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A new strategy for mobility prediction in the PCS network

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ABSTRACT

Mobility prediction is one of the main challenges that faced Personal Communication Service (PCS) network. It is probable for many users to move among cells (coverage areas) during their calls. Therefore, the network needs to predict their next location in order to reserve another resource in that next cell to keep their calls going on. In this paper, a new strategy is proposed for mobility prediction named Mixed Mobility Prediction (MMP). It is composed of two predictors. The first one is named Association Rules Predictor (ARP), and the second one is called Weighted Ant Colony Predictor (WACP). In ARP the prediction is based on Association rules in data mining and detecting the time of calls. In WACP the prediction is based on Ant Colony (AC) in swarm intelligence. In addition to that, roads lead to their predicted next locations, and priority of famous places found in those locations. Finally, MMP merges the decisions of both predictors to get the final accurate decision in the absence of sufficient history for a MT. The proposed approach outperformed the compared the state-of-arts methods in terms of; Prediction Accuracy (PA), and Quality of Measure (QM).

Keywords

PCS network, Mobility prediction, Ant-based system, Association rules.

1. INTRODUCTION

Recently, personal communication service (PCS) networks enable Mobile Terminals (MTs) to communicate regardless of their locations to guarantee an efficient service delivery. Therefore, the real-time locations of the mobile users should be perfectly managed [1]. In cellular communication, the user doesn't stay at a particular place but moves from one place to another. As PCS networks concentrate on the concept of wireless access, it permits the dynamic relocation of mobile users. Mobility in PCS networks raises the location management's problem [2], which incarnates the set of mechanisms, with which the system can locate a particular mobile user at any time. Two strategies are possible; the first one is location updating, while the second one is location prediction. Up till now, various studies as yet have been done in the field of location management, and the most of them actually focus on the problem of location update, which is interesting in reporting of the up-to-date locations of mobile users. In general, when a MT moves to a new cell, location update should be performed. As a result, the network can track the exact location of each MT [3]. The cell is simply routed through the network to its last reported location as a call arrives at a certain user. Furthermore, location prediction helps to figure the next movement of the mobile user while roving among the cells of the network. Actually, one of the essential uses in mobility prediction is allocating or reserving resources at the most probable next cells [4], instead of allocating in all neighbor cells. Resource utilization can be enhanced by effectively allocated resources. When an MT moves from a current cell into another new cell during the ongoing call, the call should be switched to the base station of such a new cell [5]. Otherwise, the call will be dropped because of the weakness of the current base station's link as the mobile regress. Actually, this ability for transference in the mobile cellular system design is called handoff [6].

The originality of this paper is concentrated on introducing the MMP strategy. The proposed MMP is composed of two predictors, which are; (i) ARP, and (ii) WACP. During ARP, the task is to predict the next cell of the mobile user with consideration of current cell. This strategy used for users having sufficient histories. It is based on applying association rules on the history of mobile user by calculating support and confidence of source, current and next cells within time intervals. The 24 hours is divided into three-time intervals, which are A, B, and C, where A includes [1:8] hours, B includes = [9:16] hours and C includes [17: 24] hours. On the other hand, predicting the next cell to users having no history or no sufficient history through WACP. The weighted cell is added to Ant colony based predictor in order to make prediction more accurate, which is based on two factors, which are; (i) the priority of famous places that are found in each cell in RA. The priority of those famous places is calculated according to the vision of the administrator's network, and (ii) roads lead to cells. By adding these two factors to the history of neighbors, the predicted next cell will be more accurate to users having no histories. The overall MMP strategy is tested to predict the next cell of mobile users whether having a history or not. Results have shown that the proposed MMP strategy outperforms recent ones as it introduces the best prediction accuracy with the minimum time penalty.

This paper is organized as follows; Section 2 shows an overview and basic concepts about Personal Communication Service (PCS) network, Association Rule Mining (ARM) and Ant colony in Swarm Intelligence (SI) Section 3 gives the previous methods about mobility prediction. Section 4 focuses on the proposed Mixed Mobility Prediction (MMP). However, section 5 depicts the experimental results. Finally in section 6 conclusions.

2. Background and Basic concept

In this section, this paper will briefly illustrate (i) the basic concepts of the ant colony in swarm intelligence, (ii) association rules in data mining, (iii) and architecture of PCS networks.

2.1 Swarm Intelligence (SI)

SI is the relatively new approach to solve problems, which takes revelation or inspiration from the social behaviors of insects and of other birds and animals. Particularly, ants have a number of techniques and methods among which the most studied and successful one is known as Ant Colony Optimization (ACO) [7]. ACO takes inspiration from the foraging behavior of some ant species. Each ant deposits a substance on the ground called pheromone which evaporates by the time. During ant's journey for searching for food, it deposits this substance. Other ants that arrive on the journey are more likely to take the path with a higher concentration of pheromone than the paths with lower concentrations of pheromones. ACO exploits a similar mechanism to solve the optimization problems. Furthermore, a substantial corpus of theoretical results is becoming available that provides useful guidelines to researchers and practitioners in further applications of ACO [8].

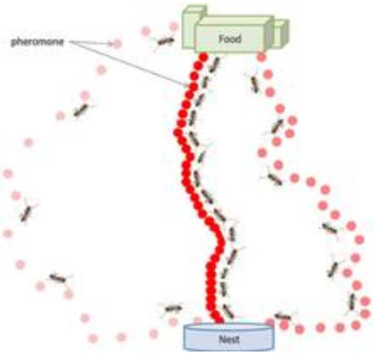


Fig 1: A colony of ants searching for food

In this system, time is seen as discrete and ants are practically blind, which have a visibility field that affects their displacements. In general, at one point *i* and at-one-moment *t*, an ant chooses the point *j* (i.e. to follow the path (*i, j*)) according to probability (1):

$$P_{i,j}(t) = \frac{\left(\tau_{i,j}(t)\right)^{\alpha}.(\eta_{i,j})^{\beta}}{\sum_{(i,k)\in C}(\tau_{i,k}(t))^{\alpha}.(\eta_{i,k})^{\beta}} \quad (1)$$

Where $\tau_{i,j}(t)$ is the pheromone intensity on the path (*i,j*) at time *t*, $\eta_{i,j}$: is the visibility field of ant on the path (*i,j*) (the ant assumes that there is food at the end of this path), α and ß: are the parameters which control the relative importance of the pheromone intensity compared to visibility field of ant and C: represent the set of the possible paths starting from point *i* ((*i,k*)is a path of C). A high value for α means that trail is very important and therefore ants tend to choose paths chosen by other ants in the past.

Each ant *a* following the path *(i, j)* adds a quantity of pheromone represented by$\Delta\tau_{i,j}^{a}$. A pheromone is a substance that evaporates. The intensity of pheromone on the path (i, j) at the time (t +1) is equal to that which remains after evaporation at time t, added to the sum of quantities deposited by all ants that followed this path at time t. This is given by (2):

$$\tau_{i,j}(t+1) = \sigma.\tau_{i,j}(t) + \sum_{a=1}^{m}\Delta\tau_{i,j}^{a} \quad (2)$$

where σ is a coefficient such as (1−σ) represents pheromone evaporation between times t and t+1. It must be < 1 to avoid pheromone accumulation and premature convergence [Dorigo & Colonri, 1996]. a represents an ant having deposited a quantity of pheromone on the path (i, j) and m is the number of ants having taken the path (i, j) at time t.

In [9], the visibility field is represented by a vector η of six elements corresponding to the number of adjacent cells. An element of this vector represents ant visibility of an adjacent cell. It is initialized by multiplying the value of the element by a factor μ > 1 in order to increase its attraction compared to other elements, in order that the ant will be predisposed to prefer an already visited cell when it searches for food as expressed in (3).

$$\eta_{ai,k} = \begin{cases} x & if\ MT_i\ (Distination\ cell) \neq K\ or\ if\ MT_i\ is\ null \\ x.\mu & if\ MT_i\ (Distination\ cell) = K \end{cases} \quad (3)$$

Where K = 1to R represents the adjacent cells. *X* is a value > 0. μ must be more than 1 to increase the cell degree of visibility if it was already visited by the mobile. MTi represents the entry I of the movement table.

2.2 Data Mining (DM)

DM refers to discovering knowledge in very large or huge amounts of data. Association Rule Mining (ARM) is one of the most important techniques in data mining [10]. It finds strong and interesting relationships among large sets of data items. An association rule has two parts, which are: (i) an antecedent (if) that is found in the data and (ii) a consequent (then) that is found in combination with the antecedent. Association rules are created by analyzing data for frequent if/then patterns, and then using the criteria of support and confidence in order to identify the most important relationships. Support is defined as the percentage of transactions in which an item-set appears with respect to a total number of transactions. In another meaning, it indicates how frequently the items appear in the database. In other words, it is defined as the percentage/fraction of records that contain X∪Y to the total number of records in the database as shown in expression (4).

$$Support\ (XY) = \frac{Support\ count\ of\ (XY)}{Total\ number\ of\ transaction\ in\ D} \quad (4)$$

Confidence(C) of an association rule is defined as the percentage/fraction of the number of transactions that contain X∪Y to the total number of records that contain X. Confidence is a measure of strength of the association rules, suppose the confidence of the association rule X⇒Y is 80%, it means that 80% of the transactions that contain X also contain Y together [11] as shown in expression (5).

$$Confidence\ (X|Y) = \frac{Support\ \ (XY)}{Support\ (X)} \quad (5)$$

2.3 PCS network

Personal Communications Service (PCS) network is a wireless phone service network similar to cellular telephone service networks but focusing on personal service and extended mobility [12]. As shown in figure (2) the PCS network consists of more than one SA. Each one is partitioned into a number of Registration Areas (RAs). Each RA is managed by a master and permanent database called Home Location Register (HLR). It maintains MT identity information including the mobile user information such as directory number, profile information, real-time location, and authentication information. In the proposed system, it is possible to get the movement history of a particular MT from the logs of such MT's HLR. Each RA is sub-divided into a number of cells. Each one serviced by a wireless coverage that is administered by a single access point called Base Station (BS). Moreover, one Mobile switching center connects to a number of BSs, which is responsible for serving one RA. Visitor Location Register is a temporary database type that attached to each MSC in order to store the profile information for the MTs currently visiting its RA. Therefore, there are two records are created when an MT visits a new RA, which are: (i) permanent record in HLR, and (ii) Temporary record in VLR [13]. MT must register with the VLR before receiving any cellular service, and then HLR is also updated to reflect the real-time location of that MT.

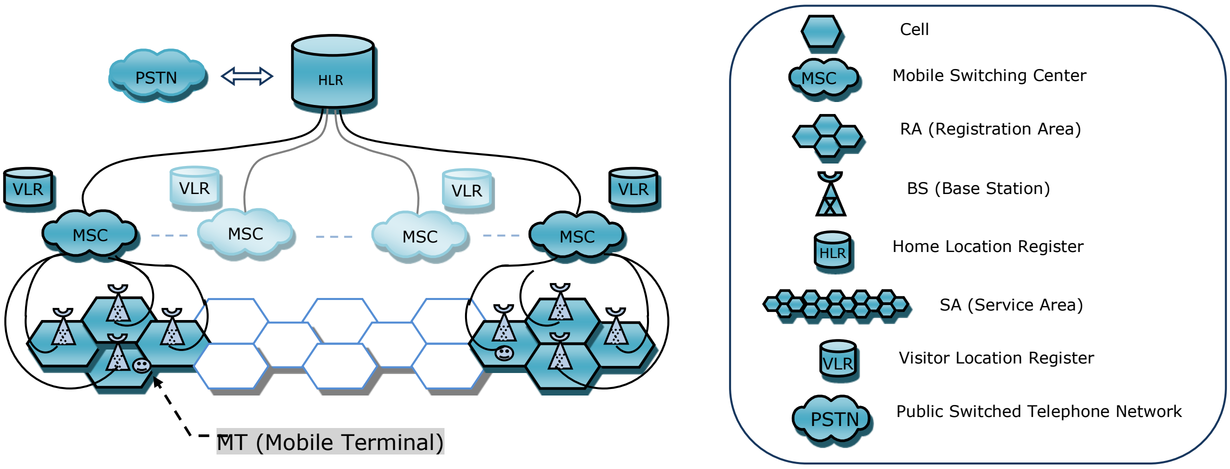


Fig 2: Architecture of PCS network

3. Previous Work

Mobility prediction constitutes one of the most significant aspects of having a great impact on several application fields. Throughout this section, some techniques of mobility predictions related to the scope of this paper will be briefly illustrated; they are as follow: (i) Dynamic Clustering based Prediction (DCP), (ii) Direction Based Prediction (DBP), (iii) Time Based Prediction (TBP), (iv) Bayes Prediction (BP), (v) Location Based Prediction (LBP), (vi) Segment Based Prediction (SBP), and Super Victor Regression (SVR).

DCP, as described in [14], is used to discover the mobility patterns of MT from the collection of recorded trajectories (MT's history). Thus, the next movement of MT will be predicted according to these patterns, as well as dynamically allocating network resources. In DBP has been proposed in [15]. It is based on the direction of MT's motion, if the previous and current cell is known. DBP used a direction criterion algorithm, which incorporates the MT's history of movements with MT's direction information, and then it can identify the present location of MT's motion and uses MT's history of this direction in order to predict the next movement of the mobile user. The predicted next cell constitutes the highest percentage. In [16], TBP depends on dividing the day into time periods in order to explore the dependency of MT's movements at a certain time of day. It assumes that mobile users have the same regular activities in their daily life. BP [17] extends the DBP algorithm by considering all departure history along the future direction of travel. Bayes' rule used for calculating the probability distribution of all possible next movements including reference point in a given travel's direction of a MT. LBP has been proposed in [18]. When MT leaves its current cell, it records the next BS and keeps track of the number of times it visits each of the cells, where it has been brought in from of probabilities distribution of next moves from MT's mobility history.

It accurately identifies the current location of MT and uses the pre-stored history of MT at this current cell to predict MT's next movement. The cell with the high rate of visiting is predicted as the next cell. Finally, SBP) has been introduced in [19]. SBP is based on partitioning all previous movements of MT into a number of segments and then stored. A segment starts with a stationary or a fixed cell in which MT stays in it for a long period of time (set by the network administrator). As MT starts to move, all cells encountered are appended to segment, the segment ends with different or the same stationary segment, which will become the beginning of the new segment. SBP matches the current segment with those segments that are already stored. The matched id found when the present segment is identical to the initial portion of a stored segment.

The predicted next cell of MT will be the cell immediately after the initial portion of matched segment In SVR strategy, training data is given to training the model which is used for applying regression for future prediction. In SVR [20], several kernel functions are used for prediction. Linear and nonlinear SVR are the main types of the SVR. The kernel functions transform the data into a higher dimensional feature space to make it possible to perform the linear separation. It uses the Radial Basis Function (RBF) kernel function for prediction which gives higher prediction probability then polynomial kernel function.

4. The Proposed Mixed Mobility Prediction (MMP) Strategy

Through this section, a new strategy will be proposed for predicting the next cell for a Mobile Terminal (MT) moving during a call. This strategy named MMP and it mixed between two predictors; the first predictor is named Association Rule Predictor (ARP). It is used for mobile users having a history of paths stored in the network. The second predictor is named Weighted Ant Colony Prediction (WACP) which is used for mobile users having no histories stored on certain RA in the network. When a MT initiates a call, the time of call will be detected by the network. The time of calling is supposed to be the time of entering the next predicted the cell. If a MT has sufficient history of paths in the current RA, then ARP predictor will be applied to predict MT's next cell. However a MT has no history stored in current RA, so WACP predictor will be applied to predict the next cell. In the end, both decisions of ARP and WACP are merged in order to get the final and more accurate decision. The strategy of mixing decisions will be illustrated in details in section4.3.

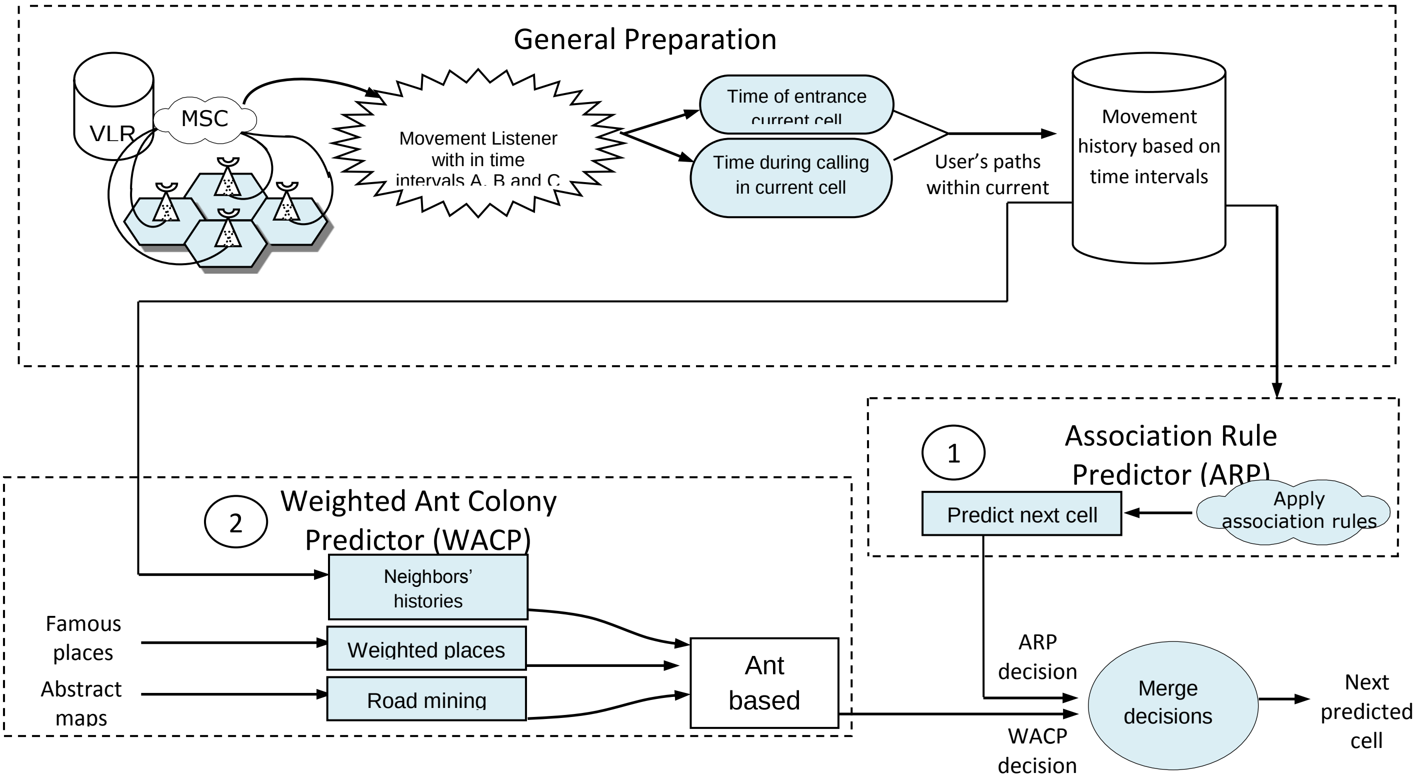


Fig 3: Proposed Mixed Mobility Predictor (MMP)

As shown in figure 3, the proposed MMP system is classified into three parts; the first part is the general preparation step that will be used for both predictors. The second part is for ARP, while the third one is for WACP. In the preparation step, the movement listener tracks the MT's movements within the current RA and collects them within time intervals A, B, and C. It also classifies the 24-hour into two types, This time is very important for predicting the time of entering the next cell in order to reserve a resource for that call to prevent dropping down of such call. After tracking the movements and classifying the time of calling for a MT, a movement history database stores both of them with in time intervals in a database called Movement History (MH).

When a MT initiates a call the system tries to detect the number of paths in the current RA for such MT from MH. If the number of Mt's paths (α) more than or equal 100 paths, then ARP decision will be taken. If (α) less than 100then the decisions of both ARP and WACP will be merged together in order to get an accurate prediction.

4.1 Association Rule Predictor (ARP)

Association rules are applied for calculating the percentage of the most predictable next cells by using these two criteria, which are: (i) Support (*S*), and (ii) Confidence (*Conf*).*S* is the percentage of transactions in which an item set appears with respect to a total number of transactions, where the *S1* of (source cell, current cell together) expressed in (6):

$$S1 = (Sc + Cc)/T \qquad (6)$$

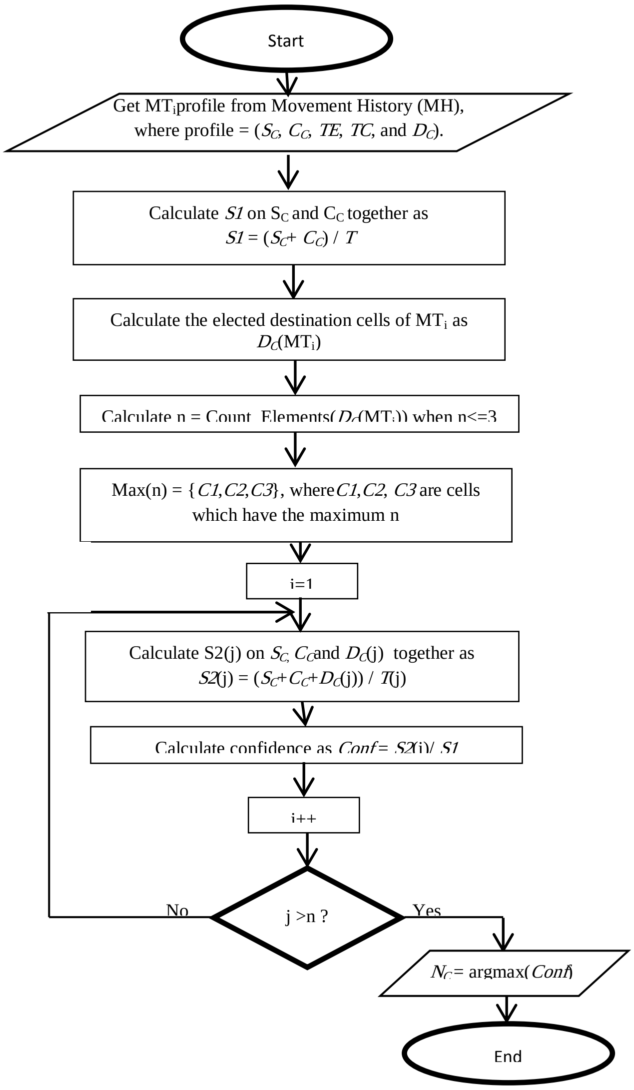
where (*Sc*+*Cc*) refers to the number of appearance of the same source and current cell together at the same time intervals, while (*T*) refers to the number of all paths appears at the same time of entering S_C.*S2* of (source cell, current cell, and next cell together) expressed in (7):

$$S2 = (Sc + Cc + Dc)/T \qquad (7)$$

where(*Sc*+*Cc*+*Dc*) refers to the number of appearance of the same source, current and destination cells together at the same time interval, and also (*T*) refers to the number of all paths appears at the same time of entering S_C. In general, the second criteria confidence is used to identify the percentage of going predicted next cell; the confidence of (source, current and destination cells together) is expressed in 8:

$$Conf = S2/S1 \qquad (8)$$

Where *S2* refers to the support of source, current and destination cells together at the same time interval and *S1* refers to support of source and current cells at the same time interval. The result of confidence will be the percentage of the most predictable next cells at a certain time interval. Figure (4) shows in details how ARP phase predicts the next cell of a MT.



- S_C: Source cell of MT_i.
- C_C: Current cell of MT_i.
- TC: Time of calling in current cell C_C.
- TE: Time entering current cell C_C.
- $S1$: The first support. It is the ratio between the number of appearance of source and current cells together at the same time interval to the number of appearance of all paths at the same time interval of source and current cells.
- T: number of all paths appears at the same TE of S_C.
- $D_C(MT_i)$: Destination cells visited by MT_i.It is a set of neighboring cells of MT_i's current cell $= \{C_U, C_V, C_W, C_X, C_Y, C_Z\}$.
- n : number of visited destination cells by MT_i
- Max(n) = {*C1,C2,C3*}: the number of maximum visited three destination cells by MT_i
- $S2$(j): The second support for each D_C(j). It is the ratio between the number of appearance of source, current and each destination cell (D_C(j)) together at the same time interval to the number of appearance of all paths at the same time interval of source, current cells and D_C(j).
- *Conf* : is the ratio between $S2$(j) to S(1), and it is used for calculating the percentage for a $MT_i$to go to next cell D_C(j) at certain time interval.
- N_C: the maximum percentage for the predicted next cell of MT_i.

Fig 4: Flow chart of ARP process

Figure (4) shows in details how ARP predicts the next cell of a MT. When MT_i (has history) initiates a call immediately ARP gets MT_i's profile from MH. The profile contains (Source cell (S_C), Current cell (C_C), Time of entering the current cell (*TE*), Time of calling in current cell (*TC*)). It elects the visited destination cells by MT_i from the S_C and C_C at the same time interval by using equations expressed in 3, 4. Finally, it calculates the maximum percentage of going to the next predicted cell (N_C) by using equation expressed in 5.

4.2 Weighted Ant Colony Predictor (WACP)

When a MT entered a new RA, where no histories of paths are stored in such RA. Immediately the predictor tries to find profiles from the MH of neighbor MTs similar to the profile of MT entering a new cell. WACP depends on three main factors, which are: (i) Neighbor's histories of the other MTs having the same profile MT entered a new cell in a new RA, (ii) Weighted places where, WACP supposes that every cell has its own famous places which have a priority given according to the vision of the network's administrator, and (iii) Road mining: which means that roads lead to cells also will be taken into consideration in the mobility prediction. Those three factors will be added to each other under calculations depends on ant colony based predictor. As illustrated in section 2.1 in expression(3), that ant has a visibility field which is represented by a vector η of six elements corresponding to the number of adjacent cells, and there is a vector μ that must be more than 1 in order to increase the cell degree of visibility if it was already visited by the mobile. WACP changed the value of μ as expressed in equation (9):

$$\mu = W_r(C_k) + W_f(C_k) \qquad (9)$$

Where μ represents the total weight of the cell k. $W_r(C_k)$ represents the weight of roads in cell *k* as expressed in(10). $W_f(C_k)$ represents the weight of famous places in cell *k* as expressed in(11):

$$W_r(C_k) = \begin{cases} 0 & if\ C_k\ has\ no\ road \\ 1 & if\ C_k\ has\ road \end{cases} \qquad (10)$$

$$W_f(C_j) = \begin{cases} 0 & if\ C_f\ has\ no\ famous\ places \\ \Sigma\ priority(f) & if\ C_f\ has\ famous\ places \end{cases} \qquad (11)$$

Each ant chooses the future cell according to the degree of visibility and pheromone intensity of the cell. The prediction equation in [9] is expressed in equation (12):

$$P^{\alpha}_{ai,k(t)} = \frac{(\tau_k(t))^{\alpha}.(\eta_{ai,k})^{\beta}}{\sum_{j=1}^{R}((\tau_j(t))^{\alpha}.(\eta_{ai,j})^{\beta})} \qquad (12)$$

According to the probability $P^{\alpha}_{ai,k(t)}$ the ant ai chooses to go to the cell *K* at moment *t*. $\tau_k(t)$ refers to the pheromone intensity that was deposited by neighbor ants on cell k. $(\eta_{ai,k})$ represents the visibility of cell *k* for ant ai. α *and* β are parameters which control the relative importance of pheromone intensity compared to ant visibility field. $\tau_j(t)$) represent the pheromone intensity in cell *j* at time *t*, where *j=1 to R* which represents the adjacent cells. $\eta_{ai,j}$ refers to the visibility of cell *j* for ant ai. After each iteration (time (t + 1)), the pheromone intensity in locations is updated according to equation (13):

$$\tau_k(t+1) = \tau_k(t).(1-\sigma) + m.Q \qquad (13)$$

where σ , (0<σ<1): represents pheromone evaporation rate, a small value of σ generates slow pheromone dissipation and a high value generates a faster dissipation, *m* represent the number of ants that choose cell *k*, and *Q* represents the quantity of pheromones deposited on the cell to encourage other ants to go towards it. Finally, the ants will converge towards the cell having the most pheromone. This will be the predicted cell.

As shown in figure (5), when a MT_i initiates a call, immediately WACP detects the MT_i's profile. The profile of MT contains source cell, current cell, time of entering, and time of calling in the current cell. Then it tries to get the similar profiles from the MH database and their destination cells. It also calculates $\mathcal{T}$ which equals the number of the most visited three cells. And then it calculates μ which is the weight of each cell. $W(C_k)$ equals to the summation of the number of MTs having the similar profile to MT_i visiting their destination cell (C_k), and the priority of famous places found in each cell $(W_f(C_k))$ with roads lead to each cell $(W_r(C_k))$. Finally, it calculates N_C which is the maximum probability of MT_i to visit the predicted cell C_k. For illustration, figure (6) shows the famous places in each cell in a certain RA.

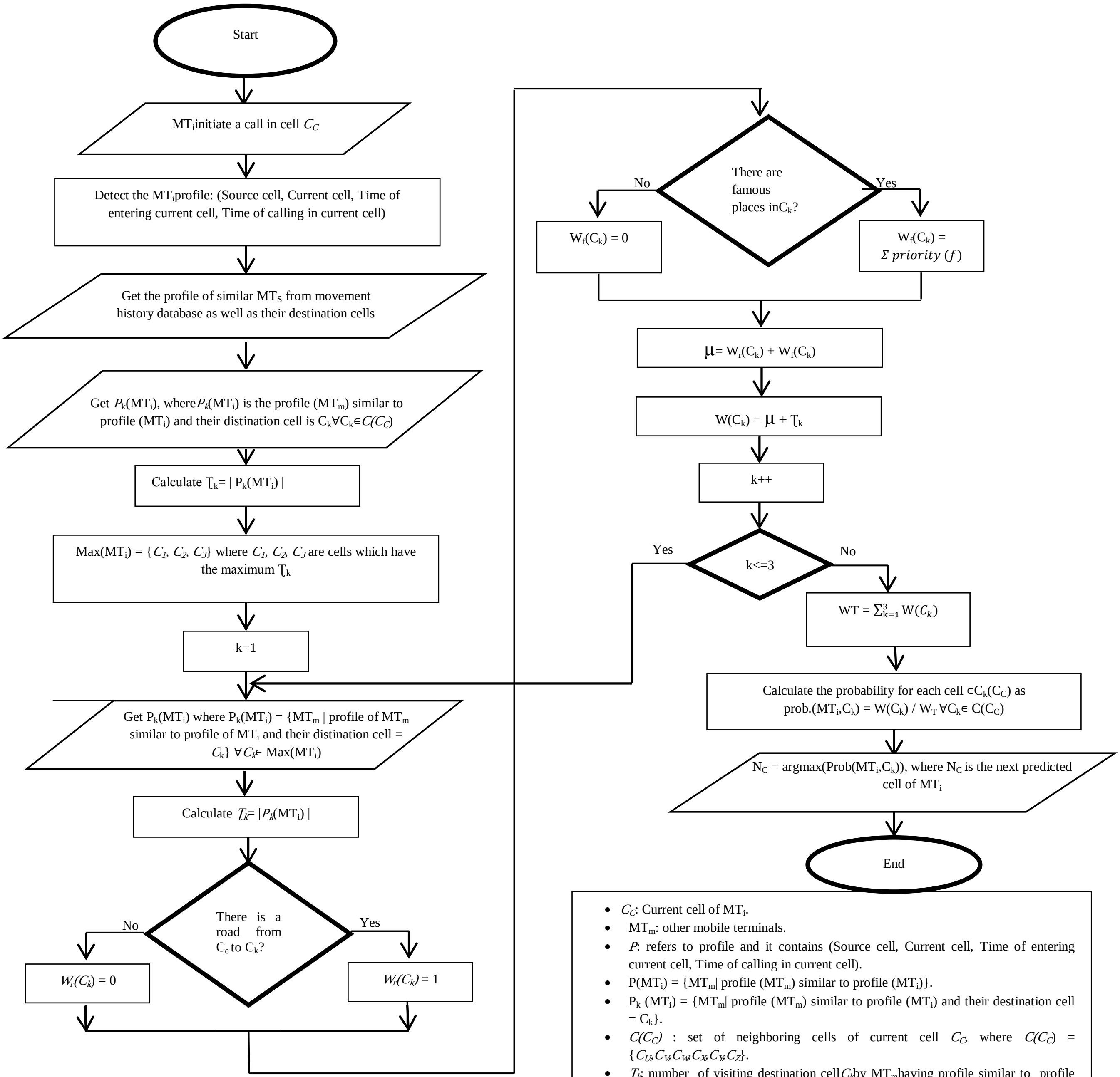


Fig 5:Flow chart of WACP

- C_C: Current cell of MT_i.
- MT_m: other mobile terminals.
- *P*: refers to profile and it contains (Source cell, Current cell, Time of entering current cell, Time of calling in current cell).
- $P(MT_i) = \{MT_m |$ profile (MT_m) similar to profile $(MT_i)\}$.
- $P_k(MT_i) = \{MT_m |$ profile (MT_m) similar to profile (MT_i) and their destination cell $= C_k\}$.
- $C(C_C)$: set of neighboring cells of current cell C_C, where $C(C_C) = \{C_U, C_V, C_W, C_X, C_Y, C_Z\}$.
- $\mathcal{T}_k$: number of visiting destination cell C_k by MT_m having profile similar to profile of M_i.
- N_C: predicted next cell of MT_i

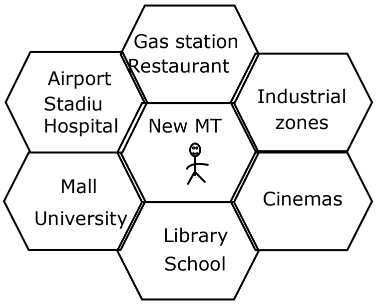


Fig 6: Example of famous places that are found in a certain RA

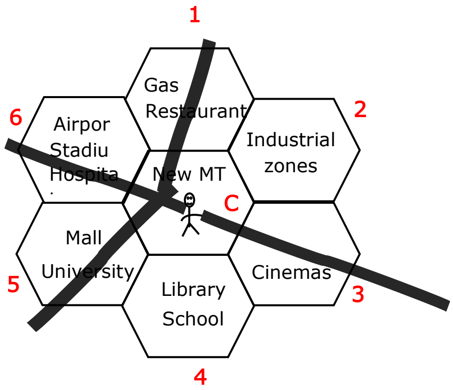


Fig 7: Famous places and roads in certain RA

Table 1 Priority of famous places in RA

Famous place	Priority
Restaurant	7
Gas station	7
Industrial zones	3
Cinemas	10
School	1
Library	2
University	6
Mall	9
Airport	9
Stadium	8
Hospital	9

For more illustration, weighted cells are linked by road as shown in figure (7). In this situation, MT entered a new RA and placed at *cell C* (current cell); where there is a road branched from the *cell C* and ends at four different neighbor cells, which are; *1, 6, 5 and 3*. According to this situation, the predictable next cell will be one of four neighbor cells that roads pass through.

However, adding the priorities of famous places and regular movements of groups having the same MT's behavior will make the weight of neighboring cells be an increase. For this example, *Gas station and restaurant* are placed at *cell 1*

of priority (7 + 7 = 14) as illustrated in table 1. *Cell 6* contains airport, stadium and hospital of priority (9 + 8 + 9 = 26). Similarly, *Cell 5* has priority (9 + 6 =15) and *Cell 3* of priority 10. For those calculations, the predictable cell of MT will be *Cell 6*, and that is because of higher priority and the connecting road between MT's current cell and *Cell 6*.

4.3 Merging decisions of ARP and WACP

The main target of MMP is to merge the decisions given by both predictors; the normalized output of each predictor is multiplied by a specific weight. And then the decision of the proposed Mixed Mobility Prediction (MMP) strategy is the weighted sum of the normalized outputs given by both predictors. Hence, the next predicted movement can be identified by (14).

$$Next\_Cell(MT)|_{MMP} = ArgMax\,[w(ARP)\cdot PD_{ARP} + w(WACP)\cdot PD_{WACP}] \quad (14)$$

where Next_Cell(MT)$|_{MMP}$ is the next movement of MT predicted by MMP and w(ARP), and w(WACP) are the weights assigned to the normalized outputs of both Association Rules Predictor and Weighted Ant Colony Predictor, PD_{ARP} and PD_{WACP} are the prediction decisions of ARP and WACP. Because of its great impact in the overall decision of MMP, the weight assigned to each predictor normalized output should be tuned carefully. It is believed that the Association Rule Predictor is the most accurate one as it depends mainly on the MT's movement history, which is the most important parameter for predicting MT's next movement. However, with the lack of MT's history or there is no sufficient history, we should resort to the history of other MTs in the same cell or predict MT's next movement based on the underlying topology of the current RA. For this purpose, the other predictor; which is; Weighted Ant Colony Predictor is useful.

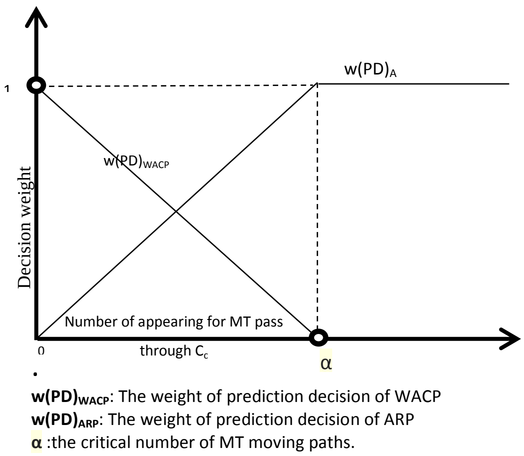


Fig 8: Merging decisions of ARP and WACP

Accordingly, the decision of the ARP is the only accepted one if MT under consideration has a sufficient history at the current cell C_c, hence, w(PD_{ARP})=1, while w(PD_{WACP})=0. On the other hand, if MT has no history at C_c, no impact for the ARP (e.g., w(PD_{ARP})=0), however, the prediction is based on WACP (e.g., w(PD_{WACP})=1). The main challenge is when MT has a mobility history at C_c but it is not sufficient to take an accurate decision. The action should be taken here is to give a weight for each predictor based on the amount of the available MT's history at C_c. to accomplish such aim, we use the two modeling functions as illustrated in figure (8), where the horizontal axis represents the available moving sequences passing through C_c, denoted as α, for the MT under consideration at C_c, while the vertical axis represents the decision weight.

The first modeling function represents the weight of ARP (i.e., w(PD_{ARP})), while the second represents the WACP weight (i.e., w(PD_{WACP}), we assume that they have equal weights).

If MT has no mobility history (i.e., α =0), no impact for ARP, while the decisions WACP is weighted equally. Hence, w(PD_{ARP})=0, while, w(PD_{WACP})=1.On the other hand, it is believed that

$w(PD_{ARP}) \propto \alpha$, hence as α increases, the $w(PD_{ARP})$ increases gradually, while $w(PD_{WACP})$ decrease.

For illustration, we consider that a MT initiates a call in his current cell (c7) and the system detects the number of his moving paths (α) which is equal to 40, where the Prediction Decisions (PD) of ARP and WACP are illustrated in table (2).

Table 2 the percentage of predicting next cells according to ARP and WACP

Neighboring cells	PD_{ARP}	PD_{WACP}
C2	50%	-
C3	20%	-
C6	30%	52%
C8	-	-
C11	-	28%
C12	-	20%

Table 2 represents the percentage of predicting next cells according to ARP and WACP. The first column represents the six neighbor cells of MT's current cell. The second column represents the prediction decision of ARP for the highest three predicted cells which are; C2, C6, and C3. The third column represents the prediction decision of WACP also for the highest three predicted cells which are C6, C11, and C12.

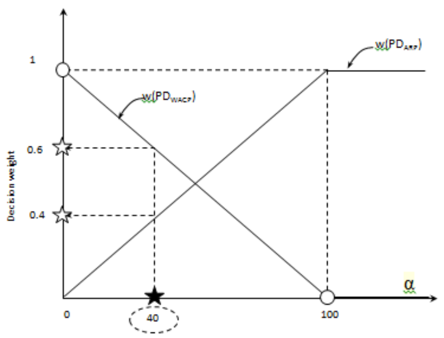


Fig 9 modeling functions for ARP and WACP assuming α=40

As shown in figure (9) the weight of Prediction Decision for ARP $w(PD_{ARP})$ and the weight of Prediction Decision for WACP $w(PD_{WACP})$ when α=40. It is clear that $w(PD_{WACP})$=0.6 and $w(PD_{ARP})$=0.4.

Table 3the output of mixed decision assuming α=40

Neighboring cell	Association Rule Predictor (ARP)		Weighted Ant colony Predictor (WACP)		Output A+B
	PD_{ARP}	(A) $PD_{ARP} \cdot w(PD_{ARP})$	PD_{WACP}	(B) $PD_{WACP} \cdot w(PD_{WACP})$	
C2	50%	(50/100)*0.4=0.2	0	0	0.2
C3	20%	(20/100)*0.4=0.08	0	0	0.08
C6	30%	(30/100)*0.4=0.12	52%	(52/100)*0.6=0.312	0.432
C8	0	0	0	0	0
C11	0	0	28%	(28/100)*0.6=0.168	0.168
C12	0	0	20%	(20/100)*0.6=0.12	0.12

Table 3 represents the calculation expressed in (14). The 1st column represents the six neighboring cells of MT's current cell. The 2nd column classified into two columns. The first one represents the Prediction Decision of ARP (PD_{ARP}) for the highest three cells as illustrated in table 2. However, the second column (A) represents the multiplication of PD_{ARP} with the weight of PD_{ARP} as illustrated in figure 9. The 3rd column also classified into two columns. The first one represents the Prediction Decision of WACP (PD_{WACP}) for the highest three cells as illustrated in table 2. However the second column (B) represents the multiplication of PD_{WACP} with the weight of PD_{WACP} as illustrated in figure 9. The output of mixed decisions is represented in the last column which is equal to the summation of A and B. Finally, It is clear in the table (3.5) that the predicted next cell will be c6 after mixing decisions of both predictors when α = 40.

5. Experimental Results

This section estimates the prediction protocol evaluation that depends on the basis of two parameters, which are; Prediction Accuracy (PA) and Quality of Measure (QM). PA is a ratio between numbers of correct prediction to the total number of all predictions as expressed in (15).QM is calculated according to three parameters $\alpha, \beta, and\ \theta$ their values will be changed according to the network administrator's view. We assumed in our system that the values of those parameters are *10, 8* and *5*respectively, where grade 10 will be multiplied by the first highest percentage of the predicted cell, grade 8 will be multiplied by the second highest percentage of the predicted cell and grade 5 will be multiplied by the third highest percentage of the predicted cell. QM is the summation of these multiplications. From a quality of service point of view, it is preferable to keep both of PA and QM as high as possible. Thus, the idea to reserve resources within future cells that a MT will visit was formed.

$$PA = \frac{NumberofCorrectPediction}{TotalNumberofPredictions} \quad (15)$$

The prediction protocol evaluation is applied in two cases, which are; (i) when all MTs have sufficient history (ii) when MTs have insufficient history. In the first case the decision of ARP will be taken. In the second case, the decision of both predictors: ARP and WACP will be mixed together in the context of MMP. The performance of those cases is evaluated in the context of mobility prediction in a cellular communication network. They compared with other five techniques, which are, (i) Location Based Prediction (LBP), (ii) Segment Based Prediction (SBP), (iii) Direct Based Prediction(DBP), (iv) Super Victor Regression (SVR), and Random Prediction (RP), where its prediction based on randomly picks a neighboring cell to be the next predicted cell for MT [21].

Table 4 Number of all MTs used by MMP

No. of all MTs	No. of MTs having sufficient histories	No. of MTs having insufficient histories
200	140	60
400	155	245
600	436	137
800	350	450
1000	730	270

As illustrated in table 4, the dataset of the proposed system contains 1000 MTs as shown in the first column where each row increased by 200 MT. A data set is divided into two parts. The first part is MTs having sufficient history of paths which means each MT has more than 100 paths stored in the network as shown in the second column. However, the second part is for the MTs have an insufficient history of paths which means each MT has less than 100 paths stored in a certain RA in the network as shown in the third column. For illustration as shown in the second row that the 140 MTs have sufficient history from the first 200 and 60 MTs have insufficient history from the first 200 MTs also.

As shown in Figures 10-17 there are five other techniques which are; RP, LBP, SBP, DBP, and SVR that are compared to the proposed strategy (MMP) as a whole and its predictors (ARP) and (WACP). The horizontal line in each Figure represents the number of MTs which are increasing by 200.

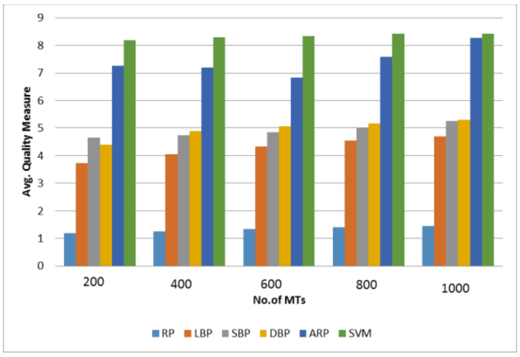


Fig 10: Avg. QM of ARP compared to other techniques

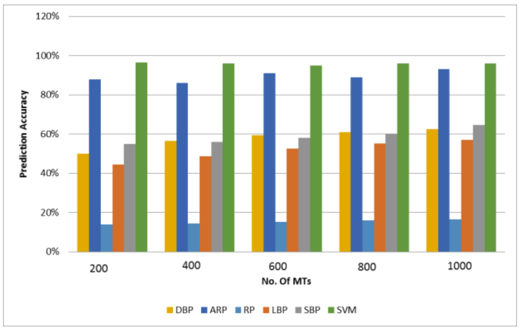


Fig 11: prediction accuracy of ARP compared to other techniques

Figure 11 provides the prediction accuracy for the five techniques compared to ARP technique. It noticed that the SVM technique is little higher prediction accuracy than such predictor, which could be attributed to ARP. It reached up to 89%, while the prediction accuracy of SVR reached up to 94.8%. And then ARP has a quality of measure reached 8.3374 as shown in figure 10. Direction based predictor, segment-based predictor, and location-based predictor produce have low prediction accuracy retched to 62%, 65%, and 57%, while Random predictor has the lowest accuracy of prediction that reached to 17%.

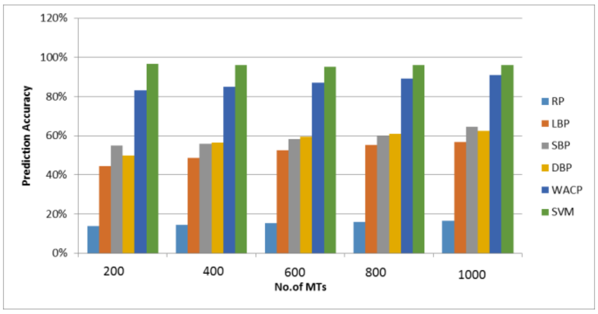


Fig 12: PA evaluation of WACP.

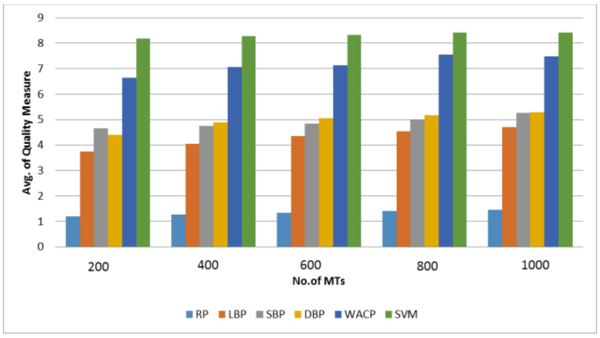


Fig 13: Avg. of QM evaluation of WACP.

Figure 12 provides the Prediction Accuracy (PA) for the same five techniques. It noticed that the proposed WACP has the second highest PA compared to the SVM technique and that's because WACP depends on histories of neighbor MTs having the same profile of a new MT which decreases the accuracy of prediction according to SVM. RP technique has the lowest prediction accuracy compared to other techniques. And therefore WACP has the second highest quality of measure reached to 7.49 compared to SVM and other techniques as shown in figure 13.

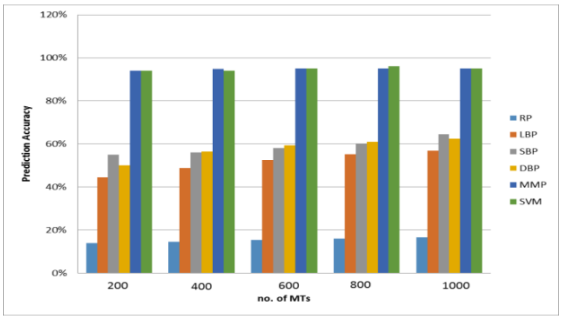


Fig 14: PA evaluation of MMP.

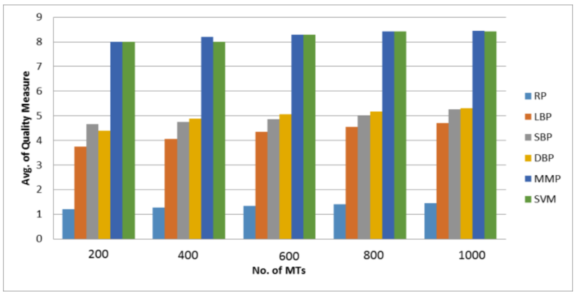


Fig 15: Avg. QM evaluation of MMP.

Figure 14 presents the prediction accuracy of the MMP, which reached 95%. However, the prediction accuracy of SVM reached 94.8 because it uses the Radial Basis Function (RBF) kernel function for prediction. The results of the prediction accuracy of LBP, SBP, and DBP are close to each other to some extent and that's because of their dependency on probability but in different ways. Figure (15) provides the average quality of measure of the proposed MMP compared to other five techniques. It's noticed that RP technique has less quality of measure than other techniques because its prediction depends on choosing the next predicted cell randomly and therefore the quality of measure decreased. However, the proposed MMP has a little higher quality of measure than SVM.

6. Conclusion

In this paper, (MMP) strategy saving the flexible usage of limited resources of PCS networks has been proposed. Such strategy blends the evidence from two different predictors, which are: Association Rule (ARP) and Weighted Ant Colony Optimization (WACP). ARP relies on two criteria (support and confidence), WACP uses the Ant-based system in addition to giving weight to each cell using famous places and roads leads to cells.

ARP is the default predictor assuming that the visitor MT has a sufficient mobility log at the current cell. However, in the absence of sufficient mobility logs for a specific MT, the system resorts to both predictors: ARP and WACP and then mixed their decisions together in order to get the final and more accurate decision in the context of MMP. It is used in the absence of mobility logs, and it exploits neighbors' behavior of new MT to predict the future movement of him/her to the current cell. ARP tries to calculate the support and confidence of the next cell with consideration of source, current cell and time interval of entering and calling in the current cell. The percentage of confidence in the next cell refers to the probability of MT to go that next cell. WACP considers MTs as ants. So, it employs the neighbors' behavior of a certain MT that came from the same location or source cell and same time interval, in addition, to give weight to the cell. Its prediction increases by increasing the weight of the cell which is based on the priority of famous places where are found in each cell and roads, highways and bridges leading to cells.

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