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A SIMULATION MODEL FOR BIO-INSPIRED CHARGING STRATEGIES FOR ELECTRIC VEHICLES IN INDUSTRIAL AREAS

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ABSTRACT

This paper presents an open-source agent-based simulation model to study bio-inspired charging policies for local sustainable energy systems in an industrial setting where electric vehicles (EVs) perform transportation jobs. Within this context, we focus on a system that allows to control the charging-schemes of individual EVs. To this end, we develop an agent-based simulation model in NetLogo. We present and implement a bio-inspired approach based on the foraging behavior of honeybees and our approach results in simple, yet effective decision-making logic. Our approach provides the necessary parameters to control and balance sustainable energy systems in terms of EV productivity and the consumption of locally generated energy. Our simulation results look promising: the balance between EV productivity and the use of sustainable energy can be efficiently tweaked in a predictable manner using the parameters and thresholds of the model, yielding close-to-optimal performance.

1 INTRODUCTION

It is widely recognized that the transition from fossil fuels to renewable energy sources is vital for achieving a sustainable future and to reduce greenhouse gas emissions. In industrial and logistics contexts, the transition to electric-powered machinery and Electric Vehicles (EVs) is gaining traction and seems to be irreversible. However, the adoption of EVs also brings significant challenges, including the need for efficient and sustainable Energy Management Systems (EMSs). Related to the notions of Industry 4.0 and Smart Grids, there is a growing interest in using advanced techniques to optimize the use and charging of EVs, both in terms of sustainable energy use as well as in productivity. Deploying EVs in an industrial context (e.g., a logistics park) allows for a certain control on when and how much to charge an EV, opposed to, for example, passenger transport requiring charging services on highways. In an industrial area, EVs typically remain on the premise and are controlled by a single or a small set of stakeholders. As such, the focus on industrial areas allows us to deploy optimization techniques to continuously coordinate energy resources (e.g., solar panels and wind turbines) and energy consumers (e.g., EVs).

Deploying sustainable EMSs involves design, planning, and control optimization problems that are typically complex and computationally challenging due to their stochastic nature (Nguyen et al. 2020). Hence, traditional optimization techniques based on global information and centralized control may be unsuitable (e.g., the use of integer programming). This is particularly relevant in systems that include multiple (competing) stakeholders, where central systems may no longer be feasible due to the required data-sharing of all stakeholders and the inability of the centralized system to adequately represent the interests of the different stakeholders (Gerrits 2023). Moreover, in stochastic and dynamic environments such as logistics parks, global optimization techniques are sensitive to information updates and are typically

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less suitable to respond in a timely manner (Mes et al. 2007). As a result, bio-inspired algorithms have gained attention in the extant literature due to their ability to mimic natural systems' efficient and adaptive behavior (Nguyen et al. 2020). Note that bio-inspired algorithms are not the only alternative solution method to traditional optimization techniques, see for example Mukherjee and Gupta (2015) for a review on central and decentral optimization techniques in the context of charging EVs in smart grids. Nonetheless, bio-inspired algorithms such as evolutionary systems and swarm intelligence have been successfully applied in numerous areas of science, including computer science, mathematics, and operations research (Fan et al. 2020; Kar 2016). In our context, to coordinate the energy resources and energy consumers in an industrial area, the behaviour of honeybees seems to be the most compatible of all bio-inspired approaches.

In this paper, we focus on a swarm-based approach, inspired by the foraging behaviour of honeybees, to divide labor and allocate tasks. Inspired by this natural phenomena, we control the charging strategy of a fleet of individual EVs that performs transport jobs at an industrial area. The goal of our approach is two-fold: (i) maximize the use of locally generated renewable energy, opposed to using energy from the grid, and (ii) minimize the job queue. Regarding the former goal, our use case allows to select which energy source (local or grid) to use at a given point in time. When local energy production is insufficient at a point in time, it can be supplemented by energy from the grid. To reach the goals, we develop a model based on fixed response thresholds, where the thresholds refer to the likelihood of reacting to task-associated stimuli (Bonabeau et al. 2001). In our problem, this corresponds to two tasks: (i) charge vehicle, and (ii) perform transport job. This paper is not the first to apply the behaviour of bees (or any social insect for that matter), where the most commonly known bee-inspired approach is the Artificial Bee Colony (ABC) algorithm. However, most of these approaches, including ABC and Ant Colony Optimization (ACO), are applied to travelling salesman types of problems and are typically promising in single objective optimization problems (Fan et al. 2020). In our approach, we focus on a bi-objective optimization problem that requires simultaneous optimization of the two abovementioned objectives and these are (as we will see) often conflicting. Therefore, there is no single optimal solution and thus we search for a set of nondominated (Pareto optimal) solutions. That is, we aim to *balance* the system in terms of the two objectives. Our bio-inspired approach allows to intuitively and effectively shift the balance based on the preferences of the decision-maker, by controlling the system' parameters. To the best of our knowledge, this is the first paper to present such an approach in the context of charging policies for EVs in industrial areas.

The remainder of this paper is structured as follows. Section 2 presents our bio-inspired approach for charging EVs. In Section 3, we present our conceptual model. The corresponding agent-based simulation model is described in Section 4 and the results are discussed in Section 5. The paper closes with conclusions and directions for further research in Section 6.

2 A BIO-INSPIRED CHARGING STRATEGY

To control the charging for each individual EV within a fleet of vehicles, we deploy a bio-inspired approach based on the foraging behaviour of bees. Let us first briefly discuss the nature of this metaphor. Honeybees need to continuously control the performance of the colony as a whole under constantly changing environmental conditions. The key aspect is the balance between the number of foragers (collecting nectar) and the number of processors (processing nectar in the hive). Based on the work of Hölldobler and Wilson (2009), the decision rules to achieve this balance can be summarized as follows. When more nectar is coming to the nest than can be processed, bees are stimulated to process nectar using the so-called *tremble dance*. When too few foragers are available to exploit a nectar source, bees alert each other by the *shaking signal*. Bees affected by the shaking signal dispatch to the food site. These simple rules followed by the individual bees, result in behavior on the colony level that is close to optimal and stays close to this level even when faced with perturbations (Hölldobler and Wilson 2009). Our bio-inspired approach consists of two main components: (i) an activation function, for which we use a fixed-threshold model, and (ii) a model to balance the use of sustainable energy and EV productivity, for which we integrate three different stimuli. In Section 2.1, we first discuss our probabilistic model in a general way. In Section 2.2, we discuss the three different stimuli for our specific use case.

2.1 A Fixed-threshold Model

Inspired by the intriguing foraging system of honeybees, this paper presents an approach to balance the performance of a fleet of EVs performing transport jobs at an industrial area in terms of two objectives: (i) maximize the use of locally generated renewable energy (solar panels and wind turbines), and (ii) minimize the job queue. We base our algorithm on a fixed threshold based approach as developed by Bonabeau et al. (1996). In this model, every individual i (i.e., an EV) has a response threshold θ_i for every task. In our case, we can simplify the model by assuming there is only one type of task (i.e., a transport job). When an individual i is not performing a job, it is always charging. Each individual engages in a transport job based on a job-associated stimulus. Let s denote the intensity of the stimulus associated with performing a transport job, where s can be the number of jobs currently in the queue, the expected lateness, or any quantitative measure indicating the urgency of the jobs to be performed. The response threshold θ_i, expressed in units of stimulus s, determines the tendency of an EV to respond to the stimulus s and perform the job. We require that θ_i is such that the probability of a response is low for $s \ll \theta_i$ (low urgency) and high for $s \gg \theta_i$ (high urgency). A family of functions that meets this requirement, and has been shown to adequately model the behaviour of honey bee foraging (Seeley 1995), is given by

$$T_\theta(s) = \frac{s^n}{s^n + \theta_i}, \tag{1}$$

where $n > 1$ determines the steepness of the threshold. Intuitively, the meaning of threshold θ_i is as follows. When $s \ll \theta_i$, the probability of performing a job is close to 0. Similarly, when $s \gg \theta_i$ the probability goes to 1. At $s = \theta_i$ the probability is 0.5. As such, individuals with a low θ_i are more likely to respond to a lower level of stimulus s. Note that Equation 1 results in an exponential response function.

Under the assumption that there is only one type of task, we can view the stimulus s as the demand for transport jobs. When demand increases, the intensity s also increases. Let X_i be the state of individual i. $X_i = 0$ corresponds to inactivity and $X_i = 1$ corresponds to performing a job by individual i. Let us assume that when an individual i becomes inactive, it instantaneously arrives at a charger. That is, we omit the travel time to and from the charger. Given that there are jobs available, an inactive EV starts performing a job with a probability P:

$$P\left(X_i = 0 \rightarrow X_i = 1\right) = T_\theta(s) = \frac{s^n}{s^n + \theta_i}. \tag{2}$$

When a job is finished, the EV automatically returns to the charger (i.e., $X_i = 0$). Although it is common in natural systems for individuals to be able to give up performing a task with a certain probability p (irrespective of stimulus), we omit this from our model due to practical reasons. Whenever an EV starts a job, it is committed and has to finish before being able to become inactive again. Using this model, whenever an individual performs a job, it reduces the intensity of the task-related stimulus (e.g., measured in number of remaining jobs), and therefore influences the stimulatory field of the remainder of the fleet. Similarly, when demand increases, so does stimulus s, stimulating individuals into performing jobs. Information about the necessity of performing jobs is thus transmitted through a combination of direct and indirect communication. Indirect communication is done through modifying the environment (i.e., influencing s) and is known as stigmergy (Theraulaz and Bonabeau 1999).

2.2 Integrating Different Types of Stimuli

To balance the use of locally generated sustainable energy and the productivity of the EV fleet, we combine three different stimuli, influenced by (i) the amount of sustainable energy, (ii) the battery level of the EV, and (iii) the number of jobs that require service. The three stimuli are discussed in the subsections below.

2.2.1 Sustainable Energy Stimulus

To capture our intention to utilize as much locally generated sustainable energy as possible, we include an *energy stimulus* in our algorithm. Intuitively, we aim to *attract* EVs to charge their batteries (i.e., transition to state $X_i = 0$) whenever there is a high amount of sustainable energy available. Although this intuition holds for all sorts of sustainable energy sources, we focus on locally generated solar energy and energy from wind turbines. Let us denote the energy-related stimulus by s_e and let t denote the hour of the day ($0 \leq t < 24$). For example, an energy-related stimulus function can be defined as follows. First, wind energy is assumed as a constant energy source over the day, producing E_W for every t (in kW). Even though wind energy shows fluctuations over the day, we justify this assumption as we expect that the share of wind energy compared to solar energy is small for our use case and solar energy shows much more fluctuation. In other use cases, the current function can be replaced by a more realistic model in Equation 4. Second, the solar system uses a Normal-distribution, producing E_S (in kW) over the day, with mean μ and standard deviation σ, such that the solar production in hour t follows:

$$E_S(t) = \mu - \left(\delta * \left(6 - \frac{t}{2}\right)\right) * \sigma\,, \tag{3}$$

where μ denotes the maximum solar energy production measured in kW (i.e., around noon) and δ is a scaling factor to capture seasonal effects. That is, when δ increases, the sun rises later during the day and vice versa, as exemplified in Figure 1. Equation 3 allows us to capture the *natural incentive* of solar power to stimulate EVs to charge their batteries. Using the expected solar production $E_S(t)$ at hour t, we calculate a probability $p_s(t)$ using the probability density function of $N(\mu, \sigma^2)$ and normalize this such that at noon, the probability is equal to 1 (i.e., $p_s(12) = 1$). Intuitively, $p_s(t)$ denotes the probability that an EV goes charging, based on the sustainable energy stimulus. The energy-related stimulus at time t is the combination of $p_s(t)$ and $p_w(t)$, where the latter denotes the probability that the wind turbines produce E_W, which is, given our example, equal to 1 for all t. Hence, the energy-related stimulus s_e at hour t can be expressed as the weighted average of both energy components, and is given by:

$$s_e(t) = \alpha * p_s(t) + \beta * p_w(t)\,, \tag{4}$$

where, $a = \mu/(\mu + E_W)$, and $\beta = 1 - \alpha$, denoting the fraction of solar energy and wind energy respectively. Using Equation 4, we are able to calculate a probability between 0 and 1, indicating the stimulus of the locally generated energy, and the balance between solar and wind energy. Equation 4 can be easily extended to include for example hydro-generated energy. However, we focus on two common sources of sustainable energy: solar and wind. Note that the energy stimulus does not depend i.

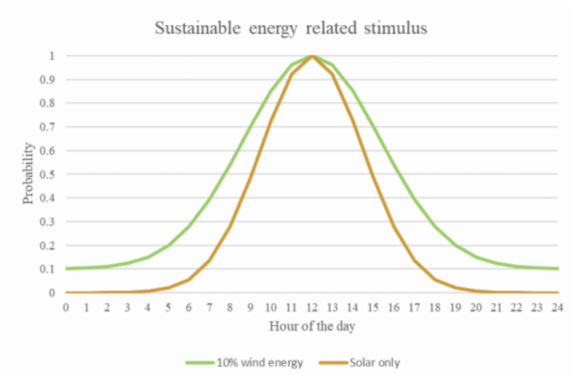

Figure 1: Illustration of sustainable energy stimulus. Stimulus curve for 10% wind energy and 90% solar energy (green), and 100% solar energy (brown).

2.2.2 Battery Stimulus

To ensure that the batteries of each individual i are sufficiently charged, we include a *battery stimulus*. This captures the intention of the EVs to maintain a certain state of charge. Obviously, when the battery of an EV is depleted, it is not able to perform jobs. We use a threshold response function similar to Equation 1. Let $s_b(i)$ denote the *battery stimulus* of individual i, expressed in percentage points (0% = empty; 100% = full), and let $p_b(i)$ denote the probability that individual i goes to the charger, which is given by:

$$p_b(i) = 1 - \frac{s_b(i)^n}{s_b(i)^n + \theta_b(i)}, \tag{5}$$

where $n > 1$ determines the steepness of the threshold, and $\theta_b(i)$ denotes the battery-related threshold for individual i (expressed in state of charge). Similarly to Equation 1, the probability of a response (i.e., go to the charger) is low for $s_b \ll \theta_b$ (low urgency, charged battery) and high for $s_b \gg \theta_b$ (high urgency, low battery). Note that Equation 5 only captures the state of charge of an individual EV, where it can be extended to also capture the state of charge of the fleet as a whole.

2.2.3 Job Stimulus

To capture the incentive of the industrial area to maintain efficient operations, we include a *job stimulus* denoting the urgency of the jobs that require processing. Let s_j denote the job-related stimulus, expressed in some quantitative measure indicating the urgency of the jobs to be processed (e.g., waiting time, length of the queue or expected tardiness). Let $p_j(i)$ denote the probability that individual i starts processing a job. As we ignored the travel time to and from the charger, the probability of an EV remaining at (or going to) the charger is $1 - p_j(i)$. The job-related probability is then given by:

$$p_j(i) = 1 - \frac{s_j^n}{s_j^n + \theta_j(i)}, \tag{6}$$

where $n > 1$ determines the steepness of the threshold, and $\theta_j(i)$ denotes the job-related threshold for individual i (e.g., expressed in queue size). Similarly to the battery-related stimulus, the probability of processing a job increases when the stimulus exceeds the threshold. Intuitively, when the queue increases, EVs are more likely to start processing a job.

2.2.4 Combining the Three Stimuli

We combine the three different stimuli discussed in the previous sections to determine the transition probability of an individual when currently charging, i.e., $P(X_i = 0 \rightarrow X_i = 1)$. Note that the transition the other way around is only possible after a job is completely finished (i.e., no preemption), although an EV may immediately start a new job if the stimulus is still high. Hence, the system can be described by two transitions: $P(X_i = 0 \rightarrow X_i = 1)$, and $P(X_i = 0 \rightarrow X_i = 0) = 1 - P(X_i = 0 \rightarrow X_i = 1)$. The probability of starting a job by individual i, when currently charging, is given by:

$$P\left(X_i = 0 \rightarrow X_i = 1\right) = w_s p_s(t) + w_b p_b(i) + w_j p_j(i), \tag{7}$$

where $0 \leq w_s \leq 1$, $0 \leq w_b \leq 1$, and $0 \leq w_j \leq 1$ are tuning parameters, denoting the weights of the solar stimulus, the battery stimulus, and the job stimulus respectively, such that $w_s + w_b + w_j = 1$.

3 CONCEPTUAL MODEL

Before presenting the implemented simulation model, an abstraction is made using a conceptual model. We aim to develop a reusable and highly configurable simulation model (e.g., to quickly analyze the impact of the tuning parameters of our bio-inspired approach), for which we require some abstraction. The following elements are described: inputs (Section 3.1), outputs (Section 3.2), experimental factors (Section 3.3), and model assumptions (Section 3.4).

3.1 Inputs

Regarding the inputs, we distinguish between (i) the local sustainable energy system, (ii) the fleet of EVs, (iii) the charging area, and (iv) the working area.

1. **Sustainable energy system.** For our purposes, it suffices to focus on three parts of the energy system: (i) the sustainable energy production, (ii) energy to/from the grid, and (iii) a buffer battery. The latter is used to temporarily store the locally produced energy at times of overproduction. That is, in our settings, the buffer battery is only charged by the local energy system and not by the grid. The EV fleet can use this buffer battery for charging purposes. In our focus, the sustainable energy production includes solar and wind energy. We include an abstract representation of these production modes. For solar energy, we suffice in including the maximum power output (in kWh) and a standard deviation to create a Normal distribution. A scaling factor is used to include seasonal effects (i.e., during summer the sun rises earlier). As discussed in Section 2.2.1, these inputs are used to model the solar production for every hour of the day. Moreover, we include a connection to the grid to either supply energy (i.e., overcapacity) or request energy (i.e., undercapacity). That is, whenever the local energy sources do not supply enough power as requested by the EVs, the deficit is supplied by the grid. Similarly, when there is a surplus of locally produced energy it is supplied back to the grid, or used to charge the buffer battery. The buffer battery is simply modelled by defining its capacity (in kWh) as an input parameter. The buffer battery is only charged in times of overcapacity of locally produced energy, and never charged from energy originating from the grid.
2. **EV fleet.** The fleet of electric vehicles is modelled using the following inputs: (i) the number of EVs, (ii) the battery capacity (in kWh), (iii) the charging speed (in %/h), and (iv) the energy consumption (in %/h).
3. **The charging area.** The charging area is a single physical area where the EVs are able to charge their batteries. The charging area is modelled as a collection of chargers, such that each EV has a dedicated charger. That is, every EV is able to charge at any given time. Each charger has a charging capacity (in %/h) equal to the charging speed of the EVs. There is thus no bottleneck in charging speed. When the battery of an EV is full, it remains at the charging area until it is allocated to a job using Equation 7.
4. **The working area.** The working area is a physical area modeled as a queuing system, and for experimentation purposes we use a $D/G/c$ queue, where c is equal to the number of EVs, where the arrival process of jobs is deterministic, and the processing time depends on (i) the bio-inspired charging strategy as discussed in Section 2, and (ii) a deterministic service time. That is, when a job arrives, an EV is available, and the stimulus to perform a job is high, the total processing time has a high probability of being close to the (deterministic) service time. However, when the stimulus is low, there is a high probability that an EV remains charging, and thus the processing time of a job increases as waiting time is induced.

3.2 Outputs

The simulation model has the following outputs: (i) the percentage of consumed energy originating from the locally generated energy, (ii) the percentage of consumed energy originating from the grid, (iii) the percentage of energy supplied back to the grid, (iv) the average and standard deviation of the job queue, (v) the average and standard deviation of the battery level for every EV, and (vi) the utilization of the buffer battery. Using these outputs, we are particularly interested in the balance between the use of locally generated energy (e.g., the degree to being *off-the-grid*), and the size and dynamics of the job queue.

3.3 Experimental Factors

Given our interest to balance the sustainable energy system in terms of consumption and EV productivity, we define several experiments. We first create a base-scenario (Scenario 0) in which the system is configured such that (i) the total required energy is equal to the total energy production over the whole simulation run, (ii) the number of deployed EVs are able to handle the workload, and (iii) the charging speed and energy consumption of the EVs lead to a realistic utilization of the fleet. That is, the system is theoretically able to be fully powered by locally generated energy, and the average required processing time is equal to the average effective operating time of the EVs (i.e., the time remaining after charging). To exemplify, we choose 7 EVs, a deterministic arrival rate of 5 jobs per hour, and a processing time of one hour per job. This results in an average utilization of 71.4%. A completely depleted battery takes 4 hours to fully charge, and a full battery takes 10 hours to fully deplete. Hence, in a cycle of 14 hours, the maximum EV utilization is also 71.4%, and, when there is no idling, the EVs are able to process all jobs. In Scenario 0, the job arrival rate is deterministic (no fluctuations) and there is no buffer battery used. In Scenario 1, we experiment with demand fluctuations to test the robustness of our approach. In this scenario, there is a constant demand of 4 jobs per hour and 6 extra jobs are generated at random hours during the day, such that the total number of jobs is equal to Scenario 0. The remainder of the settings are equal to Scenario 0. In Scenario 2, we assess the impact of a buffer battery and set the capacity to 6000 kWh (equal to the total daily required energy). The remainder of the settings are equal to Scenario 1. For each scenario, we experiment with the tuning parameters of the bio-inspired approach as given by Equation 7. We denote each experiment using the following tuple (w_s, w_b, w_j), e.g., (1,0,0) only includes the sustainable energy stimulus.

3.4 Model Assumptions and Limitations

To reduce the complexity of the simulation model, several assumptions are introduced. First, we assume no failures for the EVs. Second, we assume that EVs instantaneously move to the *working area* to start a job, when allocated to it. Similarly, when a job is finished, the EV instantaneously arrives at the *charging area* and starts charging. EVs are not allowed to prematurely stop a job. Therefore, EVs are only allowed to start a job when their State of Charge (SoC) is above 10% (i.e., the required energy to process a single job). Moreover, we assume a fixed linear charging speed (i.e., expressed in %/h) and there is always sufficient supply from the grid in case of a shortage. In case of overproduction, energy can always be supplied back to the grid. Furthermore, we control the frequency of evaluating the bio-inspired charging strategy per EV. As such, at discrete time-intervals the charging strategy is evaluated to determine whether an EV starts processing a job. We found that an interval of 15 minutes gives a good balance in the system.

4 SIMULATION MODEL

Based on the bio-inspired approach and conceptual model described, an agent-based simulation model is proposed, implemented in NetLogo. An impression of the simulation model is given in Figure 1, and the model is freely available at Gerrits and Andringa (2023) and can be run in the cloud using NetLogo Web. We invite researchers and practitioners to use and extend the model. Additional information on the inner workings and possible extensions of the model can also be found online. For experimentation and data-analysis purposes, we use an offline version of the model with a custom-build experiment manager and data-logging capabilities. Below, the main components of the simulation model are discussed: the energy system (Section 4.1), the EVs (Section 4.2), and the jobs (Section 4.3).

4.1 The Sustainable Energy System

To capture how the energy is supplied and consumed in the network, we first focus on the visualization of the flow of energy. As shown in Figure 2, we visualize a wind turbine, a solar system (both on the left), and the grid (on the right). These are connected to the charging area (visualized by an orange charging station) and a buffer battery (if used) in the middle of the model.

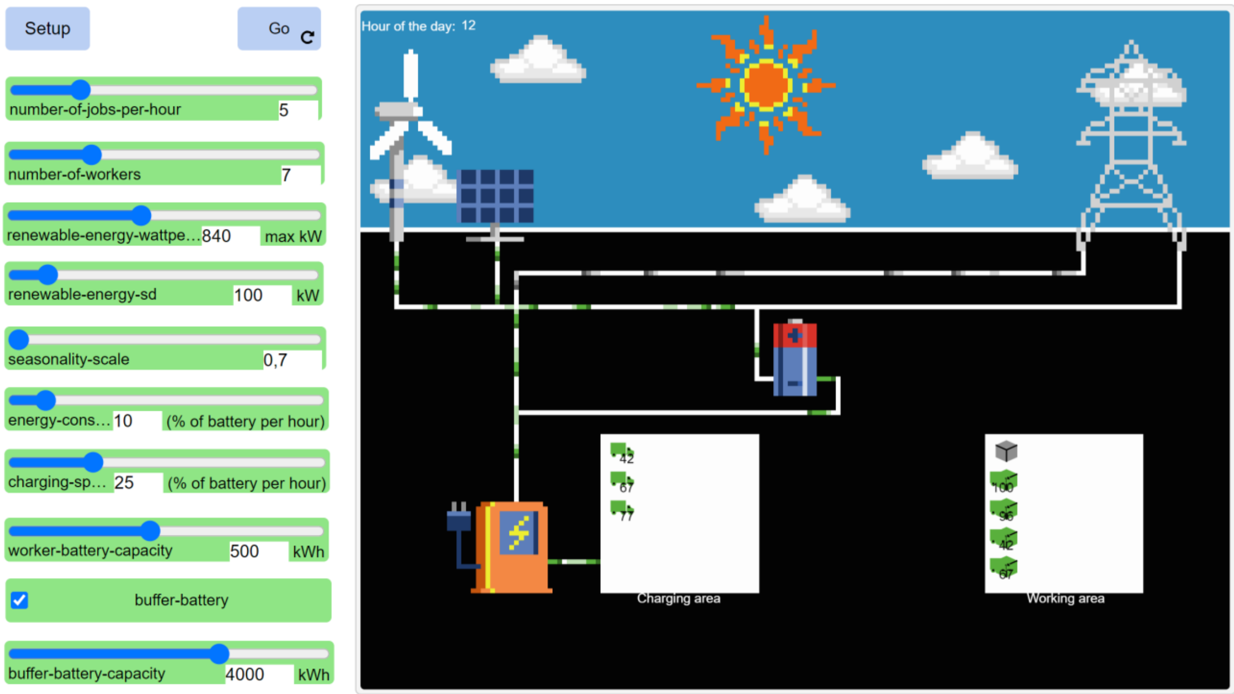

Figure 2: Screen capture of the cloud-based simulation model. The input parameters and experimental factors are shown on the left and the visualization of the energy system is shown on the right, including a charging area (left white square) and a working area (right white square).

When pressing *Setup*, the visualization is generated using NetLogo code by coloring the relevant *Patches*. For the purpose of animation, the flow of energy is visualized using color-coding: solar or wind energy (green), grid energy (grey), or a mix of both (yellow). If no buffer battery is used, the network is adjusted accordingly during initialization. Moreover, to visualize the solar production, the sun rises and sets at the top of the model (see Figure 1), with discrete (hourly) time steps in between. That is, every hour the solar production (in kW) is calculated based on the input parameters and Equation 3.

4.2 The Electric Vehicle Fleet

The EVs are modelled as an agent-set of *workers* in NetLogo. The worker-agents are initialized at individual x- and y-coordinates at the *charging area* (left white square in the simulation), based on the input parameter *number-of-workers*. The individual agents of this *breed* have the following custom-defined properties: (i) the current SoC (in %), (ii) a Boolean indicating whether the agent is processing a job, (iii) the unique identifier of the job it is currently processing (or -1 if *none*), and (iv) x-and-y coordinates when the agent is charging (for visualization purposes). Whenever an EV requires charging, it is automatically charged using the energy that is currently available, where the priority is as follows: (1) direct from sustainable source, (2) from buffer battery, or (3) from the grid. Lastly, the EVs are visualized using truck icons showing the current SoC in the bottom-right corner. The EVs are green when the SoC is higher than the minimum required charge to process a job (i.e., they are available), and yellow otherwise.

4.3 Job Generation

Similarly to the EVs, the jobs are modelled as an agent-set and each job-agent has the following custom-defined properties: (i) the ID of the worker assigned to it (or -1 if *none*), (ii) the *tick* indicating the time when the job is created, (iii) the *tick* indicating the time when a worker starts the job, and (iv) the x-and-y coordinates of the job in the working area (for visualization purposes). The jobs are generated at the start of each hour, based on the *number-of-jobs-per-hour* parameter. The job-agents are color-coded green when a worker is processing the job and grey otherwise. After completion of the job, the job-agent is removed.

5 RESULTS

This section presents the simulation results. First, the experimental design is discussed in Section 5.1. Next, we present the results of the base scenario (Section 5.2), of introducing demand fluctuations (Section 5.3), and of including a buffer battery (Section 5.3).

5.1 Experimental Design

Recall that our goal is develop and evaluate a bio-inspired approach to balance a local sustainable energy system for electric vehicles in an industrial context. To this end, we define several experiments. First, we aim to evaluate whether our bio-inspired approach is able to balance the system using the base-scenario (as discussed in Section 3.3). Next, we experiment with disturbances in the job generation pattern (Scenario 1), and test the influence of a buffer battery (Scenario 2). We use a terminating simulation representing a working week, with a run length of 5 days (120 hours). At the initialization of every simulation run, the SoC of all EVs are set at 50% and the buffer battery is fully charged (only in Scenario 2). For each scenario, we experiment with the parameters of the bio-inspired approach, denoted by the tuple (w_s, w_b, w_j). We use a step-size of 0.1 for each parameter (i.e., 0, 0.1, 0.2, …, 0.9, 1.0), resulting in a set of 66 experiments for each scenario. Five replications are used for each experiment, resulting in a relative error of at most γ = 0.01 using a significance level α = 0.05. The input values as described in Section 4 are shown in Table 1. Table 2 gives on overview of the results, which are further discussed in Sections 5.2-5.4.

Table 1: Input parameters and their values. SoC = State-of-Charge (0-100%).

Input	Value	Input	Value
Sustainable energy related		**Job related**	
Max. solar production (kWh)	840	Jobs per hour	5
Solar production (std. dev)	100	Processing time (h)	1
Seasonality parameter	0.7	Min. required SoC before starting job	10%
Max. wind production (kWh)	0		
EV related		**Buffer battery related**	
Number of EVs	7	Available	Yes (Sc. 2) or no (Sc. 0-1)
Energy consumption (%/h)	10	Capacity (kWh)	6000
Charging speed (%/h)	25		
Battery capacity (kWh)	500		

5.2 Balancing the System in the Base-scenario

Figure 3 shows the results of the experiments in terms of the average queue and the percentage of sustainable energy use for Scenario 0 (gold colored) and Scenario 1 (green colored). To compare the impact of the parameters of the bio-inspired approach, we alternatingly set one of the three parameters of the bio-inspired approach to zero, resulting in 12 remaining experiments. From Figure 3 it can be clearly seen that when the focus is fully on solar stimulus, i.e., configuration (1,0,0), that the both the average queue size and the sustainable energy use is the highest.

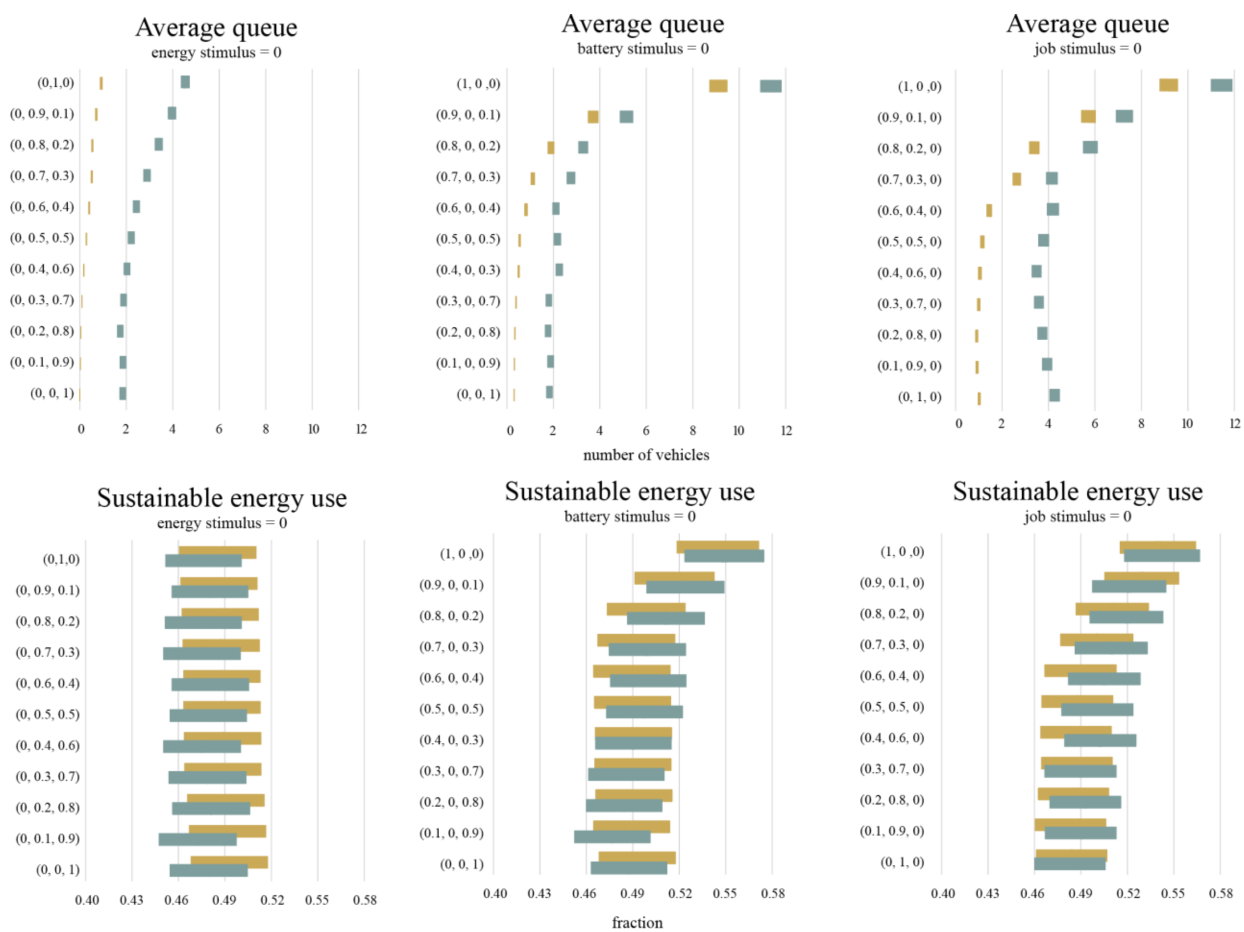

Figure 3: Simulation results. Scenario 0: gold, Scenario 1: green.

This result suggests that when sustainable energy usage is important, a sacrifice needs to be made in terms of logistics performance. In our system, the average queue size is more dependent on the parameters of the bio-inspired approach than the sustainable energy use. As a matter of fact, only a few statistical differences can be found for the latter, i.e., when the confidence-intervals do not overlap. Nevertheless, the trade-off between logistics performance and sustainable energy use is clear in our system. Hence, looking for Pareto optimal solutions is required to balance the system. As a start, we used Excel to solve an ILP tailored to our system to find the extreme points. That is, the minimum and maximum of the average queue and the sustainable energy use. Our ILP found that the minimum queue is very close to 0 with a corresponding sustainable energy use of 48.9%. Our bio-inspired approach, when focusing mainly on the job stimulus, also achieves a queue size close to zero, with a sustainable energy usage of 48.2%. At the other extreme, focusing on maximum sustainable energy usage, the theoretically maximum proved to be 62.4% in our use case, while our bio-inspired approach achieved 52.5% with a slightly smaller average queue. These results suggest that our bio-inspired approach is able to (i) intuitively control the balance in the system, and (ii) achieve good results with negligible computational power. As part of further research, we aim to explore the set of Pareto optimal solutions to further substantiate the power of our approach.

5.3 Introducing Disturbances

The goal of introducing disturbances in demand is to verify the robustness of our approach under different parameters. From Figure 3 it can be seen that disturbances increase the average queue, while the sustainable energy use remains more or less the same (i.e., the green colored values). Regarding the average queue, we find that when focusing on the job stimulus, the increase is substantially less than when focusing on the battery or the sustainable energy stimulus. When focusing on the job stimulus, the system is thus more responsive to demand fluctuations. But again, the system should be balanced in terms of both KPIs, and the user of the system needs to determine acceptable levels for both KPIs. Our simple, yet effective approach, allows the user to (automatically) configure the parameters of the bio-inspired approach in real-time to control the balance.

5.4 The Impact of a Buffer Battery

In our system, we focus on 24-hour operations and hence sustainable energy produced at night is typically insufficient to meet demand. We therefore experiment with a buffer battery that can be used to temporarily store locally generated energy. We set the capacity of the buffer battery to the total daily required energy. As a result, the surplus energy during the day is stored and used during the night. Through experimentation, we assess how the parameters of the bio-inspired approach influence the maximum required capacity to be 100% self-sufficient, as capacity is typically the main indicator of the costs of a buffer battery. Figure 4 shows the results for the experiments where $w_b = 0$, as these experiments showed the lowest and highest values for the required buffer capacity.

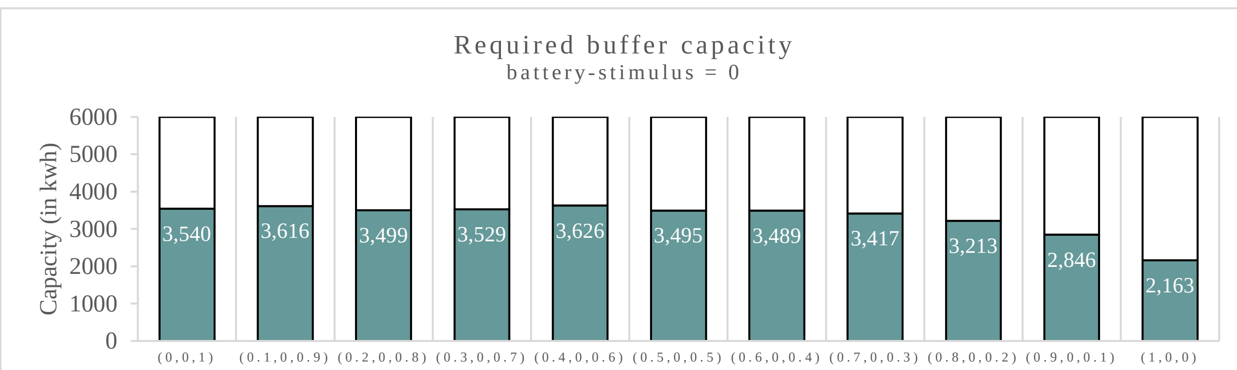

Figure 4: Impact of parameters on required buffer capacity.

From Figure 4 we see that focusing only on the sustainable energy stimulus, i.e., configuration (1,0,0), the maximum required buffer capacity is approximately 40% lower than when focusing only on the job stimulus. As discussed in Section 5.2, focusing on solar energy comes at the sacrifice of a longer average queue, but with a higher percentage of immediate use of sustainable energy, and hence, a smaller buffer is required.

6 CONCLUSIONS AND FURTHER RESEARCH

This paper proposes a bio-inspired approach based on the foraging behavior of honeybees to control the charging of a fleet of electric vehicles in an industrial setting. We present an approach based on three different stimuli to balance the system in terms of usage of locally generated sustainable energy and the performance of the logistics system. To this end, we present an open-source agent-based simulation model to study the behaviour of the bio-inspired approach in various scenarios. Results from our simulation experiments suggests that our approach (i) intuitively and effectively controls the balance between charging and working, and (ii) is able to show close-to-optimal performance at the extreme points of the Pareto optimal solutions by tweaking the parameters included in the model. Our open-source simulation model is freely available online and can be easily extended to include different bio-inspired approaches or to model different logistics systems. We invite researchers and practitioners to use and extend the model. For example, we identify the following topics for extension and further research: (i) include a more realistic model of sustainable energy production with fluctuations due to weather changes, (ii) assess the impact of the different stimuli of the bio-inspired approach for different logistics systems, and (iii) extend the model to include optimization in terms of monetary KPIs (e.g., strategically sell/buy energy).

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