Evolving robust policies for community energy system management

Supplementary Material

RUI P. CARDOSO, Imperial College London, UK

EMMA HART, Edinburgh Napier University, UK

JEREMY V. PITT, Imperial College London, UK

ACM Reference Format:

Rui P. Cardoso, Emma Hart, and Jeremy V. Pitt. 2019. Evolving robust policies for community energy system management: Supplementary Material. 1, 1 (April 2019), 12 pages. <https://doi.org/10.1145/3321707.3321763>

1 MODEL

In this work, we have modelled an energy system encompassing several CESs. While this model has been based on knowledge arising from some of the literature on CESs ([1, 2, 5, 6, 8, 10]), it is mostly intuitive. It abstracts a hypothetical energy system connecting several communities which both produce and consume energy and are able to trade it directly amongst themselves. We are not aware of an *actual system of this kind existing* or of *any theories* which can be applied directly to our model; our mental model is the only source of knowledge about the problem domain. This places our modelling approach within the System Dynamics (SD) paradigm, created by Forrester [4]. It is important to note that we are not excessively concerned with the *realism* of our model, as it has been designed mostly for enabling the study of adaptation and evolution of operating policies.

In the model which we have constructed, energy is treated as a CPR and communities as agents. The communities are part of an energy system; they have energy demands and can generate energy from a number of renewable resources. Three sources of renewable energy have been considered, namely photovoltaic cells, wind turbines, and hydropower converters. The energy system can also generate and feed energy to compensate for any lack of self-generated power. Communities are located on a *grid* and have neighbours with which they are able to trade energy, using a simplified version of the Contract Net Protocol [9]; they are also able to trade energy with the central system. A time step corresponds to an hour in the simulation time. At each time step, the energy system uses the current operating policy to determine the mode of operation of the system for that time step, as explained in detail in section 2. Figure 1 summarises the domain model of the system.

As an attempt to create a flexible model, we have defined a number of input parameters required for instantiating it. These parameters are summarised in Table 1. There are a certain number of communities connected to the energy system, given by *num_communities*. They are placed randomly on a grid, each community occupying a single cell and each cell being occupied, at most, by a single community. The size of the grid is given by parameters *width* and *height*. Each community is able to store energy up until a certain maximum amount,

Authors' addresses: Rui P. Cardoso, rui.cardoso@imperial.ac.uk, Dept. of Electrical and Electronic Engineering, Imperial College London, London, UK, SW7 2AZ; Emma Hart, e.hart@napier.ac.uk, School of Computing, Edinburgh Napier University, Edinburgh, UK, EH10 5DT; Jeremy V. Pitt, j.pitt@imperial.ac.uk, Dept. of Electrical and Electronic Engineering, Imperial College London, London, UK, SW7 2AZ.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2019 Association for Computing Machinery.

XXXX-XXXX/2019/4-ART \$15.00

<https://doi.org/10.1145/3321707.3321763>

Fig. 1. Domain model of the energy system

given by its capacity; the capacity is a random positive integer, with *min_capacity* being its minimum value and *maximum_capacity* its maximum value. The cost of storing energy is drawn from a uniform distribution, such that the minimum possible cost is given by *min_storage_cost* and the maximum cost is given by *max_storage_cost*. The neighbours of a community are determined by the parameter *neighbour_radius*, which is a positive integer representing a number of cells; all communities within this number of cells from a certain community in the grid, including diagonals, are considered its neighbours. The notion of neighbour is important, as communities are only allowed to trade energy with their neighbours. The central system is able to flexibly produce energy at each time step if there is at least one community whose demands have not been satisfied; in this case, the unit cost of production is given by *production_cost*. As part of its operation, the system will purchase energy from the communities and then resell it. The parameter *purchasing_price* is the unit price for which the central system purchases energy and the parameter *selling_price* is the unit price for which it sells it. The parameter *w* is used to update the satisfaction of each community, as in equation 7, and the parameters *alpha* and *beta* are used to calculate the system performance, as in equation 8. The parameter *n_each_resource* determines the number of resources of each kind (photovoltaic cells, wind turbines, and hydropower converters) that each community with resources possesses and the parameter *perc_with_resources* determines the proportion of communities which do have access to renewable energy resources. The parameter *seed* sets the random seed of the model, ensuring reproducible results. Leaving this parameter undefined causes the model to use sources of randomness offered by Python, the language in which it has been implemented.

The communities are initialised with some renewable energy resources, whose energy production is simulated. The energy produced by each community is obtained at each time step by summing over the energy produced by each of their energy resources. Communities also demand a certain amount of energy at each time step. We have used intuitive notions for coming up with functions which return the energy produced by each resource and each community's demand at every time step. These functions are defined by a sum of *radial basis functions* [3]. Given a set of *centres*, $\{c_i\}_{i=1}^N$, a set of *bandwidths*, $\{h_i\}_{i=1}^N$, and a set of weights, $\{w_i\}_{i=1}^N$, the sum of radial basis functions at time step t is given by:

$$S(t|\{w_i\}_{i=1}^N, \{c_i\}_{i=1}^N, \{h_i\}_{i=1}^N) = \sum_{i=1}^N w_i \times \exp(t \bmod 24 - c_i)^2 / h_i^2 \quad (1)$$

The number of radial basis functions, N , used to define this sum is given by the model input parameter *num_rbf*s. The greater the value of *num_rbf*s, the more fine-grained the sum defined by equation 1, which enables more complex functions (more inflection points) to be modelled. The weights, centres, and bandwidths are set intuitively according to each energy resource and the expected demand from communities. For each type of energy resource and for the demand of each community, the centres are set to fixed values; the weights and bandwidths, on the other hand, are drawn from probability distributions, as described ahead. For solar panels, the centres are set and the weights are drawn from Gaussian distributions such that there is a maximum at around midday everyday. The bandwidths are each drawn from a uniform distribution. The energy produced by a solar panel at time step t is then given by:

$$\begin{aligned} x &\sim \mathcal{U}(0, 1) \\ E_{\text{solar}}(t|Q = \{\{w_i\}_{i=1}^N, \{c_i\}_{i=1}^N, \{h_i\}_{i=1}^N\}) \\ &= \begin{cases} (1 - \text{loss_cloudy}) \times \max(S(t|Q), 0) & \text{if } x \leq \text{perc_cloudy} \\ \max(S(t|Q), 0) & \text{otherwise} \end{cases} \end{aligned} \quad (2)$$

The value *perc_cloudy* is the probability that the weather is cloudy at any given time step and *loss_cloudy* is the decrease (a percentage) in energy produced by the solar panel when the weather is cloudy. They are both drawn from uniform distributions. For both wind turbines and hydropower converters, the centres are set with a fixed step and the weights are drawn from a Gaussian distribution and are independent from the time of the day. The bandwidths are drawn from uniform distributions, as well as a positive *offset* intended to ensure that the energy produced by these two kinds of resources is never 0. At time step t , the energy produced by either a wind turbine or a hydropower converter is then given by:

$$E_{\text{wind,hydro}}(t|Q = \{\{w_i\}_{i=1}^N, \{c_i\}_{i=1}^N, \{h_i\}_{i=1}^N\}) = \text{offset} + \max(S(t|Q), 0) \quad (3)$$

When defining the function returning a community's demand, the weights are set, again intuitively, so that there is a peak in the early morning and in the evening, by drawing from Gaussian distributions. The demand of a community at time step t is then given by:

$$D(t|Q = \{\{w_i\}_{i=1}^N, \{c_i\}_{i=1}^N, \{h_i\}_{i=1}^N\}) = \max(S(t|Q), 0) \quad (4)$$

We defined the sum of radial basis functions, given by equation 1, by calculating the modulo 24 of the input time step t . This has enabled us to define some daily trends, such as the energy produced by solar panels peaking at around midday or the energy demands peaking in the early morning and in the evening. However, it also causes this function to repeat itself every 24 time steps. We address this by adjusting the weights according to another input parameter, *noise*. We start by generating a base set of weights, $\{w'_i\}_{i=1}^N$, as described before. When

<i>num_communities</i>	The number of communities in the energy system
<i>width</i>	Width of the grid (number of cells) where the communities are located
<i>height</i>	Height of the grid (number of cells) where the communities are located
<i>num_rbf</i> s	Number of <i>radial basis functions</i> used for defining the functions that return the energy produced by each energy resource at a given time step
<i>noise</i>	Positive value for introducing unpredictable variation in the amount of energy produced by each energy resource (equation 5)
<i>min_capacity</i>	The minimum storage capacity of any community in the system
<i>max_capacity</i>	The maximum storage capacity of any community in the system
<i>min_storage_cost</i>	The minimum unit cost for a community to store energy
<i>max_storage_cost</i>	The maximum unit cost for a community to store energy
<i>neighbour_radius</i>	Radius (number of cells) used to determine the neighbours of each community
<i>production_cost</i>	The unit cost for the central energy system of producing energy
<i>purchasing_price</i>	The unit price for which the central energy system purchases energy from the communities
<i>selling_price</i>	The unit price for which the central energy system sells energy to the communities
<i>w</i>	Weight of latest utility when updating the satisfaction of a community (equation 7)
<i>alpha</i>	Weight of the average satisfaction when calculating the performance of the system (equation 8)
<i>beta</i>	Weight of the average proportion of unsatisfied communities when calculating the performance of the system (equation 8)
<i>n_each_resource</i>	Number of resources of each kind (solar, wind, hydropower) possessed by each community that does have access to renewable energy resources
<i>perc_with_resources</i>	Proportion of communities which possess renewable energy resources ((0, 1])
<i>seed</i>	Random seed (for obtaining reproducible results)

Table 1. Model parameters

calculating the energy produced by each energy resource or the demand of a community at a given time step, we create a new set of weights, $\{w_i\}_{i=1}^N$, by adding a random perturbation to each w'_i which depends on the *noise* parameter:

$$\begin{aligned}\sigma &\sim \mathcal{U}(-noise, noise) \\ w_i &= w'_i + \sigma\end{aligned}\tag{5}$$

The greater the value of *noise*, the greater the potential difference between w_i and w'_i and, therefore, the greater the *unpredictability* of the functions which return the energy produced by each energy resource and the demand for each community. This model and particularly the functions simulating energy production are merely intuitive and make many simplifying assumptions. However, as we mentioned earlier in this section, realism has not been a major concern and the plausibility of the model we have created is satisfactory. It has enabled us to study the impact of adaptation and evolution of system policies.

Table 2 lists the input arguments in the model which have remained fixed in the experiments we have carried out in this paper.

<i>num_communities</i>	50
<i>width</i>	10
<i>height</i>	10
<i>num_rbfs</i>	10
<i>min_capacity</i>	10
<i>max_capacity</i>	30
<i>min_storage_cost</i>	0.1
<i>max_storage_cost</i>	0.3
<i>neighbour_radius</i>	5
<i>production_cost</i>	0.5
<i>purchasing_price</i>	1
<i>selling_price</i>	1.2
<i>w</i>	0.5
<i>alpha</i>	1
<i>beta</i>	5
<i>seed</i>	1995

Table 2. Model input arguments fixed throughout the experiments

2 REPRESENTATION AND APPLICATION OF POLICIES

At every time step, each community's energy demand and the total energy which they have produced from their resources is calculated. The system's operating policy is then applied, returning a *mode of operation* which will determine what to do with the energy the communities have produced and how to meet their demands. In our model, the mode of operation has three degrees of freedom:

- What the communities should do with the energy they have produced at the current time step: either use it to satisfy their own demands (self-supply) or sell it all to the central system.
- In the case of self-supply, what the communities should do with any excess of energy: sell to the central system; store as much as capacity allows and sell the excess; trade it with neighbours and sell the excess; store, trade, and sell; or trade, store, and sell.
- If any demands have not been satisfied, the central system will ensure they are met by first reselling the energy which has been purchased from the communities and producing energy on demand (accounting for production costs) when necessary. The order in which the communities receive the energy is determined by several possible criteria: greatest demand, greatest production, lowest satisfaction, random, or ration.

Table 3 summarises these degrees of freedom and the values they can be set to when instantiating a mode of operation. For example, a possible mode of operation would be the triple {SELF_SUPPLY, STORE + TRADE + SELL, GREATEST_DEMAND}. There are therefore $2 \times 5 \times 5 = 50$ possible modes of operation which can be selected at each time step.

Regarding the first degree of freedom, if the value SELL is selected, then all the energy produced by each community at the current time step will be sold to the central system, the unit price being the input parameter *purchasing_price*. We make the simplifying assumption that the central system has a sufficiently large storage capacity and may therefore purchase all the energy which the communities have produced. If the value SELF_SUPPLY is selected, then the communities will try to meet their energy demands with their own *energy assets*. The energy assets of a community are the total energy it has available at the current time step: the energy produced by its resources and the energy it has stored. The communities use the energy they have produced and

Degree of Freedom	Possible Values
Production	SELL, SELF_SUPPLY
Excess	SELL, STORE + SELL, TRADE + SELL, STORE + TRADE + SELL, TRADE + STORE + SELL
Redistribution	GREATEST_DEMAND, GREATEST_PRODUCTION, LOWEST_SATISFACTION, RANDOM, RATION

Table 3. Degrees of freedom and their possible values when instantiating a mode of operation

the energy stored, in this order, to cover their own demands; they may only use energy which has been stored after all the energy produced has been used.

When the communities are using a self-supply of energy, they may find themselves with an excess of energy produced if they are able to completely cover their own demands. This excess is handled according to the value of the second degree of freedom. The possible values represent the order in which the different options (selling to the central system, trading with other communities, or storing) should be tried. For example, the value STORE + TRADE + SELL means that communities should first attempt to store as much of the excess as their storage capacity allows; if there is still any energy left after storing, they will make it available for their neighbours to purchase (trade); and, if there is still any energy left after the trade, they will sell it to the central system. All possible values end with the option SELL because the communities may not be able to allocate all of their excess of energy by storing it or trading it with their neighbours. As before, the unit price of any energy sold to the central system is given by *purchasing_price*. Communities trade energy by using a simplified version of the Contract Net Protocol [9]; taking turns in random order, each community whose demand has not yet been satisfied attempts to purchase as much energy from its neighbours as possible, sorting them by the least selling price. When trading its excess of energy, each community has a unit selling price which is drawn from the uniform distribution $\mathcal{U}(\text{selling_price}/2, \text{selling_price})$, where *selling_price* is the model input parameter which sets the unit price for which the central system sells energy to the communities (table 1). Storing energy has a unit cost associated, which, as mentioned in section 1, is drawn from the uniform distribution $\mathcal{U}(\text{min_storage_cost}, \text{max_storage_cost})$, where *min_storage_cost* and *max_storage_cost* are also input parameters of the model.

If the communities are not using a self-supply of energy or if there are communities whose demands have not been fully satisfied, then the central system will sell them energy. It starts by selling the energy it has stored, which has been previously purchased from the communities, for the unit price *selling_price*. If the energy in the storage is not enough, then the system will produce more energy. The selling price of this additional energy now increases according to a unit production cost given by the model input parameter *production_cost*. This means that, when this energy sale takes place, the last communities may have to purchase it for a higher unit price. The third degree of freedom of the mode of operation determines the order in which the communities purchase energy from the central system. They can be sorted by greatest demand, greatest production (both measured at the current time step), lowest satisfaction (which is cumulative, as explained ahead), or randomly. If the value RATION is selected, then the energy stored by the central system will be split equally among the communities; each community receives at most this ration and any additional demand is met with energy produced by the central system at a greater unit cost.

Applying the selected mode of operation at time step t determines how much energy each community will produce for itself and how much it will sell, purchase, and store for the following time step. The resulting costs and revenues are taken into account when calculating the *utility* of this energy allocation for community i at time step t , u_t^i :

Table 4. System variables collected at each time step

Variable	Description	Value Range
N	Number of communities (fixed throughout a model run)	$\mathbb{N}$
SAT	Mean satisfaction across all communities	$\mathbb{R}$
PROD	Total energy production across all communities	$\mathbb{R}^+$
SS	Total self-supply of energy across all communities	$\mathbb{R}_0^+$
MSSDD	Mean difference between self-supplied energy and demand across all communities	$\mathbb{R}$
MADD	Mean difference between current assets (energy produced and stored) and demand across all communities	$\mathbb{R}$
UNSAT	Number of unsatisfied agents (negative satisfaction)	$\mathbb{N}_0$
STO	Total energy stored across all communities	$\mathbb{R}_0^+$
DEM	Total demand across all communities	$\mathbb{R}^+$
TADD	Total difference between current assets (energy produced and stored) and demand across all communities	$\mathbb{R}$
MCL	Mean capacity left across all communities (M is finite and the mean maximum storage capacity across communities)	$[0, M]$
GINI	Gini index of satisfaction inequality ¹	$\mathbb{R}_0^+$

$$u_t^i = \text{total_sales}_t^i - \text{total_purchases}_t^i - \text{storage_costs}_t^i \quad (6)$$

The cumulative satisfaction for community i at time step t is calculated with the most recent utility value as in equation 7. The w parameter weights the importance of past satisfactions and the current utility when updating a community's satisfaction.

$$s_t^i = (1 - w) \times s_{t-1}^i + w \times u_t^i, \text{ with } s_0^i = 0 \quad (7)$$

The operating policy which selects the mode of operation at each time step is represented by a triple of decision trees, one for each degree of freedom. The reason why we use decision trees is the need to evolve and adapt system policies using GP, which traditionally operates over tree structures. The inner nodes of the tree test the values of system-wide variables which are collected at each time step, returning a Boolean value (i.e., the decision trees are binary). Based on the literature about EIs, CPR management, and CESs, as well as on intuitive knowledge regarding the system model we have created, we have selected the system variables in table 4 to be collected and tested at each time step.

As a first step, we devised a default policy whose baseline performance could be compared to that of the evolved operating policies. As an example of the type of decision trees which are evolved and manipulated by our procedure, figures 2, 3, and 4 show the trees which make up the triple representing this default policy, selecting what the communities should do with the energy they have produced at each time step, what to do with any excess of energy in the case of self-supply, and the criteria under which the central system should redistribute energy, respectively. This default policy is the result of our intuition about the model we have created. Each function (inner) node of the decision trees could be *any test* on the values of system variables; we do not have a fixed set of function nodes. For this reason, they are represented internally as trees of operations. The root node of these trees is always a binary Boolean operator ($\leq$, $<$, $=$, $\neq$, $>$, $\geq$), whereas all the other inner nodes are binary arithmetic operators ($+$, $-$, $\times$). The leaf nodes are either the values of system-wide variables or real

Fig. 2. Default decision tree encapsulating rules which determine what the communities should do with the energy they have produced at each time step

constants. This representation has enabled us to generate random function nodes when building new decision trees automatically with our optimisation procedure.

3 OFFLINE PROCEDURE

In order to find an optimal operating policy *a priori*, we have implemented a GP algorithm which evaluates alternatives by running the model with each of a population of policies for the number of time steps corresponding to a week (168, since time steps correspond to hours). A performance metric for each policy i is calculated as shown in equation 8, where satisfaction and the proportion of unsatisfied agents are averaged out after a week has passed. An agent is unsatisfied at a certain time step if its satisfaction is negative. The α parameter determines how much the average satisfaction favours the performance measure and the β parameter determines how much the average proportion of unsatisfied agents penalises it ($\alpha > 0$ and $\beta \geq 0$). They are both input parameters of the model, as mentioned in section 1.

Fig. 3. Default decision tree encapsulating rules which determine what the communities should do at each time step with any excess of energy (in the case of self-supply)

$$\begin{aligned} \text{performance} = & \alpha \times \text{average satisfaction} \\ & - \beta \times \text{average proportion of unsatisfied agents} \end{aligned} \quad (8)$$

The procedure begins by randomly generating an initial population of operating policies (each a triple of decision trees, as explained before) using “ramped half and half” [7], with the possible values for each degree of freedom as leaf nodes. There is usually a fixed and finite set of function nodes in GP optimisation; however, as we have mentioned before, the set of possible function nodes for the decision trees is theoretically infinite in this case, as they can be any test on the values of system variables, so we randomly initialise a large set of these nodes at the start of the procedure. Since they are represented internally as trees of operations, we also use “ramped half and half” to generate them, with a fixed set of Boolean and arithmetic operators as inner nodes and the set of system variables as leaf nodes.

At each iteration of the optimisation procedure, the operating policies are evaluated by running *instances of the same model* for 168 time steps (a week) and computing a performance value, as in equation 8. Running the model in order to obtain a performance value is a costly operation; for this reason, the alternative policies are tested on the model *in parallel*. The performance values are then used as fitness values to evolve a new generation using standard GP operations, namely reproduction, crossover, and mutation, which are described by Koza [7]. Reproduction randomly selects individuals to be copied to the following generation with a probability which depends on their fitness value. If an elitist strategy is in place, then the policies with the highest fitness values are copied on to the following generation. The crossover operation randomly selects pairs of individuals, again

Fig. 4. Default decision tree encapsulating rules which determine how the central system redistributes energy

with a probability which is higher the higher their fitness, and crosses them element-wise, each element being a tree in the triple which makes up an operating policy. The mutation operation also selects individuals based on their fitness and creates new individuals by replacing parts of their trees with randomly generated subtrees; its goal is to introduce variability when searching for new solutions. For all of these operations, the probability of selecting a policy i is a Softmax probability calculated with the fitness values of the policies after they have been evaluated on the system, as in equation 9. The reason why we have used Softmax probabilities is that they grow monotonically with the fitness values and this formulation handles negative fitness values elegantly.

$$p_i = \frac{e^{\text{fit}_i}}{\sum_j e^{\text{fit}_j}} \quad (9)$$

The offline procedure has some parameters which are summarised in table 5, which also reports the values they have been instantiated with in the experiments carried out in this paper. When generating the decision trees in the initial population, the procedure requires a parameter indicating their maximum depth, max_dt_depth_gen ; the generated trees have depths ranging from 1 to max_dt_depth_gen (the root has depth 0). The “ramped half and half” method uses two approaches to generate trees, “grow” and “full”. The parameter n_dt_each sets the number of trees to be generated for each possible maximum depth (from 1 to max_dt_depth_gen) and each generation method (“grow” and “full”). As mentioned before, the function nodes in the decision trees are represented by trees of operations which are also generated using “ramped half and half”; n_ot_each and max_ot_depth_gen are the analogous parameters for generating these trees. When evolving a new generation, the crossover operation

Parameter	Description	Value used in the experiments
<i>n_dt_each</i>	Number of decision trees to be generated for each tree depth and generation method (“grow” and “full”) using “ramped half and half”	3
<i>max_dt_depth_gen</i>	Maximum depth for the decision trees generated using “ramped half and half”	3
<i>max_dt_depth</i>	Maximum depth for decision trees resulting from the crossover operation	5
<i>n_ot_each</i>	Number of trees of operations, which represent the function nodes in the decision trees, to be generated for each tree depth and generation method (“grow” and “full”) using “ramped half and half”	20
<i>max_ot_depth_gen</i>	Maximum depth for the trees of operations generated using “ramped half and half”	3
<i>copy_perc</i>	Percentage of policies to be copied on to the following generation (by either an elitist or non-elitist strategy)	0.1
<i>cross_perc</i>	Percentage of policies in the following generation resulting from the crossover operation	0.4
<i>mut_perc</i>	Percentage of policies in the following generation resulting from the mutation operation	0.5
<i>elitist</i>	Boolean parameter indicating whether or not to employ an elitist strategy when copying policies on to the following generation	False, copy individuals probabilistically

Table 5. Parameters of the offline procedure and their values throughout the experiments in this paper

may produce decision trees whose depth is larger than *max_dt_depth_gen*; the parameter *max_dt_depth* sets the maximum permissible depth for trees resulting from crossover to be included in the following generation.

The procedure keeps track of the best operating policy it has found so far and returns it after a certain number of generations have been evolved. This policy is the one which led to the greatest performance value after running the model, and, therefore, is approximately optimal. Algorithm 1 describes the procedure in pseudocode.

REFERENCES

- [1] Aikaterini Bourazeri and Jeremy Pitt. 2014. An agent-based serious game for decentralised community energy systems. *Lecture Notes in Computer Science* 8861 (2014), 246–253. https://doi.org/10.1007/978-3-319-13191-7_20
- [2] Scott Bucking and Vasken Dermadiros. 2018. Distributed evolutionary algorithm for co-optimization of building and district systems for early community energy masterplanning. *Applied Soft Computing* 63, Supplement C (2018), 14–22. <https://doi.org/10.1016/j.asoc.2017.10.044>
- [3] M D Buhmann and Jeremy Levesley. 2004. Radial Basis Functions: Theory and Implementations. *Math. Comp.* 73, 247 (2004), 1578–1581. <https://doi.org/10.1017/CBO9780511543241>

Algorithm 1 Finding an optimal policy *a priori* using GP

```

Choose model params to generate instances of the same model
Choose parameters for the initial population: max_dt_depth_gen, n_dt_each, max_ot_depth_gen, n_ot_each
Choose parameters for evolution: max_dt_depth, copy_perc, cross_perc, mut_perc, elitist
Choose number of iterations: N
population  $\leftarrow$  generate_initial_population(max_dt_depth_gen, n_dt_each, max_ot_depth_gen,
n_ot_each)
max_fit  $\leftarrow -\infty$ 
best_policy  $\leftarrow \emptyset$ 
for Gen = 1, Gen  $\leq$  N; Gen  $\leftarrow$  Gen + 1 do
    fits  $\leftarrow \emptyset$ 
    for policy  $\in$  population do
        model  $\leftarrow$  Model(params)
        model.set_policy(policy)
        for i = 0, i < WEEK_DURATION, i  $\leftarrow$  i + 1 do
            model.step()
        end for
        fit = model.get_average_fitness() (Equation 8)
        if fit > max_fit then
            max_fit  $\leftarrow$  fit
            best_policy  $\leftarrow$  policy
        end if
        fits  $\leftarrow$  fits  $\cup$  {(policy, fit)}
    end for
    population  $\leftarrow$  evolve_new_generation(population, fits, max_dt_depth, copy_perc,
    cross_perc, mut_perc, elitist)
end for
return best_policy

```

- [4] J. W. Forrester. 1971. Counterintuitive Behavior of Social Systems. *Simulation* 16 (1971), 61–76. <https://doi.org/10.1177/003754977101600202>
- [5] Zishuo Huang, Hang Yu, Zhenwei Peng, and Mei Zhao. 2015. Methods and tools for community energy planning: A review. , 1335–1348 pages. <https://doi.org/10.1016/j.rser.2014.11.042>
- [6] Binod Prasad Koirala, Elta Koliou, Jonas Friege, Rudi A. Hakvoort, and Paulien M. Herder. 2016. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. , 722–744 pages. <https://doi.org/10.1016/j.rser.2015.11.080>
- [7] John R. Koza. 1992. *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. MIT Press, Cambridge, MA, USA.
- [8] Gonalo Mendes, Christos Ioakimidis, and Paulo Ferro. 2011. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. , 4836–4854 pages. <https://doi.org/10.1016/j.rser.2011.07.067>
- [9] R. G. Smith. 1980. The Contract Net Protocol: High-Level Communication and Control in a Distributed Problem Solver. *IEEE Trans. Comput.* 29, 12 (Dec. 1980), 1104–1113. <https://doi.org/10.1109/TC.1980.1675516>
- [10] Xiandong Xu, Xiaolong Jin, Hongjie Jia, Xiaodan Yu, and Kang Li. 2015. Hierarchical management for integrated community energy systems. *Applied Energy* 160 (2015), 231–243. <https://doi.org/10.1016/j.apenergy.2015.08.134>