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ABSTRACT

The optimized link state routing (OLSR) is a link state type, table driven and proactive routing that uses the multipoint relays (MPRs) selection for forwarding the network packets. In this book, the MPRs selection algorithm is enhanced using particle swarm optimization (PSO). PSO sigmoid increasing inertia weight (PSO-SIIW) is proposed as a new variation of PSO algorithm for improving the convergence speed and generating the optimum solution in the multidimensional space. Four standard non-linear functions have been used to confirm its validity. The comparison has been simulated using sigmoid decreasing and linearly increasing inertia weight. The simulation results show that PSO-SIIW give better performance with faster convergence capability and aggressive movement towards the solution region. This book also presents the investigation on the development of OLSR with standard PSO and PSO-SIIW, called OLSR-PSO and OLSR-PSOSIIW. The new fitness functions consist of packet delay and degree of willingness are introduced to support MPRs selection in standard PSO and PSO-SIIW. The challenge faced by the proposed method is on how to select MPRs node and find the optimal path in delivering data packets under different scenarios with good performance in term of throughput, end-to-end delay, and packet loss. The OLSR-PSO gives better performance in throughput compared to the standard OLSR of up to 50 nodes in File Transfer Protocol (FTP) application and achieves good performance up to 40 nodes in voice application. In term of end-to-end delay, the OLSR-PSO achieves good performance up to 40 nodes in FTP application and 20 nodes in voice application. On the contrary, the standard OLSR shows better performance at 50 nodes in packet loss for FTP application. The OLSR PSO-SIIW gives good performance in throughput and end-to-end delay compared to standard OLSR and OLSR-PSO. It has been observed that the performance of packet loss gives comparable results in both applications. The work has been further extended to developing and integrating OLSR-PSOSIIW into wireless routers. The algorithm has been validated and verified in indoor wireless mesh networks environment. The experimental and simulation results show that the OLSR-PSOSIIW is able to find optimal path and gives better performance than standard OLSR and OLSR-PSO. In conclusion, the selection of MPRs using PSO-SIIW provides a good performance in throughput (2,368.60 and 1,633.70 kbps), end-to-end-delay (4.99 and 1.41 ms), and packet loss (0.13% and 0.19%) for FTP and voice applications.

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S_i^k	-	The position of particle i at time step k
S_i^{k+1}	-	The update position of particle i at time step k
v_i^k	-	The velocity of particle i at time step k
v_i^{k+1}	-	The update velocity of particle i at time step k
pbest	-	The personal best position
gbest	-	The group best position
c_1	-	Cognitive coefficient in PSO process
c_2	-	Social coefficient in PSO process
w	-	Inertia weight
$Vmax$	-	The maximum velocity in PSO process
χ	-	The constriction coefficient
k	-	The parameter that controls the exploration and exploitation abilities of swarm
θ	-	The constant of constriction factor
w_{start}	-	The inertia weight at the start
w_{end}	-	The inertia weight at the end
gen	-	generation
u	-	The maximum number of generations
n	-	The constant to set partition of sigmoid function
$f_{mn}(k)$	-	The fitness function for transmission of packet k from node m to node n
$d_{mn}(k)$	-	The time delay required by transmission of packet k from node m to node n

$W_{mn}(k)$	-	The degree of willingness of packet *k* transmission from node *m* to node *n* (the value is integer)

LIST OF ABBREVIATIONS

AODV	-	Ad hoc On-Demand Distance Vector
CCA	-	Common Channel Assignment
DARPA	-	The Defense Advanced Research Projects Agency
dBi	-	Decibel Isotropic
dBm	-	Decibel Milliwatt
DS	-	The Distribution System
DSR	-	Dynamic Source Routing
ESS	-	Extended Service Set
ETX	-	Expected Transmission Count
FSR	-	Fisheye State Routing
FTP	-	File Transfer Protocol
GA	-	Genetic Algorithm
GB	-	Giga Byte
GHz	-	Giga Hertz
GPSR	-	Greedy Perimeter Stateless Routing
HNA	-	Host and Network Association
HWMP	-	Hybrid Wireless Mesh Protocol
IANA	-	Internet Assigned Numbers Authority
IEEE	-	Institute of Electrical and Electronics Engineers
IETF	-	Internet Engineering Task Force
IMEP	-	Internet MANET Encapsulation Program
INRIA	-	Institute for Research in Computer Science and Automatic Control

IPv4	-	Internet Protocol version 4
IPv6	-	Internet Protocol version 6
Kbps	-	Kilo Bit per Second
MAC	-	Medium Access Control
Mbps	-	Mega Bit per Second
MPRs	-	Multipoint Relays
NN	-	Neural Network
ns-2	-	Network Simulator 2
OLSR	-	The Optimized Link State Routing
OLSR-MD	-	OLSR Minimum Delay
OLSR-PSO	-	OLSR using PSO
OLSR-PSOSIIW	-	OLSR using PSOSIIW
OSPF-MANET	-	Open Shortest Path First Mobile Ad hoc Network
OTcl	-	Object Tool Command Language
PHY	-	Physical
PSO-SIIW	-	PSO Sigmoid Increasing Inertia Weight
QOLSR	-	QoS OLSR
QoS	-	Quality of Service
RA-OLSR	-	Radio Aware OLSR
RFC	-	Request for Comments
RM-AODV	-	Radio Metric AODV
SA	-	Simulated Annealing
SDIW	-	Sigmoid Decreasing Inertia Weight
SYM	-	Symmetric
TBRPF	-	Topology Broadcast based Reverse-Path Forwarding
TC	-	Topology Change
TCP	-	Transport Control Protocol
TS	-	Tabu Search
UDP	-	Uni Datagram Protocol
ULP	-	Upper Layer Protocol
UM-OLSR	-	Module OLSR in ns-2 developed by University of Murcia, Spain

VINT	-	Virtual Inter Network Test bed
WDS	-	Wireless Distribution System
WLAN	-	Wireless Local Area Network
WMNs	-	Wireless Mesh Networks
ZRP	-	Zone Routing Protocol

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The need for Wireless Mesh Networks (WMNs) is necessitated by the desire arises because of the need to substitute for larger coverage using wireless infrastructure. The WMNs consist of mesh routers and mesh clients, where mesh router have minimal mobility and form the backbone of WMNs. They provide network access between mesh nodes (client or router) to existing networks. The integration of WMNs with other communication technologies such as IEEE 802.11, IEEE 802.15, IEEE 802.16, sensor networks, internet cellular etc can be achieved using mesh nodes in order to carry the data packets (Akyildiz et al., 2005). The WMNs use the existing physical (PHY) layer of the IEEE 802.11 a/b/g/n operating in the unlicensed spectrum of 2.4 and 5 GHz frequency bands (Zhang et al., 2007). Beside the capability for larger coverage, the WMNs can dynamically organize and configure itself in order to maintain connectivity between the nodes. These features become WMNs advantages for low cost installation, easy network maintenance, robustness, and reliable service coverage (Waharte et al., 2006; Zhang et al., 2007).

As the traffic nodes in the WMNs increase, so will the complexity of routing between nodes. WMNs also faced with the challenge of realizing efficient bandwidth sharing that generally effect quality of service (QoS) requirements such as throughput, delay and packet loss. For example, the data packet transmitted from the source node to the destination node through intermediate nodes is affected by delay transmission of packet due to the number of nodes it passed through in WMNs. One of the solution to the above matter is the design of routing scheme to support data transmission, since the link quality must fulfill user expectation (Aguiar et al., 2011). The WMNs share many common features with ad hoc networks, like routing protocol. The routing protocol in ad hoc network can be implemented in WMNs. Same characteristic between WMNs and ad hoc network allows for the sharing of property of routing protocol. The classification of routing protocol in WMNs will be explained in chapter 2.

The Optimized Link State Routing (OLSR) protocol is a well-known proactive routing protocol. It employs the classical shortest path based on the number of hop count for routes selection in wireless ad hoc (mesh) networks. It is developed by the French National Institute for Research in Computer Science and Automatic Control (INRIA) and has been proposed as standard at Internet Engineering Task Force (IETF) as experiment Request for Comments (RFC) 3626 (Automatique, 2003). The multipoint relays (MPRs) selection as substituted classical link state method for dividing network into subset of node to reduce broadcast that flood the WMNs. In the classical link state data packets re-transmitted by all intermediate nodes to give high probability each node will receive the data packets. It is simple and easy to implement but have some drawbacks regarding diffuse network with broadcast the data packets. This phenomenon in classical link state has already been examined and compared with MPRs selection by researchers (Viennot, 1998; A. Qayyum et al., 2002; Jacquet et al., 2006). They concluded that MPRs is an efficient technique used to minimize flooding packet through the entire WMNs.

However, if MPRs node increased as a result of the number of data packets, it will affect the QoS parameters such as throughput, end-to-end delay, and packet loss. This will result in more use at MPRs nodes to deliver the re-transmission data packets and floods in the WMNs. Another drawback of OLSR is that the MPRs selection cannot establish route in order to support the applications with QoS requirements. Therefore, the MPRs selection only build route without considering the QoS parameters. In order to solve this problem, many researchers propose methods of MPRs selection with different techniques so as to improve OLSR performance.

In early development of MPRs selection algorithm, the researchers applied the QoS parameter in selecting the MPRs node for delivering the data packets (Hakim Badis et al., 2003; Obilisetty et al., 2005; Cordeiro et al., 2007; Gantsou and Sondi, 2007; Nguyen and Minet, 2007). They proposed the QoS parameters such as available bandwidth, delay, loss rate, link stability and residual energy into MPRs selection. The achievement has been shown in the results in term of network performance. But the proposed methods cannot reduce the MPRs nodes while re-transmitting the data packets to minimize set of MPRs. Minimizing the MPRs node equally will decrease the number of nodes MPRs to broadcast the data packets.

Other methods using artificial intelligence techniques are introduced by researchers to use some advantages for improving MPRs selection algorithm performance in WMNs. Simulated annealing (SA), tabu search (TS), genetic algorithm (GA), greedy algorithm and neural network (NN) are method that have been proposed by researchers. These approaches enriched the development of MPRs selection algorithm in OLSR.

Chizari et al.(2010) examined the MPRs selection algorithm using three artificial intelligence technique (GA, TS and SA) and compared to standard MPRs selection algorithm. The proposed methods were evaluated in energy efficiency and propagation time. The energy efficiency and propagation time able to decrease with reducing the number of MPRs nodes. However, Chizari et al.(2010) did not observe further network benchmarks such as throughput, end-to-end delay and packet loss to prove the proposed method is good in term of QoS performance. Other researchers (Guo and Malakooti, 2007; Nguyen and Minet, 2007) also introduced greedy algorithm and NN applied in MPRs selection algorithm. Guo and Malakooti (2007) evaluated the proposed method using NN with end-to-end delay and packet delivery ratio as network benchmark. On the contrary, Nguyen and Minet (2007) only considered network density to examine their proposed method using greedy algorithm.

Existing methods of MPRs selection algorithm aim at reducing re-transmission node and maximizing the QoS performance for delivering the data packet in the WMNs with different scenarios. However, existing proposed methods are unable to meet with network performance requirements. The problem faced by MPRs selection in OLSR can be resolved with QoS parameters using particle swarm optimization (PSO) algorithm. This proposed method of MPRs selection can be adapted with network characteristic.

1.2 Problem Statement

Routing in the WMNs extends network connectivity to end users through intermediate node as multi-hop relay including mesh router and gateway (Waharte et al., 2006). Extending the network connectivity with larger number of nodes will cause transmission delay from source to destination node. If the time limit has been reached and the destination node still has not received the data packet, the source node will send again the data packet. The problem arises when more data packet flood into the WMNs thereby increasing network load. This will affect the QoS performance such as throughput, delay and packet loss in the WMNs.

An efficient technique to reduce flooding is introduced in OLSR using MPRs selection. The MPRs selection function selects the node of MPRs which have the obligation to forward data packet to other node in the WMNs. Many researchers found the new methods of MPRs selection to reduce re-transmission node and to maximize the QoS performance for delivering the data packet such as file transfer and voice applications in the WMNs. But the innovation is still wide open for proposing a new method of MPRs selection. Optimizing network utilization by reducing the node re-transmission and accommodating the QoS parameters will increase the network performance. Therefore, the propose algorithm should has good quality in term of QoS compare than standard MPRs selection in OLSR.

1.3 Aim and Objectives

The aim of the research is to propose an optimized the wireless mesh routing protocol (OLSR) using PSO in reducing re-transmission node and maximizing the QoS performance for MPRs selection in the WMNs.

The objectives of the research are:

1. To investigate the PSO parameters such as inertia weight for improving convergence speed and obtaining nearest optimum solution.
2. To design and develop a new method of inertia weight in the PSO process for optimal MPRs selection algorithm.
3. To design and develop the MPRs selection using standard PSO with new fitness function.
4. To design and develop the MPRs selection algorithm using proposed method of inertia weight of PSO.
5. To validate and evaluate the performance of proposed method of MPRs selection algorithm using proposed method of inertia weight of PSO on wireless router broadband.

1.4 Scope

The scopes of the research can be stipulated as follows:

1. Comparison of constriction factor and inertia weights (constant, linear decreasing, linear increasing, tracking and dynamic, and sigmoid decreasing) using four non-linear functions (Sphere, Rosenbrock, Rastrigrin, and Griewank).
2. Simulation and experimentation of proposed MPRs selection algorithm using File Transfer Protocol (FTP) and voice applications in N x 2 grid topology with number of nodes up to 50. Spacing among nodes are 1 and 200 m.
3. Throughput, end-to-end delay and packet loss were used for evaluate the proposed MPRs selection algorithm in OLSR.

4. Implementation and verification of the algorithm of MPRs selection using proposed method of inertia weight of PSO in wireless router.

1.5 Original Contributions

The original contributions of this research are:

1. The new method of inertia weight of PSO called PSO Sigmoid Increasing Inertia Weight (PSO-SIIW). This method considers the modification of the inertia weight to increase convergence ability and find near optimum solution.
2. The new method of MPRs selection in OLSR using standard PSO, delay and degree of willingness as new fitness function, for reducing the number of re-transmission node and improving QoS performance in WMNs. This method called OLSR-PSO
3. The propose PSO-SIIW is used for MPRs selection algorithm to improve the performance of QoS in WMNs.
4. The OLSR-PSOSIIW is examined in indoor environment (test bed) to validate and verify the performance obtained in simulation results.

1.6 Outline of Book

This book consists of six chapters. Chapter one, gives a general introduction on the importance of this research, problem statement, aim and objectives, scope, original contributions and outline of the thesis.

Chapter two provides an extensive overview of wireless mesh routing and particle swarm optimization, and describes the main background theory of this research: innovation milestones of PSO.

Chapter three describes the overview of Optimized Link State Routing Protocol, and describes the main background theory of this research: innovation milestones method of MPRs selection algorithm in OLSR.

Chapter four describes the methodology used in the simulations and experimentations.

Chapters five presents the analysis of the results and the discussions of the results and describe the analysis of simulation and experimental results. A detailed discussion of the new method of inertia weight of PSO called PSO-SIIW, MPRs selection using PSO (OLSR-PSO) and PSO-SIIW (OLSR-PSOSIIW), and experimental results are presented.

Chapter six presents the summary conclusions and the recommendations for future research.

CHAPTER 2

WIRELESS MESH ROUTING PROTOCOL

2.1 Introduction

The last decade has seen the rapid change of wireless technology, attracting end users by providing efficient communication. Wireless technology has become an important component in providing networking infrastructure for localized data delivery. This revolution has been changed by new paradigm which is becoming more and more popular: peer-to-peer communications, where wireless nodes communicate with each other and create ad hoc mesh networks independently of the presence of any wireless infrastructure.

Due to the complexity and limitation of WMNs which are associated with the increasing number of users, it becomes challenging to route data packet from source to destination node with good QoS performance. The wireless mesh routing protocol uses different approach to handle traffic in the WMNs. The reactive, proactive and hybrid are three type of wireless mesh routing protocol based on route discovery.

This chapter also describes and reviews some issues related to the improvement of PSO in many application. The advantages of PSO bring some benefit in the development of the applications. Inertia weight and increasing constriction factor that researchers are concern within improving the performance of PSO are presented.

2.2 Routing Protocol in Wireless Mesh Networks

The routing in WMNs can be categorized into two types of routing protocol: topology and position based as shown in Figure 2.1. Topology based uses topology information from node to select route in the networks. Position based uses location or position information of node in the networks such as Greedy Perimeter Stateless Routing (GPSR) (Karp and Kung, 2000). Based on route discovery, the topology based is divided into three types: reactive, hybrid and proactive. Reactive routing protocol initiates route computation when there is demand from node in the network. The source node asks permission to transfer the data packet and need a route for transmitting to destination node. If there is no change in the network then the route assumed remains valid. Therefore, when destination is unreached because the link is broken or the node is no longer available, then routing protocol will update routing table. A number of on-demand routing protocols have been proposed, for example Ad hoc On-Demand Distance Vector (AODV) (M. A. H. N. W. Group, 2003), Radio Metric AODV (RM-AODV) (T. I. W. Group, 2005), and Dynamic Source Routing (DSR) (N. W. Group, 2007).

In proactive routing protocol, the node regularly updates one or more routing table that contains routing information from other nodes. This process will apply to all nodes in the network and consistently update the routing table on topology change in the WMNs. A number of proactive routing protocols have been proposed, for example Optimized Link State Routing Protocol (OLSR) (Automatique, 2003), Radio Aware OLSR (RA-OLSR) (P802.11s™/D0.01, 2006), Topology Broadcast based Reverse-Path Forwarding (TBRPF) (N. W. Group, 2004), Open Shortest Path First Mobile Ad hoc Network (OSPF-MANET) (N. W. Group, 2010), and Fisheye State Routing (FSR) (I. M. W. Group, 2002). Hybrid protocols, like Zone Routing Protocol (ZRP) (I. W. Group, 2002) and Hybrid Wireless Mesh Protocol (HWMP) (P802.11s™/D0.01, 2006) use a combination of both proactive and reactive activities to collect route information for transmitting the data packet to the destination in WMNs.

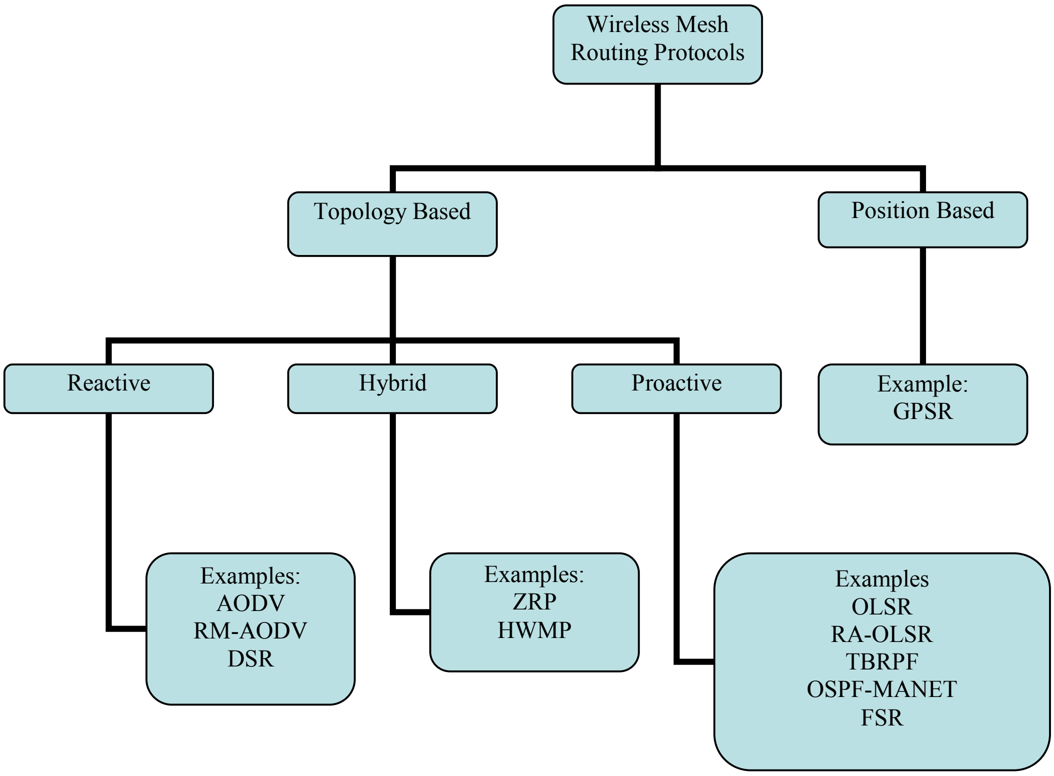

Figure 2.1 Classification of the wireless mesh routing protocols (Zhang et al., 2007)

The OLSR is one of proactive routing protocol designed for quick response in order to re-structure the routing table due to link failure and minimized the overhead for maintaining data packet in WMNs. The features become completed with advantage of OLSR using MPRs selection algorithm to cover weakness of proactive routing protocol. The efficient technique called MPRs selection algorithm embedded in OLSR is able to minimize the flooding through WMNs.

The development of MPRs selection algorithm has been proposed by researchers to improve the performance in term of QoS parameters. They modified the algorithm and evaluated in difference scenarios and applications. Reduce number of MPRs node and increase the QoS performance are main issue to solve the problem in MPRs selection.

In Corson et al. (1998) a heuristic approach for MPRs selection was proposed and documented as an internet draft. The draft describes multipurpose network-layer protocol called Internet MANET Encapsulation Program (IMEP) which is designed to support the operation of many routing algorithms, network control protocols and other Upper Layer Protocols (ULP) such as the algorithm of MPRs selection. The MPRs selection algorithm is defined by Viennot (1998), Qayyum et al.(2002), and Jacquet et al. (2006) as NP-complete problem. They analyzed and proved that the MPRs selection algorithm is NP-complete using dominating set. Qayyum et al.(2002) examined the MPRs selection algorithm with different approach with Viennot (1998) in term of NP-complete problem. The difference in their work is that Qayyum et al.(2002) used simulation approach and Viennot (1998) use mathematical analysis approach. The comparison between MPRs selection and classical link state routing protocol is simulated and analyzed by A. Qayyum et al.(2002). MPRs selection heuristic approach using dominating set problem was addressed by Garey and Johnson (1990). Simulation is done to compare two types of algorithms, which are pure flooding and MPRs heuristics, for the diffusion of packets in the radio network. Viennot (1998), Qayyum et al.(2002), and Jacquet et al. (2006) explained that flooding of data packet can effectively be reduced by the MPRs algorithm. The evaluation performances of MPRs selection that was proposed in Corson et al. (1998) was analyzed with analytical methods (generating function, asymptotic expansion) for indoor (random graph) and outdoor (unit graph) environment models by Minet et al.(2002). They (Minet et al., 2002) made comparison between MPRs OLSR with non-optimized link state routing protocols. These researches (Viennot, 1998; Minet et al., 2002; A. Qayyum et al., 2002; Jacquet et al., 2006) provided the proof of MPRs selection as efficient technique to minimize the flooding without examined using QoS parameters.

Other INRIA Technical Report written by D. Nguyen and P. Minet (2007) added QoS parameters such as available bandwidth, delay, loss rate and residual energy into MPRs selection. They made comparison in MPRs selection using non-QoS and QoS parameters respectively. This research set number of nodes up to 10,000 nodes is unrealistic scenarios if implement in real environment. The drawback of this approach is that QoS MPRs flooding generates more re-transmissions per flooded message than MPRs flooding in large and dense network.

The optimal path in MPRs selection using QoS parameters is an interesting issue for the enhancement of the OLSR. The methods of MPRs selection have been proposed for OLSR that select MPRs node by aiming to optimize some aspects related to QoS, such as bandwidth and delay. Two algorithms (QOLSR_MPR1 and QOLSR_MPR2) for MPRs selection based on QoS parameters are introduced (H. Badis et al., 2004). These approaches continue work from same authors to select MPRs node using bandwidth and delay as QoS parameters called QOLSR (Hakim Badis et al., 2003). In this study, the maximum bandwidth and minimum delay was chosen as QoS parameters to improve quality requirements of the MPRs selection and routing information. The comparison among standard OLSR, QOLSR, QOLSR_MPR1 and QOLSR_MPR2 were made in order to examine each methods so as to finding the optimum path. According with Leguay et al. (2006), QOLSR has a number of drawbacks. First, QOLSR does not have backward compatibility with other OLSR versions. TC and HELLO messages from QOLSR cannot be understood by standard OLSR (RFC 3626). Second, bandwidth and delay are very difficult to measure when using the IEEE 802.11 MAC layer. Third, QOLSR has lack of flexibility due to the responsibility to use bandwidth and delay as basic metrics.

Irrespective of the three methods mentioned above, the QoS parameters are used in different method of MPRs selection such as link stability (Obilisetty et al., 2005), link delay measurement (Cordeiro et al., 2007), and probability of delivery in data packet transfer (A. Qayyum et al., 2002; Gantsou and Sondi, 2007). Therefore, Härri et al.(2005), Obilisetty et al. (2005), and Gantsou and Sondi (2007) also combine probability or prediction approach using QoS parameters. The probability and prediction using QoS parameters cannot determine network density whether in small or large networks. This effect can increase MPRs size because of the collision occurring in the receiver nodes.

The OLSR based link delay measurement called OLSR-MD can be used to solve the weaknesses reported by Leguay et al. (2006). The OLSR-MD results demonstrate that the minimum delay metric performs best in terms of average packet loss probability (Staehle et al., 2009). An analysis of the throughput and per-flow delay reveals that OLSR-MD results in low throughput and high delay for nearly half of all flows. This happened because the one-delay are determined with small probe packets before setting up the routing topology without consider traffic characteristic. The link will experience higher delay or re-transmission due to congestion when larger data packets are sent on links in WMNs.

The artificial intelligence algorithm such as genetic algorithm (GA), simulated annealing (SA), tabu search (TS), greedy algorithm and neural network (NN) also contribute to the improvement of MPRs selection algorithm in OLSR. The MPRs selection using GA, SA and TS is introduced by Chizari et al. (2010). Nguyen and Minet (2007) and Guo and Malakooti (2007) are proposed the greedy algorithm and NN for achieving the improvement of the OLSR. These methods of MPRs selection aim to minimize node re-transmission by selecting the MPRs node and to deliver the data packet efficiently with less packet loss in WMNs. The drawback of these methods is the computation time consumed in the node when calculation the MPRs selection in WMNs.

2.3 Particle Swarm Optimization

PSO introduced by Kennedy and Erberhart (Kennedy and Eberhart, 1995) is a population based stochastic optimization technique inspired by fish schooling and bird flocking. A PSO algorithm maintains a swarm of particles as potential solution in search space dimension. In paradigm of evolutionary computation, a swarm is analogous to a population; a particle is analogous to an individual. The particles are flown through search space dimension, where the position of each particle is updated regarding to its own knowledge and that of its neighbors. The adjustment of trajectories have been made by each particle to get best position from its previous attained by any member of its neighborhood or globally, the whole swarm. Each particle moves in search space dimension with adaptive velocity and keeps the best position of the search space dimension it has ever visited. The searching of best particles will continue until a relatively unchanging state has been encountered or limit of generation/iteration has been exceeded.

Since its introduction, PSO has gone through many improvements and has successfully been used in many applications (see section 2.6). Improving convergence of the PSO and increasing the diversity of the swarm are among the most PSO modifications proposed by researchers (R. Eberhart and Kennedy, 1995). The advantages of PSO algorithm are its simplicity and ability to converge to good solutions. A number of modifications have also been made to the PSO including improving the speed of convergence and the quality of solution. Bai (2010) reported that the modifications in PSO could be categorized into four: inertia weights, increase convergence factor, selection and hybridization with other intelligent algorithms. The detail of the improvement in PSO will be discussed in section 2.6.

2.4 Particle Swarm Optimization Algorithm

The basic PSO concept consists of the position of the particle, velocity, social and cognitive component. The particles change its condition based on inertia weight, finding the condition according to its most optimist position and searching to the swarm's most optimist position. In the Figure 2.2, each particle flew searching its personal best position (*pbest*) and global best (*gbest*) positions at each time step. The *pbest* is the best position that the particle has visited since the first time step. Moreover, the *gbest* is the best value in the group among *pbest*. The *pbest* and *gbest* of particles are calculated as follows (Kennedy and Eberhart, 1995):

$$v_i^{k+1} = v_i^k + c_1 * rand(.) * (pbest - S_i^k) + c_2 * rand(.) * (gbest - S_i^k) \qquad (2.1)$$

where v_i^{k+1} is the velocity of particle *i* at time step *k*. Velocity (v_i^k) is weighted by a random term, with separate random numbers generated for velocity toward *pbest* and *gbest* positions. The fitness function is identified based on problem solved by PSO. The terms c_1 and c_2 are cognitive and social coefficients that influence the experimental knowledge of the particle and socially exchange information from the particle's neighborhood.

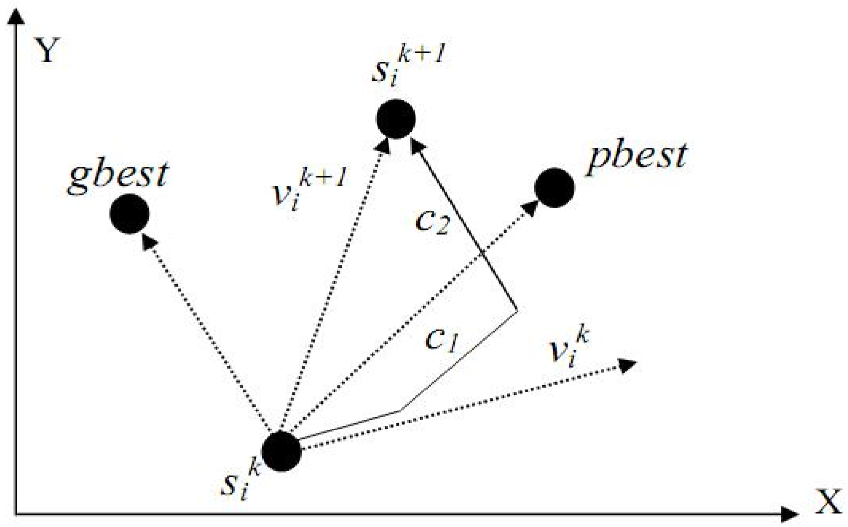

Figure 2.2 Particle movements in PSO

The process of PSO can be described as follows:

1. Initialize an array of population of particles, S[n], with random positions, S_i^k, and velocities , v_i^k, on dimensions in the problem space.
2. Evaluate the optimization of fitness function in variables for each particle.
3. Compare particle's fitness evaluation with particle's *pbest*. If current value is better than *pbest*, then set *pbest* position equal to current position in search space dimension.
4. Compare fitness evaluation with the population's overall previous best. If current value is better than *gbest*, then reset *gbest* to the current particle's array index and value, S_i^{k+1}.
5. Change the velocity and position of the particle according to equations (2.1) and (2.2) respectively:

$$v_i^{k+1} = v_i^k + c_1 * rand(.) * (pbest - S_i^k) + c_2 * rand(.) * (gbest - S_i^k) \quad (2.1)$$

$$S_i^{k+1} = S_i^k + v_i^{k+1} \quad (2.2)$$

where v_i^k, v_i^{k+1}, and S_i^k are velocity vector, modified velocity and positioning vector of particle i at generation k, respectively. The c_1 and c_2 are learning factors. Loop to step 2 until a criterion is met, usually a sufficiently best fitness or a maximum number of generations.

2.5 The Advantage of Particle Swarm Optimization against Genetic Algorithm

Evolutionary computations are stochastic population based on optimization approach that is inspired by the behavior of nature. Comparison of PSO with other evolutionary computation especially with genetic algorithm (GA) has been done by other researchers such as (Angeline, 1998; R. C. Eberhart and Shi, 1998; Boeringer and Werner, 2003; Elbeltagi et al., 2005; Hassan et al., 2005; Jones, 2006; Panda and Padhy, 2008). All evolutionary computation processes have same paradigm, which are updating the population by applying some iteration/generation. Thus, the similarity between the techniques is that they do not require gradient information of the fitness function to be considered. However, all techniques begin with a group of a randomly generated population and utilize a fitness value to evaluate the population. Thus, searching process is done in parallel based on the population. Finally, the particles update the population and search for the optimum value based on the objective of fitness function.

The main difference between the PSO and GA is that PSO does not have genetic operators, such as crossover and mutation as in GA. The population will change when the particle in PSO updates its velocity. In GA, the chromosome share information with each other. Thus, the population moves like one group towards an optimal value based on objective of fitness function. In PSO, only the best particle carries the information to others. All particles are kept as members of the population in PSO through the direction of the run.

Based on computation process, there are some advantages of PSO compared to other evolutionary algorithms. PSO is easy to implement and computationally inexpensive since its memory and CPU speed requirements are low (Hassan et al., 2005; Jones, 2006). Jones (2006) states that GA needs at least ten steps to realize a basic GA and basic PSO needs only five steps. Furthermore, the PSO requires less parameter to be adjusted than others. Thus, the PSO has quick convergence ability in searching for optimum or near-optimum solution (Angeline, 1998). It can be concluded that PSO has been proven to be an efficient method for numerous general optimization problems (Kennedy and Eberhart, 1995).

2.6 Improvement of Particle Swarm Optimization

As far as PSO algorithm is concerned, solution swarm is compared to the bird swarm, the birds' moving from one place to another is equal to the development of the solution swarm, good information is equal to the most optimist solution, and the food resource is equal to the most optimist solution during the whole course. The most optimist solution can be worked out in the PSO algorithm by the cooperation of each individual. The particle without quality and volume serves as each individual, and the simple behavioral pattern is regulated for each particle to show the complexity of the whole particle swarm. This algorithm can be used to work out the complex optimist problems.

The PSO has been remarkably successful in a number of problems and applications such as:

- antenna design (Jin and Rahmat-Samii, 2008; W. T. Li et al., 2008)
- communication networks (Jiabin et al., 2010; Xuemei et al., 2010)
- wireless routing (Shahzad et al., 2010; Xuemei et al., 2010)
- control (Oliveira et al., 2009; Wei and Kangling, 2009)
- distribution networks (Alinejad-Beromi et al., 2008; Qianjin and Chuanjian, 2010)
- robotics (Vatankhah et al., 2009; Adam et al., 2010; Ma and Lei, 2010) and etc as reported by Poli (2008).

Engelbrecht (2006) added the improvement of PSO also including standard function optimization problems (Angeline, 1998; Ho et al., 2006; Jong-Bae et al., 2006), training multi-layer neural networks (Chaurasia and Daware, 2009; Ye, 2009; Zhang Yu et al., 2010) and solving permutation problems (Zhixiong and Shaomei, 2006; Moraglio and Togelius, 2010).

The PSO proved to be able to solve various numbers of problem and applications for improving performance. The application research involves continuing its advantages, overcoming its shortcomings and developing its application ranges. Among the optimization algorithm, PSO become the solution for solving the problems that only require less computation process and memory. These advantages give opportunity to our research in OLSR especially MPRs selection algorithm to achieve better performance and compete with standard OLSR.

In Bai (2010) it was shown in that there are four parameters that researchers focused on in order to improve on PSO in several applications including wireless mesh routing protocol. The parameters are inertia weight, increase convergence factor, selection mechanism and hybridization with other intelligent algorithms. According Bai (2010), these parameters are the most that researchers are conceded with to modify the PSO process and to get better performance when implemented in systems or applications.

In the next section, we focus on the inertia weight and the convergence factor only, because their functions are able to fulfill the requirement of MPRs selection in OLSR and replace the standard one. Comparative analysis is conducted using several methods of inertia weight and convergence factor to find suitable method for improving MPRs selection performance in OLSR.

2.6.1 Inertia Weight

The concept of an inertia weight was developed in order to provide better control of exploration and exploitation. The aim of inertia weight was to be able to control the exploration and exploitation mechanism and to ensure convergent behavior. Exploration is the capability of search algorithm to search different search space dimension in order to find a good optimum. On the other hand, exploitation is the capability to concentrate the search around a promising area in order to refine a candidate solution. The balance between exploration and exploitation provides optimum optimization algorithm. Thus, these objectives are addressed by the velocity update equation.

The inclusion of an inertia weight parameter in the PSO algorithm was first published in 1998 (Shi and Eberhart, 1998a) and the impact of inertia weight is analyzed in (Shi and Eberhart, 1998b). The inertia weight (w) controls the momentum of the particle by weighting the contribution of the previous velocity.

Equation (2.3) and (2.4) describe the velocity and position update equations with an inertia weight. It can be seen that these equations are identical to equations (2.1) and (2.2) with the addition of the inertia weight (w) as a multiplying factor of v_i^k in equation (2.3).

$$v_i^{k+1} = w * v_i^k + c_1 * rand(.) * (pbest - S_i^k) + c_2 * rand(.) * (gbest - S_i^k) \qquad (2.3)$$

$$S_i^{k+1} = S_i^k + v_i^{k+1} \qquad (2.4)$$

Engelbrecht (2006) divided two types of inertia weight (w) based on value:

- For $w \geq 1$, velocities increase over time, accelerating towards the maximum velocity with limited using velocity clamping and the swarm diverges. Particle failed to change direction in order to move back to promising areas.
- For $w < 1$, particles decelerate until the velocities reach zero. Reaching zero value depend on the values of the acceleration coefficients (c_1 and c_2).

If value of inertia weigh is set larger it facilitates exploration with increased diversity. And smaller value of inertia weight promotes local exploitation. On the other hand, when the value of inertia weight is too small it will eliminate the exploration swarm capability. But for the smaller inertia weight, the position update will be able to be controlied by the cognitive and social components.

Five different approaches to vary the inertia weight are introduced by Engelbrecht (2006) briefly as follows:

- **Random adjustments**, where different inertia is randomly selected at each iteration. The random inertia weight is calculated using Gaussian distribution (Jinchun et al., 2000; Pant et al., 2007).

- **Linear decreasing**, where an initially large inertia weight (usually 0.9) is linearly decreased to a small value (usually 0.4) (Shi and Eberhart, 1999).

- **Nonlinear decreasing,** where initial large value decreases nonlinearly to a small value. Nonlinearly decreasing methods allow a shorter exploration time than the linear decreasing methods, with more time spent on refining solutions (exploiting). There are many researchers proposed nonlinearly decreasing methods such as sigmoid function (Adriansyah and H.M.Amin, 2006), nonlinear function modulated inertia weight adaptation with time varying (Chatterjee and Siarry, 2006), tracking and dynamic system (R. C. Eberhart and Shi, 2001) and develop velocity updates without the cognitive component (Clerc, 2001).

- **Fuzzy adaptive inertia,** where the inertia weight using fuzzy logic sets and rules (Shi and Eberhart, 2001). Shi and Eberhart (2001) define a fuzzy system for inertia adaptation to consist of:
  - Two inputs, one represent the fitness of the global best position, and the other is the current value of inertia weight.
  - One output to represent the inertia weight change
  - Three fuzzy sets, LOW, MEDIUM and HIGH, consecutively, represented as a left triangle, triangle, and right triangle membership function (Shi and Eberhart, 2001).

- **Increasing inertia,** where the inertia weight is linearly increased from 0.4 to 0.9 (Yong-Ling et al., 2003a, 2003b).

Moreover Engelbrecht (2006) describes four parameters of type of inertia weight, that are type of inertia weight proposed by other researchers:

- (Shi and Eberhart, 1998b) proposed **constant inertia weight.** Shi and Eberhart (1998b) proposed constant inertia weight to define relationship between maximum velocity (*Vmax*) and inertia weight. It is concluded the *Vmax* is small (≤ 2) and the inertia weight set to 1. When *Vmax* ≥ 3 then the inertia weight set to 0.8. Another method of