

TreeC: a method to generate interpretable energy management systems using a metaheuristic algorithm.

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Highlights

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- TreeC generates performant and interpretable energy management systems.
- TreeC can perform better than model predictive control and reinforcement learning.
- TreeC's interpretability provides valuable insights on the controlled energy grid.
- A more complex energy management system model does not guarantee better performance.
- Reproducible benchmark cases are key to compare control methods.

TreeC: a method to generate interpretable energy management systems using a metaheuristic algorithm.

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Abstract

Energy management systems (EMS) have classically been implemented based on rule-based control (RBC) and model predictive control (MPC) methods. Recent research are investigating reinforcement learning (RL) as a new promising approach. This paper introduces TreeC, a machine learning method that uses the metaheuristic algorithm covariance matrix adaptation evolution strategy (CMA-ES) to generate an interpretable EMS modeled as a decision tree. This method learns the decision strategy of the EMS based on historical data contrary to RBC and MPC approaches that are typically considered as non adaptive solutions. The decision strategy of the EMS is modeled as a decision tree and is thus interpretable contrary to RL which mainly uses black-box models (e.g. neural networks). The TreeC method is compared to RBC, MPC and RL strategies in two study cases taken from literature: (1) an electric grid case and (2) a household heating case. The results show that TreeC obtains close performances than MPC with perfect forecast in both cases and obtains similar performances to RL in the electrical grid case and outperforms RL in the household heating case. TreeC demon-

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strates a performant application of machine learning for energy management systems that is also fully interpretable.

Keywords: energy management system, machine learning, decision tree, metaheuristic, control

1. Introduction

With the decreasing costs of renewable energy sources and energy storage [1], more energy is produced and stored in local energy grids without having to transit through a national grid. This also means that energy management systems (EMS) are necessary to manage these local energy grids and their assets [2]. EMSs have been deployed in wide-variety of scales and use cases of energy systems - from household levels with few assets, to nation-wide levels with various assets types and sizes. Most EMSs nowadays are implemented based on rule-based control (RBC) or model predictive control (MPC)[2, 3]. However these methods are deterministic and therefore do not adapt to the possible errors in forecasting or the differences between modeled and real grid behaviour. Research is done to make these methods adaptive [4, 5, 6, 7] as well as exploring different machine learning methods [2, 3].

Reinforcement learning (RL) seems very well suited to the problem as it has mastered many complex games [8], adapts to the case it is implemented in and does not require a model of the controlled system contrary to the MPC approach [9]. RL has been shown to work in simulation in heating, ventilation, and air conditioning cases [10, 11, 12], in cases with multiple house appliances [13, 14, 15, 16], in larger scale multi-energy systems [17, 18] and in a distribution grid with PV production [19]. Some of these studies obtain better results than MPC with imperfect forecasting [11, 15, 18, 19] or even MPC with perfect forecast due to differences in the MPC and simulation models [17]. It is difficult to reproduce or compare against these studies as in general the data and code used is not shared and some studies use commercial simulators [12] and data sets [14].

To allow comparison between different EMS solutions, Henry and Ernst [20] and Arroyo et al. [21] have both published results comparing RL and MPC based EMS with open access data and open source simulation environment. Moreover, Citylearn challenge, a yearly occurring EMS solution competition, also aims to establish benchmark cases with the first two editions requiring the participants to use RL based approaches [22, 23].

There has been a push recently to use interpretable models for decision making when using machine learning techniques [24, 25, 26]. However the current research on RL based EMS uses uninterpretable models (i.e. black box models) such as neural networks. The main reason to use a black box model would be if it has a significant performance advantage over the interpretable models. Making decision modes more interpretable would provide multiple benefits such as having total confidence in the deployed model, being able to interpret either in advance or retrospectively why an EMS could not work and makes it easier to transfer the knowledge gained on how to control one system to another.

Decision trees are interpretable models appreciated in the machine learning due to their good performances in many applications [26, 27, 28].

Huo et al. [29] uses decision trees based EMS for an energy grid application. The method first generates a good policy with an MPC and then generates the decision trees to reproduce the MPC behaviour by using classification. Dai et al. [30] uses a RL based EMS with a neural network model then generates a decision tree to explain the behaviour of the neural network using classification. Both these papers produce interpretable or explainable EMS but in an indirect way where the optimised actions of the EMS are generated by another method then this behaviour is approximated using decision trees.

Generating interpretable and black box control models using a metaheuristic algorithms is common practice in fields such as robotics [31, 32, 33], power systems [34] and also EMS [35]. Generating decision trees specifically has also been done to solve control problems [36, 37] but to the best of the author's knowledge not for EMS.

A metaheuristic based approach generally generates a model in simulation before deploying it in real-life. The advantage of this approach is being able to do many simulations to find a good model. However it exposes the generated model to a drop in performance due to the difference between simulation and real life [38] and requires to have a simulation of the case. RL on the other hand can be implemented directly in real-life without a need of a simulation but the performance is generally very poor for the first steps meaning some additional transfer learning is necessary to improve the performance, a problem to which no satisfying solution has been found yet [9].

This paper presents TreeC, a machine learning method based on the metaheuristic algorithm covariance matrix adaptation evolution strategy (CMA- ES). TreeC generates an EMS modeled as interpretable decision trees. The performance of this method is evaluated against the EMS presented in [20] and [21] which both made available the code and data necessary to perform a comparison with the RL and MPC based methods they have implemented.

2. Method

2.1. TreeC generation method

TreeC has three important operations:

- Encoding (Fig. 1a): to translate a list of numbers to the tree EMS.
- Optimisation (Fig. 1b): to successively improve the trees.
- Pruning (see Fig. 1c): to reduce the size of the tree by removing unused leafs and nodes.



Figure 1: Illustration of TreeC for a household heating case. Fig. 1a shows an decision tree energy management system and how it is encoded as a list of numbers, Fig. 1b shows the optimisation process of the covariance matrix adaptation evolution strategy algorithm and Fig. 1c shows an example of how a tree is pruned when a leaf node is not visited.

The decision tree used is a complete binary tree. The tree is encoded on 3N + 1 variables with N number of parent or split nodes and N + 1number of leafs. The first 2N variables represent the features $(f_0, f_1, ..., f_N)$ and the values $(v_0, v_1, ..., v_N)$ of the node split. The remaining N+1 variables $(l_0, l_1, ..., l_{N+1})$ are the values that represent which actions should be taken on each leaf as illustrated in Fig.1a. This approach is commonly used in many applications with different variations as shown in the review by Barros et al. [39].

Note that the number of parent nodes N is an important hyperparameter that influences the complexity of the behaviour and how interpretable the decision tree is. In this method, the N value is set to 20 as this allows a relatively complex behaviour while keeping the tree interpretable after pruning.

The proposed method uses the state-of-the-art metaheuristic algorithm CMA-ES [40]. CMA-ES was chosen due to its high performance in different optimisation problems [41] and it having almost no user-defined hyperparameters. In CMA-ES, a set of random individuals are generated for the initial population, these individuals are evaluated by an objective function. The score obtained by this evaluation then modifies the distribution parameters used to generate the individuals of the next population. This process is repeated multiple times in order to obtain individuals with a better score over the generations. The final selected EMS is the individual that obtained the best score over the whole optimisation process (see Fig. 1b).

The default CMA-ES population size of $4 + 3\lfloor ln(n) \rfloor$ is used here with n being the number of variables defining the decision tree [42].

It is important that the score obtained by each individual are comparable meaning that the evaluation conditions should be exactly the same (i.e. same start time, evaluation period, ...).

Finally the decision trees generated have leafs that were never reached during the training phase and therefore should be pruned. The pruning methods checks if each leaf has been reached and if not removes the leaf and replaces the parent node by it's other child node. This process is repeated until all remaining leaves have been visited at least once (see Fig.1c).

2.2. Parallel training and multi-threading properties

Metaheuristics algorithms are good to solve complex problems but are non-deterministic so two separate trainings will not find the same solution. To obtain a better solution, five different trainings are executed with the same problem conditions but different initial population for the CMA-ES algorithm. The tree with the best score in training is then evaluated to obtain the results. Doing this also allows to observe if the trees stemming from different trainings have recognisable similar behaviours or which are the most used features.

This method can be executed using many parallel threads. The CMA-ES algorithm allows the evaluation of the individuals within a population to be done in parallel. This means the maximum number of possible threads is equal to the number of individuals within a population used for the training multiplied by the number of different parallel training (five in this case).

2.3. Case study 1: ANM6easy case - electrical grid

2.3.1. Case description

The first case study is ANM6easy a test case proposed by [20] and provided in the gym-anm simulator. The version 1.0.2. of gym-anm was used in this work. ANM6Easy simulates an electrical grid as shown in Fig. 2 It is composed of three passive loads (an industrial complex, a residential area and an electric vehicle charging garage), a slack fossil fuel generator, and controllable assets that consist of two renewable energy sources (i.e., a windturbine farm and a photovoltaic (PV) plant) and one large electrical storage unit. The renewable energy sources and the large electrical storage unit are controllable. For the renewable assets, the EMS decides the curtailment of real power and the reactive power. For the electrical storage unit, the EMS decides the real and reactive power set-point. The decisions are taken by the EMS for the next 15 minutes. The simulation repeats the same day over and over in which there are three distinct periods.

- From 23:00 to 06:00: Windy night with very low demand from the three passive loads.
- From 08:00 to 11:00 and from 18:00 to 21:00: Typical arrival time at work or home. Very high demand from the electric vehicle charging garage due to people plugging in their vehicles to charge. A low amount of power is produced by both renewable asset plants. The demand from the residential area is high while for the industrial complex it is moderate.
- From 13:00 to 16:00: Typical working hours. The demand for the industrial area is high while the residential area demand is low. Both renewable asset plants produce a lot of power. There is no power demand from the electric vehicle charging garage.

During the hours not included in the three characteristic periods, the noncontrollable powers shift linearly from the powers of the preceding period to the powers of the next period.

The electrical grid can collapse if mismanaged, most often this occurs due to a voltage collapse problem [43].

The objective of the EMS in this test case is to control the real and reactive powers of the renewable asset plants and large electrical storage unit in order to: (1) avoid exceeding the maximum power allowed on the branches, (2) maintain the voltage within nominal range with a tolerance of $\pm 5\%$ and (3) minimise energy loss.

2.3.2. Training and validation

During the training, six trees are evolved simultaneously. A different tree is used for the reactive power and real power of each of the three controllable assets. There are 18 possible split features to select from. These features are the real and reactive power for each asset (14 features), the real power of the renewable asset plants if they were not curtailed (two features), the state of charge of the large electrical storage unit and the time of the day. The values of the leafs sets the power for the next time-step.

For the results, 20 sets of six trees are generated using the method described in Section 2. The problem has 366 variables, a population of 21 is used and the training was done over 1500 generations. During training, the population's individual are evaluated over a period of 300 time-steps (3 days). The start time of this time-period is defined by a random seed and a different random seed is assigned to each generation process of the final 20 sets of six trees.

The objective function of the training (Fig. 1b) and validation both use the reward r_t provided by the simulator. Eq. (1) shows how r_t is calculated:

$$r_t = clip(-100, \Delta E_{t:t+1} + 1000\phi(s_{t+1}), 100) \tag{1}$$

where $\Delta E_{t:t+1}$ is the total energy loss between time-step t and t + 1 and $\phi(s_{t+1})$ is a penalty term associated with the violation of the constraints of the grid. The penalty term $\phi(s_{t+1})$ increases when the maximum power of a branch is exceeded and when a bus voltage magnitude is not kept within the 0.95 to 1.05 per unit range. Both $\Delta E_{t:t+1}$ and $\phi(s_{t+1})$ are both expressed in per unit with the base power of the system set to 100 MVA. When the electrical grid collapses, r_t is set to 20 000.

The objective function for training O_{train} is a sum of the rewards for 300 time-steps (see Eq. (2)).

$$O_{train} = \sum_{t}^{300} r_t \tag{2}$$

The objective function for validation O_V is the same as defined in the original paper [20]. It is calculated over 3 000 time-steps and uses an additional discount factor 0.995^t (see Eq. 3).

$$O_V = \sum_{t}^{3000} r_t * 0.995^t \tag{3}$$

The discount factor was removed for the training objective function O_{train} because it favors earlier time-steps of the simulation and since the start-time of the validation evaluation is different from the start-time of the training evaluation. By removing the discount factor, the aim is to make the reward of all time-steps equally important.

The final results show the average score obtained using the validation objective function (see Eq. 3) over 10 different random start times (seeds 0 to 9 in gym-anm simulator). The results for the benchmark EMSs MPC with constant forecast, MPC with perfect forecast, Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC) were recalculated using the method of the original paper [20] and evaluated using the metric described in the previous sentence.



Figure 2: ANM6easy case visualisation for a typical working hour period using the EMS presented in Fig. 4. All the assets are shown with their respective real and reactive power as well as the constraints on the grid lines and voltage magnitude of the busbars [44].

2.4. Case study 2: BOPTEST Hydronic Heat Pump case - household heating 2.4.1. Case description

The second case study is BOPTEST Hydronic Heat Pump a test case provided in the BOPTEST simulator [45]. The version 0.1.0. of BOPTEST was used in this work. The case is a heating management problem in a household. In particular, this test case consist of a five person house with a rectangular floor of 12 by 16 meters and a height of 2.7 meters. The house is equipped with a water based floor heating, the water is heated by an airto-water modulating heat pump of 15 kW nominal heating capacity. The interior temperature is impacted by the outdoor weather conditions. The walls, floor, roof and windows have thermal properties described extensively in the documentation of the test case [46]. The simulation uses one year of weather data from Brussels provided by the simulator [45].

Three different energy pricing scenarios are made available by the simulator:

- The constant electricity price: Fixed electricity cost of $0.2535 \in /kWh$.
- The dynamic electricity price: During on-peak hours between 07:00 and 22:00 the electricity cost is 0.2666 €/kWh and between 22:00 and 07:00 the electricity cost is 0.2383 €/kWh.

• The highly dynamic price: Hourly dynamic electricity price taken from the Belgian day-ahead energy prices of 2019. The median electricity price is 0.2389 €/kWh with a lowest quartile price of 0.2317 €/kWh and an upper quartile price of 0.2392 €/kWh.

The simulator also provides two validation periods of 14 days each. The first spans from the 17^{th} to the 31^{st} of January and is centered around the peak heat day of the year, the second period spans from the 19^{th} April to the 3^{rd} May and is centered around the typical heat day of the year.

The house is considered occupied before 7:00 and after 20:00 every weekday and at all times during the weekend. The comfort range is between 21°C and 24°C during occupied hours and between 15°C and 30°C during unoccupied hours.

The objective of the case is to control the heat pump modulation signal for compressor frequency in order to keep the temperature of the house within the comfort range when occupied and minimise the electricity costs.

The compared results in Fig. 5 were taken from the original paper [21].

2.4.2. Training and validation

For this case, only one tree is necessary to control the heat-pump. The tree has the same inputs and outputs as the SS2 RL based EMS presented in [21]. There are 5 possible split features which are the price of electricity, the indoor house temperature, the lower and upper comfort range bounds and the time of the week. The values of the leafs sets the heat pump modulation signal for compressor frequency for the next time-step. They are discretised to 11 values between 0 and 1 with a step of 0.1.

Two different trees are generated for each pricing scenario and validation period. The problem has 61 variables, a population of 16 is used and the training was done over 150 generations. The evaluation of the individuals was done over 14 days starting 15 days before the start of the validation period and with a warm-up period of 1 day performed by the simulator. The heat-pump is controlled every 15 minutes.

The objective function O_{train} used for training is the same used by [21] to obtain his results also shown in this paper. A weighted objective function is used to take into account the discomfort and operational cost aspects of the case. The following Eq. (4) shows how O_{train} is calculated:

$$O_{train} = \sum_{t}^{T} w_1 * \delta_t + w_2 * (p_t * e_t)$$
(4)

where T is the set of simulated time-steps, w_1 and w_2 are the weights given to the discomfort and operational cost metrics. They are set to 100 and 192 respectively to match the weights used in [21]. The discomfort metric δ_t has two different possible values: (1) when the indoor house temperature is out of the comfort range it equals the absolute difference between the indoor house temperature and the closest comfort temperature range bound, (2) when the indoor house temperature is within the comfort range it, $\delta_t = 0$. p_t is the price of electricity and e_t is the electrical consumption of the heat-pump.

3. Results

The results and code necessary to reproduce the following results are available on the public treec-paper-results GitHub repository¹. The training for the results of the two case studies were obtained on a high performance computer composed of 880 Intel(\mathbb{R})Xeon(\mathbb{R})Gold 6148 processors.

3.1. ANM6easy case

In the first study case, running the evaluation of one individual simulation of 300 time steps lasted 10 seconds. The time to update the CMA-ES optimisation model is negligible here. The trees generated for the results shown in Fig. 3 all ran for 157 500 evaluation which amounts to 18 days 5 hours and 30 minutes of training using a single thread and to 4 hours and 10 minutes using the maximum number of 105 threads (population size of 21 \times 5 parallel training).

¹https://github.com/EVERGi/treec-paper-results



Figure 3: Swarm plot representation of the results obtained for the ANM6easy case with each point being the validation of independant EMSs and the horizontal lines being the validation of the MPC EMSs. The TreeC and SAC EMSs both obtain results close to the MPC with perfect forecast. Disregarding its outliers, SAC performs slightly better than TreeC. PPO performs worse than the two other methods. Three outliers for PPO with a score higher than 130 are not shown in the plot.

In this case, the TreeC EMS perform much better than PPO and MPC with constant forecast methods and slightly worse than the MPC with perfect forecast and SAC method (see Fig. 3). The average score of SAC method is worse than TreeC due to outliers but it would be unfair to claim that TreeC performs better since it selects the best tree form five trainings to avoid such outliers. Implementing such a mechanism in the SAC method would improve its average score greatly.

All methods perform much better than an EMS sampling random actions from the possible action range of each controllable asset. This random EMS obtains an average score of 13 348 over a 100 runs (score calculated with Eq. (3)). The electrical grid collapsed in each of the 100 runs after 159 steps on average. All EMS methods presented in Fig. 3 avoid collapses consistently.



Figure 4: TreeC EMS which obtained the best score in Fig. 3. Each tree controls the real power or reactive power of each controllable asset. To keep them simple for visualisation, nodes that were visited 10 times or less during evaluation were removed.

The trees that obtained the best performance shown in Fig. 4 provide a simple and interpretable EMS shown in 4 that obtains performances only slightly worse than an MPC based EMS with perfect forecast. The tree in Fig. 4a curtails PV at 21.2 MW when the power of the wind-turbines is low and otherwise curtails at 14.5 MW when the large electrical storage charges and at 6.2 MW when the large electrical storage discharges. The tree in Fig. 4b keeps the reactive power of the PV at -8.8 MVAr. The tree in Fig. 4c curtails wind-turbines at 31.7 MW when the industry load exceeds 13 MW and curtails at 21.7 MW otherwise. The tree in Fig. 4d keeps the reactive power of the wind-turbines at -2.6 MVAr. The tree in Fig. 4e charges the large electrical storage at 16.2 MW when there is no demand from the electric vehicle charging garage otherwise charges at 2.9 MW when the wind-turbines can produce more than 23.7 MW and discharges at 7.1 MW when they can produce less. The tree in Fig. 4f sets the reactive power of the large electrical storage to -0.5 MVAr MVAr when the wind-turbines can produce more than 34.3 MW and to 4.9 MVAr otherwise.

The interpretability of the trees gives interesting insight on the problem itself, for example in this case the reactive power are very easy to control efficiently since the trees obtained have a maximum of two different power settings for each assets (see Figs. 4b, 4d and 4f).

3.2. BOPTEST Hydronic Heat Pump case

In the second study case, running the evaluation of one individual simulation of two weeks lasted 150 seconds. The time to update the CMA-ES optimisation model is negligible here. The trees generated for the results shown in Fig. 3 all ran for 12 000 evaluation which amounts to 20 days and 20 hours of training using a single thread and to 6 hours and 15 minutes using the maximum number of 80 threads (population size of 16×5 parallel training).



Figure 5: BOPTEST results for the different pricing scenarios and validation time periods. The red stars are the results of the TreeC EMS. The orange dot is the RL based EMS that had exactly the same inputs and actions as the TreeC EMS. For MPC and RL based EMS, the different dots use different combination of parameters, inputs and actions. Some RL based EMS have scores with a worse operational cost and total discomfort than the visualisation range selected here (see [21] for full and detailed results).

As shown in Fig. 5 the TreeC EMS obtains similar performances to the best performing MPC based EMS for all price scenarios of the peak heating

period and the highly dynamic price scenario of the typical heating period. For the dynamic and constant price scenarios of the typical heating period, the TreeC EMS performs similarly in terms of comfort and slightly worse in terms of cost than the MPC based EMS. In all scenarios the TreeC EMS performed better than the RBC baseline EMS and the RL EMS even the RL based EMS that has exactly the same inputs and actions as the TreeC EMS.



Figure 6: TreeC EMS with best score obtained on the BOPTEST case for the constant price and peak heating period scenario.

The trees obtained in training were all very similar to the one shown in Fig. 6. It is a very simple tree that maintains the room temperature around 21.2°C which is just above the 21°C lower bound of the comfort range when the house is occupied. This behaviour ensures that the house temperature is always above the lower bound of the comfort range while keeping a relatively low temperature and therefore not having to buy too much electricity (see Fig 7). The MPC behaviour is similar during occupied time periods but sometimes goes close to 20°C during unoccupied time periods when calculated as profitable. The TreeC EMS results show that going close to 20°C during the unoccupied time periods does not improve the score compare to simply keeping the temperature just above 21°C.

In this case TreeC found an EMS that is very performant and much more practical to implement than an MPC or RL based EMS.



Figure 7: TreeC EMS presented in Fig. 6 controlling the heat pump for the first week of the peak heating validation period. The top plot shows that the indoor temperature always stays just above the lower bound of the comfort range during occupied hours. The increase in indoor temperature particularly noticeable on the 20th of January is mainly caused by solar irradiation.

4. Discussion

4.1. Advantages and disadvantages of different EMS methods

Based on the studies done in this paper, we identify advantages and disadvantages of different EMS methods and summarised them in Tab. 1.

| | TreeC | MPC | RL | RBC |
|----------------------------------|---------------|----------|--------------|-------------|
| ANM performance | Good | Good | Good | None |
| BOPTEST performance | Good | Good | Bad | Average |
| Common real implementations | No | Yes | No | Yes |
| Many possible output values | No | Yes | Yes | Moderate |
| Can adapt to the problem | In simulation | No | In real case | No |
| Scales well with case complexity | Yes | No | Yes | Yes |
| Interpretability of model | Very good | Good | Bad | Very good |
| Relies on good forecasting | No | Yes | No | No |
| Training time | Very high | Forecast | High | No training |

Table 1: Relevant comparison criteria for the TreeC, MPC, RL and RBC methods.

The outstanding advantages of the MPC method are that the performance is good and has proven itself in several real use cases. The disadvantages are that the method is deterministic and does not have a learning behaviour. Therefore MPC does not adapt to the case it is implemented in, it relies on good forecasting of the system's various inputs and the system it controls must be modeled using mathematical programming. This last point has the disadvantage that one must understand the system very well in order to be able to model it, and in almost all cases model simplifications are necessary in order to be able to solve the mathematical programming problem in the required time. The interpretability is good (i.e. the MPC controls the EMS perfectly assuming all given models and inputs are accurate) but in most cases a lot of inputs and model constraints need to be taken into account to completely interpret the decision process of the MPC.

On the other hand, the TreeC and RL methods both have the advantage of being able to learn and adapt to the controlled system.

The RL method is capable of learning online meaning that RL can adapt the EMS while it is controlling the system. This is a real advantage as it would receive a very accurate feedback from the system and not have to rely on a less accurate simulation of the system. Nonetheless many training steps, corresponding to multiple years, of bad performance are needed for the RL model to obtain a good performance [17]. Hence, either training in simulation or a transfer learning method would still be necessary to implement this in a real case.

The RL method uses a neural network as control model. This allows

the model to have very complex behaviours sometimes necessary to solve certain problems. On the other hand it is a black box model which is not interpretable and therefore could lead to unexpected behaviours which is not desirable for an EMS.

For the two studied cases, RL fails to obtain consistently a good performance. In the ANM6Easy case, SAC obtained a good performance but not PPO. In the BOPTEST case, all RL algorithm performed poorly even compared to the simple RBC baseline. The trade-off of RL for using a model that is not interpretable should be that it is capable of solving simple and complex cases equally but there is no clear methodology in literature yet shown to obtain consistently good results over different benchmark cases.

The main advantage of the TreeC method is the interpretability of its models as shown in Fig. 4 and 6. This allows total confidence in the EMS when implementing it in a real case, the possibility to recognise some possible wrong behaviour that can be caused by the difference between the simulation and real case and makes it easier to transfer the knowledge gained on how to control this system to another similar system.

Another advantage is that the method does not require much customisation other than the necessary ones for any machine learning problem (i.e. choosing good model inputs and outputs, which training steps to use and for how long should the training process run). The CMA-ES algorithm performs very well with default hyper-parameters and the number of nodes of the tree can be defined to make the tree more or less interpretable. TreeC obtained consistently good performance over both the ANM6Easy and BOPTEST cases changing only the part of the methodology specific to the problem (i.e. inputs, outputs, training steps and training length).

One main disadvantage is that it cannot learn online and therefore requires an accurate simulation of the system it needs to control. This simulator also needs to be relatively fast as TreeC needs to simulate many steps to find a good solution. The CMA-ES algorithm allows to parallelise the evaluation of individuals within a generation but a fast simulator is still important to be able to do the individual's evaluation over many steps and the training over many generations.

Another disadvantage is that the complexity of the behaviour of the model is limited by the size of the tree, one tree has a maximum number of output values limited to the number of leafs of the tree and the tree should remain small to keep it interpretable. For certain more complex problems this can definitely be an issue that needs to be addressed.

4.2. Improvements

TreeC can be improved and further validated in the following ways:

- To address the issue of not being able to have a complex behaviour, the leafs could be a RBC or MPC variations instead of single output values. This would allow to tune RBC and MPC methods based on the case they are implemented in.
- CMA-ES could be replaced by a metaheuristic algorithm that optimises directly in the mixed continuous and discrete search space instead of optimising in the continuous space and discretising variables when necessary.
- The time periods used to perform the training were chosen in a rather arbitrary manner, a further study is need to define what is a good training period and how to improve an already trained model when new data becomes available.
- The method should be evaluated on more complex cases. This would contribute to understand which are the limits for the applicability of the proposed method.
- The method should be implemented and evaluated in a real case to measure the importance of the drop in performance between simulation and reality.

5. Conclusion

This paper presents TreeC, a new methodology to generate EMS modeled as decision trees. The method aims at making the learned EMS model interpretable while also obtaining good performances. TreeC was compared with different MPC and RL methods in the ANM6Easy and BOPTEST cases. It was shown to consistently perform only slightly worse than MPC methods with perfect forecast in the ANM6Easy and BOPTEST cases and even performing among the best MPCs in 4 out of 6 scenarios of the BOPTEST case. Compared to RL methods implemented in the ANM6Easy case, TreeC performed better with the same inputs and outputs as the PPO based method and slightly worse than the SAC based method but only when excluding bad performing outliers. In the BOPTEST case, TreeC consistently outperformed the different RL methods using very simple decision trees. TreeC generates interpretable EMS and obtains consistently good performances over the two evaluated cases without needing to change the method between cases. Future works should address the limited complexity of the possible behaviour of the EMS and evaluate it in more difficult cases as well as implement the method in a real life case.

CRediT authorship contribution statement

Julian Ruddick: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. Luis Ramirez Camargo: Conceptualization, Writing - Review & Editing, Supervision. Muhammad Andy Putratama: Writing - Review & Editing, Visualization, Supervision. Maarten Messagie: Supervision, Funding acquisition. Thierry Coosemans: Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The results and code necessary to reproduce the results are available on the following public GitHub repository: https://github.com/EVERGi/tr eec-paper-results.

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