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***Abstract*—In this article we study the use of the Support Vector Machine technique to estimate the probability of the reception of a given transmission in a Vehicular Ad hoc NETwork (VANET). The transmission takes place between a vehicle and a RoadSide Unit (RSU) at a given distance and with a given transmission rate. The RSU computes the statistics of the receptions and is able to compute the percentage of successful transmissions versus the distance between the vehicle and the RSU and the transmission rate. Starting from this statistic, a Support Vector Machine (SVM) scheme can produce a model. Then, given a transmission rate and a distance between the vehicle and the RSU, the SVM technique can estimate the probability of a succcessful reception. This probability can be used to build an adaptive technique which optimizes the expected throughput between the vehicle and the RSU. Instead of using transmission values of a real experiment, we use the results of an analytical model of CSMA that is customized for 1D VANETs. The model we adopt to perform this task uses a Matern selection process to mimic the transmission in a CSMA IEEE 802.11p VANET. With this model we obtain a closed formula for the probability of successful transmissions. Thus with these results we can train an SVM model and predict other values for other couples : distance, transmission rate. The numerical results we obtain show that SVM seems very suitable to predict the reception probability in a VANET.**

## I. Introduction

Recently, great progress in wireless transmission technology has paved the way to large networks with massive transmission patterns. Such networks can be Wireless Sensor Networks (WSNs) or Vehicular Ad hoc NETworks (VANETs). VANETs are considered to be one of the main tools to help reduce traffic accidents and fatalities. In these networks, vehicles exchange pakets between themselves but also can sent packets to RoadSide Units (RSUs) or receive packets from them.

VANETs can produce a huge volume of data which can be exchanged and aggregated. VANETs are thus conducive to the use of Machine-Learning techniques, which aim at various goals. Machine-learning is used for vehicular networks in the following areas:

- Positioning : The information received or sent by the vehicles in Vehicular Ad-hoc NETworks can be used to establish their positions. Such a situation is ideal for the application of the machine-learning approach [1], [2]. In vehicles, there are many sources of information such as GPS, map analysis, radar, lidar, etc. A huge volume of data can be collected, analyzed and shared by the vehicles and the RoadSide Units (RSUs);
- Automatic Incident Detection (AID) can be performed by Machine-learning algorithms. The Support Vector Machine technique has been used in recent studies, such as [3], [4]. Older studies such as [5], [6] use Neural Networks and Fuzzy logic. A Wavelet scheme is used for AID in [7].
- Machine-learning algorithm can analyze vehicle trajectories in order to predict dangerous situations and warn drivers if such situations are detected;
- Routing in VANETs can benefit from Machine-learning; examples of such a use are given in [8], [9], [10];
- Security in VANETs : Machine-learning has been proposed to improve security in VANETs. The collection of packets sent in VANETs can be used to find compromised vehicles which do not perform suitable actions such as relaying when it is appropriate or sending forged messages over the network. We find such a use of machine-learning in [11], [12], [13],

In the first areas the machine-learning schemes offer other services in addition to those that help the functioning of the VANETs, whereas in the last areas the machine-learning techniques are used solely to help the functioning of the VANETs.

In this paper we study how machine-learning can be used to predict the transmission performances within the VANETs. More specifically we aim at computing the probability of the successful reception of a transmission between a vehicle and a Roadside Unit located at a given and known position and with a given transmission rate[1]. This is very important since the performance of the transmission is a key parameter for the safety applications which use transmissions of packets; tuning the transmission of safety messages is crucial to optimize their efficiency. In Europe, ETSI standards define two safety messages for VANETs: Car Awareness Messages (CAMs) and Decentralized Emergency Notification Messages (DENMs). DENMs are sent in broadcast and generally relayed (in multihop mode) to warn vehicles of hazards. Each vehicle sends CAMs to neighboring vehicles; for a given vehicle, these messages contain its position (obtained by GPS) and speed. RoadSide Units can easily compute the statistics of the transmission i.e. for a given location and a given transmission rate, the probability of success. This probability can be computed by averaging the number of successful receptions. These statics can be used by a Machine learning scheme which can produce a model used the RSU and also by the the vehicles themselves around the RSU.

Since it is very difficult to obtain real data in VANETs, for a first step we use an analytical model to compute the reception probability in a CSMA network and to build our database. The main mechanism for access in a VANET is the carrier Sense Multiple Access scheme (CSMA). The main idea is that before transmitting a packet a node (in our case a vehicle) senses the channel to determine whether there is already a transmission on the channel. We model the location of the vehicles as an homogeneous Poisson Point Process which eases the computation and has been proved a good assumption. To build the model of the simultaneously transmitting vehicles, we use the Matern selection process [14] which was first used in [15] to evaluate the pattern of simultaneous transmissions in CSMA. The model of [15] was improved by [16], [17], which is the model that is used and extended in this paper. Our analytical model allows us to build a database which provides for a given position the probability of successful reception. We then use the Support Vector Machine (SVM) scheme to build a model. Finally we use this model to predict the probability of successful transmission given the position of the vehicle. SVM has been selected as machine learning since it is a widespread technique but other techniques would have be possible as discussed in the conclusion.

The remainder of this paper is organized as follows. Section II describes the model we propose to study CSMA and develops the corresponding analytical model. Section III is a brief description of the Support Vector Machine technique. The prediction results obtained with SVM are reported in Section IV. Finally Section V concludes the paper.

## II. System model for the VANET performance

### A. Network nodes

The nodes are randomly deployed according to a Poisson Point Process $\Phi$. We denote by $\lambda$ the intensity of the process. In this paper we consider a 2D infinite plan, $\mathcal{S} = \mathbb{R}^2$ or a 1D infinite line, $\mathcal{S} = \mathbb{R}$. The 2D model is for Mobile Ad-hoc NETworks (MANETs) or Wireless Sensor Networks (WSNs). The 1D model is more relevant to Vehicular Ad-hoc NETworks (VANETs).

### B. Propagation law, fading and capture model

We suppose that the signal received in a transmission is the result of a random fading F and a power-law in the distance decay $1/r^{\beta}$ where $\beta$ is the decay factor and is generally between 3 and 6. In our study, the fading will be Rayleigh i.e exponentially distributed with parameter $\mu$ and thus is of mean $1/\mu$. Thus the signal received when the transmitter and the receiver are at distance $r$ from each other is $F/l(r)^2$ with $l(r) = r^{\beta}$.

We use the well-accepted SIR[3] (Signal over Interference Ratio) with a capture threshold $T$.

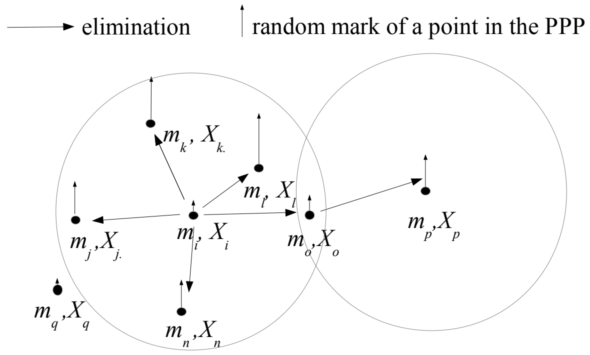


Fig. II.1. Matern CSMA selection process and an example of over-elimination.

### C. Model for CSMA

Using the model developed in [16], we adopt a Matern selection process to mimic the CSMA selection process. The points $X_i$ in $\Phi$ receive a random mark $m_i$. We also call $F_{i,j}$ the fading for the transmission between $X_i$ and $X_j$ . The idea of the Matern selection is to select the points $X_i$ with the smallest random marks $m_i$ in their neighborhood. To define the neighborhood of a point $X_i$ we need to introduce the carrier sense threshold $P_{cs}$ which is the power threshold under which the channel is considered as busy. We define $\mathcal{V}(X_i) = \{X_j \in X_i \; F_{i,j}/l(|X_i - X_j|) > P_{cs}\}$ the neighborhood of $X_i$. $X_i$ will be selected in the Matern selection process if and only if $\forall X_j \in \mathcal{V}(X_i) \; m_i < m_j$. In other words, this means that $X_i$ has the smallest mark $m_i$ in its neighborhood. The Matern selection is illustrated in Figure II.1. Node $i$ has the smallest mark $m_i$ within its neighborhood. Although node $q$ does in fact have a smaller mark, it is not within node $i$'s neighborhood. We should point out that, for the sake of simplicity, here we

[1]This can be used also to compute the probability of the successful reception of a transmission between two vehicles.

[2]The power received $P = \frac{P_0 F}{l(r)}$ and we set $P_0 = 1$

[3]We omit the thermal noise but it could be easily added, as is explained below.

have not taken into account any Rayleigh fading ($F \equiv 1$) and thus the neighborhood of node $i$ is a disc.

The technique based on marks used by the Matern selection process results in an over-elimination of nodes. When a node is eliminated by a node with a smaller mark, the node which has the smallest back-off in its neighborhood can start transmitting. The nodes which have been eliminated should not further eliminate other nodes. But this over-elimination can occur, as shown in Figure II.1. Node $o$ is eliminated by node $i$, but node $o$ eliminates node $p$ in the Matern selection process, whereas in a CSMA system, node $o$ is correctly eliminated by node $i$, but, being eliminated, node $o$ can not eliminate another node. We do not take this case into account in our model.

We note the medium access indicator of node $X_i$ $e_i = \mathbb{I}(\forall X_j \in \mathcal{V}(X_i) \;\; m_i < m_j)$

**Proposition II.1.** *The mean number of neighbors of a node is:*

$$\mathcal{N} = \lambda \int_{\mathcal{S}} P\{F \geqslant P_{cs} l(|x|)\} dx.$$

*In a 2D network we have :*

$$\mathcal{N} = \frac{2\pi\lambda\Gamma(2/\beta)}{\beta(P_{cs}\mu)^{2/\beta}}.$$

*In a 1D network we have :*

$$\mathcal{N} = \frac{2\lambda\Gamma(1/\beta)}{\beta(P_{cs}\mu)^{1/\beta}}.$$

This result is very simple. Let $F_j^0$ be the fading between the node at the origin $X_i$ and node $X_j$

This is just the application of Slivnyak's theorem and Campbell's formula, see [18], [16]

$$\begin{aligned} \mathcal{N} = & \quad E^0\Big[\sum_{X_j \in \phi} \mathbb{I}(F_j^0 l(|X_j - X_i|) \geqslant P_{cs}\Big] \\ = & \quad \lambda \int_{\mathcal{S}} P\{F \geqslant P_{cs} l(|x|)\} dx \end{aligned}$$

A straightforward computation provides the explicit value of $\mathcal{N}$ in the 1D and 2D cases.

**Proposition II.2.** *The probability $p$ that a given node $X_0$ transmits i.e. $e_0 = 1$ is:*

$$p = \mathbf{E}^0[e_0] = \frac{1 - e^{-\mathcal{N}}}{\mathcal{N}}.$$

**Proof.** The proof is obtained by computing the probability that a given node $X_0$ at the origin with a mark $m = t$ is allowed to transmit. The result is then obtained by deconditioning on $t$. The details of the proof can be found in [16]. ■

Thus $p$ measures the probability of transmission in a CSMA network. If $p$ is close to 1 this means that the carrier sense does not restrain transmissions. In contrast, if $p$ is small, this means that the carrier sense imposes a severe restriction on transmissions.

**Proposition II.3.** *The probability that $X_0$ transmits given that there is another node $X_j \in \Phi$ at distance $r$ is $p_r$ with*

$$p_r = p - e^{-P_{cs}\mu l(r)}\Big(\frac{1 - e^{-\mathcal{N}}}{\mathcal{N}^2} - \frac{e^{-\mathcal{N}}}{\mathcal{N}}\Big)$$

**Proof.** The proof is the same as that of Proposition II.2. ■

**Proposition II.4.** *Let us suppose that $X_1$ and $X_2$ are two points in $\Phi$ such that $|X_1 - X_2| = r$. We suppose that node $X_2$ is retained by the selection process. The probability that $X_1$ is also retained is:*

$$h(r) = \frac{\frac{2}{b(r)-\mathcal{N}}\big(\frac{1-e^{-\mathcal{N}}}{\mathcal{N}} - \frac{1-e^{-b(r)}}{b(r)}\big)(1 - e^{-P_{cs}\mu l(r)})}{\frac{1-e^{-\mathcal{N}}}{\mathcal{N}} - e^{-P_{cs}\mu l(r)}\big(\frac{1-e^{-\mathcal{N}}}{\mathcal{N}^2} - \frac{e^{-\mathcal{N}}}{\mathcal{N}}\big)}$$

*with*

$$b(r) = 2\mathcal{N} - \lambda \int_{\mathcal{S}} e^{-P_{cs}\mu(l(|x|)+l(|r-x|)} dx.$$

*In a 2D network, we have:*

$$b(r) = 2\mathcal{N} - \lambda \int_0^\infty \int_0^{2\pi} e^{-P_{cs}\mu(l(\tau)+l(\sqrt{\tau^2+r^2-2r\tau cos(\theta)}))} d\tau d\theta.$$

*In a 1D network, we have:*

$$b(r) = 2\mathcal{N} - \lambda \int_{-\infty}^{\infty} e^{-P_{cs}\mu(l(\tau)+l(|r-\tau|))} d\tau$$

**Proof.** The proof can be found in [16] ■

**Proposition II.5.** *Given the transmission of a packet, we denote by $p_c(r, P_{cs})$ the probability of successfully receiving this packet at distance $r$ in a CSMA system (modeled by a Matern selection process with a carrier sense threshold $P_{cs}$) and with a capture threshold $T$. We have:*

$$p_c(r, T, P_{cs}) \simeq \exp\Big(-\lambda \int_{\mathcal{S}} \frac{h(|x|)}{1 + \frac{l(|x-r|)}{Tl(r)}} dx\Big)$$

*In a 2D network, we have:*

$$p_c(r, T, P_{cs}) \simeq \exp\Big(-\lambda \int_0^\infty \int_0^{2\pi} \frac{\tau h(\tau)}{1 + \frac{l(\sqrt{\tau^2+r^2-2r\tau cos(\theta)})}{Tl(r)}} d\tau d\theta\Big)$$

*In a 1D network, we have:*

$$p_c(r, T, P_{cs}) \simeq \exp\Big(-\lambda \int_{-\infty}^{\infty} \frac{h(\tau)}{1 + \frac{l(|r-\tau|)}{Tl(r)}} d\tau\Big)$$

**Proof.** The idea of the proof is to consider a transmitter at the origin and to compute the probability of successful reception by a receiver at distance $r$. To do so, we condition by the presence of another transmitting node at distance $\tau$. According to proposition II.4, the density of such nodes is $\lambda h(\tau)$. We approximate the interference by the interference of a Poisson

Process of density $\lambda h(\tau)$. The result is obtained by integrating on $\tau$. The details of the proof can be found in [16]. ■

It is easy to add a thermal noise $W$ to the model. The expression of $p_c(r, P_{cs})$ must then be multiplied by $\mathcal{L}_W(\mu T l(r))$ where $\mathcal{L}_W(.)$ is the Laplace Transform of the noise.

## III. The Support Vector Machine Technique

The idea is to use the Support Vector Machine technique to compute the reception probability of $p_i$ versus $x_i = (r_i, T_i)$. In the first step we assume that we know the $p_i$ and the related value $x_i$ (thus we know $(p_i)_{1\leqslant i\leqslant N}$ and $(r_i, T_i)_{1\leqslant i\leqslant N}$) and we have to predict the reception probability using other values: $(p'_i)_{1\leqslant i\leqslant N}$ knowing $(r'_i, T'_i)_{1\leqslant i\leqslant N}$. We assume that

$$p_i = w^T\phi(x_i) + b \tag{III.1}$$

where $w$ and $b$ are two unknown vectors and $\phi(x)$ an unknown function of a vector $x$.

To solve these equations, we introduce the following convex optimization problem:

$$\text{minimize} \quad \frac{1}{2}||w||^2$$

$$\text{subject to } -\epsilon \leqslant w^T\phi(x_i) + b \leqslant \epsilon. \tag{III.2}$$

This problem assumes that the function given in III.1 can approximate the set of points that is given *i.e* $(p_i, T_i)_{1\leqslant i\leqslant N}$ with an accuracy of $\epsilon$. Sometimes this is not possible and some errors must be accepted. In this case, slack variables, which allow us to cope with impossible constraints, are introduced. This relaxation procedure uses a cost function. The convex problem then becomes :

$$\text{minimize} \quad \frac{1}{2}||w||^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*)$$

$$\text{subject to } -\epsilon - \xi_i^* \leqslant w^T\phi(x_i) + b \leqslant \epsilon + \xi_i \ \ with \ \ \xi_i^*, \xi_i > 0 \tag{III.3}$$

This problem can be solved by using Lagrange multipliers. The problem becomes:

$$\begin{aligned} L: \ &= \ \frac{1}{2}||w||^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) - \sum_{i=1}^{N}(\nu_i\xi_i + \nu_i^*\xi_i^*) \\ &- \ \sum_{i=1}^{N}\alpha_i(\epsilon + \xi_i - p_i + w^T\phi(x_i) + b) \\ &- \ \sum_{i=1}^{N}\alpha_i^*(\epsilon + \xi_i^* + p_i - w^T\phi(x_i) - b) \end{aligned}$$

where $L$ is the Lagrangian and $\nu_i, \nu_i^*, \xi_i^*, \xi_i^*$ are the Lagrangian multipliers which are thus positive *i.e* $\nu_i, \nu_i^*, \xi_i^*, \xi_i^* > 0$

We know that the minimum of $L$ is attained when the partial derivatives are zero, thus:

$$\partial L/\partial b = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0$$

$$\partial L/\partial w = w - \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\phi(x_i) = 0$$

$$\partial L/\partial \xi_i^{(*)} = C - \alpha_i^{(*)} - \nu_i^{(*)} = 0$$

The substitution of these equations in the Lagrangian leads to the following problem:

$$\begin{aligned} maximize \ &- \ \frac{1}{2}\sum_{i,j=1}^{N}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\phi(x_i)^T\phi(x_j) \\ &- \ \epsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{N}y_i(\alpha_i - \alpha_i^*) \end{aligned}$$

subject to

$$\sum_{i,j=1}^{N}(\alpha_i - \alpha_i^*) = 0 \text{ and } \alpha_i, \alpha_i^* \in [0, C].$$

Thus it follows that:

$$w = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\phi(x_i)$$

and

$$p_i(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\phi(x_i)^T\phi(x) + b$$

This formula is called the Support Vector expansion. The complexity of the function representation only depends on the dimensionality of the input space.

The next step of the analysis uses the Karush-Kuhn-Tucker (KKT) conditions. These conditions imply that at the solution the product between the constraints and the dual variable must vanish. In other words, we have

$$\begin{aligned} \alpha_i(\epsilon + \xi_i - p_i + w^T\phi(x_i) + b) = 0 \\ \alpha_i^*(\epsilon + \xi_i^* + p_i - w^T\phi(x_i) - b) = 0 \end{aligned} \tag{III.4}$$

and

$$\begin{aligned} (C - \alpha_i)\xi_i = 0 \\ (C - \alpha_i^*)\xi_i^* = 0 \end{aligned}$$

We can deduce that only the samples which do not satisfy the constraint of III.3 have $\alpha_i^{(*)} = C$. Moreover, since the two values of the right part of III.4 can not be simultaneously 0 then we have $\alpha_i \alpha_i^* = 0$. Thus after some observations we have :

$$\max(-\epsilon + p_i - w^T \phi(x_i) | \alpha_i < C \text{ or } \alpha_i^* > 0) \leqslant b \leqslant \min(-\epsilon + p_i - w^T \phi(x_i) | \alpha_i < C \text{ or } \alpha_i^* > 0)$$

This part is adapted from [11] a tutorial by Smola.

## IV. Numerical Results

In this part we use the results of Section II to build the database with which we train the SVM model as defined in Section III.

For the radio model we use a Rayleigh fading with $\mu = 10$ and a density of vehicles $\lambda = 0.02$ vehicles per meter. We assume that $\beta = 4$ and we use the 1D model, which is more suitable for VANETs than the 2D model.

The database is built as follows: $r$ varies from $10m$ to $250m$ by steps of $10m$ and we vary $T$ from 1 to 10 by step of 0.2. For each of these couples $(r, T)$ we use the analytical model to compute the probability $p$ of successful reception. We also assume that $P_{cs} = 4.5e^{-10}$ which is approximately the value that optimizes the density of successful transmission for $r = 50m$ and for $T = 10$.

### A. Results with no errors in the database

The database is built as described above. Initially we do not include any errors in the measurement of the probability of successful transmission given by the analytical model. For the Support Vector Machine algorithm we use the libsvm program in regression mode with the option:

'-s 3 -c 10 -p 0.00000001 -e 0.000000001'

to build the SVM model. Thus the kernel used is an exponential kernel. In Figures IV.1 and IV.2, we present the probability of successful reception versus $T$ for respectively $r = 75m$ and $r = 125m$. The results compare the prediction of the SVM algorithm with the results of the analytical model. We observe a perfect matching between the two approaches. Thus we can foresee that SVM (with an exponential kernel) is very suitable to predict the probability of successful transmission in a VANET using RSUs and a CSMA-based access scheme.

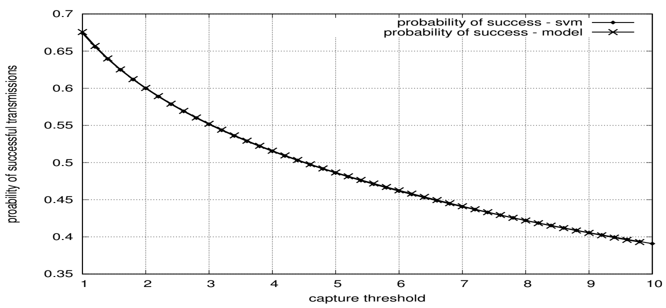


Fig. IV.1. Probability of successful reception versus $T$ ($x$= 75m , $\mu = 10$, $\beta = 4$).

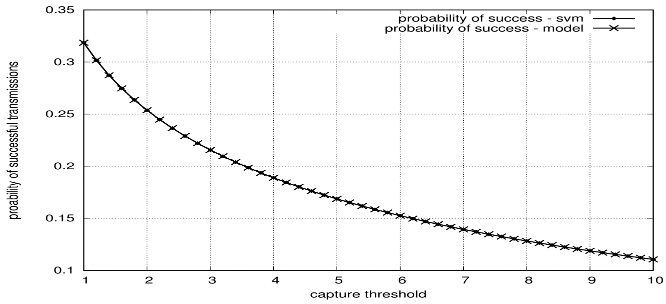


Fig. IV.2. Probability of successful reception versus $T$ ($x$= 125m , $\mu = 10$, $\beta = 4$).

### B. Results with errors in the database

We suppose that the database includes errors in the measurements. We assume that the values in the database are the real values multiplied by $(1 + N(0, 0.05))$ where $N(0, 0.05)$ is the normal random variable of mean 0 and variance 0.05.

Here again the prediction by the SVM model is very good. Even with noise measurements, SVM remains very good at predicting the transmission probability in VANETs using an access protocol based on CSMA.

In Figures IV.3 and IV.4, we present the probability of successful reception versus $T$ for respectively $r = 75m$ and $r = 125m$ with these assumptions and we can compare the prediction of the SVM model with the direct analytical model.

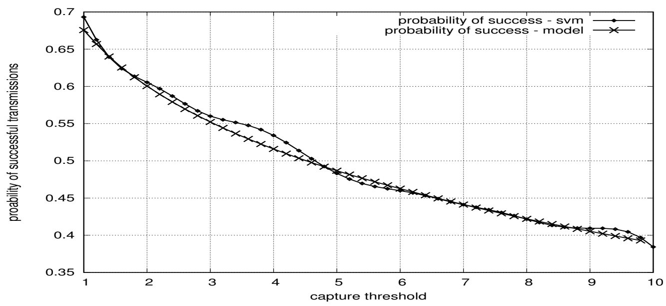


Fig. IV.3. Probability of successful reception versus $T$ with error in the database ($x$= 75m , $\mu = 10$, $\beta = 4$).

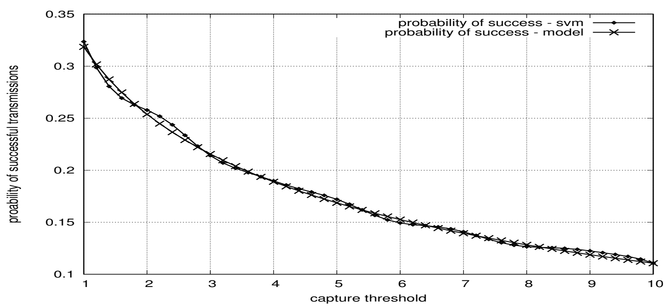


Fig. IV.4. Probability of successful reception versus $T$ with error in the database ($x$= 125m , $\mu = 10$, $\beta = 4$).

### C. Optimal data rate with SVM

Here, the idea is to use the prediction of SVM to predict the transmission probability. Then it is possible for a vehicle to compute the expected throughput : $Wp_c(r, T, P_{cs})$ versus the capture threshold used $T$ and to choose the best transmission rate $W$ corresponding to a given value of $T$. We assume a throughput of $W = 6Mbits/s$ with $T = 1$ , a throughput of $W = 9Mbits/s$ with $T = 4.65$ and a throughput of $W = 12Mbits/s$ with $T = 7$. These values of $T$ are compatible with the Shannon law $W = k\log_2(1 + T)$.

In Figure IV.5 we have shown the optimal data-rate algorithm which optimizes the expected throughput. We observe that up to $154m$ the best data-rate is $12Mbits/s$ and then we have to use the lowest data rate of $6Mbits/s$.

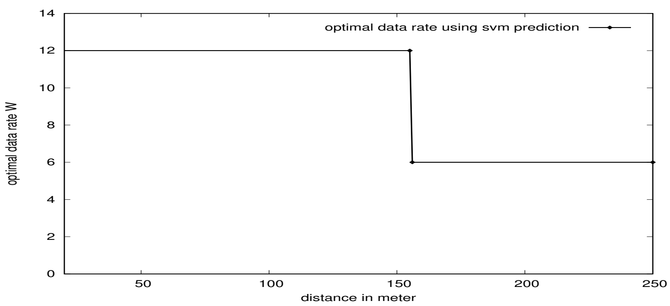


Fig. IV.5. Optimal data rate versus distance vehicle-RSU, $\mu = 10$, $\beta = 4$).

## V. Conclusion

In this paper we use SVM to predict the probability of successful transmissions in a VANET using a CSMA access scheme such as IEEE 802.11p. The prediction of the SVM technique is excellent when we use a data base built with an analytical model. We observe that even with errors the prediction of the SVM technique very good. The SVM technique can be used to build a dynamic rate control algorithm which optimizes the VANET average throughput. Although this initial study is very encouraging further investigations such as introducing more errors, changing the fading law, using real figures for the database etc. should be carried out to confirm our first results. Moreover other machine learning techniques such as Random Forest, K Nearest Neighbor (KNN), etc. could be used to optimize the transmission in VANETs. We think that similar good results would be obtained. This study and a careful comparison of these techniques is left as future work.

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