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Cooperation Promotion from the Perspective of Behavioral Economics: An Incentive Mechanism Based on Loss Aversion in Vehicular Ad-Hoc Networks

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Abstract: As a special mobile ad-hoc network, Vehicular Ad-hoc Networks (VANETs) have the characteristics of high-speed movement, frequent topology changes, multi-hop routing, a lack of energy, storage space limitations, and the possible selfishness of the nodes. These characteristics bring challenges to the design of the incentive mechanism in VANETs. In the current research on the incentive mechanism of VANETs, the mainstream is the reward-based incentive mechanism. Most of these mechanisms are designed based on the expected utility theory of traditional economics and assume that the positive and negative effects produced by an equal amount of gain and loss are equal in absolute value. However, the theory of loss aversion points out that the above effects are not equal. Moreover, this will lead to a deviation between the final decision-making behavior of nodes and the actual optimal situation. Therefore, this paper proposed a Loss-Aversion-based Incentive Mechanism (LAIM) to promote the comprehensive perception and sharing of information in the VANETs. This paper designs the incentive threshold and the threshold factor to motivate vehicle nodes to cooperate. Furthermore, based on the number of messages that the nodes face, the utility function of nodes is redesigned to correct the assumption that a gain and a loss of an equal amount could offset each other in traditional economics. The simulation results show that compared with the traditional incentive mechanism, the LAIM can increase the average utility of nodes by more than 34.35%, which promotes the cooperation of nodes.

Keywords: vehicular ad-hoc networks; loss aversion; incentive mechanism; message transmission

1. Introduction

VANETs are a service system integrating information perception, processing, and interaction [1]. Through wireless communication, VANETs can exchange information with vehicles, roads, pedestrians, and the Internet and can comprehensively perceive and share various static information of traffic participants and the traffic environment.

VANETs contribute to the construction of smart cities [2–5], which can greatly improve the urban environment and improve the living standards of residents, such as traffic congestion [6,7], environmental pollution [8], and so on. However, at the same time, due to the highly dynamic topology, frequently disconnected links [9], restricted movement directions (subject to road directions, signal lights, etc.), the lack of energy, and storage limitations [10–12], the message transmission among nodes cannot be effectively guaranteed. Moreover, the time for vehicle nodes to pass through the coverage of a Road Side Unit (RSU) is usually less than one minute. Therefore, it is difficult for vehicle nodes to download large files directly from the RSU in a short time (for example, videos may be as large as 100 MB). Similarly, the vehicle node cannot always be in the communication range of the RSU, and the transmission of information has a high delay. Therefore, it is necessary

to establish a self-organizing network among vehicle nodes.

Existing works had shown that the message transmission status of VANETs can be improved through the incentive mechanism [13–16]. Since VANETs requires a large number of mobile vehicles to participate in cooperative behaviors, cooperative guarantee mechanisms [17–21] are proposed based on incentives. For example, reference [19] proposed a bidding mechanism to encourage vehicles to contribute storage resources. Reference [20] designed a task assignment mechanism based on a contract to improve the utilization rate of vehicle resources. Reference [21] used block chain technology to protect users' privacy while encouraging users to provide reliable information in the form of remuneration and a margin. Most of these mechanisms assume that the same amount of gain can offset the same amount of loss and that nodes transmit messages to surrounding nodes in order to maximize their utility. Behavioral economics studies [22,23] show that an equal amount of loss will have a much more significant impact on nodes than an equal amount of gain, and nodes do not always make decisions to maximize benefits. If this problem is ignored, the actual revenue of users and the number of users who choose to cooperate will be lower than the expected result. Therefore, we need to design an incentive mechanism that takes loss aversion into account.

For a single node, this paper designs an incentive mechanism based on loss aversion by establishing the mapping of loss aversion in a vehicle network. When designing the utility function of a node, this paper first analyzes the number of messages faced by the nodes and then proposes the incentive threshold and the threshold factor. This paper also redesigns the utility function of the nodes, which corrects the assumption that the same amount of gain and loss could offset each other in traditional economics. When designing the decision model of the node, this paper uses the cost and utility of the node as the influencing parameters to define the node's p for different coalitions. Furthermore, this paper designs the merger and separation strategy of coalitions and proposes an algorithm for incentive mechanism based on loss aversion.

The main contributions of this paper are summarized as follows:

1. The Loss-Aversion-based Incentive Mechanism (LAIM) is proposed. Taking the coalition formation game as the analysis tool, this paper proposes the incentive threshold and threshold factor to improve the cooperation rate of vehicle nodes.
2. The coalition merger strategy M and the coalition separation strategy P based on loss aversion are proposed. Vehicle nodes can maximize their utility based on these two strategies.

The remainder of this paper is organized as follows. Section 2 introduces related work on the incentive mechanism of VANETs based on traditional economics while detailing loss aversion. Section 3 introduces a system model for the LAIM. Section 4 verifies the effectiveness of the proposed LAIM through simulation experiments. Finally, Section 5 is the conclusion.

2. Related Work

This section discusses the incentive mechanism of VANETs based on traditional economics and related research on loss aversion.

2.1. Incentive Mechanism of VANETs

In order to further improve people's traveling environment, Intelligent Traffic Systems (ITS) are gradually applied to VANETs. Through the use of ITSs, computer technology and sensor technology can be linked to enhance people's travel experiences. The development of ITSs has solved many problems in VANETs, such as communication difficulties and traffic congestion. Whether in communication technology or practical applications, the success of VANETs needs the message transmission incentive mechanism to ensure the effective transmission of messages. The incentive mechanisms of message transmission in VANETs can be divided into four aspects: reward-based [24], reputation-based [25–28], punishment-based [29], and mobile-social-network-based [30–32].

The incentive mechanisms based on reward provide rewards for nodes to promote cooperation. Reference [24] proposed a Reward and Bonus-based Incentive mechanism (RBI). RBI provides rewards for the nodes participating in message transmission according to their efforts and provides an additional bonus for the last two nodes participating in forwarding. In [25], an incentive-based cooperation content downloading mechanism was proposed. The incentives obtained by nodes were jointly determined by the rewards and the consumption of content transmission. In the incentive mechanism based on reputation, nodes tend to cooperate with nodes with higher reputation values. The Privacy-preserving Trust-based Relay Selection scheme (PTRS) proposed in [26] used the Dirichlet distribution to calculate the feedback reputation, which made the vehicle reputation evaluation more reliable and maintained the robustness of the system at the same time. Reference [27] counted the information of the nodes that had participated in the transmission of messages in the past and calculated the reputation value of the nodes based on these messages. The judgment of the reliability of information in [28] depended on whether the reputation value of the node that generated the information was high. The incentive mechanism based on punishment will detect the behavior of nodes in the network and punish the nodes that show malicious or selfish behaviors in the network. Furthermore, it clears the malicious nodes out of the network to ensure the regular operation of the system. Reference [29] proposed a Payment Punishment Scheme (PPS). The node with the most resources will be selected as the cluster-head node, and the node in the cluster that deliberately provides false information will be punished accordingly. Reference [30] used the tit-for-tat strategy to restrict malicious nodes. The incentive mechanism based on social networks [31] drew on the idea of the mobile social network, explored the possible social relations among nodes in VANETs, and used the social relations among nodes to promote node participation in cooperation. In [32], a Vehicular Social Network Protocol (VSPN) was proposed to establish a social network by collecting the communication information of vehicles to promote cooperation among nodes.

However, current incentive mechanisms are mostly based on traditional economics and ignore the irrational aspects of participants, resulting in the following problems.

They all assume that the more rewards the vehicle nodes receive, the more cooperative they are [24–26]. For example, reference [24] proposed a scheme to allocate rewards to intermediate nodes to increase coalition and proposed an efficient scheme based on an additional reward to increase availability in the network. Reference [25] formulated the cooperative vehicle selection problem as an optimal multiple stopping problem and derived the optimal multiple stopping rules for cooperative downloading to maximize the utilization of benefits. Reference [26] combined rewards and credibility to motivate vehicle nodes to cooperate.

They all assumed that the utility function of nodes is just the revenue minus the cost [28–30]. Reference [28] analyzed the cost of rejoining the system with a new identity. The nodes make decisions based on the compensation minus costs. Reference [29] established models to encourage truth telling during the election process of the nodes in a cluster and directly used the revenue minus the cost as a utility function. Reference [30] changed the node-to-node cooperation decision by rewarding the cooperative nodes and punishing the selfish nodes. The utility of nodes is the reward they finally get. To address the above two issues, this paper introduces loss aversion theory to VANETs. In the following sections, we present the theoretical research on loss aversion from behavioral economics.

Aiming at addressing the deficiencies in the current research, this paper introduces loss aversion theory in behavioral economics to VANETs. Loss aversion in behavioral economics [33] means that people are more averse to lose than gain. Behavioral economics has been widely used in the computer field [34–36]. In mobile crowdsourcing [34], loss aversion is used to redefine the utility function of nodes. Reference [35] used reciprocal altruism in behavioral economics to promote message delivery in the Internet of Vehicles. Reference [36] used reciprocal altruism to improve the cooperation rate of social networks and to promote the spread of cooperation behaviors.

2.2. Loss Aversion

Loss aversion [37] refers to the fact that when people face the same amount of gain and loss, the pain caused by loss is much higher than the pleasure brought by gain. Figure 1 shows the different value curves of decision-makers in traditional economics and behavioral economics. The origin *o* in the graph represents the point at which the decision-maker measures his/her gain or loss: the positive half axis of *x* represents the decision-maker's gain; the negative half axis of *x* represents the decision-maker's loss; and the *y*-axis represents the actual perceived value of the loss or gain.
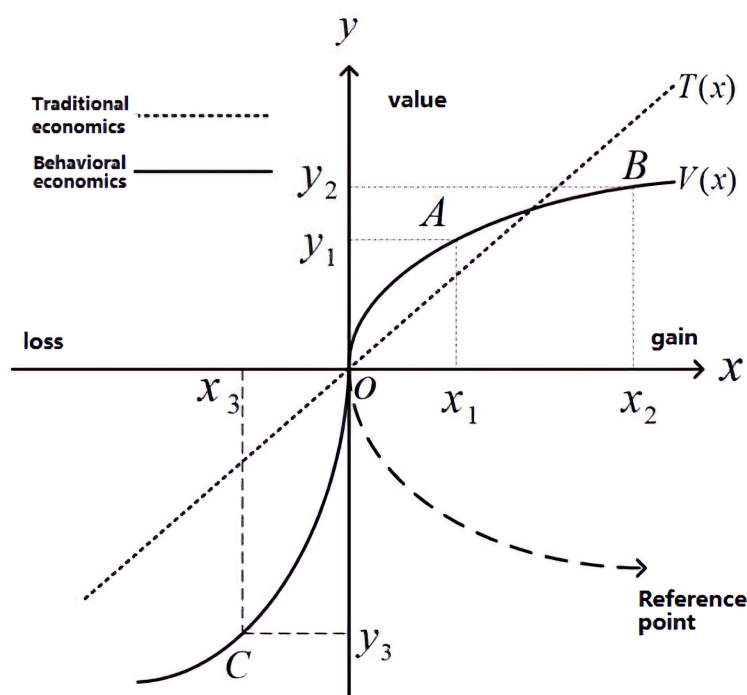

Figure 1. Value function of loss aversion.

As shown in Figure 1, the value curve $T(x)$ of traditional economics reflects the decision-maker's gain and loss of the same amount, and the actual value perceived by the decision-maker is also equal. In other words, for the decision-maker, the happiness brought by an equal amount of gain and the pain caused by the equal amount of loss can offset each other, with $T(x) = x$.

As for the value curve $V(x)$ of behavioral economics, when the point is on the positive half axis of *x*, the decision-maker acts based on gain; on the negative half axis of *x*, the decision-maker shows a loss, and it has $|x_1| = |x_3|$ and $|V(x_3)| = |V(x_1)|$ for point $A(x_1, y_1)$ and point $C(x_3, y_3)$. In other words, for decision-makers, the pain caused by the loss is much higher than the pleasure of obtaining the gain. In order to facilitate the analysis, this paper draws on the utility function model of loss aversion [38–43] based on piece-wise linear function, which has seen good research results in the field of behavioral economics. It is an approximation of the nonlinear utility function model proposed by Kahneman and Tversky [37].

At present, there are many types of research on loss aversion in economics. In the aspect of supply chain research, reference [44,45] studied the coordination of the supply chain in the case of retailers and suppliers with loss aversion. In the aspect of auction mechanism research, reference [46] studied bidders with loss aversion. References [47,48] respectively took all-pay auction and reverse auction as research objects and analyzed the impact of participants with loss aversion on the auction. In terms of game theory, reference [49] studied the influence of loss-averse participants on the two-matrix game. Reference [50] studied the Nash balance in the case of loss aversion based on the newsboy

game model. Reference [51] took gambling behaviors as the research object and studied the phenomenon that loss aversion makes gamblers prefer to take risks. In the field of biology, reference [52] studied the changes of neural cells' state when people are faced with loss and gain, to introduce the causes of loss aversion.

In summary, no previous study has applied loss aversion to VANETs. Therefore, this paper introduces loss aversion to design the incentive mechanism in VANETs.

3. Design and Analysis of the LAIM

The model in this paper is mainly inspired by the marketing strategy of Amazon's online bookstore. It uses individual nodes' loss aversion psychology to amplify individual nodes' perception of loss and promote nodes to form coalition groups, thereby achieving the purpose of promoting node cooperation.

3.1. Mapping of Loss Aversion

In real life, many merchants will launch preferential activities such as full discounts and free shipping. These activities use consumers' loss aversion to attract customers to spend money [53]. Inspired by the marketing strategy of Amazon's online bookstore, this paper introduces loss aversion into VANETs. The brief introduction of the marketing strategy is as follows:

Amazon's online bookstore has introduced a promotional method that allows free shipping if someone purchases books over a certain amount. For example, if someone only buys a book for $16.95, he/she will also need to pay $3.95 for shipping. However, if he/she buys another book, the total amount of which exceeds $30, there will be no shipping charge. Many book buyers may not have intended to buy another book, but free shipping is so attractive that they are willing to pay for another book in exchange for free shipping [54].

In this example, exempting shipping costs makes people willing to spend more money. This strategy reflects the impact of loss aversion on people's decision-making behaviors. We assume that the incentive threshold is X; in other words, when the consumers' consumption amount reaches X, they can get free freight for d. Since the purchasing behavior only occurs when the utility U_1 of the commodity is higher than the price paid for it, assuming that the consumer has consumed P_c, then the expected utility obtained by the consumer is $U_1 - P_c$. If consumers do not choose to continue to consume, then they will lose the free shipping. For consumers, due to the existence of loss aversion, they will get a loss aversion utility U_2, with $U_2 > d$. At this time, the utility of the consumer is $U_1 - P_c - U_2$. If the consumer chooses to keep consuming and reaches the incentive threshold X, this paper assumes that the utility brought by continued consumption is U_3, then $U_3 > X - P_c$, and the expected utility of the consumers is $U_1 + U_3 - X$. Obviously, with $U_1 + U_3 - X > U_1 + X - P_c - X = U_1 - P_c > U_1 - P_c - U_2$, consumers will choose to continue to consume.

Based on the above example, this paper maps the specific application of loss aversion in promotional means and nodes in VANETs participating in cooperation. The mapping table is shown in Table 1.

3.2. System Model
3.2.1. Physical Model

As shown in Figure 2, our system model mainly includes RSU nodes and vehicle nodes. We suppose that the network involves N vehicle nodes. The set of vehicle nodes is represented by $V = \{V_1, V_2, ..., V_N\}$, where $V_i (i \in [1, N])$ represents the ith vehicle node. At the same time, there are M messages in the network, and $S = \{S_1, S_2, ..., S_M\}$ represents the set of messages. These M messages may be stored in RSU or vehicle nodes. To facilitate the discussion here, the copy of the same message $S_i (i \in [1,M])$ stored in different RSUs or vehicle nodes belongs to the same message.

Table 1. Mapping of loss aversion in VANETs.

	Amazon Online Bookstore	VANETs
Incentive object	Consumer	Vehicle node
Incentive threshold	Consumption amount reaches X dollar amount	Participate in cooperation Y times
Event	The consumer has bought the goods with a value of P_c dollars $(P_c < X)$	The number of nodes participating in cooperation reaches T_n $(T_n < Y)$
Incentive process	In order to get free shipping by d dollars, consumers choose to continue to consume p dollars, making $P_c + p \geq X$	In order to get additional bonus utility U, the node chooses to continue to participate in cooperation t times, making $T_n + t \geq Y$
Incentive results	The additional consumption of p dollars by consumers increases the profits of the bookstore	Nodes participate in cooperation t times, which improves the cooperation rate of nodes in the system
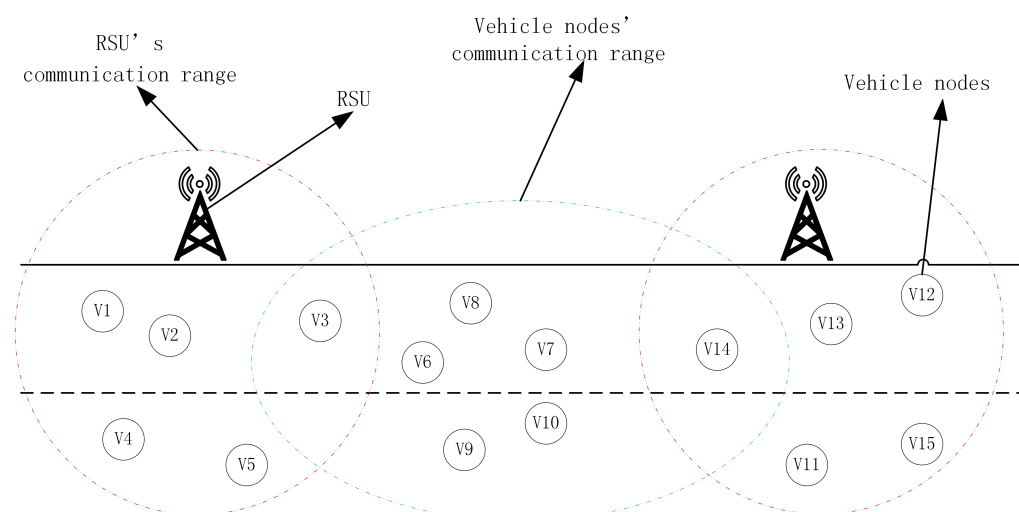
Figure 2. Physical model of VANETs.

When the vehicle node V_i wants to request the message S_i, if it is within the communication range of an RSU, then the node V_i can request to obtain the message S_i from the RSU. If the RSU stores the message S_i, the RSU will directly send the message S_i to the node V_i. If the RSU does not store the message S_i or the node V_i is outside the communication range of the RSU, it can request the message S_i from surrounding qualified nodes, such as the node V_8 in Figure 2. It can first request the message S_i from surrounding nodes, such as V_6 or V_7; if these nodes do not store the message S_i, these nodes can continue to request the message S_i from the nodes around them. Assuming that the node V_3 stores the message S_i, then the message S_i will be transmitted to the node V_8 through the communication link $V_3 \rightarrow V_6 \rightarrow V_8$.

After receiving the message S_i, the node V_8 will store the cooperation record $C = \{ID, L, Time, PK\}$ in the memory, where ID represents the ID of the cooperation record and L is the set of cooperation nodes in the cooperation record. *Time* represents the time of the cooperation, and PK represents the private key of the node to verify the validity of the cooperation record. When the node moves to the RSU communication range, the cooperation record will be submitted to the RSU for storage, and for the convenience of discussion, the node will submit the cooperation record honestly.

3.2.2. Logical Model

The physical model of VANETs is discussed above, and then, the whole process of the incentive mechanism is discussed.

- As is shown in the logic diagram of Figure 3, in Step 1, the RSU determines the number of messages faced by all individual nodes by analyzing the number of messages Υ_{V_i}. Then, in Step 2, the RSU sets the incentive threshold Θ of the nodes. Only when the number of messages transmitted by the vehicle node satisfies $\Pi_{V_i} \geq \Theta$ can the nodes get the extra reward; when $\Pi_{V_i} < \Theta$, the nodes cannot get the extra reward, and they will regard the reward that cannot get as a loss. The incentive threshold set above is to change the nodes' selection behavior.

- In the third step, the nodes will determine the gain and loss balance point Ω_{V_i} according to the incentive threshold Θ determined by the RSU. After the node V_i calculates the gain and loss balance point Ω_{V_i}, the node V_i can hence get the relationship between the number of messages Π_{V_i} to complete transmission and the number of messages Υ_{V_i}, so that the nodes themselves can determine the number of messages Π_{V_i} to complete transmission. The incentive threshold Θ set by the RSU in Step 2 will cause the loss aversion of nodes, which will affect the choices made by nodes in Step 4.

- After determining the number of tasks chosen, the node will be in a random coalition $C^{V_{cur}} = C_i$ in Step 5, where $C^{V_{cur}}$ represents the current coalition the node will be in as a random coalition and C_i represents one of all those coalitions. Once in the coalition, the node will continuously adjust the strategies shown in Step 6 to maximize its utility. (1) The coalition merger strategy is adopted: if two coalitions merge, to be more specific, the first strategy in Step 6 is called the coalition merger strategy. When this strategy is adopted, the expected utility of the new coalition is less than the original coalition $\Lambda_{C_i \cup C_j} > \Lambda_{C_i} + \Lambda_{C_j}$, where $\Lambda_{C_i \cup C_j}$ represents the expected utility of the new coalition and Λ_C represents the expected utility of the original coalition, and the cost is higher than the original coalition $P_{C_i \cup C_j} < P_{C_i} + P_{C_j}$, where $P_{C_i \cup C_j}$ represents the cost of the new coalition and P_C represents the cost of the original coalition. (2) However, for the second strategy—the coalition separation strategy, once adopted, a coalition will be divided into several coalitions, then the sum of the expected utility of the new coalition is higher than that of the original coalition by $\Lambda_{C_i \cup C_j} < \Lambda_{C_i} + \Lambda_{C_j}$, and the transmission cost is lower than that of the original coalition by $P_{C_i \cup C_j} > P_{C_i} + P_{C_j}$. In Step 7, the node completes the task and obtains the corresponding utility. The main parameters used in this paper are shown in Table 2.
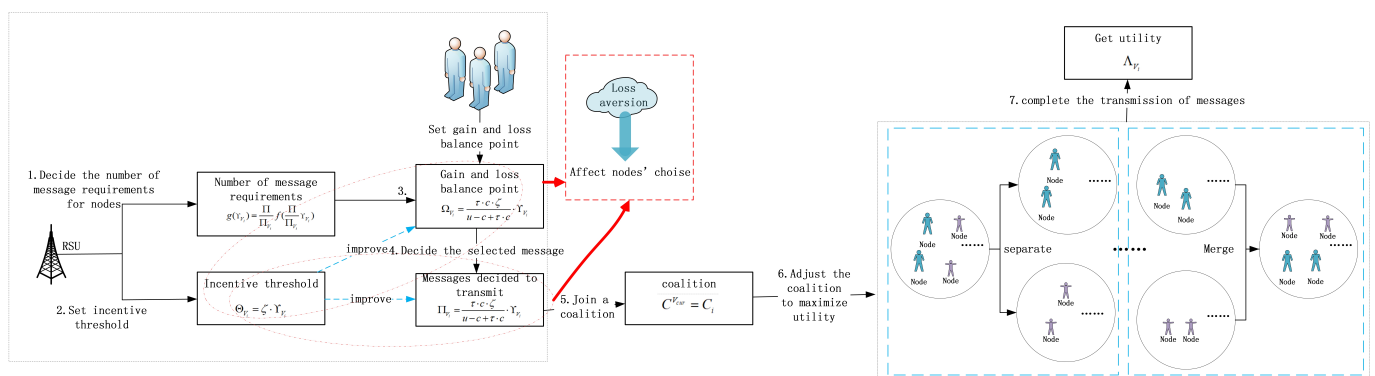

Figure 3. Logical model.

Table 2. Parameter table.

Parameter Name	Description of Parameters
Θ	Incentive threshold
Y	Message demands
Π_{V_i}	Number of messages that the node V_i has completed
Ω_{Vi}	Gain and loss balance point of node V_i
ζ	Threshold factor
u	Transmission reward
c	Transmission cost
c_o	Threshold of participation
τ	Reward factor
P	Cost of coalition
Λ	The expected utility

3.3. Design of LAIM

In the model, each cooperation of the nodes will bring about consumption. Based on the mapping established in Section 3.1 and the utility function proposed in [37], the utility function of nodes based on loss aversion in VANETs is designed, and the incentive threshold is proposed to encourage nodes to participate in the cooperation. By evaluating the cost of the previous cooperation, additional rewards are given to the nodes who continue to participate in the cooperation. Therefore, the nodes are encouraged to choose to keep participating in the cooperation.

3.3.1. Design of Node's Utility Function Based on Loss Aversion

The primary purpose of this section is to design a utility function based on loss aversion. For the vehicle node V_i in the network G, whenever V_i helps to transmit a message S_i, V_i will obtain a utility function with a positive value. However, due to the consumption of the channel and energy for the transmission of messages, the transmission cost will be brought to the node, that is a negative utility. In order to facilitate the discussion, each time a node participates in the transmission of the message S_i, the node will get a reward u, and the transmission cost c satisfies $u \geq c$. The node will participate in the transfer only if the node's revenue is greater than the threshold c_o. In other words, without considering loss aversion, if $u - c - c_o > 0$, the node will think that participating in the transmission will bring benefits, then it will participate in the transmission; if $u - c - c_o < 0$, the node will think that participating in the transmission will bring loss, and hence will not participate in the transmission.

In this section of the network model, whenever a node needs to obtain messages from other nodes, a message demand will be generated. The number of messages will ultimately affect the overall utility of the nodes. Therefore, before designing the utility function of the node, the total messages Y in the network G will be discussed here first.

1. Number of messages:

In a certain period T, assume that there are Y messages in the network, that is to say the number of messages to be obtained from other nodes is Y. All possible values of Y obey the normal distribution at time T (since the normal distribution is the most common distribution in nature), that is $Y \sim N(\mu, \sigma^2)$, where μ represents the mathematical expectation of all possible values and σ is the standard deviation of all possible values. Then, it is easy to know that the probability density function $f(Y)$ of messages Y satisfies Formula (1):

$$f(Y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(Y-\mu)^2}{2\sigma^2}} \tag{1}$$

At the same time, the probability distribution function $F(Y)$ of messages satisfies Formula (2):

$$F(Y) = \int_{-\infty}^{Y} f(Y)dY = \int_{-\infty}^{Y} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(Y-\mu)^2}{2\sigma^2}} dY \tag{2}$$

In Formula (2) $Y \in R$, since the number of messages Y in time T satisfies $Y \geq 0$, Formula (2) can be further simplified as Formula (3):

$$F(Y) = \frac{1}{\sqrt{2\pi}\sigma} \int_0^Y e^{-\frac{(Y-\mu)^2}{2\sigma^2}} dY \tag{3}$$

In time T, for the node V_i, the number of messages that need to be transmitted by the node V_i is Y_{V_i} and with $Y_{V_i} \leq Y$. Similarly, Y_{V_i} satisfies the normal distribution, and the probability density function and the probability distribution function of Y_{V_i} are $g(Y_{V_i})$ and $G(Y_{V_i})$ respectively. Suppose that the total number of messages that all nodes that choose to complete transmission at time T is $\prod$, the number of messages that the node V_i chooses to complete transmission at time T is $\prod_{V_i}$, and the sum of messages selected by other nodes to complete transmission at the same time is $\prod_{-V_i}$; since the number of messages is constant, there is $\prod = \prod_{V_i} + \prod_{-V_i}$. In the system model of this section, for the node V_i, the more messages Y_{V_i} the node faces and messages $\prod_{V_i}$ it chooses to help complete, the more utility the node finally obtains. Therefore, Y_i is directly proportional to $\prod_{V_i}$, which satisfies Formula (4):

$$Y_{Vi} = \frac{\prod_{V_i}}{\prod} Y \tag{4}$$

According to Formulas (3) and (4), we have Formulas (5) and (6):

$$G(Y_{Vi}) = F\left(\frac{\prod}{\prod_{V_i}} Y_{Vi}\right) \tag{5}$$

$$g(Y_{Vi}) = \frac{\prod}{\prod_{V_i}} f\left(\frac{\prod}{\prod_{V_i}} Y_{Vi}\right) \tag{6}$$

The purpose of analyzing the number of messages Y is to model the messages faced by the whole network and a single node. Furthermore, through analysis, it can provide a theoretical basis for the analysis of the possible value of the message number, the choosing of the cooperative behavior of the node, and the final utility.

2. Incentive threshold and threshold factor:

The incentive threshold Θ refers to the number of messages required for nodes to obtain additional rewards; in other words, nodes can only get additional rewards if they cooperate more than a few certain times. The reward factor is defined as τ, $\tau \in (0,1)$, and the bigger τ is, the more additional rewards the node will get. Due to the loss aversion characteristic of nodes, according to the previous hypothesis, the perceived gain Γ_{V_i} of node V_i is defined as shown in Formula (7):

$$\Gamma_{V_i} = (u - c - c_o) \cdot \prod_{V_i} + \tau \cdot (c + c_o) \cdot \left(\prod_{V_i} - \Theta_{Vi}\right) \tag{7}$$

According to Formula (7), when $\prod_{V_i} < \Theta_{V_i}$, there is $\Gamma_{V_i} = (u - c - c_o) * \prod_{V_i} - \tau * c * (\Theta_{V_i} - \prod_{V_i})$. This is because according to the analysis in Section 3.1, the node will regard the additional reward that cannot be obtained as a loss under the influence of loss aversion, which is further explained by Lemma 1.

Lemma 1. *For the node V_i, when $u - c - c_o < 0$ and $\tau > 1 - \frac{u}{c+c_o}$, the node V_i will still choose to continue the cooperation.*

Proof of Lemma 1. When the loss utility is not considered, the profit of the node V_i is: $u - c - c_o < 0$, then nodes will not participate in the cooperation. When the loss utility is considered, the profit of the node V_i is $\Gamma_{V_i} = (u - c - c_o) + \tau * (c + c_o)$. As $\tau > 1 - \frac{u}{c+c_o}$, then $\Gamma_{V_i} > 0$, so the node V_i will choose to continue the cooperation. $\square$

According to Lemma 1, Θ_{V_i} should be at least $\Theta_{V_i} \geq \prod_{V_i}$ in order to motivate nodes to choose to continue the cooperation. At the same time, one of the purposes of the

mechanism proposed in this section is to promote the nodes to complete the messages of the surrounding nodes, as many as possible. Therefore, assume that the incentive threshold Θ_{V_i} corresponding to the node V_i satisfies $\Theta_{V_i} \propto Y_{V_i}$, and the relationship between Θ_{V_i} and Y_{V_i} is defined as the following Formula (8):

$$\Theta_{Vi} = \zeta \cdot Y_{Vi} \tag{8}$$

In Formula (8), ζ is the threshold factor that represents the ratio of the incentive threshold Θ_{V_i} of the node V_i to the number of messages Y_{V_i}, which is $0 < \zeta \leq 1$.

After bringing Formula (8) into Formula (7), we have Formula (9):

$$\Gamma_{V_i} = (u - c - c_o) \cdot \Pi_{V_i} + \tau \cdot (c + c_o) \cdot \left(\Pi_{V_i} - \zeta \cdot Y_{Vi} \right) \tag{9}$$

3. Expected utility of nodes:

According to Formula (9), the gain Γ_{V_i} of the node V_i is related to the messages faced by the node Y_{V_i} at time T and the number of messages that the node chooses to complete the transmission $\prod_{V_i}$. Therefore, before analyzing the expected utility function of the node V_i, the balance point of the perceived gain and loss of the node V_i is defined as follows:

Definition 1 (The gain and loss balance point of node V_i (Ω_{V_i})). *According to the analysis in the previous section, when the conditions are met, the node can choose the number of messages to complete the transmission at will. This means that the number of messages that the node chooses to transmit N and the number of messages Y_{V_i} it faces satisfies $\prod_{V_i} \in [0, Y_{V_i}]$. If $\Omega_{V_i} \in (0, Y_{V_i})$ and $\prod_{V_i} \in (0, \Omega_{V_i})$, then we have $\Gamma_{V_i} < 0$; when $\prod_{V_i} = \Omega_{V_i}$, we have $\Gamma_{V_i} = 0$; when $\prod_{V_i} \in (\Omega_{V_i}, Y_{V_i}]$, we have $\Gamma_{V_i} > 0$, then Ω_{V_i} is called the gain and loss balance point of node V_i.*

According to the characteristics of loss aversion, the node's perception of equal loss and gain is different. Therefore, the definition of gain and loss balance point Ω_{V_i} is to distinguish the loss and gain part of the node V_i when analyzing the utility Λ_{V_i} of the node. The detailed analysis of Ω_{V_i} is shown in Theorem 1.

Theorem 1. *There is Ω_{V_i} that allows the node to distinguish between the gains and losses of its own utility.*

Proof of Theorem 1. According to Formula (9), when $\Pi_{V_i} \geq Y_{V_i} * \zeta$, we have $\Gamma_{V_i} = (u - c - c_o) * \prod_{V_i} + \tau * (c + c_o) * (\prod_{V_i} - \zeta * Y_{V_i})$, because $\tau * (c + c_o) * (\prod_{V_i} - \zeta * Y_i) \geq 0$, $u > (c + c_o)$1 therefore, in this case, $\Gamma_{V_i} > 0$. If $\prod_{V_i} < \zeta * Y_{V_i}$, $\Gamma_{V_i} = 0$ is possible. Therefore, when $\prod_{V_i} < \zeta * Y_{V_i}$, $\Gamma_{V_i} = (u - c - c_o) * \prod_{V_i} - \tau * (c + c_o) * (\zeta * Y_{V_i} - \prod_{V_i})$ can be calculated; let $\Gamma_{V_i} = 0$, then $(u - c - c_o) * \prod_{V_i} = \tau * (c + c_o) * (\zeta * Y_{V_i} - \prod_{V_i})$. By simplifying the formula, the following result can be calculated: $\prod_{V_i} = \frac{\tau * (c + c_o) * \zeta}{u - c - c_o + \tau * (c + c_o)} * Y_{V_i}$, according to Definition 1, when $\Omega_{V_i} = \prod_{V_i} = \frac{\tau * (c + c_o) * \zeta}{u - c - c_o + \tau * (c + c_o)} * Y_{V_i}$, the gain and loss balance point of the node is deduced. □

According to Theorem 1, after the gain and loss balance point Ω_{V_i} of node V_i is obtained, the user utility affected by the cost and benefit can be further discussed. The relationship between the number of messages $\prod_{V_i}$ chosen by the node V_i and the number of messages Y_{V_i} that the node V_i faces satisfies Formula (10):

$$\Pi_{V_i} = \frac{\tau \cdot (c + c_o) \cdot \zeta}{u - c - c_o + \tau \cdot (c + c_o)} Y_{Vi} \tag{10}$$

According to Formula (10), the following Formula (11) is met when the balance point of gain and loss Ω_{V_i} is reached:

$$Y_{Vi} = \frac{u - c - c_o + \tau \cdot (c + c_o)}{\tau \cdot (c + c_o) \cdot \zeta} \Pi_{V_i} \tag{11}$$

According to Formulas (9) and (11), the expected utility Λ_{V_i} of the node V_i can be deduced as shown in Formula (12):

$$
\begin{aligned}
\Lambda_{Vi} =& \lambda_i \cdot \int_0^{\frac{u-c-c_o+\tau\cdot(c+c_o)}{\tau\cdot(c+c_o)\cdot\zeta}\Pi_{V_i}} \left[(u-c-c_o)\cdot\Pi_{V_i} - \tau\cdot(c+c_o)\cdot\left(\zeta\cdot Y_{Vi} - \Pi_{V_i}\right)\right] dY_{Vi} \\
&+ \int_{\frac{u-c-c_o+\tau\cdot(c+c_o)}{\tau\cdot(c+c_o)\cdot\zeta}\Pi_{V_i}}^{\frac{\Pi_{V_i}}{\zeta}} \left[(u-c-c_o)\cdot\Pi_{V_i} - \tau\cdot(c+c_o)\cdot\left(\zeta\cdot Y_{Vi} - \Pi_{V_i}\right)\right] dY_{Vi} \\
&+ \int_{\frac{\Pi_{V_i}}{\zeta}}^{+\infty} \left[(u-c-c_o)\cdot\Pi_{Vi} + \tau\cdot(c+c_o)\cdot\left(\Pi_{Vi} - \zeta\cdot Y_{Vi}\right)\right] dY_{Vi}
\end{aligned}
\tag{12}
$$

In Formula (12), λ_i is the loss aversion coefficient of the node V_i, indicating the degree of the node's loss aversion, and it satisfies $\lambda_i > 1$. Since the distribution of the number of messages that a node faces Y_{V_i} is an uncertain value and we only know its distribution $\int_0^{+\infty} g(Y_{V_i}) dY_{V_i} = 1$, this paper hence needs to calculate the expected value according to the distribution function of Y_{V_i}. According to Formulas (10) and (11), the distribution function of Y_{V_i} can be divided into three parts. The first part represents the probability that a node will lose when participating in the cooperation, that is to say, in the interval $\left(0, \frac{u-c-c_o+\tau*(c+c_o)}{\tau*(c+c_o)*\zeta} * \Pi_{V_i}\right)$ calculated in Formula (11), and the utility of the node corresponding to this part of the probability is the first part of Formula (12). The second part represents the probability that the node participating in the cooperation will benefit, but fails to reach the threshold,;in other words, in the interval $\left(\frac{u-c-c_o+\tau*(c+c_o)}{\tau*(c+c_o)*\zeta} * \Pi_{V_i}, \frac{\Pi_{V_i}}{\zeta}\right)$. The utility of the node corresponding to this part of the probability is the second part of Formula (12). The third part represents the probability that a node will benefit from cooperation and reach the threshold, that is in the interval $\left(\frac{\Pi_{V_i}}{\zeta}, +\infty\right)$. The utility of the node corresponding to this probability is the third part of Formula (12).

3.3.2. Design of the Node's Decision Model Based on Loss Aversion

This section uses the loss aversion of nodes to promote individual nodes to choose cooperation behavior and finally form the coalition group. Since the coalition formation game [55–57] is a common tool for analyzing the coalition group formed by the participants in the network, this section takes the coalition formation game as the analysis tool. The nodes in the network are considered as participants in the coalition game, and the nodes in the coalition can act as relay nodes to forward messages for the nodes outside the communication range of the source node. Based on loss aversion, the node's decision model is designed.

1.　Node decision model based on loss aversion:

In the model proposed in this section, the coalition formation game is used as the analysis tool. Assume that the coalition i is represented by $C_i \in C$ and C is the coalition set of the current network, with $C = \{C_1, C_2, ..., C_i, ..., C_n\}$ and $n \in N$. Each coalition contains at least one node, and the node V_i can choose to join or leave a certain coalition C_i. Nodes cannot exist in two coalitions at the same time.

Suppose that the coalition game in this section is represented by $G = \{C, V, \Lambda, S, F\}$, where V is the set of nodes in the model, then there is $V = \{V_1, V_2, ..., V_i, ..., V_n\}$, where $n \in N$. Λ_{V_i} is the expected utility of nodes V_i, and S is the strategy set of all nodes, then we have $S = \{S_1, S_2, ..., S_i, ..., S_n\}$ and $n \in N$. Furthermore, S_i is the strategy combination of

the node V, $S_i = \{s_i1, s_i2, ..., s_in\}$, and s_in is the single strategy of the node V_i. F is the decision function of the node, which is the decision-making basis that the node chooses whether to leave the current coalition or continue staying in the current coalition.

Definition 2 (The selection p of the node V_i ($\succ_i$)). *For the node V_i, when the following Formula (13) is true:*

$$\sum_{k=1}^{\Pi_{V_i}^{C_i}} c < \sum_{k=1}^{\Pi_{V_i}^{C_j}} c \wedge \Lambda_{V_i}^{C_i} > \Lambda_{V_i}^{C_i}, \tag{13}$$

then node V_i is inclined to prefer coalition C_i to coalition C_j, which is expressed as $C_i \succ_i C_j$. Among them, C_i is assumed to be the current coalition of the node, and C_j is a coalition that the node can choose to join or not. $\prod_{V_i}^{C_i}$ and $\prod_{V_i}^{C_j}$ represent the number of messages that the node V_i chooses to complete transmitting in coalitions C_i and C_j respectively. $\Lambda_{V_i}^{C_i}$ and $\Lambda_{V_i}^{C_j}$ represent the expected utility that the node V_i can require in coalitions C_i and C_j, respectively.

It can be seen from Definition 2 that when the node is in the coalition C_i, if the cost of transmitting messages in the coalition C_i is less than that in the coalition C_j and the expected utility of nodes in the coalition C_i is higher than that in the coalition C_j, then nodes will preferentially join or remain in the coalition C_i.

According to Definition 2, the F of the node V_i is defined as the following Formula (14):

$$F = \begin{cases} 0 & , C_i \succ_i C_j \\ 1 & , Other \quad situation \end{cases} \tag{14}$$

When the value of F is zero, this means that the node will continue staying in the current coalition C_i. When it is one, this means that the node will leave the current coalition and join the new coalition C_j.

One of the main purposes of the model proposed in this section is to promote nodes to join or form a coalition, to enhance the expected utility of nodes, to encourage nodes to participate in the message cooperation transmission. Different scales of coalitions can form a whole new bigger coalition while a bigger coalition can also be separated into several coalitions of different scales.

Definition 3 (Coalition merger strategy M). *For any node in the coalition C_i, if the p for the new coalition after merging is better than that of the original one and the condition is also satisfied for the nodes in the coalition C_j, then the merger of the coalition C_i and C_j is a coalition merger strategy M.*

According to Definition 3, when Formula (15) is right between any two coalitions, these coalitions will form a new coalition:

$$\left[\forall V_m \in C_i, C_i \succ_m (C_i \cup C_j) \right] \wedge \left[\forall V_n \in C_j, C_j \succ_n (C_i \cup C_j) \right] \tag{15}$$

In Formula (15), $C_i \cup C_j$ represents the new coalition after the coalitions C_i and C_j are merged.

Definition 4 (Coalition separation strategy P). *When there is at least one node in coalitions C_i or C_j and the node's p for coalitions C_i or C_j is higher than that for the coalition $C_i \cup C_j$, then the coalition $C_i \cup C_j$ is separated into coalitions C_i and C_j, which is a coalition separation strategy.*

According to Definition 4, when Formula (16) is true, the coalition will be separated into different coalitions:

$$\left[\forall V_m \in C_i, (C_i \cup C_j) \succ_m C_i \right] \wedge \left[\forall V_n \in C_j, (C_i \cup C_j) \succ_n C_j \right] \tag{16}$$

From Definitions 3 and 4, it can be seen that when a node joins or leaves a coalition, the merger and separation of the coalition will have an impact on the formation of the coalition game in the system model. Therefore, in the following summary, this paper will discuss and analyze these situations and evaluate the performance of the loss-averse node's decision-making model proposed in this section.

2. Analysis of model performance:

According to the previous analysis, the cost and expected utility of nodes participating in the message transmission in the system model will affect the cooperation degree of nodes. Therefore, the expected utility and cost of the coalition to evaluate the performance of the model is proposed in this section.

Definition 5 (Expected utility of coalition C_i (Λ_{C_i}))**.** *The expected utility of the coalition C_i is the sum of the expected utility of all nodes in the coalition.*

According to Definition 5, we have Formula (17):

$$\Lambda_{C_i} = \sum_{V_i \in C_i} \Lambda_{V_i}^{C_i} \tag{17}$$

Definition 6 (The transmission cost of coalition C_i (P_{C_i}))**.** *The transmission cost of the coalition C_i is the sum of the transmission costs of all nodes in the coalition.*

According to Definition 6, we have Formula (18):

$$P_{C_i} = \sum_{V_i \in C_i} \sum_{K=1}^{\Pi_{V_i}^{C_i}} c \tag{18}$$

In the coalition formation game, one of the purposes of the nodes forming the coalition is to improve their expected utility and reduce their costs through cooperation. Therefore, one of the purposes of analyzing the expected utility and cost of the coalition is to evaluate the rationality of the formation of the coalition. If a new coalition is formed, the expected utility of the new coalition will be less than that of the original one, and the cost will be higher than that of the original one, then the coalition is unreasonable. The analysis of the coalition merger strategy is given by Theorem 2.

Theorem 2. $\forall C_i, C_j, \forall V_i \in C_i, \forall V_j \in C_j$ of the coalition separation strategy M has $\Lambda_{C_i \cup C_j} > \Lambda_{C_i} + \Lambda_{C_j}$ and $P_{C_i \cup C_j} < P_{C_i} + P_{C_j}$.

Proof of Theorem 2. According to Formulas (17) and (18), the following formula can be used: $[\forall V_m \in C_i, (C_i \cup^{C_j}) \succ_m C_i] \wedge [\forall V_n \in C_j, (C_i \cup^{C_j}) \succ_n C_j]$, and $\forall V_m \in C_i, \forall V_n \in C_j$, satisfy $\Lambda_{V_m}^{C_i \cup C_j} > \Lambda_{V_m}^{C_i}, \Lambda_{V_n}^{C_i \cup C_j} > \Lambda_{V_n}^{C_j}, \sum_{\kappa=1}^{\Pi_{V_m}^{C_i \cup C_j}} c < \sum_{\kappa=1}^{\Pi_{V_m}^{C_i}} c, \sum_{\kappa=1}^{\Pi_{V_n}^{C_i \cup C_j}} c < \sum_{\kappa=1}^{\Pi_{V_n}^{C_i}} c$, so there are $\Lambda_{C_i} + \Lambda_{C_j} = \sum_{V_i \in C_i} \Lambda_{V_i}^{C_i} + \sum_{V_j \in C_j} \Lambda_{V_j}^{C_j} < \sum_{V_i \in C_i} \Lambda_{V_i}^{C_i \cup C_j} + \sum_{V_j \in C_j} \Lambda_{V_j}^{C_i \cup C_j} = \Lambda_{C_i \cup C_j}$, and $P_{C_i} + P_{C_j} = \sum_{V_i \in C_i} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i}} c + \sum_{V_j \in C_j} \sum_{\kappa=1}^{\Pi_{V_j}^{C_j}} c > \sum_{V_i \in C_i} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i \cup C_j}} c + \sum_{V_j \in C_j} \sum_{\kappa=1}^{\Pi_{V_j}^{C_i \cup C_j}} c = P_{C_i \cup C_j}$ □

It can be seen from Theorem 2 that when the coalition satisfying Formula (15) forms a new coalition, the expected utility of the new coalition will be higher than that of the original coalition, and the transmission cost is lower than that of the original coalition. In other words, the coalition merging strategy can allow each node to obtain higher expected utility and lower transmission cost in the new coalition. In this way, the nodes

are facilitated to participate in the cooperation. The analysis of the coalition separation strategy is given by Theorem 3.

Theorem 3. $\forall C_i, C_j \in (C_i \cup {}^{C_j}), \forall V_i \in C_i, \forall V_j \in C_j$ *of the coalition separation strategy P has* $\Lambda_{C_i \cup {}^{C_j}} < \Lambda_{C_i} + \Lambda_{C_j}$ *and* $P_{C_i \cup C_j} > P_{C_i} + P_{C_j}$

Proof of Theorem 3. According to Theorem 2, it is known that: $[\exists V_m \in C_i, C_i \succ_m (C_i \cup {}^{C_j})] \wedge [\exists V_n \in C_j, C_j \succ_n (C_i \cup {}^{C_j})]$, and $\exists V_m \in C_i, \exists V_n \in C_j$ satisfy $\Lambda_{V_m}^{C_i \cup {}^{C_j}} < \Lambda_{V_m}^{C_i}, \Lambda_{V_n}^{C_i \cup {}^{C_j}} <$

$$\Lambda_{V_n}^{C_j}, \sum_{\kappa=1}^{\Pi_{V_m}^{C_i \cup {}^{C_j}}} c > \sum_{\kappa=1}^{\Pi_{V_m}^{C_i}} c, \sum_{\kappa=1}^{\Pi_{V_n}^{C_i \cup {}^{C_j}}} c > \sum_{\kappa=1}^{\Pi_{V_n}^{C_j}} c, \text{ then } \Lambda_{C_i} + \Lambda_{C_j} = \sum_{V_i \in C_i} \Lambda_{V_i}^{C_i} + \sum_{V_j \in C_j} \Lambda_{V_j}^{C_j} =$$

$$\sum_{V_i \in \{C_i \setminus V_m\}} \Lambda_{V_i}^{C_i} + \sum_{V_m \in C_i} \Lambda_{V_m}^{C_i} + \sum_{V_j \in \{C_j \setminus V_n\}} \Lambda_{V_j}^{C_j} + \sum_{V_n \in C_j} \Lambda_{V_n}^{C_j} > \sum_{V_i \in \{C_i \setminus V_m\}} \Lambda_{V_i}^{C_i} + \sum_{V_m \in C_i \cup {}^{C_j}} \Lambda_{V_m}^{C_i \cup {}^{C_j}} +$$

$$\sum_{V_j \in \{C_j \setminus V_n\}} \Lambda_{V_j}^{C_j} + \sum_{V_n \in C_i \cup {}^{C_j}} \Lambda_{V_n}^{C_i \cup {}^{C_j}} = \sum_{V_i \in C_i \cup {}^{C_j}} \Lambda_{V_i}^{C_i \cup {}^{C_j}} + \sum_{V_j \in \{(C_i \cup {}^{C_j}) \setminus V_i\}} \Lambda_{V_j}^{C_i \cup {}^{C_j}} = \Lambda_{C_i \cup {}^{C_j}}, P_{C_i} +$$

$$P_{C_j} = \sum_{V_i \in C_i} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i}} c + \sum_{V_j \in C_j} \sum_{\kappa=1}^{\Pi_{V_j}^{C_j}} c = \sum_{V_i \in C_i \setminus V_m} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i}} c + \sum_{V_m \in C_i} \sum_{\kappa=1}^{\Pi_{V_m}^{C_i}} c + \sum_{V_j \in C_j \setminus V_n} \sum_{\kappa=1}^{\Pi_{V_j}^{C_j}} c + \sum_{V_n \in C_i} \sum_{\kappa=1}^{\Pi_{V_n}^{C_i}} c <$$

$$\sum_{V_i \in C_i \setminus V_m} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i}} c + \sum_{V_m \in C_i} \sum_{\kappa=1}^{\Pi_{V_m}^{C_i \cup {}^{C_j}}} c + \sum_{V_j \in C_j \setminus V_n} \sum_{\kappa=1}^{\Pi_{V_j}^{C_j}} c + \sum_{V_n \in C_i} \sum_{\kappa=1}^{\Pi_{V_n}^{C_i \cup {}^{C_j}}} c = \sum_{V_i \in C_i} \sum_{\kappa=1}^{\Pi_{V_i}^{C_i \cup {}^{C_j}}} c + \sum_{V_j \in C_j} \sum_{\kappa=1}^{\Pi_{V_j}^{C_i \cup {}^{C_j}}}$$

$$c = P_{C_i \cup {}^{C_j}}. \quad \square$$

It can be seen from Theorem 3 that the coalition satisfying Formula (16) will be separated into multiple coalitions. It can be found that the sum of the expected utility of the new coalition is higher than that of the original one, and the transmission cost is lower than that of the original one. In other words, coalition separation can make at least one node obtain higher expected utility and lower transmission cost in the new coalition, thus promoting the nodes to participate in the cooperation.

From the analysis of Theorems 2 and 3, it can be concluded that the coalition merger strategy *M* and the coalition separation strategy *P* can bring higher utility and lower costs to nodes by merging or separating coalitions among nodes. Next, this paper will analyze whether there is an optimal expected utility in the coalition through Theorem 4.

Theorem 4. $\forall V_i \in C_i, \exists \Pi_{V_i}^{C_i *}$ *makes* $\Lambda_{V_i}^{C_i}$ *get the optimal value when* $\Pi_{V_i}^{C_i} = \Pi_{V_i}^{C_i *}$, *that is to say the node obtains the maximum utility.*

Proof of Theorem 4. The integral of Formula (12) by parts is as follows:

$$\Lambda_{V_i} = \lambda_i \cdot \int_0^{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}} (u-c) \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i} - \lambda_i \cdot \int_0^{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}} \tau \cdot c \cdot \zeta \cdot \Upsilon_{V_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i}$$

$$+ \lambda_i \cdot \int_0^{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}} \tau \cdot c \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i} + \int_{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}}^{\frac{\Pi_{V_i}^{C_i}}{\zeta}} (u-c) \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i}$$

$$- \int_{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}}^{\frac{\Pi_{V_i}^{C_i}}{\zeta}} \tau \cdot c \cdot \zeta \cdot \Upsilon_{V_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i} + \int_{\frac{u-c+\tau \cdot c}{\tau \cdot c \cdot \zeta} \cdot \Pi_{V_i}^{C_i}}^{\frac{\Pi_{V_i}^{C_i}}{\zeta}} \tau \cdot c \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i}$$

$$+ \int_{\frac{\Pi_{V_i}^{C_i}}{\zeta}}^{+\infty} (u-c) \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i} + \int_{\frac{\Pi_{V_i}^{C_i}}{\zeta}}^{+\infty} \tau \cdot c \cdot \Pi_{V_i}^{C_i} \cdot g(\Upsilon_{V_i}) d\Upsilon_{V_i}$$

$$- \int_{\frac{\Pi_{V_i}^{C_i}}{\zeta}}^{+\infty} \tau \cdot c \cdot \zeta \cdot Y_{V_i} \cdot g(Y_{V_i}) dY_{V_i} = \lambda_i \cdot \tau \cdot c \cdot \zeta \cdot \int_0^{\frac{u-c+\tau\cdot c}{\tau\cdot c\cdot\zeta}\cdot\Pi_{V_i}^{C_i}} G(Y_{V_i}) dY_{V_i}$$

$$+ \tau \cdot c \cdot \zeta \cdot \int_{\frac{u-c+\tau\cdot c}{\tau\cdot c\cdot\zeta}\cdot\Pi_{V_i}^{C_i}}^{\frac{\Pi_{V_i}^{C_i}}{\zeta}} G(Y_{V_i}) dY_{V_i} - \tau \cdot c \cdot \zeta \cdot \int_{\frac{\Pi_{V_i}^{C_i}}{\zeta}}^{+\infty} G(Y_{V_i}) dY_{V_i}.$$

The first derivative of $\Pi_{V_i}^{C_i}$ in the above formula can be obtained $\frac{\partial \Lambda_{V_i}}{\partial \Pi_{V_i}^{C_i}} = (\lambda_i - 1) \cdot$

$(u - c + \tau \cdot c) \cdot G(\frac{u-c+\tau\cdot c}{\tau\cdot c\cdot\zeta} \cdot \Pi_{V_i}^{C_i}) + 2\tau \cdot c \cdot G(\frac{\Pi_{V_i}^{C_i}}{\zeta})$. The probability distribution function satisfies $0 \le G(Y_{V_i}) \le 1$, where $G(Y_{V_i})$ is a monotone non-decreasing function, and $\lim\limits_{Y_{V_i} \to -\infty} G(Y_{V_i}) = 0$. In this paper, the domain of $Y_{V_i} \in [0, +\infty)$, then $\frac{\partial \Lambda_{V_i}}{\partial \Pi_{V_i}^{C_i}} > 0$. In other words, Λ_{V_i} increases monotonically in the domain of $\Pi_{V_i}^{C_i}$ and gets the unique maximum value at the right endpoint of the definition domain. That means that the node V_i has a unique optimal choice $\Pi_{V_i}^{C_i*}$ to complete the transmission of messages, making the expected utility Λ_{V_i} of the node V_i optimized when $\Pi_{V_i}^{C_i} = \Pi_{V_i}^{C_i*}$. □

Through Theorem 4, it can be concluded that for any node in the coalition, there is always a unique choice to complete the transmission of messages, which makes the expected utility of the node maximum.

3.　Algorithm of the incentive mechanism based on loss aversion:

Based on the above analysis of the decision-making model, it can be seen that the node will choose to join or leave the coalition, and the coalition will merge or separate to form a new coalition, which makes the nodes in the coalition able to obtain higher expected utility. Finally, it will urge the nodes to choose to cooperate. The algorithm of the incentive mechanism based on loss aversion is shown in Algorithm 1.

Algorithm 1: Algorithm of the incentive mechanism based on loss aversion.

Input :
　　　Set of nodes $V = \{V_1, V_2, ..., V_i, ..., V_n\}$;
　　　Set of coalitions $C = \{C_1, C_2, ..., C_i, ..., C_n\}$;
　　　The current node V_{cur};
Output:
　　　The current coalition C_{cur};
　　　The node's utility $\Lambda_{V_{cur}}^{C_{V_{cur}}}$;
Loss aversion-based coalition formation $i = 1, j = 1, k = 1, l = 1$;
while $i \le n$ **do**
　　if $C_i \succ_{cur} C^{V_{cur}}$ **then**
　　　　$C^{V_{cur}} = C_i$;

Calculate incentive $\Lambda_{V_i}^{C_{V_i}}$;
while $j \le n$ **do**
　　while $k \le n$ **do**
　　　　if $\forall V_a \in C_j, (C_j \cup^{C_k}) \succ_a C_j$ and $\forall V_b \in C_k, (C_j \cup^{C_k}) \succ_b C_k$ **then**
　　　　　　Merge coalition (C_j, C_k);

while $l < n$ **do**
　　$C_l = C_a \cup^{C_b}$ **if** $\exists V_a \in C_a, C_a \succ_a C_l$ and $\exists V_b \in C_b, C_b \succ_b C_l$ **then**
　　　　Split coalition (C_l);

---

4. Performance Evaluation

The free mobility model proposed in [58] is used to build the freeway mobile model scene. The expressway consists of two lanes, with a length of 3 km and a width of 300 m. At the initial time, vehicle nodes are distributed randomly in any position on the road, and their communication range is 300 m. They move from left to right. The minimum moving speed of the vehicle node is 10 m/s, and the maximum moving speed is 30 m/s. In practice, on the road section that vehicles often pass through, vehicles usually pass through the section from left to right or from right to left in different periods. In the experiment, in order to simplify the experiment, the time span of the vehicle on the road will be ignored, and the vehicle travels back and forth in a certain section in the experiment. The time of the experiment is 20 min. Due to the fact that the node cannot be the source node, the relay node, and the destination node at the same time, at the beginning of each round of the experiment, we set 50% of the randomly selected nodes to be the source nodes. The experimental data are all averaged after 1000 runs to eliminate the influence of some uncertain factors. See Table 3 for the specific experimental parameters.

Table 3. Parameters for simulation.

Parameter Name	Value or Range
Number of paths	2
Number of nodes N	[20, 80]
path length	3000 m
Path width	300 m
Node's maximum speed	30 m/s
Node's minimum speed	10 m/s
Node's communication range	300 m
Total messages Y	[400, 1600]
Threshold factor ζ	0.1, 0.3, 0.5, 0.7, 0.9
loss aversion coefficient λ	(1, 3.5]

4.1. Influence of the Loss Aversion Coefficient on the Average Utility of Nodes

The loss aversion coefficient indicates the node's aversion to loss. Generally speaking, the higher the loss aversion coefficient is, the smaller the node's acceptance of loss will be, that is the more "averse" the node is to loss. According to the introduction of loss aversion in Section 2.2, $\lambda > 1$ is known, and according to [39], $\lambda = 2.25$ is what is usually set. However, in order to better analyze the impact of the loss aversion coefficient on the LAIM proposed in this section, we set $\lambda \in (1, 3.5]$ to observe the relationship between λ_i and the average node utility in the system.

When $Y = 400, N = 20$, as the value of λ_i changes, the trend of the average utility of nodes with time is shown in Figure 4.

It can be seen from Figure 4 that the average node utility increases with time, because with the increase of time, the nodes will have more time to participate in the message transmission. At this time, more and more nodes are selected to help complete the message transmission. The total utility obtained by the nodes will hence increase, and the average node utility will also increase.

It can also be seen from Figure 4 that when the value of λ_i increases from 1.25 to 3.25 and ζ from 0.3 to 0.9, the average node utility increases with the increase of λ_i, because when the value of λ_i increases, in other words, when the node's loss aversion increases, the node tends to choose cooperation behaviors. It can also be understood as the fact that it is more difficult for the node to bear the loss. Therefore, the final utility of the node will increase, and the average node utility will also increase. In the following experiment, $\lambda = 2.25$ is taken. At the same time, with the increase of ζ, the average node utility decreases. This is because the higher ζ is, the more messages the node needs to help complete the transmission to get additional rewards.
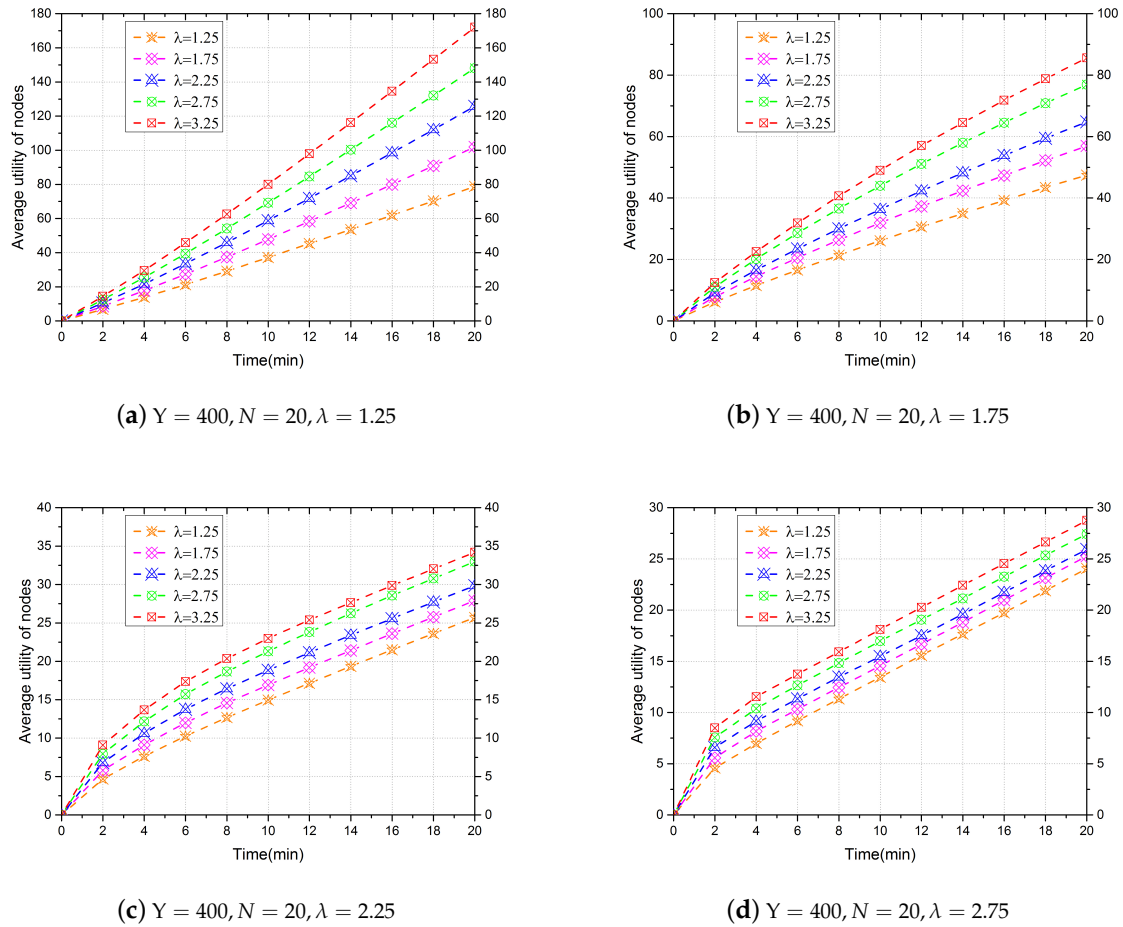
(a) Y = 400, N = 20, λ = 1.25

(b) Y = 400, N = 20, λ = 1.75

(c) Y = 400, N = 20, λ = 2.25

**(d)** Y = 400, N = 20, λ = 2.75

Figure 4. The influence of the λ value on the average node utility.

4.2. Effect of the Threshold Factor on the Average Utility of Nodes

The threshold factor ζ represents the proportion of the number of messages that need to be completed when the node wants to get additional rewards. Only when the number of messages that the node helps to complete the transmission reaches a specific proportion can the node get additional rewards.

Figure 5 shows that when Y = 400, N = 20 and the threshold factor ζ increases from 0.1 to 0.9, the average node utility decreases with the increase of ζ. This is because when ζ increases, the incentive threshold Θ will also increase. As a result, the number of messages that the node completes transmitting is difficult to meet the demand of Θ. Then, the node's utility decreases due to the lack of additional rewards. At the same time, it can be seen that when ζ = 0.1, the average node utility is much higher than other conditions when ζ = 0.3, 0.5, 0.7, and 0.9, respectively. This is because when ζ = 0.1, it is easy for nodes to reach the incentive threshold Θ, so that more nodes get additional rewards. From Figure 4, it can also be seen that the average node utility at the point of 0.7 and 0.9 is relatively similar, as the number of completed message transmissions of nodes has difficulty reaching the incentive threshold in these two cases; the additional incentives cannot be obtained, so in the following experiment, ζ = 0.5.
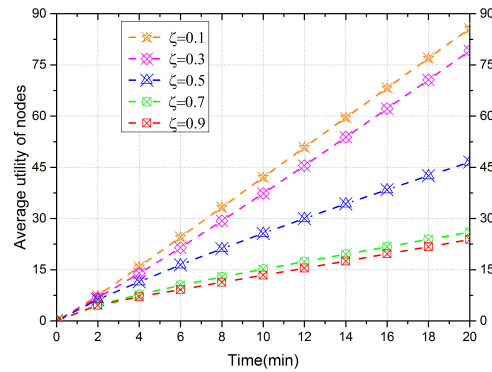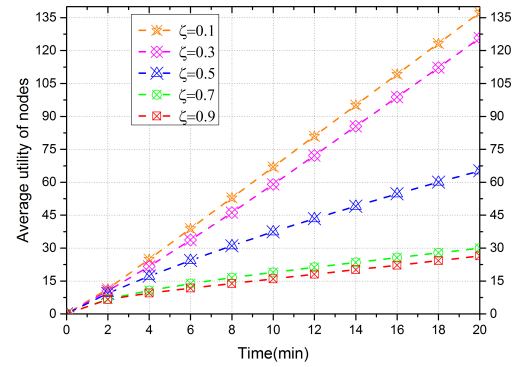
(**a**) $Y = 400, N = 20, \lambda = 1.25$

(**b**) $Y = 400, N = 20, \lambda = 1.75$
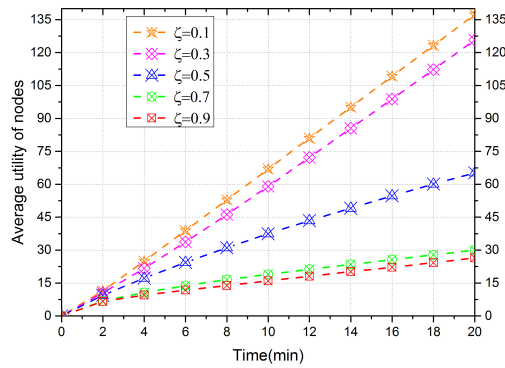
(**c**) $Y = 400, N = 20, \lambda = 2.25$
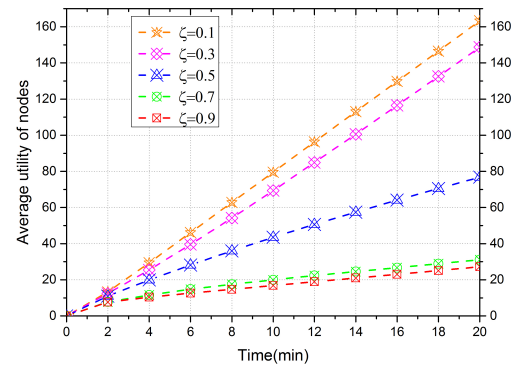
(**d**) $Y = 400, N = 20, \lambda = 2.75$

Figure 5. The influence of the ζ value on the average node utility.

4.3. Comparison with COMES and IMCS

This paper compares the LAIM with COMES [59] and IMCS [60]. COMES is comprised of a coalition formation algorithm which implements the peer-to-peer (P2P) approaches by introducing a coalitional graph game to model the cooperation among nodes. IMCS proposes a dynamic pricing incentive mechanism to solve the problem that users are unwilling to actively participate in content sharing. As the goal of the work is to improve the cooperation rate among vehicle nodes, this paper takes COMES and IMCSas a comparison. It mainly compares the LAIM and COMES from two aspects to analyze the performance of the LAIM: average node utility and average node proportion to acquire utility.

In addition to analyzing the growth of time, it also analyzes the changes in the number of messages and the number of nodes. The total number of messages represents the total number of messages faced by nodes in the system. In other words, the number of messages existing in the current system needs nodes as relay nodes to help the source node forward messages to the destination node. The higher the total message demand is, the more the average messages faced by each node are. In the case of the node choosing to cooperate, the more messages the node can help complete their transmission, the higher the utility of the node will be. Similarly, if there are more nodes in the system, the probability that a particular message demand will be completed at the same time T may also increase. Therefore, when comparing the LAIM and COMES from the two aspects of average node utility and average utility node proportion, in addition to the analysis of time growth, the impact of changes in total messages and the node number of the LAIM and COMES will also be analyzed.

4.3.1. Utility of Average Node

The average node utility refers to the average utility acquired by each node. The higher the average utility of the node, the more times the node participates in cooperation; otherwise, the fewer times the node participates in cooperation. Figure 6 compares the average node utility of the LAIM and COMES in terms of time.
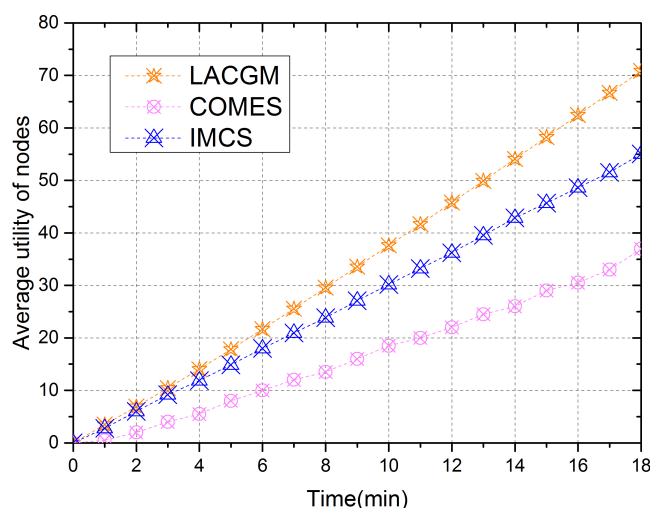

Figure 6. Average node utility changing with time ($Y = 400, N = 20$).

It can be seen from Figure 6 that the average node utility of the LAIM and COMES increases with time. This is because as time goes on, the times nodes participate in cooperation increases, and the final node utility and the average node utility will increase. In Figure 6, the average node utility of the LAIM is higher than that of COMES and IMCS. This is because, in the LAIM, the loss aversion of nodes makes it hard to bear the loss, and then, they will choose to cooperate, which hence leads to more cooperation times than COMES and IMCS. At the beginning, the average node utility of the LAIM is 591% higher than that of COMES at the 30th second, which gradually decreases with time, and finally decreases to about 112% at the 16th minute. Compared with IMCS, the average utility of LAIM users is only slightly higher than that of IMCS users, and the gap between the two gradually widens over time. This is because the LAIM has a significant promoting effect on the increase of utility due to the existence of loss aversion.

Figure 7 describes the relationship between the average node utility and both the number of messages and nodes. When the number of nodes and the number of messages have different values, the average node utility of the LAIM, IMCS, and COMES will increase with the increase of time, and the average node utility of the LAIM will be higher than that of the other two mechanisms. In Figure 7a,b, when the number of nodes remains unchanged and the number of messages increases, then the final average node utility will also increase, because when the number of nodes remains unchanged, the increase of messages will increase the average messages. Then, the number of messages that the node ultimately completes transmitting will also increase. As a result, the final average node utility will increase.

From Figure 7b,c, when the total number of nodes increases and the total number of messages remains unchanged, the utility of the average node will eventually decrease. This is because when the total number of messages remains unchanged and the number of nodes increases, the average number of messages faced by each node will decrease, and the average number of messages completed by each node will also decrease. Therefore, the utility of the final average node is reduced. By observing Figures 6 and 7a,c,d, the same situation as discussed above can be found. From Figure 7, it is easy to find that the average node utility of the LAIM is 34.35% higher than that of COMES and IMCS.
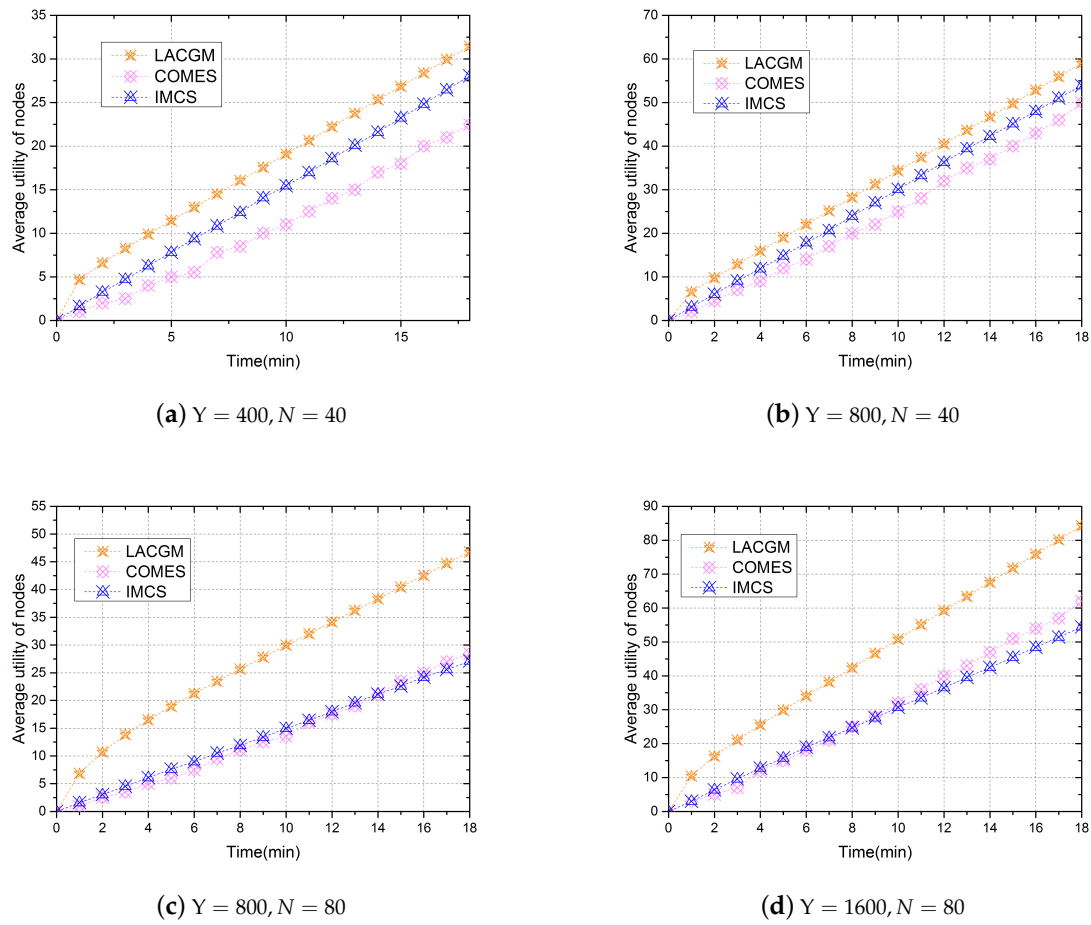
(a) $Y = 400, N = 40$

(b) $Y = 800, N = 40$

(c) $Y = 800, N = 80$

(d) $Y = 1600, N = 80$

Figure 7. Average node utility changes with the number of messages and nodes.

4.3.2. Utility of Average Node

The proportion of nodes acquiring utility refers to the proportion of the nodes that have acquired utility among the total number of nodes. The higher the proportion, the more nodes that have participated in cooperation in the system will be, and otherwise, the fewer nodes that have participated in cooperation in the system will be. First, this part needs to compare the proportion of nodes acquiring utility in the LAIM and COMES.

As is shown in Figure 8, with the increase of time, the node proportion of the LAIM, COMES, and IMCS also increases. This is because more and more nodes that have not participated in the cooperation participate in the cooperation over the time. At the same time, the node proportion increases rapidly before 8 min. However, the growth is slower, because if there are n nodes in the network, the nodes randomly send messages to each other, and the messages are sent from the source node to the destination node through one or more relay nodes. Suppose m nodes are participating in the message cooperation transmission after the $(i)^{th}$ random interaction; the proportion of nodes that do not get utility after the interaction is $(n - m)/N$. When the $(i + 1)^{th}$ interaction starts, if the value is higher, then the proportion of nodes having participated in the $(i + 1)^{th}$ cooperation will be higherand that of the nodes having not participated in any cooperation will hence be smaller. Therefore, the proportion of nodes acquiring utility in the latter half will grow slower than that in the previous half. It can also be seen from the figure that the proportion of nodes acquiring utility in the LAIM is higher than that in COMES and in IMCS since the loss aversion of the nodes is considered. As nodes are more likely to achieve cooperation behaviors in the LAIM, the proportion of nodes in the LAIM will be higher. It can be found

that the gap in the average proportion of nodes acquiring utility among the LAIM, COMES, and IMCS is stable over time. The gap is within the interval [0.0409%, 0.0567%], with the average of 0.05409%.
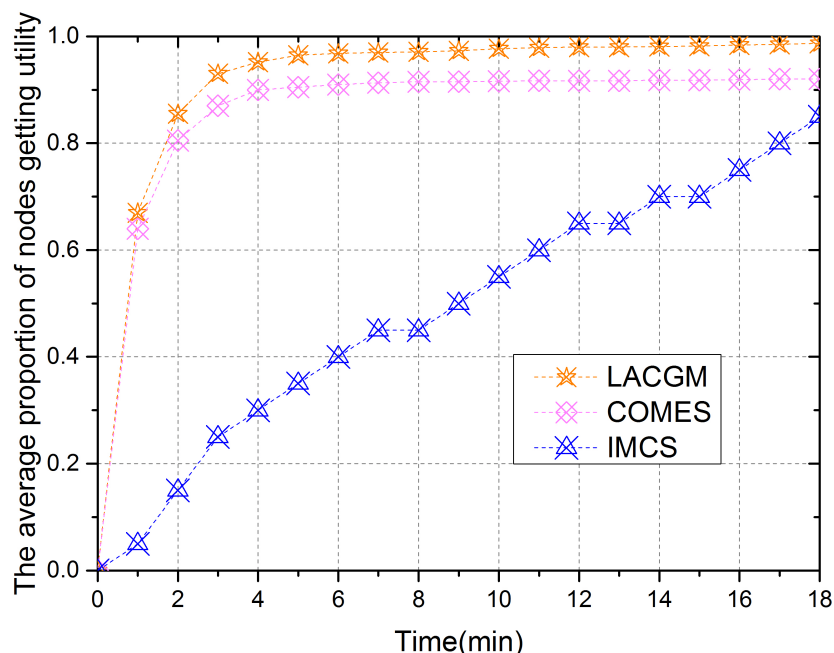

Figure 8. Average node utility changing with time ($Y = 400, N = 20$).

Figure 9 describes the relationship between the proportion of nodes and the number of messages and nodes. When the number of nodes and the number of messages have different values, the proportion of nodes in the LAIM and COMES will increase with time, and the proportion of nodes in the LAIM will be higher than that of COMES and IMCS. At the same time, it can be seen from Figure 9a,b that when the number of nodes remains the same and the number of messages increases, the proportion of nodes with utility will increase at the same time. This is because when the number of nodes remains the same, the increase of the number of messages will accordingly increase the average number of messages. Then, nodes without utility have a higher probability of getting utility by participating in cooperation. As a result, the proportion of nodes acquiring utility will increase. From Figure 9b,c, when the total number of nodes increases while the total number of messages remains unchanged, the proportion of nodes acquiring utility will eventually decrease, because when the total number of messages remains unchanged and the number of nodes increases, the average number of messages faced by each node decreases. Therefore, the probability of acquiring utility by participating in cooperation without acquiring utility will be also reduced. As a result, the proportion of nodes getting utility will be reduced. By observing Figures 8 and 9a,c,d, the same situation can be found as the discussion above.
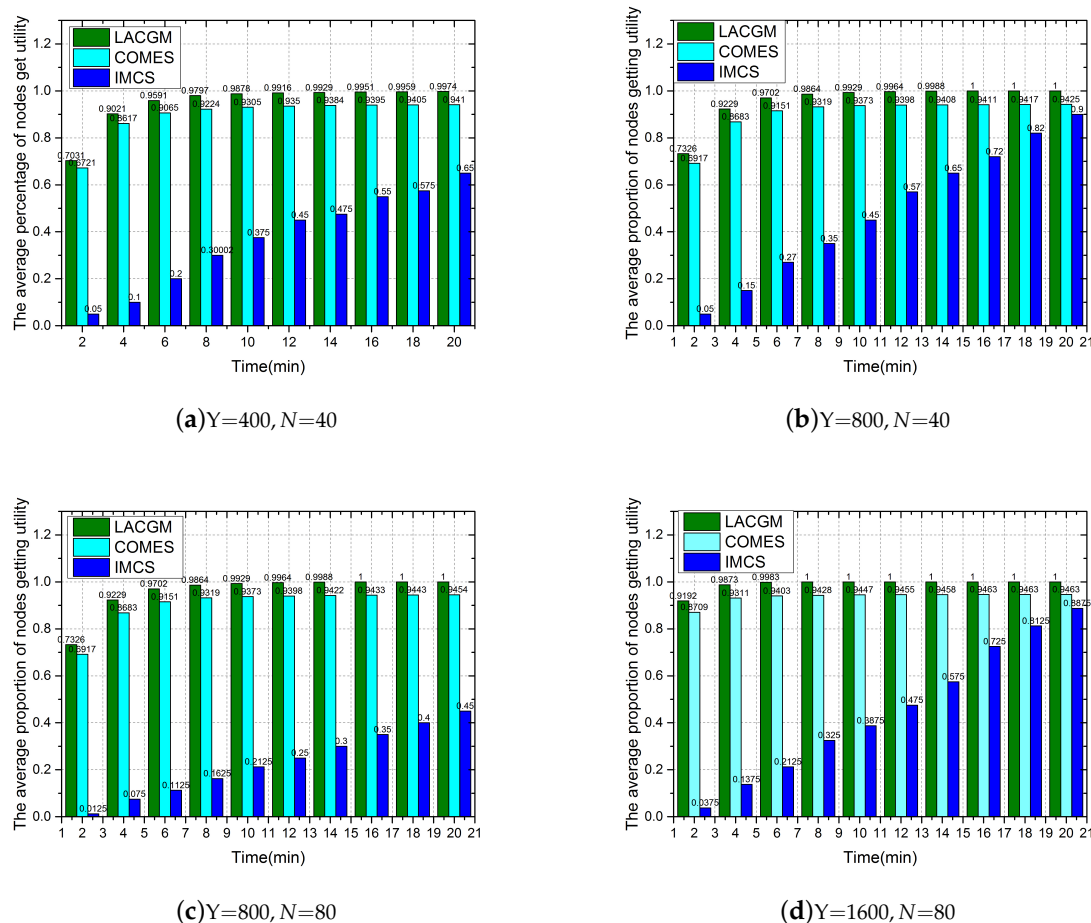
(**a**)Y=400,N=40

(**b**)Y=800,N=40

(**c**)Y=800,N=80

(**d**)Y=1600,N=80

Figure 9. Proportion of nodes acquiring utility vs. the number of messages and nodes.

5. Conclusions

Inspired by the marketing strategy of Amazon's online bookstore, a new incentive mechanism considering loss aversion called the LAIM is constructed. By introducing loss aversion, the incentive threshold and the threshold factor are proposed based on the number of messages faced by the node. According to the cost of the message transmission, the utility function of the node is reconstructed. Based on the reconstructed utility function, the decision-making model of the node is designed by using the coalition formation game as an analysis tool to promote nodes to form coalitions. Through the simulation analysis, we find that the LAIM mechanism can play a role when the vehicle node participates in the transmission of the first message. Considering that the time of meeting among vehicles is short and limited, the LAIM mechanism can play an active role in reality. Moreover, when the vehicle is in operation, the speed, direction, and position of the vehicle nodes change, and the vehicle nodes will frequently be in different coalition ranges. Therefore, the strategy of changing the coalition proposed in this paper can effectively improve the effectiveness of vehicle nodes.

Simulation results show that the LAIM has a higher node utility and cooperation rate than the traditional VANETs cooperation guarantee mechanisms COMES and IMCS, which is based on the cooperation formation game.

In this paper, we focus more on the utility of vehicle nodes, and we encourage participants to cooperate based on this. Future research will be carried out to consider the impact of throughput and other related factors of VANETs.

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