Distributed Timeslot Allocation in mMTC Network by Magnitude-Sensitive Bayesian Attractor Model

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***Abstract*—In 5G, flexible resource management, mainly by base stations, will enable support for a variety of use cases. However, in a situation where a large number of devices exist, such as in mMTC, devices need to allocate resources appropriately in an autonomous decentralized manner. In this paper, autonomous decentralized timeslot allocation is achieved by using a decision model for each device. As a decision model, we propose an extension of the Bayesian Attractor Model (BAM) using Bayesian estimation. The proposed model incorporates a feature of human decision-making called magnitude sensitivity, where the time to decision varies with the sum of the values of all alternatives. This allows the natural introduction of the behavior of making a decision quickly when a time slot is available and waiting otherwise. Simulation-based evaluations show that the proposed method can avoid time slot conflicts during congestion more effectively than conventional Q-learning based time slot selection.**

***Index Terms*—Bayesian Attractor Model, Timeslot Allocation, mMTC, 5G NR, Value-based Decision Making**

I. Introduction

In recent years, 5G coverage areas have been gradually expanding, and 5G is on the verge of becoming widespread. The main feature of 5G is that different communication qualities can be provided simultaneously by defining the communication quality to be provided for each communication requirement of the service [1]. Particularly representative are eMBB (enhanced Mobile Broadband), URLLC (Ultra-Reliable and Low Latency Communications), and mMTC (massive Machine Type Communications). To realize these different communication types simultaneously on the same communication infrastructure, different technological elements have to be assembled, and this is likely to be the case for future communication schemes beyond 5G.

One of the key features in satisfying these different communication requirements simultaneously on the same substrate is time slot allocation. 5G divides radio resources into time and frequency and allocates them accordingly to satisfy different communication requirements simultaneously. Basically, in the case of 5G, the base station centrally determines the time slot and frequency, and the terminal often follows accordingly [2], [3]. However, in some cases, such as communication start time and mMTC, where a large number of terminals are expected, random access is used, where terminals select their time slots autonomously.

In particular, in mMTC, there are many other devices, and it is necessary to select a timeslot that does not collide with other devices based on limited information about the movements of all devices, which is not known. A simple way to avoid collisions would be for all devices to transmit sparingly [4], but excessive sparing of transmission will reduce overall throughput. A method [5] that uses reinforcement learning to determine the time slots to transmit has also been proposed, but it does not include control over waiting to transmit and is limited to situations where each device only sends a certain number of packets.

In this paper, we propose an autonomous decentralized timeslot allocation scheme, including transmission latency, inspired by the human decision-making property [6]. Magnitude sensitivity refers to the human tendency to make choices when there are multiple alternatives with different values and is influenced by the sum of the values of the alternatives (called magnitude). It allows waiting to make a choice for a better choice in the future [7]. Such properties are also known to play an important role in consensus building in group decision-making [8]. Autonomous decentralized timeslot allocation can be viewed as consensus building regarding the timeslot to be used by each device, which is a problem compatible with magnitude sensitivity.

Our research group has applied a decision model called the Bayesian Attractor Model (BAM) to several network control problems (e.g., [9]). BAM is a model that takes observed information as input, updates the internal state of the BAM itself, and outputs the results of the decision process. The original BAM does not take values as input, but rather instances for typical patterns, but in this paper, we extend this to a value-based decision model. As we will show later, there is some magnitude sensitivity in the BAM itself when extended to value-based decision-making. In addition, its similarity to other decision models makes it easy to incorporate models with other magnitude sensitivities.

Due to the applicability of such BAMs to network control and their compatibility with magnitude sensitivity, this paper proposes a method for autonomous decentralized timeslot allocation using an extended model of value-based BAMs. In this method, each terminal independently determines the timeslot to be used. At this time, the terminal also considers the option of not making a decision, i.e., waiting for transmission, according to the magnitude sensitivity. After selecting a timeslot, the base station provides feedback to the terminal on the availability of the timeslot, and the terminal updates the value of the choice and moves on to the next choice. Through the evaluation by simulation, we show that the proposed method can determine when to wait for a decision and when to make a decision, depending on the situation, and make an appropriate choice.

The remainder of this paper is organized as follows. In Section II, we propose a new model of magnitude-sensitive decision-making that extends the Bayesian attractor model. In Section III, we present an application of the proposed model to achieve distributed timeslot allocation in a random access environment at mMTC. In section IV, we evaluate the behavior of the proposed model. Finally, in section V, we summarize and discuss future work.

II. Magnitude-Sensitive Bayesian Attractor Model

In this chapter, we propose a new model of decision-making that is magnitude sensitive and highly applicable to engineering. First, we introduce the basic model, BAM. Our research group has applied BAM to various network control problems, and BAM is a model with high applicability. However, since the original BAM is a feature-based classification model, which is different from the value-based decision-making targeted in this paper, we introduce an extended BAM for value-based decision-making. We then propose a new model that integrates the conventional magnitude sensitivity models, LCA and IDN, into the value-based BAM.

A. Value-based BAM

1) Bayesian Attractor Model: BAM [10] is a model of brain decision-making that involves the process of updating internal states based on observations, and making decisions based on the updated internal states.

The original BAM models the process of reaffirmation, in which features are used as input and representative values are updated by comparing them to representative values bound to a previously given choice, called an attractor. The specific state update is performed by Bayesian updating based on observed values, using the relationship between attractors and representative values, and the endogenous dynamics of the state as a generative model. The generative model is as follows

$$\boldsymbol{z_t} = f(\boldsymbol{z_{t-1}}) + q\boldsymbol{w_t} \tag{1}$$
$$\boldsymbol{x_t} = M\sigma(\boldsymbol{z_t}) + s\boldsymbol{v_t} \tag{2}$$

where x_t is the observed value, z_t is the internal state, and w_t, v_t is the noise. Eq. (1) is an expression for the internal variation of the state, where f is the Hopfield dynamics with K attractors $\phi_1, \cdots, \phi_K$. Eq. (2) is an expression for the relation between representative values and attractors, where M is a matrix of representative values μ_i corresponding to the attractor ϕ_i and $M = (\mu_1, \cdots, \mu_K)$. The $\sigma(z_t)$ is an element-wise sigmoid function. Also, q, s are the parameters for the magnitude of each noise term, called dynamic uncertainty and sensory uncertainty.

2) Values as Observations and Representatives: As noted above, the original BAM is a recognition model and does not address the value of alternatives. In this paper, the observed and representative values are changed to value-based values of the alternatives in order to make value-based decisions in the BAM.

Let $V_{i,t}$ be the value of choice ϕ_i at time t, and let BAM obtain a value estimated value $\bar{v}_{i,t}$ through reward feedback information. This sequence of value estimates is the information that BAM can observe at time t, and the observed value as value is defined as $\boldsymbol{x}_t = (\bar{v}_{1,t}, \cdots, \bar{v}_{K,t})$.

In value-based decision-making, we need to find the highest-value alternative. To handle this in the recognition scheme of BAM, the representative value μ_i of the choice ϕ_i is the observed value such that the choice is of maximum value. That is, using the standard value $\bar{v}$ and the maximum value $\bar{v}_{max} = \max\{\bar{v}_{1,t}, \cdots, \bar{v}_{K,t}\}$, we determine the representative value as follows

$$\boldsymbol{\mu}_i = (\bar{v}_0, \cdots, \bar{v}_0, \overset{(i)}{\bar{v}_{max}}, \bar{v}_0, \cdots, \bar{v}_0). \tag{3}$$

In this paper, $\bar{v}_0 = 0$. The representative value closest to the observed value $\boldsymbol{x}_t$ is $\boldsymbol{\mu}_{max}$, corresponding to the option with the largest value ϕ_{max}. Therefore, it is possible to choose the option with the largest value as the scheme to recognize the observed value.

In a normal BAM, the observed and representative values are often normalized, but here the values are used as they are without normalization. This leads to a large deviation from the left-hand side of Eq. (2) in the case of large values. As a result of Bayesian estimation, which attempts to eliminate this bias, the magnitude sensitivity property is at work, shifting the update of z_t to a larger value.

3) Decision Process: In the original BAM, the alternative is selected for which the confidence $P(\boldsymbol{z}_t = \phi_i | x_{1..t})$ is above the threshold. On the other hand, in a value-based BAM, the confidence level is determined by the relative proximity to the largest value, so it is not appropriate to set a threshold that is an absolute standard for the confidence level.

Therefore, ϕ_{first} and ϕ_{second} are selected if the ratio of the confidence level of the top two options ϕ_{first} and ϕ_{second} is greater than some threshold θ. In other words, ϕ_{first} is selected if the following conditions are met, otherwise we wait for the decision.

$$\frac{P(\boldsymbol{z}_t = \phi_{first} | x_{1..t})}{P(\boldsymbol{z}_t = \phi_{second} | x_{1..t})} > \theta \tag{4}$$

where $x_{1..t}$ is a sequence of observations from time 1 to time t.

B. BAM-LCA

LCA is a model of magnitude sensitivity decision-making based on the diffusion model [11], [12].

In the diffusion model, the internal state is updated by a drift term and a noise term, and decisions are made when the internal state exceeds a threshold; in LCA, magnitude sensitivity is expressed by varying the drift term in the diffusion model in a stimulus size-dependent manner. Specifically, the internal state X_i for each option is updated according to the following equation.

$$X_{i,t+1} = I_i(t) + (1-\gamma)X_{i,t} - \beta \sum_{j \neq i} X_j \tag{5}$$

where $I_i(t)$ represents the stimulus magnitude, and γ, β are the parameters. The first term indicates that the more valuable the choice, the larger the movement of the state. The second term indicates self-activation, and the third term indicates suppression of other choices by the active choice. In the steady state, only one higher-value option is active, similar to BAM.

In value-based BAM, the definition of $M, \boldsymbol{x}_t$ in eq. (2) indirectly causes an internal state update according to the magnitude of the value. However, it is s that controls the effect of Eq. (2) on the state update. The smaller s is, the more strictly $\boldsymbol{x}$ follows the equation, and the more deterministically $\boldsymbol{x}$ updates in the Bayesian update.

Therefore, by varying s as a function of magnitude, the value-based z update can be more directly controlled. In this paper, s is varied by the reciprocal of the magnitude as follows.

$$s = \frac{s_0}{V_t} \tag{6}$$

where s_0 is the reference sensory uncertainty and $V_t = \sum_i \bar{v}_i$ is the magnitude. Assume $s_0 = 1$ unless otherwise noted.

C. BAM-IDN

IDN is also a model of decision-making with magnitude sensitivity based on the diffusion model. Specifically, the noise term $\xi_{i,t}$ is given by

$$\xi_{i,t} \sim N(0, \pi \bar{v}_i^2 + \sigma^2) \tag{7}$$

where π, σ are parameters. When the value is large, the variance of the noise term is larger and the diffusive state change is accelerated. As a result, the time it takes for the state to cross the threshold is reduced and decisions are made faster in situations where the value is large.

In the BAM, the parameter that controls the magnitude of the noise term is q. Therefore, by varying the magnitude of q in a value-dependent manner, an effect similar to that of IDNs can be realized. In this paper, the generating distribution of q and the gamma distribution are given by the following equation, so that the expected value of q depends on the magnitude.

$$q \sim \Gamma(k_\Gamma, \theta_\Gamma) \tag{8}$$

$$E[q] = k_\Gamma \theta_\Gamma = \pi V_t^2 + \sigma^2 \tag{9}$$

where k_Γ, θ_Γ are the parameters of the gamma distribution and satisfy Eq. (9). However, since there remains 1 degree of freedom in the parameters, we shift θ_Γ and set $k_\Gamma = \frac{\pi V_t^2 + \sigma^2}{\theta_\Gamma}$. In this paper, $\theta_\Gamma = 6, \pi = 1, \sigma = 0$ unless otherwise noted.

III. Distributed Timeslot Allocation with Value-based BAM

Autonomous decentralized timeslot allocation is performed using the value-based extended BAM model proposed in the previous chapter. In this method, each device independently makes decisions based on the value-based BAM model and selects a timeslot to transmit. Appropriate timeslots are selected by receiving value-based feedback from the base station about timeslot congestion. First, the assumed system model is described. Then, the specific application of value-based BAM to timeslot decision-making is described.

A. System Model

In this paper, we assume a system model that is nearly equivalent to that in Ref. [5]. The main change is that in the reference [5], the number of packets to be sent by the device is assumed to be fixed at the beginning, whereas in this paper, the packets to be sent by the device are assumed to be generated on a continuous basis. This is considered to be more compatible with mMTC use cases, such as sensor networks.

Assuming an mMTC network, all N devices send data to the base station. A subframe consists of K timeslots.

Only if only one device chooses to send a packet for a given time slot, the packet transmission is considered successful. If two or more devices are in use in the same time slot, there is a collision and the packet transmission will fail. If the transmission fails, it is up to the application to decide whether to retransmit the packet, which is described by the packet generation process. To simplify the analysis, physical channel losses such as multipath fading are assumed to be negligible.

Before the start of the next subframe, the base station feeds back to the devices the congestion in the time slot quantized in b bits. When the number of devices is less than the subframe length, it is more efficient to provide feedback on a per-device basis, but when the number of devices exceeds the subframe length, it is more efficient to broadcast information on a per-timeslot basis. mMTC mainly assumes a large number of devices, so it is more efficient to broadcast information on a per-timeslot basis. Feedback is assumed to broadcast the congestion level of each timeslot.

B. Timeslot Allocation

Each device independently makes decisions about timeslot selection and transmission waiting through value-based BAM. Each device updates its internal state based on feedback from the base station and incorporates it into the next decision. The following sections describe the attractors and how to map decisions to timeslot selection in value-based BAM.

1) Attractor: K attractors $\phi_1, \cdots, \phi_K$ corresponding to the K timeslots in the subframe are prepared. The attractor ϕ_K corresponds to the selection of the Kth time slot.

2) Value of Timeslot: The value-based BAM estimates the value of each attractor from the feedback and uses the estimated $\bar{v}_{k,t}$ as the observed value to update the internal state.

In the feedback information, a value of 1 is given for a successful transmission, and a negative value is given for a collision, discretized by b bits of congestion in the timeslot. More specifically, the value of timeslot k at time t is given by

$$v_{k,t} = \begin{cases} +1 \text{ if transmission succeeds} \\ -\mathscr{M}_b(\frac{N_{k,t}}{N}) \text{ otherwise} \end{cases} \quad (10)$$

where $\mathscr{M}_b(x)$ is the discretized value of congestion in b bits, and $B = 2$, $\mathscr{M}_b(x) \in 0.25, 0.5, 0.75, 1$. Let $N_{k,t}$ denote the number of devices that have selected timeslot k at time t. We assume broadcast feedback in this paper.

The feedback value reflects instantaneous congestion in a subframe. Since this value includes temporary congestion, we try to get a more stable understanding of congestion by using time-smoothed estimates. That is, as feedback is received, the estimates are updated as follows

$$\bar{v}_{k,t} = (1-\alpha)\bar{v}_{k,t} + \alpha v_{k,t} \quad (11)$$

where α is the smoothing parameter. Unless otherwise noted, $\alpha = 0.3$ is used in this paper. This corresponds to the Q value. In the case of Q-learning, updating all time slots is negative because Q-value synchronization causes congestion in a time slot. In value-based BAM, on the other hand, the BAM itself has the consistency of decision-making as an internal state, so even if value updates are synchronized, each device can remain in a different selection state. Therefore, for value-based BAMs, the update of $\bar{v}_{k,t}$ is performed for all timeslots.

3) Decision: In value-based BAM, the maximum confidence selection is made if the ratio of the confidence levels for the top two choices exceeds the threshold, otherwise, a decision is awaited. If the attractor ϕ_k is selected, it selects timeslot k and attempts to transmit the packet. On the other hand, if no decision is made in this subframe, no timeslot is selected and packet transmission waits until the next subframe.

IV. Evaluation

The proposed model and its application to autonomous decentralized timeslot allocation are evaluated by simulation. In this chapter, we confirm that the proposed model is magnitude sensitive and investigate how the selection tendency is affected by magnitude. Then, we evaluate by simulation the behavior of the proposed model when applied to timeslot allocation under the assumption of mMTC.

A. Magnitude Sensitivity of the Model

Using a numerical example, we confirm the magnitude sensitivity of the value-based BAM described in section II. By directly changing $\bar{v}_{1,t}, \cdots, \bar{v}_{K,t}$, the inputs in the value-based BAM, we can see how the behavior of the model changes with the magnitude of the value.

Figure. 1 shows the decision time and accuracy for different magnitudes. In the figure, "BAM" represents value-based BAM, "IDN" represents BAM-IDN, and "LCA" represents the results of BAM-LCA. accuracy indicates the percentage of time the decision at each time point is consistent with the correct answer.

The figure shows that all models show magnitude sensitivity, which means that the speed of decision-making increases as the magnitude increases. This tendency is particularly pronounced for BAM-IDN and BAM-LCA, which are magnitude-sensitive extensions of value-based BAM.

Accuracy is also found to improve with increasing magnitude. In general, it seems that the earlier the decision is made, the lower the accuracy. However, in the present case, the total number of correct answers increases with the earlier decision, because the state of waiting for a decision is automatically assumed to be incorrect.

BAM-LCA has better decision time and accuracy than other models, but this may be due to the magnitude improvement in decision behavior. Originally, in BAM, the decisive action brings us closer to the prepared choice, so by emphasizing this behavior, we quickly arrive at the correct answer.

B. Simulation of Timeslot Allocation in mMTC

To confirm the effectiveness of autonomous decentralized timeslot allocation in mMTC with magnitude-sensitive BAM, we evaluate the proposed method by simulation. In the simulation, each device continuously sends packets to the base station, and the proposed method is used to select the timeslot in which the packets are sent.

1) Setting: As described in section III-A, N devices occupy K timeslots simultaneously. A device decides whether to transmit a packet per subframe and, if so, chooses a timeslot. The number of timeslots per subframe is determined by the numerology μ, where $K = 2^{\mu}$. Unless otherwise noted, $\mu = 4$. Since we wanted to check the response to changes in spatial load, N was allowed to vary during the simulation.

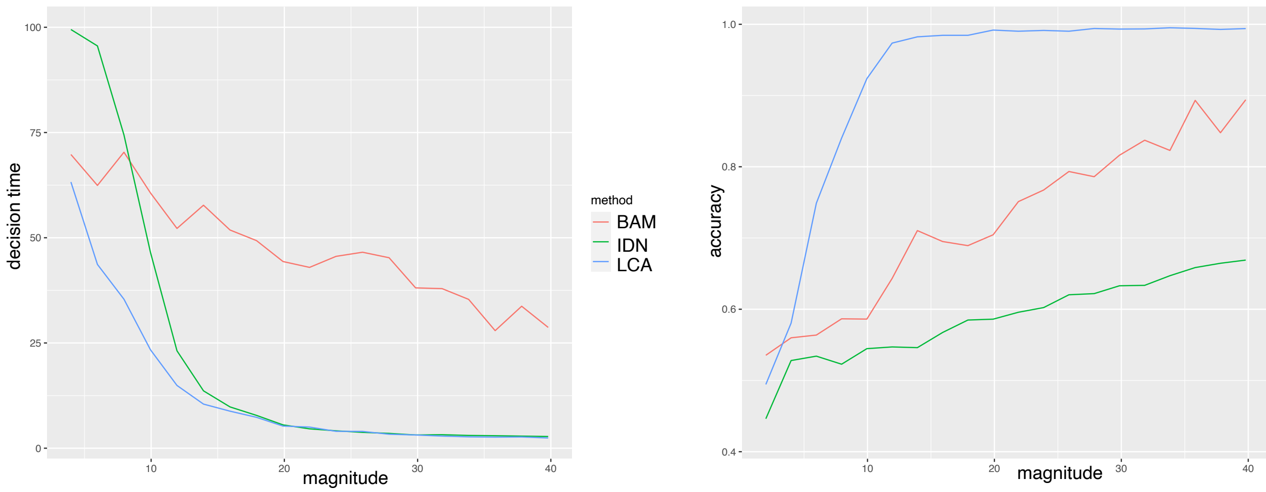
Before the next subframe starts, the base station gives feedback to the device. The feedback is a discretized value of congestion in b bits. We chose $b = 2$ to match the settings in Ref. [5].

Collision and efficiency are used as performance metrics. collision is the ratio of the number of timeslots in which collisions occur out of K timeslots. Efficiency is the ratio of the number of timeslots in which communication succeeds out of K timeslots. Therefore, the smaller the collision and the higher the efficiency, the more appropriate timeslot allocation can be achieved by avoiding collisions.

2) Behavior of Each Model: To verify the behavior of each model, we first check the time slot allocation for value-based BAM and BAM-IDN and BAM-LCA, respectively. The number of devices is assumed to be $N = 10$ to see if collision avoidance can be achieved in a situation where collisions are in principle avoidable.

Figure 2 shows the time series of collisions resulting from the time slot allocation when using each model. One step on the horizontal axis represents one subframe and the vertical axis is the percentage of collisions that occurred during that subframe. "BAM", "IDN" and "LCA" represent the results of value-based BAM, BAM-IDN, and BAM-LCA, respectively.

The figure shows that BAM-LCA achieves collision avoidance. Value-based BAM also shows a gradual decrease in collisions, but not to the point of collision avoidance. In addition, BAM-IDN shows an increase and decrease in collisions due to noise-induced changes in decision-making.



(a) Decision Time

(b) Accuracy

Fig. 1. Magnitude Sensitivity of Each Model's Decision Time and Accuracy

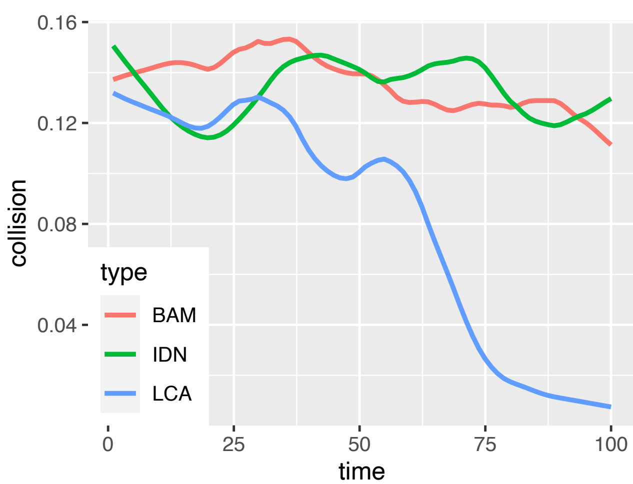


Fig. 2. Timeseries of Collision for Each Value-based Decision Model

V. Conclusion

In this paper, magnitude-sensitive decision models are applied to achieve autonomous decentralized timeslot allocation for mMTC networks. Based on these models, we proposed the magnitude-sensitive BAM, BAM-LCA, and BAM-IDN, which are extensions of BAM. Using these models, we proposed a method in which each device autonomously and decentrally selects an appropriate timeslot through feedback that reflects the value of timeslot congestion. Through simulation-based evaluation, we showed that BAM-LCA can avoid timeslot collisions compared to other methods. We also showed that BAM-LCA is more efficient in timeslot utilization, especially when the number of devices is large.

Future work includes a comprehensive performance evaluation in various settings and a study of how to switch to more appropriate decisions based on the number of devices.

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