Mobility Prediction and Resources Reservation in WLAN Networks Under a 2D Mobility Model

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***Abstract*—This papers presents a 2D reservation scheme in WLAN environment. A two-dimensional wireless mobility model called Smooth Random Mobility Model (SRMM) has been considered, because it makes the movement of users smoother and more realistic than well-known in literature random mobility models. A general prediction technique based both on the analysis of Cell Stay Time and on the direction probabilities of hand-in and hand-out events of mobile nodes from wireless cells is outlined. Three different reservation policies are considered: the first scheme reserves a fixed number of cells for each hand-off; the second one permits to reserve on a greater number of cells in the first hand-off and a lower number of cells in the next hand-off events; the last policy uses an increasing adaptive reservation scheme, trying to take advantage of the lower prediction error for the first hand-off and the greater prediction error for the next hand-off. Many simulations have been carried out and a comparison between the three reservation schemes has been performed.**

***Index Terms*—MRSVP, WLAN, MIP, Smooth Random Mobility Model, Predictive Reservation.**

I. INTRODUCTION

This work is based on a wirelessLAN 802.11 scenario, where MIP users [1,4,7] make service requests to the access points, requiring some QoS guarantees, like low delay-jitter or low call dropping probability during hand-off events; the only way to avoid service degradations or disruptions during a mobile session is to make in-advance reservations (i.e. passive reservations) [1,4], having some information about users mobility behavior [2,3,7].

We employed the Smooth Random Mobility Model (SRMM) proposed in [3] for a two-dimensional set of cell clusters; this model makes users' movements smoother and more realistic than previous random models, because it relates speed and direction changes. The proposed technique is of general application and does not depend on the specific mobility model; it is based on the knowledge of two important statistics: Cell Stay Time (CST) distribution and Hand-off Directions Probabilities values (HDP); in [7] it is shown that the CST random variable, under the SRMM, follows a Gaussian trend, depending on the preferred speeds of users; in addition to the CST statistic, HDP values are necessary in order to consider future positions of mobile hosts; so, combining CST and HDP info, a prediction technique is proposed for a two-dimensional environment. Generally, a wireless LAN coverage area has a circular shape and, without loss of generality, in this work it has been approximated with a hexagonal coverage, only because we considered six possible hand-off directions. This paper is organized as follows: section II presents the Mobile RSVP protocol, applied in our work to make passive reservations and the SRMM, used as reference for hosts' movements; the prediction and regression analysis of CST and mobility directions probabilities are presented in section III; the tree reservation policies for the WLAN network are introduced in section IV; finally, simulation results and conclusions are respectively summarized in sections V and VI.

II. MOBILE RSVP PROTOCOL AND SRMM

In order to handle users' mobility and to offer guaranteed services (independent from mobility) the ReSerVation Protocol [9] has been extended, with the MRSVP [1]; in this way, hand-off events can be managed in an adequate manner and mobile users can make reservation requests over more than one cell, by their proxy agents: there are local proxy agents (which handle the active reservations) and remote proxy agents (which deal with passive reservations). An active reservation is made by a user only on the current access point (for *Mobility Dependent Predictive* class, as we see later), while passive reservations are made only on the remote cells that the user will visit during its connection (users belonging to *Mobility Independent Predictive* class request passive reservations). A MRSVP connection starts with a proxy-discovery protocol phase, with which the user can discover the addresses of its remote agents; then a resource request can be made. After the proxy addresses are discovered, users send active_RESV messages to their local access points and passive_RESV messages to their remote access points, so the system must effect an admission control, in order to accept or refuse users' requests. When a user moves from a coverage area to another one, the hand-off event is managed by making a new request (MDP class) or by a reservation switch (MIP class): the reserved resources in the old access point are released in both cases and, if the user belongs to MIP class, the passive resources can be assigned by switching to an active reservation. For more details about MRSVP to see [1].

A. MIP and MDP Classes

In a real network, resources reservations can be made by protocols, in order to satisfy QoS requirements and to offer to mobile hosts a service "better than best-effort", accounting the inherent time varying environmental conditions, accentuated in radio communications (e.g. fading). In Integrated Service (IS) networks, each flow can receive different QoS, which must be negotiated at the beginning of sessions, between flows and network, by the RSVP protocol [9] or the MRSVP protocol, in mobile scenarios [1]. There are three provided service classes [1,4,8]: Mobility Independent Guaranteed (MIG, for hard and intolerant applications, that need absolute guarantees on packet delays), Mobility Independent Predictive (MIP, for tolerant real-time applications, that can suffer limited bounds on packet delays) and Mobility Dependent Predictive (MDP, for applications that can suffer continuous QoS degradations or connection droppings). In this paper, only MDP and MIP classes have been considered. MRSVP protocol is used for exchanging state information of wireless networks and it can offer soft QoS (adaptive QoS) for MIP and MDP services.

B. Smooth Random Mobility Model

The choice of a mobility model has an heavy impact on the obtained results, that can be unrealistic if the model is not appropriate. This work employs the Smooth Random Mobility Model (SRMM) proposed in [3] for a two-dimensional set of cell clusters; this model makes users' movements smoother and more realistic than previous random models, because it relates speed and direction changes; in addition it leads to a general set of analytical expressions, that can be used for different wireless scenarios. The main concepts of the SRMM are two stochastic processes for direction φ and speed v: their values are correlated to previous ones, in order to avoid unrealistic patterns and speed/direction changes; e.g. if a user is moving with high speed, a direction change cannot have high φ variations. Speed and direction changes follow two Poisson processes and different typical patterns or environments can be modeled by setting some parameters, like the preferred speeds set. This model is also based on a set of preferred speeds in the range $[v_{min}, v_{max}]$ and a mobile host moves with constant speed until a new target speed v^* is chosen by the stochastic process, so it accelerates/decelerates in order to reach v^*. The set of preferred speeds $\{v_{pref0}, v_{pref1}, \ldots, v_{prefn}\}$ is also defined in order to obtain a non-uniform speed distribution, with $p(v_{pref}) = p(v_{pref0}) + p(v_{pref1}) + \ldots + p(v_{prefn}) < 1$, $v_{pref0} < v_{pref1} < \ldots < v_{prefn}$ and v_{max} is a fixed threshold. Let t^* denote the time at which a speed change event occurs and a new target speed $v^* = v^*(t^*)$ is chosen; an acceleration $a(t^*) \neq 0$ is set (it is set to 0 only if $v^*(t^*) = v(t^*)$). Then, other two variables are used: a_{max} and a_{min}. The first one represents the maximum possible acceleration and the second one the maximum possible deceleration. In discrete instant times, the new speed $v(t)$ is changed, according to the uniformly accelerated motion, until $v(t)$ achieves $v^*(t)$. a_{max} and a_{min} values are fixed to the values specified in table III in the section V.

III. PREDICTIVE ESTIMATION OF CELL STAY TIME AND MOBILITY DIRECTIONS PROBABILITIES

The considered system consists of a certain number of two-dimensional wireless clusters, as illustrated in Fig.1.

As mentioned above, we used the SRMM and mobile hosts follow the stop-turn-and-go behavior with toroidal topology such as in [3], with two preferred speeds v_{pref0}=0 Km/h, $v_{pref1}=v_{max}$ Km/h; a Poisson call arrival time distribution with an exponentially distributed call holding time (CHT) has been considered and, in order to obtain the predictive evaluation of the number of effective visited cells *C*, that the mobile host will cross during its call, the Cell Stay Time of mobile hosts has been evaluated; simulations results have shown that the CST distribution can be well approached by a Gaussian distribution, for different values of v_{max} [7].

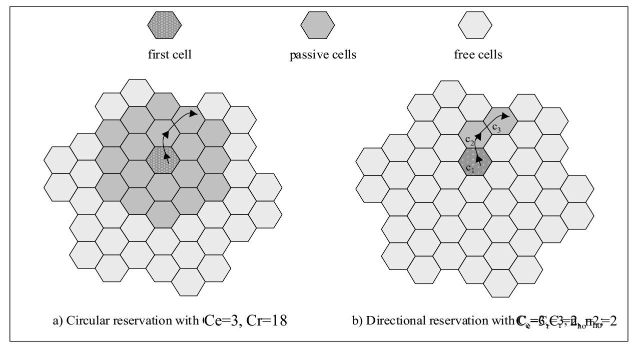

Fig.1 Simulated network topology with two types of pre-reservation policy: a) circular; b) directional.

Unfortunately, without directional information about user's mobility pattern, the predicted value of C_e can be only used to make passive reservations in a circular way, around the current cell (where the call has been admitted): following the same approach in [8], only the value of C_e can be a-priori obtained, so the number of required passive reservations C_r for MIP services increases with polynomial trend, such as follows

$$C_r = 3 \cdot C_e \cdot (C_e - 1) \tag{1}$$

as shown in table I. So, if the system has no knowledge about the possible mobile hosts directional movements, then there will be a lot of resources wastage, due to the enormous amount of passive pre-reserved bandwidth over C_r cells, which increases for longer calls or for higher values of v_{max}, for fixed values of CHT and v_{max} respectively.

If additional information about the directional behavior of users is employed, above problems can be avoided and the value of C_e can be decreased, making it near or equal to C_e. Directional info can be obtained as follows: referring to a generic coverage cell, for example with a hexagonal shape as shown in Fig.1, a finite set S_{ho} of K possible hand-off directions can be defined as S_{ho}={1, 2, 3, 4, 5, 6} (in this case, each direction univocally identifies the next adjacent coverage cell, K=6). With the CST evaluation model in [9], the value of C_e can be obtained for a generic MIP call c_{MIP}, so the predicted number of hand-off events for c_{MIP} is n_{ho}=C_e-1. The probability of hand-out on direction *y* an incoming MIP from direction *x* for a wireless cell *c* can be defined as $p_{x,y}$, where *x* is the hand-in direction, *y* is the hand-out direction and $x,y \in S_{ho}$:

$$p_{x,y} = p_{c_{MIP}}(x,y) = p(y \in S_{out}, t = t_0 + \mu_{CST} / x \in S_{in}, t = t_0) \quad (2)$$

where $S_{out} \subset S_{ho}$ is the set of hand-out events, $S_{in} \subset S_{ho}$ is the set of hand-in events, t_0 is the time instant in which the mobile host enters in a considered cell and μ_{CST} is the average value of the CST p.d.f..

For the first hand-off event, the hand-in direction *x* can be considered as the c_{MIP} call born-region, where born-regions are delimited by six equilateral triangles composing the hexagonal cell. So, for the first hand-off, the S_{in} set is substituted by the S_{born} one, where $S_{born}=\{r_1, r_2, r_3, r_4, r_5, r_6\}$. In this way, for the first hand-off event, expression (2) is rewritten as follows:

$$p_{r_{x,y}} = p_{c_{MIP}}(x,y) = p(y \in S_{out}, t = t_0 + \mu_{CST} / r_x \in S_{born}, t = t_0) \quad (3)$$

The values of *p(x,y)* can be resumed in a KxK matrix M, as shown in the next section (K =$|S_{ho}|$). As example, the probability to enter a cell from direction 6 and to go out to direction 3 is depicted in Fig.2. As it can be seen, if the user has a low probability of a direction change p_φ and a low probability of preferred speed v_0, there is a low standard deviation of the CST probability distribution and a high probability to go out to direction 3 from direction 6, that is to say the user moves like straight away; if only the probability of preferred speed v_0 is increased, the CST mean μ changes and the standard deviation σ increases, as consequence of the higher number of stops of the user; the probability $p_{6,3}$ remains high because of the low value of p_φ.

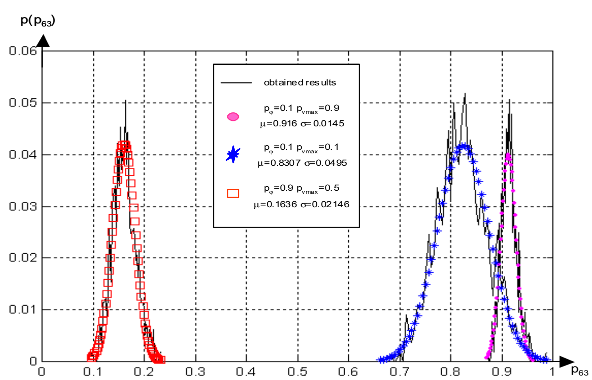

Fig.2 $p_{6 \to 3}$ in SRMM model with different direction probabilities and preferential speeds.

Table I shows the obtained values of the number of cells on which MIP users make passive requests with a CHT exponentially distributed (λ_{CHT}=180 seconds): C_r values are obtained through (1), following the same approach in [7], while $C_e(P)$ values are obtained following the approach proposed in the next section, for different reservation policies; however, it can be seen that there is a resource gain if directional info are introduced. The notation P(i-j-k) indicates that the reservation policy P makes passive reservations on *i* cells for first hand-off, *j* cells for second hand-off and *k* cells for third hand-off.

We obtained different values of μ and σ for the CST distribution, by assigning different discrete values to the probability of a direction change p_φ; the Kolmogorov-Smirnov (KS) test [10] has been employed to evaluate the correctness of a Gaussian approximation of the CST distributions under the SRMM; table II summarizes the obtained *p*-values for different values of p_φ, with p_{v0}=0.4 and p_{vmax}=0.5 (for details about goodness-of-fit techniques to see [10]).

TABLE I
NUMBER OF CELLS INVOLVED IN THE BANDWIDTH RESERVATION PHASE, FOR DIFFERENT POLICIES P.

	P(1-1-1)		**P(1-2-3)**		**P(3-3-3)**	
	Ce(P)	Cr	Ce(P)	Cr	Ce(P)	Cr
p_{vmax} = 0.9, p_φ = 0.1 μ=29.26s, σ=0.45729s	5	60	22	60	52	60
p_{vmax} = 0.1, p_φ = 0.1 μ=62.22s σ=5.09547s	2	6	3	6	4	6
p_{vmax} = 0.9, p_φ = 0.5 μ=32.46s σ=8.18356s	4	36	16	36	21	36

Another similar KS-test has been carried out on the K^2 values of direction probabilities *p(x,y):* from different simulations runs, it resulted that *p(x,y)* values are also distributed with a Gaussian trend, so every element of the KxK matrix M can be represented by a mean and a standard deviation $\mu_{p(x,y)}$ and $\sigma_{p(x,y)}$, so the matrix M can be substituted by M_μ and M_σ.

TABLE II
VALUES OF μ AND σ OF CST DISTRIBUTIONS AND KS P-VALUES FOR DIFFERENT MOBILITY PARAMETERS.

p_φ	μ_{CST}	σ_{CST}	KS p-value
0.1	62.7861	1.4075	0.5305
0.3	63.8491	1.4487	0.5087
0.5	64.4721	1.5342	0.6712
0.7	64.5944	1.586	0.6147
0.9	64.6055	1.6792	0.4994

In order to obtain an analytical expression for CST mean μ_{CST} and standard deviation σ_{CST} in function of p_φ, a polynomial regression on the obtained discrete values has been carried out [11]; Fig.3 shows the polynomial approximation, while eq.4 and eq.5 are their analytical expressions (of 3rd and 1st order).

$$\mu_{CST}(p_\varphi)=2.9061 \cdot p_\varphi^3 - 8.9476 \cdot p_\varphi^2 + 8.5898 \cdot p_\varphi + 61.9867. \quad (4)$$

$$\sigma_{CST}(p_\varphi)= 0.3406 \cdot p_\varphi + 1.3595. \quad (5)$$

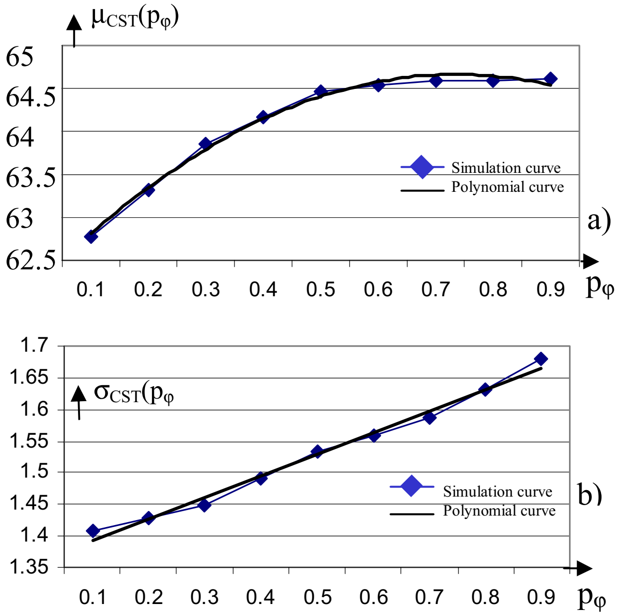

Fig.3. a) Polynomial regression approximations for CST mean ; b) Polinomial approximation for a CST standard deviation.

The expressions above come in handy for the resource allocation schemes introduced in the next section, because they give the values of μ_{CST} and σ_{CST} on a continuous space.

IV. Bandwidth Reservation Schemes

In order to avoid bandwidth wastage and low network utilization, adaptive bandwidth reservation schemes that select the right number of cells where to make passive reservations according to some parameters, such as maximum speed, average speed, CST and directionality, need to be deployed. Three schemes are considered in our scenario:

1) ***increasing-trend reservation***: users reserve on an increasing number of cells for increasing hand-off number (i<j<k);
2) ***decreasing-trend reservation***: users reserve on a decreasing number of cells for increasing hand-off number (i>j>k);
3) ***constant-trend reservation***: users reserve on the same number of cells for every hand-off number (i=j=k).

If no preferential directions are obtained from the input mobility parameters, pre-reserving over only one future cell can lead to high error in predicting next visited cells, as illustrated in next section. This problem can be solved by making next reservations not only over one next cell, but pre-reserving over multiple hand-out directions, so the values of i, j and k must be chosen in a right way. The directional probabilities matrix M is used to predict the next cell direction y: if the current hand-in direction is x, then $y=index\{max[M(x,y)]\}$, with $x,y \in S_{ho}$; this is repeated i, j, k times for 1st, 2nd and 3rd hand-off respectively; for every iteration, previous chosen values are not considered yet when picking up the current maximum.

V. Performances Evaluation

In our simulations, users can move among 7 clusters of 7 access points, as depicted in Fig.7. We assume a 2D toroidal topology and a single cell radius of 250 meters; users move accordingly to [3], with the following parameters listed in table III for an urban environment.

TABLE III
Simulation Parameters of the SRMM.

Number of preferred speeds	n_{pref}=2
Preferred speeds (m/s)	V_{pref0}=0; v_{pref1}=13.9;
Maximum acceleration (m/s^2)	a_{max}=+2.5
Minimum acceleration (m/s^2)	a_{min}=-4
Preferred speed probability p_v	p_{v0}=0.1; p_{v1}=0.8;
Direction change prob. p_φ	p_f=0.1;

In the simulated, each access point has a capacity of 11Mbps and users can receive discrete levels of bandwidth, from 512Kbps up to 896Kpbs, with 128Kbps of gap between two levels. Remember that there are no rules about choosing the value of K: simulations results shown that K=6 is a good trade-off between accuracy and computational complexity of the proposed algorithm; higher value of K makes better the approximation of the wireless cell coverage area.

Fig.4 shows the directional probabilities matrix M, expressed in terms on $\mu_{p(x,y)}$, $\sigma_{p(x,y)}$ as introduced in section III. It can be seen that on each row there are at least two or three higher values than other ones, so making reservation over only one next cell leads to high prediction errors as illustrated later.

0.0137, 0.0061	0.0244, 0.0128	0.2779 ,0.0429	0.3663, 0.0497	0.3034, 0.0476	0.0256, 0.0132
0.0325, 0.0166	0.0132, 0.0044	0.0399 ,0.0198	0.3700, 0.0525	0.5056, 0.0554	0.0549, 0.0251
0.3708, 0.0545	0.0430, 0.0203	0.0125 ,0.0030	0.0316, 0.0174	0.0521, 0.0227	0.5054, 0.0552
0.3692, 0.0462	0.2798, 0.0464	0.0249 ,0.0133	0.0129, 0.0060	0.0248, 0.0138	0.2994, 0.0461
0.3743, 0.0554	0.5094, 0.0581	0.0440 ,0.0210	0.0328, 0.0173	0.0127, 0.0031	0.0437, 0.0213
0.0318, 0.0170	0.0426, 0.0223	0.5094 ,0.0579	0.3769, 0.0556	0.0427, 0.0212	0.0145, 0.0071

Fig.4 Matrix M in terms of μ,σ for the parameters of table III.

Fig.5 shows the average number of admitted MIP flows versus the cell prediction sequence of second and third hand-off (j-k): as mentioned above, if the number of possibly visited cells increases, then the amount of passive and unused bandwidth is higher and there will be a lower number of MIP users that can be admitted into the system. The spikes for i-2-1 and i-3-1 sequences are due to the fact that for these particular sequences the number of predicted cells is lower than the previous ones: for example, if i=1, j=2 and k=1 there are n=9 cells predicted for 5 hand-off events, while if i=1, j=1 and k=3 there will be n=11 predicted cells, with a lower number of admitted flows.

Fig.6 illustrates the percentage of MIP flows that do not find a passive reservation after the first handoff; as it is expected, it does not depend on the prediction sequence for second and third hand-off (the trend is almost constant if *i* is fixed); in addition to this, the error is widely reduced from 5% to 0.04% if the number of predicted cells for first handoff is increased from 1 to 3.

Fig.7 depicts the average error for MIP flows on the second hand-off event. The error is higher if j=1, but it is reduced from 45-55% to 8-19% by choosing j=2, and it falls below 5% for j=3; this is due to the fact that, for the chosen mobility parameters, matrix M, has often three higher values for each row, so there are three "equi-probable" preferred directions that MIP users may follow to make their second handoff (it is also true for the other hand-offs). The error on the second hand-off is not independent from i and k: increasing these values there is a higher probability of making a passive reservation on the cell that the MIP user will visit on the second handoff, so the error reduces itself.

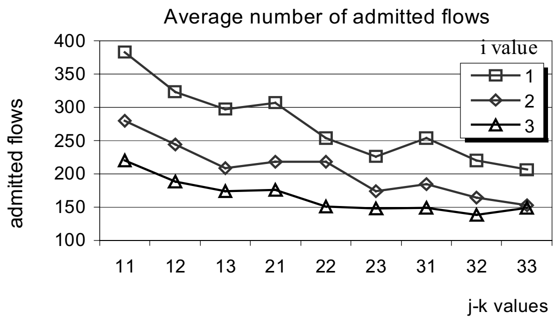

Fig.5 Admitted flows vs reserved cells at 2nd and 3rd hand-off.

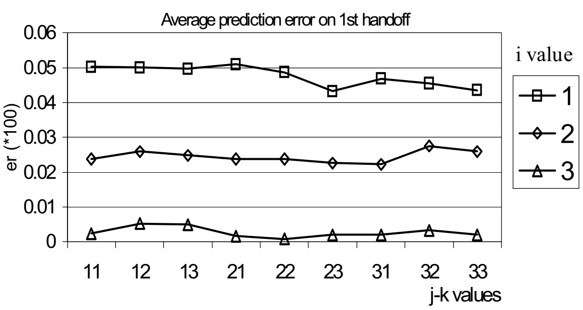

Fig. 6 Prediction error of the 1st hand-off vs predicted cells.

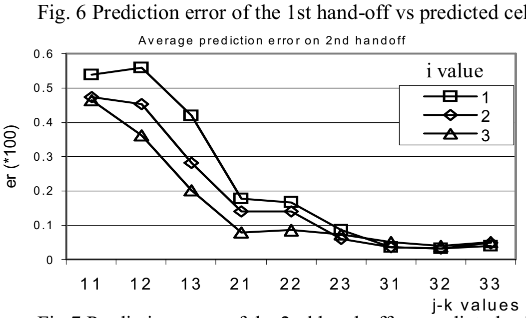

Fig.7 Prediction error of the 2nd hand-off vs predicted cells.

VI. CONCLUSIONS

This paper faces some problems regarding QoS requirements in wireless networks; in order to guarantee service continuity during hand-off events for MIP users in a 2D wireless environment, a prediction policy has been proposed, based on the analysis of users' mobility behaviour. The proposed idea has been verified under the SRMM but it is of general application. The knowledge about users' mobility behaviour makes possible the introduction of some passive reservations prediction policies, necessary for QoS guarantees in WLANs environment. It has been shown that the hand-off error, that is to say the probability of dropping a MIP flow during a hand-off event, can be drastically reduced, without the need of pre-reserving passive bandwidth over all system cells, but choosing them with the knowledge of some mobility info. Three different policies has been tested, varying the number of predicted cells for consecutive hand-off events and it resulted that the third policy, based on the increasing trend reservation, performs better than other techniques offering a good trade-off between bandwidth utilization and prediction error.

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