performance in increasingly difficult environments.

We note a potential weakness in our investigation such that our implementation of sensor energy costs only took sensor number and type into account and did not incorporate variations in other sensor parameters (e.g. range and field of view). It is suggested that future research should attempt to address this shortfall.

Overall, this research provides novel insights into the impacts of evolving task-performing robots with energy costs on morphological complexity. Furthermore, it outlines an original approach to single-objective neuroevolution which, by indirectly factoring in energy expenditure, more closely resembles natural evolution.

7 FUTURE WORK

Recommendations are made for future work regarding the measurement of morphological complexity, the investigation of energy cost impacts on collective robot behaviour and the number of experimental replications.

Firstly, it is recommended that a refined measurement of morphological complexity is devised which takes the number of sensors, types of sensors and other sensor parameters (including range and field of view) into account. Ideally, an approach is suggested which combines our estimates of relative real-world sensor energy costs with the measures of morphological complexity employed by Nagar, Furman and Nitschke [19].

Secondly, the effect of morphological energy costs on performance in collective robot behaviours should be further investigated. Specifically, it is suggested that more environment and/or task definitions with varying collaboration requirements are tested with and without energy costs.

Finally, it is suggested that the number of replications performed for each experiment is expanded to produce increasingly reliable results.

8 ACKNOWLEDGEMENTS

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