

Z-learning of linearly-solvable Markov Decision Processes*

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We consider methods for solving the problem of discrete Markov Decision Process. For certain class of MPDs which greatly simplify Reinforcement Learning. In this paper we adapt a modification (Z - learning) to the case of Markov Decision Process discussed in the context of energy systems and solve the optimal control problem by incomplete data. Comparing with standard Q-learning, show that modification of algorithm gives faster and more reliable solution.

Keywords: *Markov Decision Process, Z - learning, Q-learning.*

1 Introduction

In the area of power systems there is a huge demand on fast reinforcement learning algorithms. Especially they are needed in energy systems, which are very dependent on external influences and external conditions. These algorithms allow you to quickly and adequately respond to changes around the system, make decisions about changing the state of the system, and help you optimally adapt to customer requests.

For example, reinforcement learning is used for the derivation of efficient operating strategies for hybrid electric vehicles [8]; for solar microgrid energy management [7]; or for a smart energy building [5]. In [6] they use reinforcement learning for system with wind generator to predict available wind power for selecting the optimal battery scheduling actions under different time-dependent environmental conditions and increasing the consumer independence from the external grid.

In this paper we solve the problem of optimal energy system from [2]. Given a set of devices that can be in a certain number of states at a particular point in time. We need to transfer this system from the initial state to the optimal one. Each transition has a certain probability; being in each state has some cost; the system responds to each transition. It is necessary to minimize the waste of energy (or other resources) that we will require to transfer the system from the initial state to the final state. At the same time, we should not forget about the qualitative description of each state (some may be unacceptable for us).

The behavior of the system of devices in time is considered as a discrete Markov decision process [3]. In the general case, the solution of the discrete optimization problem is NP complete [1] and we can not solve it simply. But in [10] there is description of a specific MDP class – LS-MDPs, which we can solve optimally. Most methods require knowledge of what happens if a system "left alone" long enough. But in practice it often happens that we don't have this information.

In this paper it is proposed to use the Z - learning method (stochastic modification of Q-learning from [4, 9]). Together with the solution of the main task of the MDP in parallel to restore unknown data on the behavior of the system. With this algorithm, a working model of system management will be built based only on limited samples of representative behavior. We compare the speed and quality of the two algorithms: Z-learning and Q-learning, when solving

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the MDP, describing via transition probability matrix. Given initial state vector (probability of being in a state at time zero), we generate data for the time evolution of the state vector.

2 Theoretical statement of the problem

2.1 Formal statement of the problem

As mentioned above, we work with a system of devices. Their behavior can be described by MDP:

Definition 1. *Markov decision process consists of*

1. set of states S ,
2. set of actions A ,
3. $P(t)$ is the transition probability matrix. The matrix element $p_{ij}(t)$ is the probability for a device which was at state j at time t to transition to state i at $t + 1$.
4. $\Upsilon(t)$ is the cost matrix. The matrix element $\gamma_{ij}(t)$ is encouraging for the transition from j to state i .

This is the classic definition of MDP. In this paper and in [2] we work with other definition of MDP. There is no set of actions A , but P is variable. We turn to a similar model of the MDP. In this model different matrixes P correspond to different actions in the classical understanding of the MDP.

Other notations:

- vector $\rho(t)$, where $\rho_i(t) \geq 0$ is the probability to find a device in state i at time t . The vector is normalized at all times ($\sum_i \rho_i(t) = 1, \forall t, \forall j$). considered
- vector $u(t)$, where $u_i(t)$ is the cost for being in state i at time t .

The task formulated in [2] looks like:

$$\min_{p, \rho} \sum_{t=0}^{T-1} \sum_j \rho_j(t) \left(\sum_i p_{ij}(t) \left(U_i(t+1) + \gamma_{ij} \log \frac{p_{ij}}{\bar{p}_{ij}} \right) \right) \quad (1a)$$

$$\text{s.t. } \sum_i p_{ij}(t) = 1, \quad \forall t, \quad \forall j \quad (1b)$$

$$\rho_i(t+1) = \sum_j p_{ij}(t) \rho_j(t) = 1, \quad \forall t, \quad \forall i \quad (1c)$$

$$\text{initial conditions: } \rho_i(0), \quad \forall i \quad (1d)$$

where (1a) is target "cost vs welfare", (1b) - (1c) are stochastic restrictions.

P is the optimization/control variable. \bar{P} is stochastic matrix describing the transition probabilities corresponding to normal dynamics within the ensemble (\bar{P} explains the dynamics that the system would show if $u = 0$).

In practice, we do not have access to knowledge about the system, so methods of Q-learning and Z-learning will be suitable for solving our problem.

2.2 Machine learning statement of the problem

Let's give a couple of definitions for Q-learning and Z-learning:

Definition 2. *Reward function is a function showing rewards for $T - 1$ steps:*

$$R_t = \sum_{t=0}^{T-1} r_t \quad (2)$$

Definition 3. *Optimal value function is an expected total the profit that an agent will receive if he starts with this states and will follow the optimal strategy:*

$$V(i) = \max \left[\mathbb{E} \left(\sum_{t=0}^{T-1} r_t \right) | s_0 = i \right] \quad (3)$$

Z - function is for Z - learning:

$$Z(i) = -\log(V(i)) \quad (4)$$

We works with an obvious stochastic approximation \bar{Z} to the function Z . In the notation of our model:

We have a set of datas

$$\mathfrak{G} = (i_k, j_k, u_k)$$

where i_k is a current state, j_k - the next state, u_k - cost for being in i_k , $k = \mathfrak{G}$ - sample size.

$$\bar{Z}(i_k) = (1 - \alpha_k) \bar{Z}(i_k) + \alpha_k \exp(-q_k) \bar{Z}(j_k) \quad (5)$$

Definition 4. *Optimal action-value function is n expected total the profit that an agent will receive if he starts with this states and chooses this action and will follow the optimal strategy:*

$$Q(i, p) = \max \left[\mathbb{E} \left(\sum_{t=0}^{T-1} r_t \right) | s_0 = i, a_0 = p \right] \quad (6)$$

We have a set of datas

$$\mathfrak{G} = (i_k, j_k, l_k, p_k)$$

where $k = \mathfrak{G}$ - sample size, i_k is a current state, j_k - the next state, l_k isn't cost for being in i_k , but a total cost, which depends on u and Υ .

$$\bar{Q}(i_k, p_k) = (1 - \alpha_k) \bar{Q}(i_k, p_k) + \alpha_k \min_{p'} (l_k + \bar{Q}(j_k, p')) \quad (7)$$

Algorithm 1 Q - learning

- 1: **Initialize:** Strategy $\pi_0(p|s)$ and s_0
 - 2: **for** $t = 0, 1, 2, \dots, T - 1$
 - 3: Choose the matrix $p_t \sim \pi_t(p|s_t)$:

$$p_t = \arg \max_p Q(s_t, p)$$
 - 4: Answer of the system: $r_{t+1} \sim p(r|p_t, s_t)$ and $s_t \sim p(s|p_t, s_t)$
 - 5: $Q(s_t, p_t) := Q(s_t, a_t) + \alpha_t (r_{t+1} + \max_{p'} Q(s_{t+1}, p') - Q(s_t, p_t))$
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