Enhancing Channel Estimation in Cognitive Radio Systems by means of Bayesian Networks

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Abstract – This paper proposes enhancements to the channel(-state) estimation phase of a cognitive radio system. Cognitive radio devices have the ability to dynamically select their operating configurations, based on environment aspects, goals, profiles, preferences etc. The proposed method aims at evaluating the various candidate configurations that a cognitive transmitter may operate in, by associating a capability e.g., achievable bit-rate, with each of these configurations. It takes into account calculations of channel capacity provided by channel-state estimation information (CSI) and the sensed environment, and at the same time increases the certainty about the configuration evaluations by considering past experience and knowledge through the use of Bayesian networks. Results from comprehensive scenarios show the impact of our method on the behaviour of cognitive radio systems, whereas potential application and future work are identified.

Keywords: Cognitive networks, Channel-State Information (CSI), Machine learning, Bayesian networks

1. Introduction

An increasingly important engineering challenge is the proper management of the electromagnetic radio spectrum, a valuable yet limited natural resource. The current static assignment of the radio spectrum, e.g., [1], may lead to underutilization situations. Thus, there is need for the development of efficient spectrum management schemes, capable of exploiting the available, underutilised frequency bands.

A direction for spectrum efficiency is to equip the infrastructure with *cognitive radio* capabilities [2][3][4][5]. In general, *cognitive systems* determine their behaviour, in a reactive or proactive manner, based on the external stimuli (environment aspects), as well as their goals, principles, capabilities, experience and knowledge. In this respect, cognitive radio devices dynamically select their configurations, through management functionality [6] that takes into account the context of operation (device status and environment aspects), goals and policies [7], profiles, and machine learning [8] (for representing and managing knowledge and experience). In the more general sense, the term *configuration* refers to a spectrum carrier and a specific Radio Access Technology (RAT), but the list could also be expanded to include modulation type, transmit power etc. This definition also allows a spectrum band to be used for operating different RATs, in accordance with the flexible spectrum management concept [5].

A typical cognitive radio operation can be divided into three, tightly interconnected, phases (Figure 1) [3]. In the *radio-scene analysis* phase the respective environment conditions, especially related to spectrum and interference, are sensed. During the *channel-state estimation* phase, channel-state information (CSI) is collected and also used to estimate the channel capacity; moreover, past experience and knowledge can be exploited in this phase. Finally, in the configuration selection phase the transmitter decides on the "best" configuration, for sending the desired signals, based on the information of the previous two phases. This paper aims at complementing and enhancing the channel-state estimation phase by proposing a method to integrate knowledge and experience in the process, as the term *cognitive* dictates the need to do so.

In any manifestation, proper mechanisms for channel-state estimation are imperative for adaptive, cognitive radio systems operating in dynamically changing environments. Channel-state estimation is needed for calculating the channel capacity which, in turn, is required in order to assist the transmitter for evaluating its candidate operating configurations. More specifically, the cognitive receiver exploits the CSI in order to feed a well known theoretical formula (e.g. Shannon theorem) for the calculation of the achievable bit rate.

This is exactly where the focus of our work is placed on. More specifically the objective of this work is to use the calculated bit rate in order to associate each of the candidate transmitter's configurations with an anticipated capability (e.g. in terms of achievable bit rate). As long as there is a clear picture about the capabilities of each configuration, the transmitter will be able, in a sequent step, to select the optimum one to use. The decision rules governing such selection will be subject of our future work.

In order to increase the certainty about the configuration evaluations, we propose and develop a learning solution that integrates knowledge and experience in the process and relies on Bayesian Networks, which are a category of advanced machine learning schemes, suitable for reasoning about probabilistic relationships [8][9][10]. Such integration in the channel-state estimation phase can be especially important for improving the robustness of the evaluation of the configuration capabilities.

The rest of the paper is organized as follows: Related work and motivation are presented in Section 2. Our solution is presented in sections 3 and 4. Section 5 provides results from comprehensive scenarios that reveal the behaviour of the proposed scheme. Finally, concluding remarks are reached in section 6.

2. Related work and Motivation

At first, our work complements the used channel-state estimation mechanisms. In general, channel estimation can be either training-based [11][12] or blind [13][14][15][16], with both cases exhibiting pros and cons in terms of bandwidth efficiency, convergence speed and estimation accuracy. When it comes to cognitive radio, the majority of channel state estimation techniques proposed in the literature, regardless of being training-based or blind, assume Orthogonal Frequency Division Multiplexing (OFDM)-based systems [17][18][19]. This can be easily justified by the fact that OFDM's inborn features, such as spectral efficiency and flexibility, render it a modulation strategy that commends itself to cognitive radio [3], albeit other proposals for the modulation scheme of cognitive radio have come since the introduction of the idea [17].

On the other hand, a cognitive radio will inherently have the ability to improve its performance through learning. Learning systems require collection of data from the environment sensed, in order to draw conclusions about the observed variables. Machine learning techniques such back-propagation Neural Networks, Self-Organising Maps, Fuzzy Systems, Evolutionary Algorithms, Case-based Systems and of course Bayesian Networks enable such behaviour and can be used to optimize the performance by adapting the radio parameters with respect to the input variables.

Especially a Bayesian Network, [9][10], is a graphical model that encodes probabilistic relationships-dependencies among a set of variables of interest. Some of the benefits that Bayesian Networks offer when used for handling input data [20], are the abilities to handle incomplete data sets, to allow learning of causal relationships (e.g. causes and symptoms), to use prior knowledge and also, to avoid data overfitting [21] (i.e. when the network adheres to a training data set, thus being unable to perform correctly on unseen data).

Apart from medicine, bioinformatics or economics, Bayesian networks have also been used in the engineering literature e.g. for fault detection, self-management or automated diagnosis, destined for the application to wireless, cellular networks [22][23][24], and also for modeling user preferences and profiles in B3G/4G devices [25][26]. Our work applies Bayesian networks for improving the performance of a cognitive radio through learning. In particular, in this paper, we formulate a Bayesian Netowrk in order to model the probabilistic relationship among the achievable bit rate and corresponding configuration of a cognitive transmitter.

3. Formulation as a Bayesian Network

Figure 2(a) depicts the approach for formulating the problem as a Bayesian network. As stated, the objective is to associate each candidate configuration with a specified capability. In the Bayesian network, random variable CFG represents the configuration that is probed, and random variable BR represents a configuration's capability, e.g., the achievable bit-rate as calculated using CSI and Shannon's theorem. CFG is the Bayesian network's predictive attribute (parent node), while BR is the target attribute (node), which can take a set of values from a reference set as will be discussed in the following. In a similar manner, although a simplified approach with one capability is assumed herewith, more capabilities, e.g., the bit error rate, etc., can be considered readily. The method relies on the constant update and maintenance of conditional probability values, of the form $Pr[BR|CFG]$, which reveal the probability that a capability (in this case the bit-rate) will be at a certain level, given that a certain configuration is used.

Conditional probability tables (CPTs) can, therefore, be organized. Every node in a Bayesian Network has an associated CPT to express the probability of its state in condition to its parent states. Figure 2 (b) depicts the structure of the CPTs in our case, with particular focus on the bit rate. Each column of a CPT refers to a specific configuration. If there are n possible configurations, the CPT will include n columns. Each line of the CPT corresponds to a reference, achievable bit-rate value. Those reference bit-rates comprise the set, from which random variable BR may take values. This set is selected here to be discrete [24]. Let M be that discrete set of reference, achievable bit-rate values. Without loss of generality, enumeration can be done in ascending order (i.e., $br_1 < br_2 < \ldots < br_{|M|}$). The cell at the intersection of line j ($1 \le j \le |M|$) and column i ($1 \le i \le n$) provides the value of the conditional probability $Pr\left[BR = br_j \middle| CFG = cfg_i\right]$, which expresses the probability that bit-rate br_j will be achieved, given that configuration cfg_i is selected.

Given a configuration, the most probable achievable bit-rate is the one that is associated with the maximum conditional probability in the respective column. In order to take into account different contexts (e.g., times in the day) there can be several CPTs. Moreover, the CPT can also be maintained as a list, sorted in descending order of the probabilities. Figure 2(c) provides an example. Configuration and bit rate pairs with high probabilities can be in the top of the list, in order to facilitate configuration selections. In the example, bit rate br_k is the most probable for configuration cfg_i.

4. Learning Strategy

4.1 Principles

The capabilities of configurations are provided by the CPT. This section describes how to update the values within CPT, i.e. the learning strategy of the Bayesian Network. In order to address the continuously changing environment (received data) an online learning strategy is required [27][28].

The learning strategy takes into account the bit rate calculations, which are conducted using the CSI provided by the channel estimation phase, and more specifically, the "distance" (absolute difference) between those calculated values and each reference value. Let us assume that, according to the calculations, a specific configuration can achieve bit-rate br_{calc}. This value can be exploited, in order to fine-tune (enhance or decrease) the values of the CPT, and therefore, increase the confidence of the capability estimations.

Let dif_{max} be the maximum difference between the reference bit-rate values, i.e. $dif_{max} = br_{|M|} - br_1$. Then, the following correction factor, cor_j, can be computed for each reference achievable bit-rate value br_j:

$$cor_j = 1 - \frac{|br_j - br_{calc}|}{dif_{\max}} \tag{1}$$

It holds that $0 \le cor_j \le 1$. A value close to one reflects that the corresponding reference value br_j is close to the calculated value br_{calc}, thus the corresponding conditional probability value should be reinforced accordingly. The opposite stands for a value that is close to zero.

Given a candidate configuration cfg_i, the correction of the CPT values can then be done as follows, for each candidate value br_j:

$$Pr\left[BR = br_j \middle| CFG = cfg_i\right]_{new} = L \cdot cor_j \cdot Pr\left[BR = br_j \middle| CFG = cfg_i\right]_{old} \tag{2}$$

Parameter L is a normalizing factor that guarantees that all "new" probabilities sum up to one. It can be computed through the following relation:

$$L \cdot \sum_{j \in M} cor_j \cdot Pr\left[BR = br_j \middle| CFG = cfg_i\right]_{old} = 1 \tag{3a}$$

It can be defined that the proposed learning scheme *converges* when the conditional probability of the reference value, which is closest to the measured value, becomes the highest. At this point, the conditional probabilities that correspond to the other (candidate) reference values are either being reduced or reinforced less.

Convergence can also be defined differently, e.g., it can also be associated with the difference between the conditional probability of the value indicated by the calculations and all the rest. After convergence to a certain condition, there can be a set of measures that may be taken for enabling fast adaptations to future conditions. First, the number of consecutive updates, upd, which can be applied on the conditional probabilities, may not be allowed to exceed a certain maximum threshold, upd_{max}. Second, the conditional probability of a reference bit-rate value may not be allowed to fall under a certain threshold, $a/|M|$, where $0 \le a \le 1$ (recall that $|M|$ is the number of reference bit-rates). Third, the number of conditional probabilities, which fall under the minimum threshold, $a/|M|$, may not be allowed to exceed a certain maximum threshold, thr_{max}. In other words, there should be $|T| \leq thr_{max}$, where T ($T \subseteq M$) is the set of probabilities that should be assigned equal to the minimum threshold in a certain step of the learning method. In this case, the normalization factor, L, is computed by requiring all the other "new" probabilities to sum up to 1-($|T| \cdot a/|M|$). This can be expressed as follows:

$$L \cdot \sum_{j \in (M \setminus T)} cor_j \cdot Pr\left[BR = br_j \middle| CFG = cfg_i\right]_{old} = 1\text{-}(|T| \cdot a/|M|) \qquad (3b)$$

4.2 Algorithm

The following sequence of actions takes place during the channel-estimation phase of the cognitive radio process (Figure 3).

Step 1. Acquisition of CSI knowledge for calculating instant achievable bit rate, and inspection of whether the learning method is at a convergence stage.

The value, br_{calc}, is considered. The value derives from the calculations made, for configuration cfg_i, exploiting CSI form the previous step of the channel estimation phase of the cognitive radio process. Convergence is identified if the following two conditions hold: (i) the br_{calc} value is the same with that of the previous invocation, (ii) the probability $\Pr\left[BR = br_{calc} \middle| CFG = cfg_i\right]$ is larger than all the rest. In case there is no convergence the variable upd is set to zero, and a transition to *step 3* occurs.

Step 2. Inspection of whether further updates of the CPT are allowed, in case the channel estimation phase is at convergence stage.

Inspection of whether the number of consecutive updates that can be applied after convergence, upd, has reached the maximum threshold, upd_{max}. If the answer is positive, there is migration to *step 6*. Inspection of whether the number of conditional probabilities, that have fallen below the minimum threshold, $|T|$, has reached the maximum threshold, thr_{max}. If the answer is positive, there is migration to *step 6*.

Step 3. Computation of the new probability values.

Computation of: (i) the correction factor, cor_j, through the set of relations (1); (ii) normalization factor, L, through relation (3a); (iii) new probability values through the set of relations (2).

Step 4. Inspection of whether the CPT should be updated.

Computation of the set, T ($T \subseteq M$), which comprises the probabilities that have fallen under the minimum allowed threshold $a/|M|$. If the number of probabilities in the T set exceeds the maximum allowed number, thr_{max}, i.e., if $|T| > thr_{max}$, there is migration to *step 6*.

Step 5. Update of CPT.

If $|T|$>0 the following set actions are conducted: (i) The probabilities of the T set are assigned equal to the minimum threshold $a/|M|$; (ii) The new normalization factor is computed through relation (3b); (iii) the new values of the probabilities out of the T set are re-computed through the set of relations (2).

The new probability values (computed in step 3 or above) are stored in the CPT.

In case of convergence, the counter upd (consecutive updates after convergence) is increased.

Step 6. End.

5. Results

5.1 Set-up

Various sets of scenarios are used for investigating the behaviour of the proposed method. More specifically, our focus is on how this learning method, enabled by Bayesian networks, influences and enhances the channel estimation phase of a cognitive radio process.

The scenarios concern an arbitrary configuration, denoted as c. It is assumed that there are $|M|$= 6 reference bit rate values (in Mbps). M includes the values br_1 = 6, br_2 = 12, br_3 = 24, br_4 = 36, br_5 = 48, br_6 = 54. Hence, $dif_{\max}$ =48 Mbps.

As can be seen, the capabilities of the configuration c have been chosen equivalent to those of legacy or emerging standards for wireless local and metropolitan area networks. In addition, parameter a, used in 3(b), has been set equal to 0.1.

In order to ensure comprehensive testing, two categories of scenarios will be considered. In the first category the assumption is that there is no prior knowledge on the capabilities of the configuration. In the second category of scenarios (will comprise four sets), it will be assumed that the proposed method has some knowledge regarding the capabilities of the configuration. Comprehensiveness is ensured by considering, in both categories, the impact of all the potential changes from the initial conditions.

5.2 Presentation

Figure 4 depicts the results from the first category of scenarios, in which it is assumed that there is no prior information for configuration c. The x-axis denotes the discrete time steps during which the channel estimation conducts and provides calculations for feeding our method. The y-axis shows the values of conditional probabilities of the form, $\Pr\left[BR = b \middle| CFG = c\right]$, where b can be equal to 6, 12, 24, 36, 48, 54 Mbps. Figure 4(a)-(f) shows the evolution of the probabilities when the bit rate calculations indicate that the configuration can achieve 6, 12, 24, 36, 48, 54 Mbps, respectively.

Initially, in each chart, all conditional probabilities are equal ($\Pr\left[BR = b \middle| CFG = c\right] = 0.166$), since there is no prior information for configuration c. As can be observed, the scheme readily learns the configuration capabilities, and converges to the condition indicated by the calculations. These remarks are backed up by the fact that the conditional probability, which corresponds to the calculated bit rate value, immediately becomes significant and, very soon, larger compared to all the rest.

For instance, in Figure 4(b) the calculations indicate that the configuration can achieve br_2=12 Mbps. Therefore, the probability $\Pr\left[BR = br_2 \middle| CFG = c\right]$ immediately becomes significant (equals to 0.432 and 0.709 after three and ten time steps, respectively), and soon is much higher than the rest (e.g. the probability for a “neighbouring” bit-rate br_1=6 Mbps equals to 0.289 and 0.186 after three and ten time steps, respectively). Moreover, the behaviour of the probabilities of the bit rates br_1 and br_3=24 Mbps should be noted. Initially, they are increased, then they remain at a certain high level for an important amount of time, and after a point they start being reduced. These bit-rates are “neighbouring” to br_2. Through this behaviour, the channel estimation phase has learned and shows that these bit rates (even though less probable than br_2) are more representative of the configuration capabilities compared to br_4, br_5 and br_6. As can be observed, after three, five, thirteen and twenty-nine measurements, there are $|T|$=2, 3, 4 and 5, respectively, probabilities that reach the minimum threshold. Likewise, in Figure 4(d) the calculations indicate that the configuration can achieve br_4=36 Mbps. Therefore, the probability $\Pr\left[BR = br_4 \middle| CFG = c\right]$ immediately reaches high levels and soon becomes larger than all the others. In this case, as well, the probabilities corresponding to values br_3 and br_5 remain at high levels for several steps. Within five, eight, thirteen steps there are $|T|$=2, 3 and 5, respectively, probabilities that reach the minimum threshold.

Figure 4(e) and (f) display the same behaviour as Figure 4(b) and (a), respectively. This is expected since the initial conditions are the same for all cases and also the indicated bit-rates are at the edges of the set M, for br_6 and br_1 (Figure 4(f),(a)), and near the edges of the set M, for br_5 and br_2 (Figure 4(e),(b)).

Next there is the presentation of a second category of scenarios, which comprises four sets (two – five) showcased in Figure 5 – Figure 8, respectively. In these sets there is prior information on the capabilities of configuration c. Specifically, different situations from the first scenario will be considered as initial conditions. Then, it will be assumed that the bit rate calculations during channel estimation indicate that the capabilities of the configuration change. The objective is to see the behaviour of the proposed scheme.

Figure 5 presents the results from the second set of scenarios. It is assumed that the channel estimation phase has learned that configuration c can achieve 6 Mbps, and moreover that $|T|$=2 conditional probabilities have reached the minimum threshold. This is the initial condition in this scenario. In other words, the initial condition is the one of Figure 4(a), at time step = 2.

Figure 5(a)-(e) show the evolution of the probabilities when the bit rate calculations indicate that the configuration can achieve 12, 24, 36, 48, 54 Mbps, respectively. Again, in each chart, the x-axis is the time domain, during which there are calculations conducted in discrete steps and provided to our method. The y-axis shows the values of conditional probabilities of the form, $\Pr\left[BR = b \middle| CFG = c\right]$, where b can equal to 12, 24, 36, 48, 54 Mbps.

As can be observed in all cases, the scheme immediately starts to move towards the new situation. This is shown by the fact that immediately the conditional probability, corresponding to the value indicated by the calculations, becomes significant. The fact that there is prior knowledge on the configuration capabilities prevents the immediate convergence (which was the case in the first scenario). This is a desirable property, for preventing oscillations regarding the estimates of the configuration capabilities, which can be due to temporarily changing environment conditions, e.g., the temporary disappearance or appearance of interferers. Nevertheless, if the change in the environment is not temporary, convergence occurs in a few steps, which range from three (Figure 5(a),(b),(e)) to five (Figure 5(d)) (3.6 average).

In the third set of scenarios (Figure 6) it is assumed that during the channel estimation phase, the proposed method has learned that configuration c can achieve 6 Mbps, and moreover that $|T|$=3 conditional probabilities have reached the minimum threshold. In other words, the initial condition is the one of Figure 4(a), at time instant four. The difference of this scenario, with respect to the second one, is that there is a "higher level of convergence" to the initial condition. This means that more probabilities have fallen under the minimum threshold. The question is whether this influences the behaviour of our method, and especially, the speed of convergence to the new condition.

Figure 6(a)-(e) show the evolution of the conditional probabilities when it is calculated that the configuration can achieve 12, 24, 36, 48, 54 Mbps, respectively. As can be observed, in all the cases of the third scenario the method converges to the new condition within few steps. The number of steps ranges again from two (Figure 6(e)) to six (Figure 6(c)) (4.0 average). The number of steps is slightly increased, compared to the second set of scenarios.

In the fourth and fifth set of scenarios it is assumed that the initial condition indicates that the configuration can achieve 24 Mbps. So the difference with respect to the previous two scenarios is that now a "middle" bit-rate value is taken as the initial condition.

In the fourth scenario (Figure 7) the initial condition is that the configuration can achieve 24 Mbps and that $|T|=2$ conditional probabilities have reached the minimum threshold. In other words, the initial condition is the one of Figure 4(c), at time step=6. Figure 7(a)-(e) show the evolution of the conditional probabilities in case the configuration can achieve 6, 12, 36, 48, 54 Mbps, respectively. The remarks that can be drawn from this scenario are similar to those of the second set of scenarios. Specifically, the proposed method starts immediately to move towards convergence to the new condition; convergence occurs in a few steps which ranges from five (Figure 7(e)) to nine (Figure 7(a)) (7.0 steps average).

In the fifth scenario (Figure 8) the initial condition indicates that the configuration can achieve 24 Mbps and that $|T|=3$ conditional probabilities have reached the minimum threshold. In other words, the initial condition is the one of Figure 4(c), at time instant eight. Figure 8(a)-(e) show the evolution of the conditional probabilities when according to calculations, the configuration can achieve 6, 12, 36, 48, 54 Mbps, respectively. The behaviour is similar to the previous scenario (8.0 steps average for convergence). Also, when the indicated bit-rate is close to the initial bit rate (i.e. br_2, br_4 (Figure 8(b), (c))), the probability of the "neighbouring" bit-rate immediately raises, while all the rest probabilities drop to the minimum threshold. Contrarily, when the indicated values are not "neighbouring" (see Figure 8(a), (d), (e)), the "middle" values remain at a high level for a certain number of time steps, until finally reaching the minimum threshold. The results of this scenario also indicate that the "higher level of convergence" minimally impacts the overall behaviour and the speed of convergence.

5.3 Analysis

In summary, the behaviour of the proposed Bayesian networks' based method was tested in various scenarios, split in two categories. In the first category (Figure 4) the assumption was that there is no prior knowledge on the capabilities of the configuration. In the first category the method phase readily converged to all the situations that can be signalled (calculated) by exploting the CSI from channel estimation phase. Moreover, the conditional probabilities of the bit rates, which were neighbouring to the bit rate indicated by the calculations, remained at significant levels for a certain amount of time. Therefore, these “neighbouring” bit rates appear as second-best representatives of the configuration capabilities.

In the second category of scenarios (Figure 5 – Figure 8), it was assumed that the channel estimation phase has learned the capabilities of the configuration. In the first set of scenarios of this category, the initial condition was an “extreme” value, namely, 6 Mbps (scenario sets two and three). In the second set, the initial condition taken was a “middle” value, namely, 24 Mbps (scenario sets four and five). In this category, as well, there was comprehensive investigation with respect to all the potential alterations that can be signalled, resulting from calculations of the bit rates by channel estimation phase (e.g., change from 24 Mbps to all the other values).

In the second category of scenarios it was observed that the scheme immediately starts to move towards convergence to the new condition. Convergence takes more steps compared to the first category. However, it is something positive for avoiding the impact of temporary environment changes. In any case, convergence happens in a few number of steps. Convergence is slightly faster in case the initial condition is an “extreme” value, compared to when it is a “middle” value. The “degree of convergence” to the initial condition minimally impacts the speed of convergence.

Our proposed method can exploit any legacy, robust channel estimation mechanism. Assuming a mechanism is available for that purpose, it has been shown that our method can exploit the provided CSI in order to increase the level of certainty that a configuration will achieve a specific bit rate. To strengthen the importance of this statement, we state that the results of the method can be exploited to drive the selection of one of the alternative configurations and thus, ensuring that a cognitive transmitter will always optimize its operation.

6. Conclusions

Cognitive radios require machine learning functionality for knowing, with high enough assurance, the capabilities of the alternative configurations in which they might operate, e.g. the achievable bit-rate. Within a cognitive radio operation, channel-state estimation provides significant information (CSI) in order to calculate achievable bit rate values and associate them with a probed configuration. In this respect, this paper contributes to the enhancement of the channel-state estimation of a cognitive radio process, by proposing a learning method based on Bayesian networks. The objective is to increase the level of certainty that a specific configuration will achieve a definite bit rate.

The next step of our work is to integrate the proposed scheme of this paper with diverse radio scene analysis (environment sensing) mechanisms, as well as configuration selection algorithms. For the radio scene analysis there will be integration of mechanisms relevant to CDMA and OFDM air-interfaces. For the selection phase, a direction that will be pursued is the optimum choice of configurations for a set or all the cognitive transmitters in an area in accordance to the examined capabilities that they can achieve. Both fully-distributed and cooperating techniques will be studied. Furthermore, in our future studies we will expand our scheme so as to consider and investigate Bayesian Networks with more variables and their probabilistic relationships.

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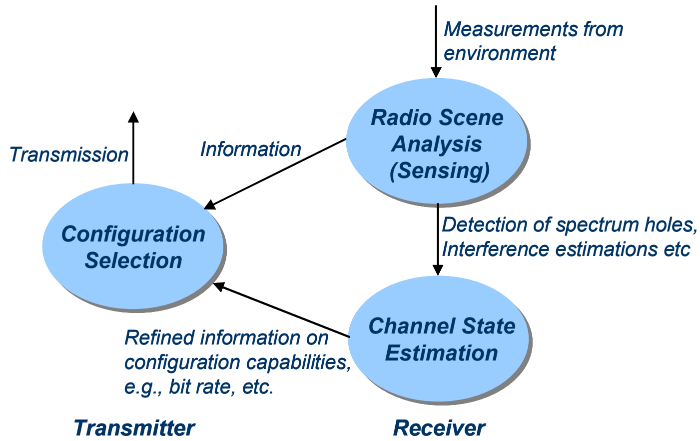

Figure 1: Representation of cognitive radio cycle

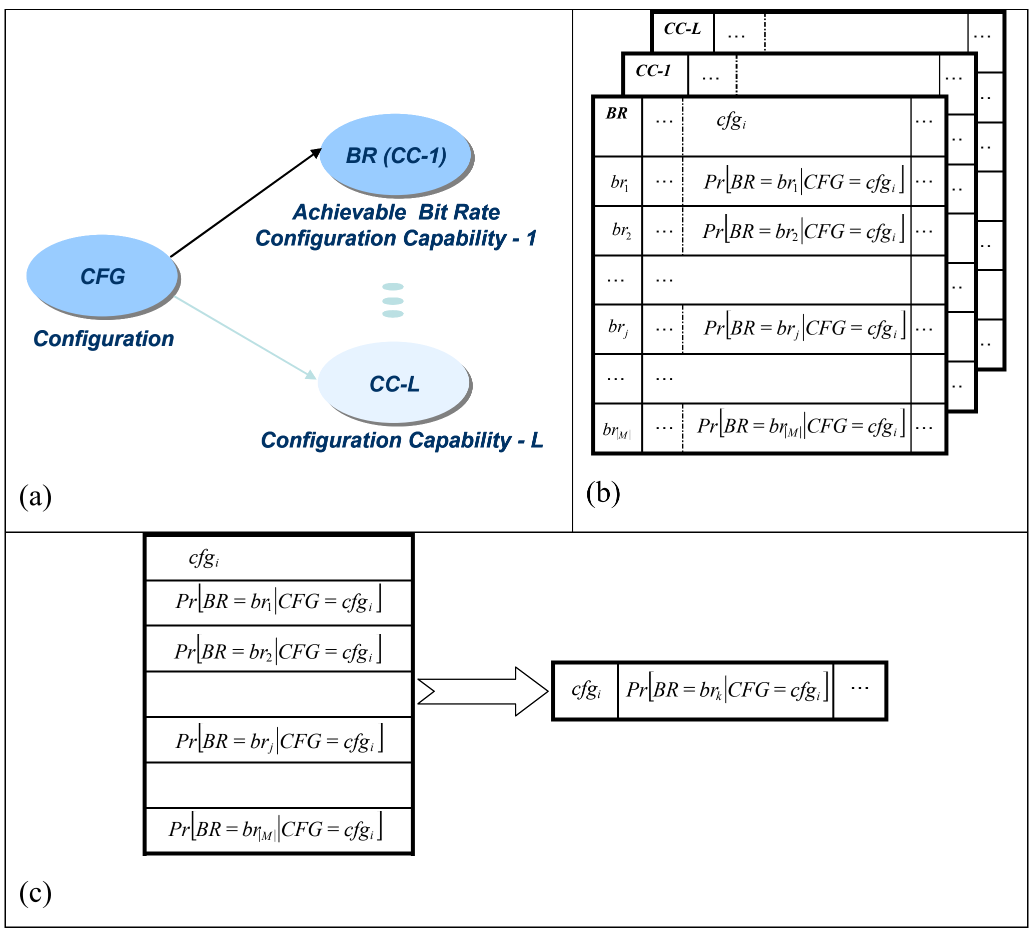

Figure 2: (a) Structure of the Bayesian network. (b) Structure of the Conditional Probability Tables (CPTs). (c) Organization of CPT columns as ordered lists, for enabling fast adaptations.

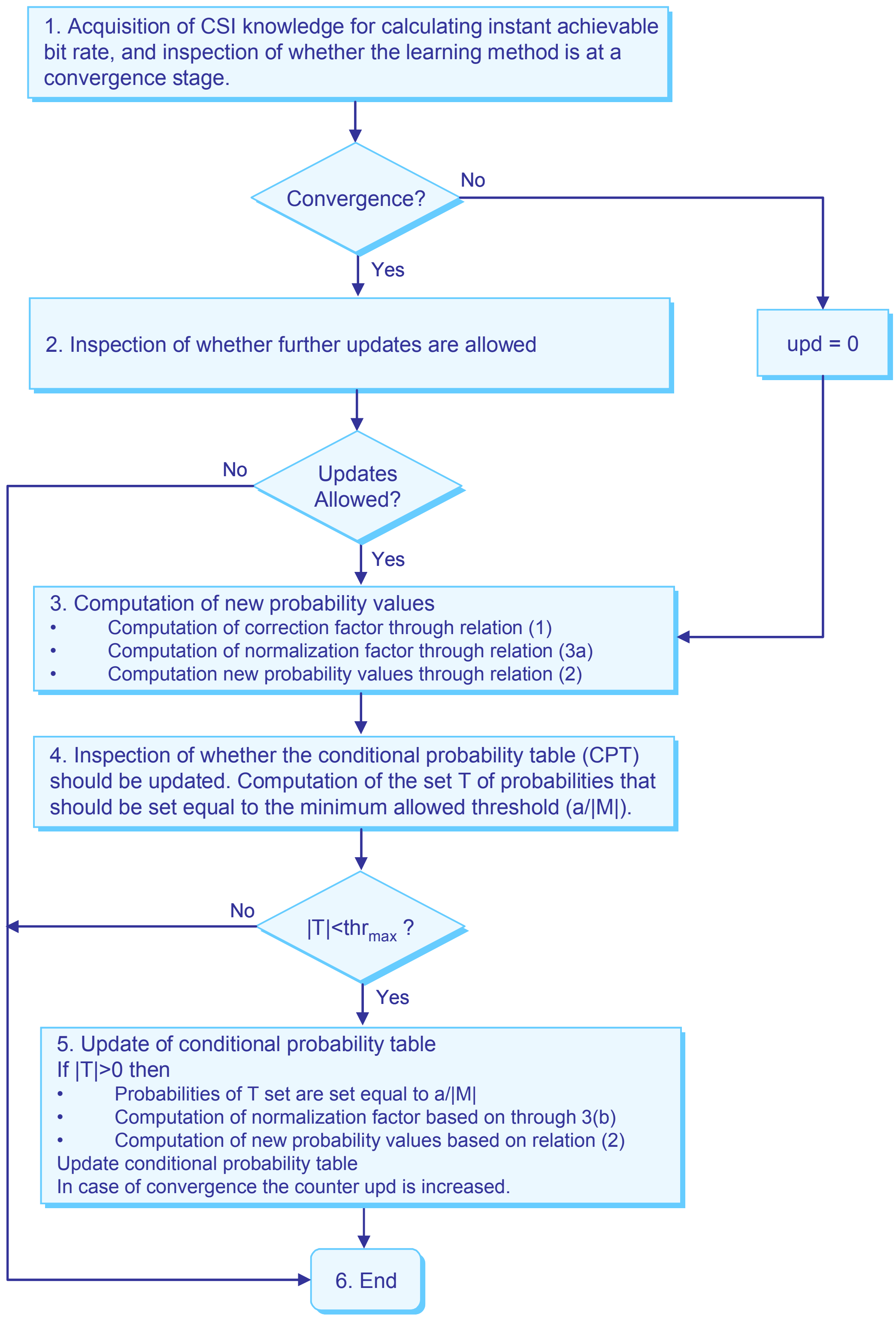

Figure 3: Behaviour of the channel estimation phase: strategy for learning the configuration capabilities

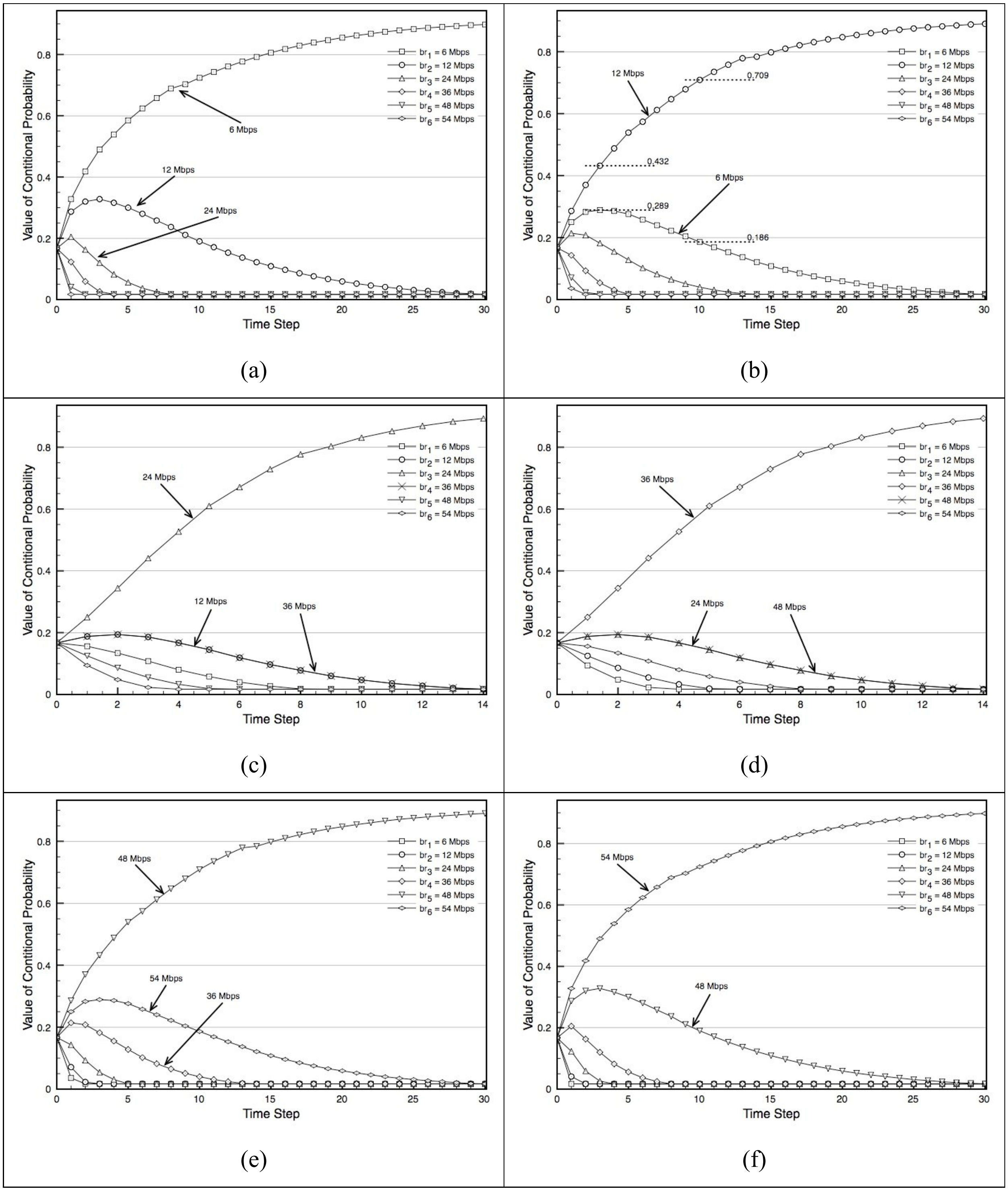

Figure 4: First category (set) of scenarios. The focus is on an arbitrary configuration, for which there is no prior information on its capabilities. Behaviour of the proposed method when it has learned that the configuration can achieve: (a) 6 Mbps; (b) 12 Mbps; (c) 24 Mbps; (d) 36 Mbps; (e) 48 Mbps; (f) 54 Mbps.

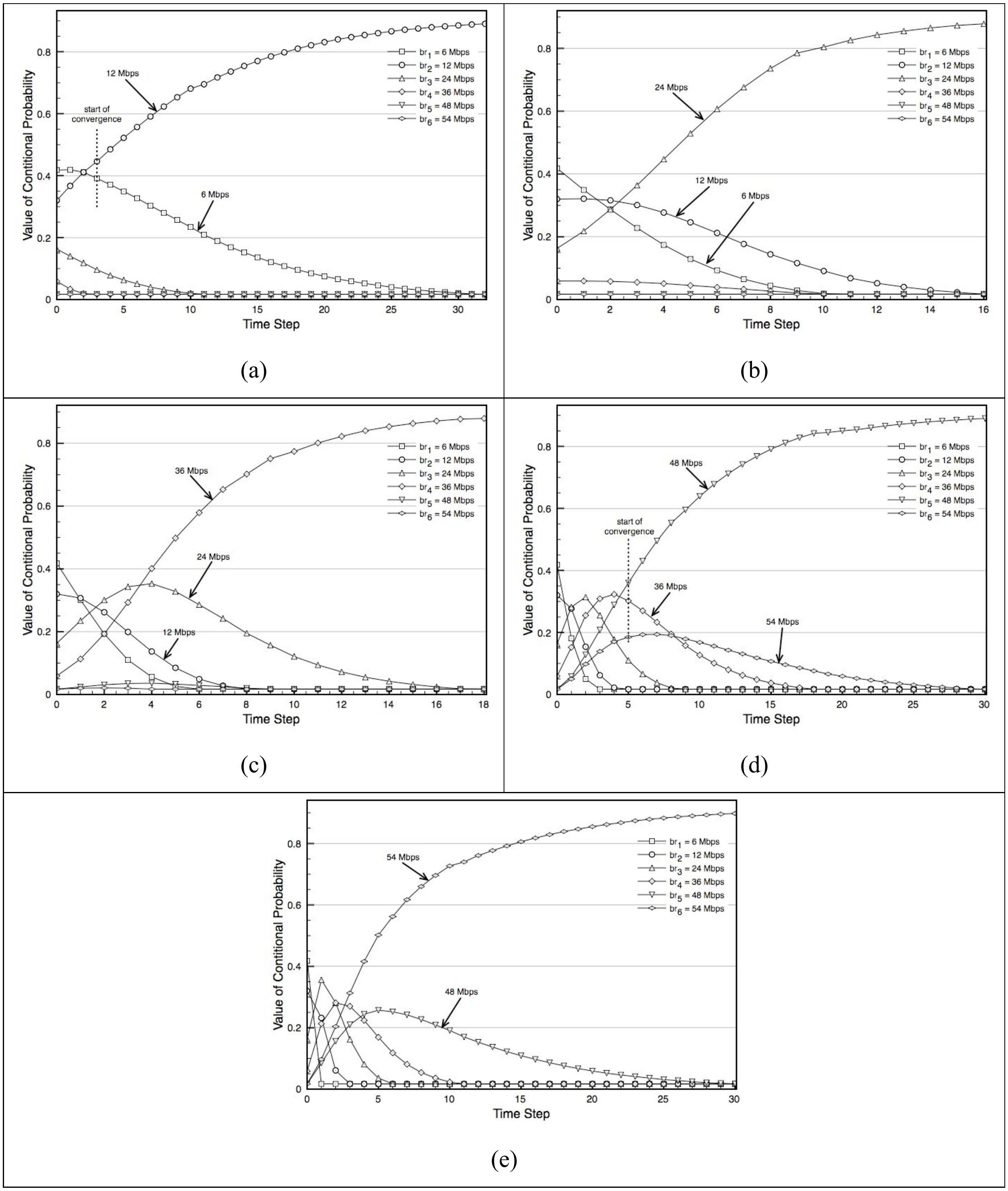

Figure 5: Second set of scenarios. Behaviour of the proposed method when the calculated bit-rate changes from 6 Mbps and $|T|$=2 to: (a) 12 Mbps; (b) 24 Mbps; (c) 36 Mbps; (d) 48 Mbps; (e) 54 Mbps.

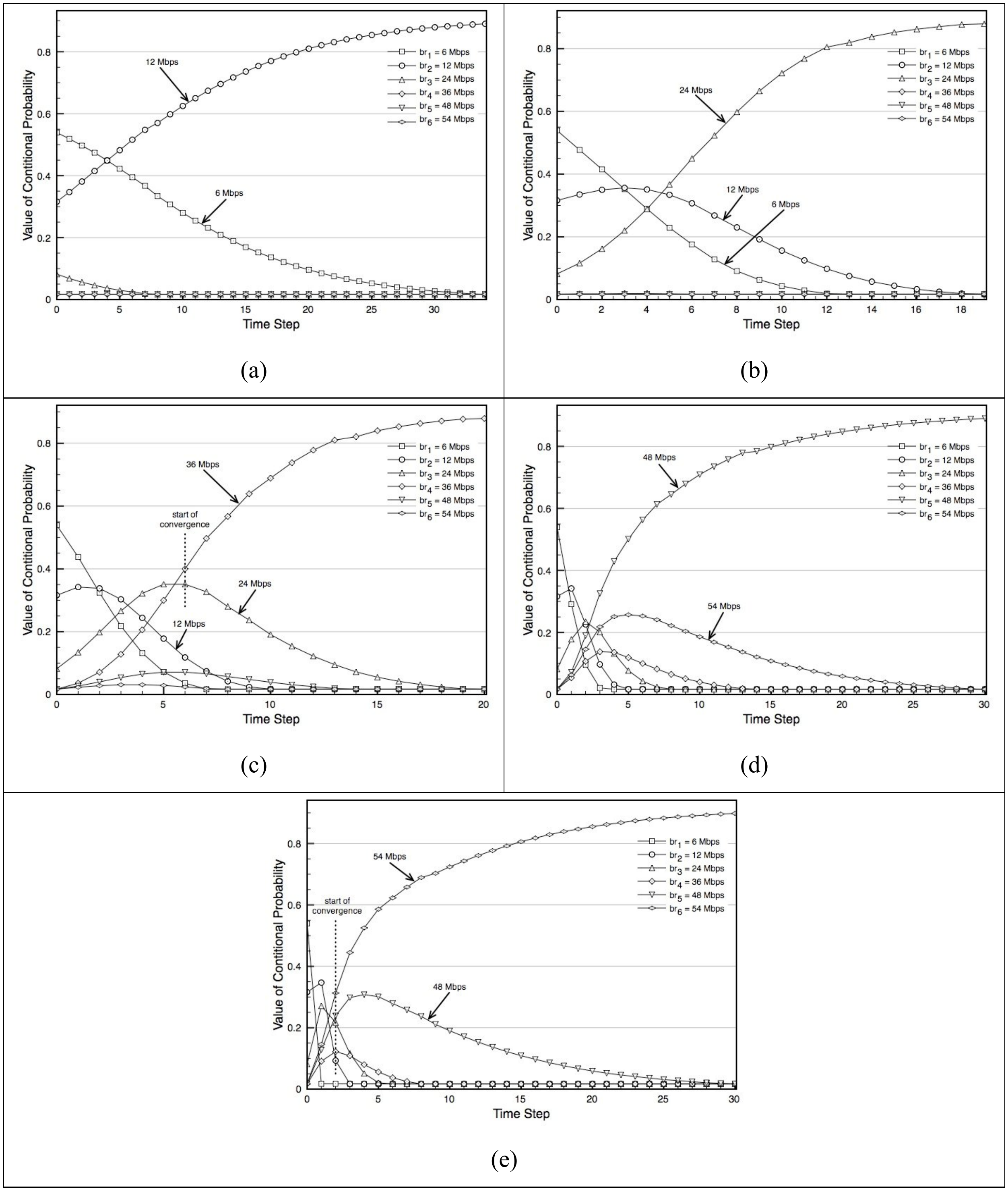

Figure 6: Third set of scenarios. Behaviour of the proposed method when the calculated bit-rate changes from 6 Mbps and $|T|$ =3 to: (a) 12 Mbps; (b) 24 Mbps; (c) 36 Mbps; (d) 48 Mbps; (e) 54 Mbps.

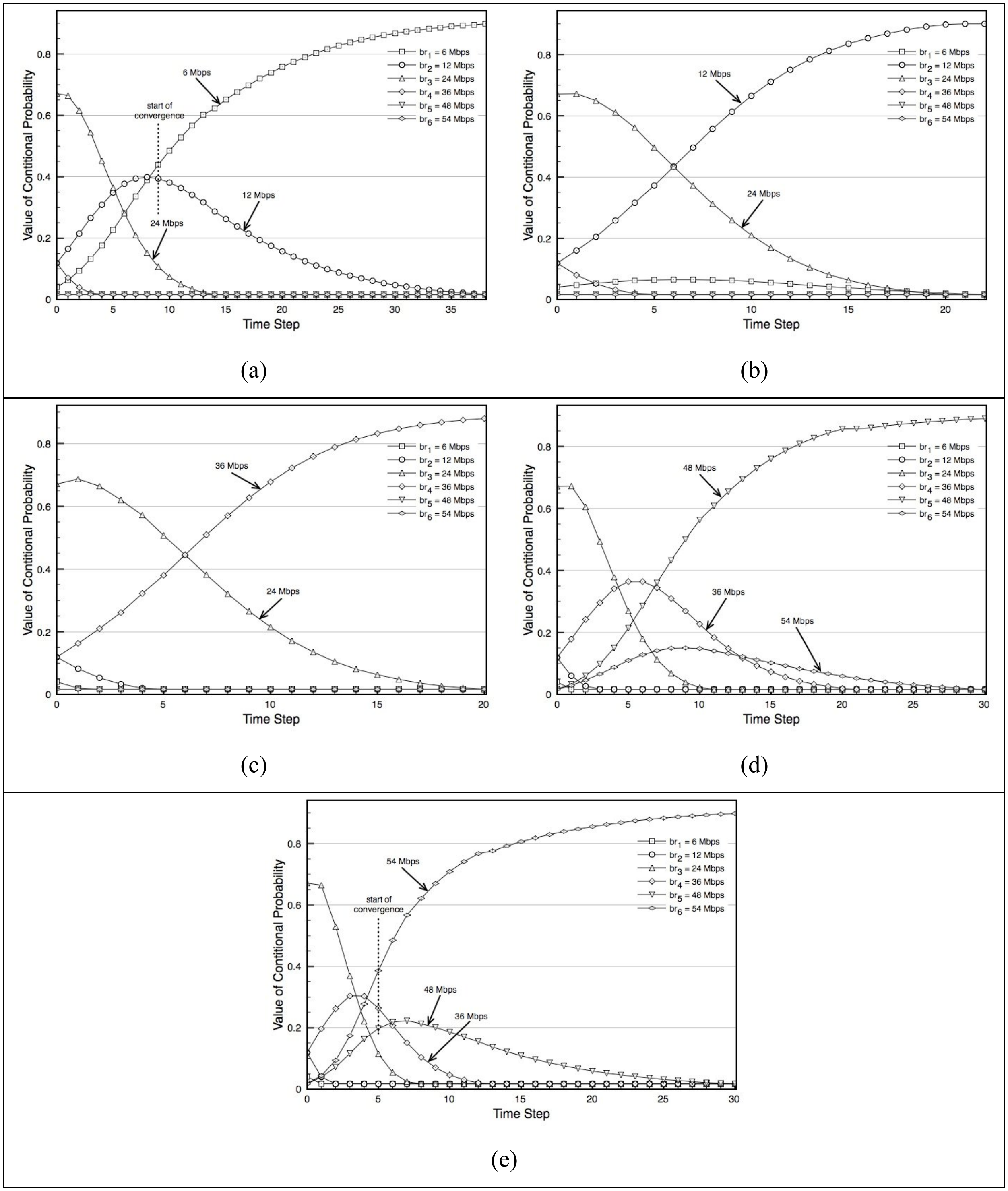

Figure 7: Fourth set of scenarios. Behaviour of the proposed method when the calculated bit-rate changes from 24 Mbps and $|T|$=2 to: (a) 6 Mbps; (b) 12 Mbps; (c) 36 Mbps; (d) 48 Mbps; (e) 54 Mbps.

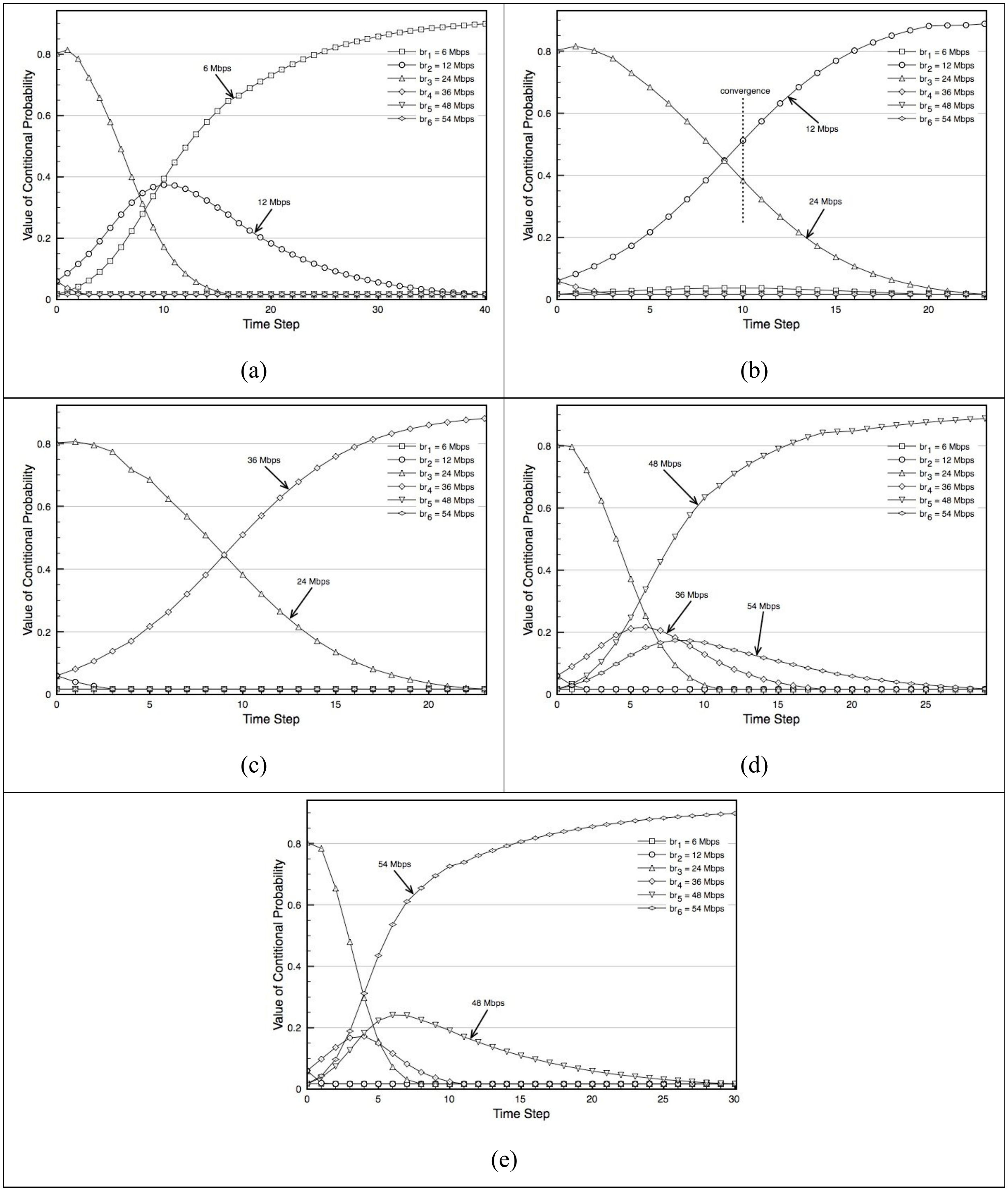

Figure 8: Fifth set of scenarios. Behaviour of the proposed method when the calculated bit-rate changes from 24 Mbps and $|T|$=3 to: (a) 6 Mbps; (b) 12 Mbps; (c) 36 Mbps; (d) 48 Mbps; (e) 54 Mbps.